ESSAYS ON THE ECONOMIC VALUATION OF FLOOD RISK

by

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Abstract

The frequency and intensity of flooding has increased over the last few decades. The UK is not an exception, despite large amounts of money invested every year in flood risk management, flooding is a prevalent issue in the country causing millions of losses every year. In this thesis we contribute to debate on the economic valuation of flood risk in the UK from a household perspective using a non-market valuation approach from the housing market. In the first chapter we investigate the capitalisation of flood risk in property prices by means of a meta-analysis. In the second and third chapters we use a repeat-sales specification of a hedonic model to investigate the capitalisation of flood defences and the effect of flooding in the price of properties in England. The results suggest that the current benefit estimates used by the UK Government to determine the allocation of resources to flood relief projects results in a misallocation of resources. We highlight the importance of rethinking the strategy for flood risk management in the UK. Our results provide a sound economic basis to guide the allocation of resources for flood alleviation strategies in a socially efficient way.

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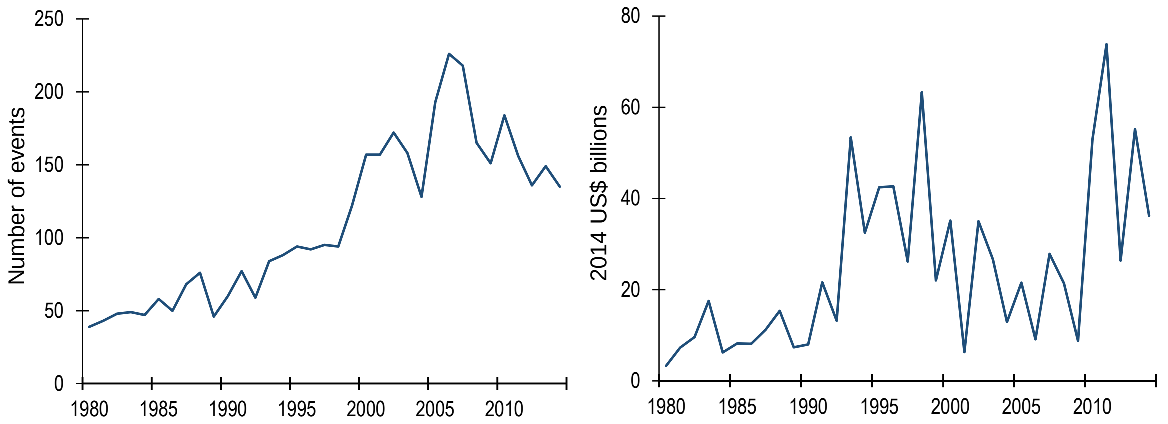
Introduction

Floods are the leading cause of natural disaster-related deaths worldwide (Guha-Sapir et al., 2013). Since the mid-20th century there has been a marked increase in the frequency of floods and related damages. Although part of this increase is attributed to improvements in reporting (Kundzewicz et al., 2013), there is general agreement that events since 1980 have been well documented (Di Baldassare et al., 2010; Jongman et al., 2012). Figure 1.A shows the evolution of the number of major flood events worldwide for the period 1980 – 2014. During this period, the number of floods reported every year worldwide has increased from an average of 50 floods in the 1980s to over 160 during the last decade (EM-DAT, 2016). The increase in the number of events has been accompanied by an increase in related damages. Figure 1.B shows that yearly flood damages increased from an average of US$ 9 billion per year in the 1980s to some US$ 31 billion in the last decade (2014 prices) (EM-DAT, 2016). This upward trend is associated with a greater exposure and vulnerability to floods due to population increase and urbanization in flood-prone areas, and it is expected to continue in the future as a consequence of climate change (IPCC, 2014; Kundzewicz et al., 2013; Peduzzi et al., 2009). By 2050 flood losses are expected to exceed 1 trillion USD annually (Munich Re, 2013; World Bank, 2013).

Figure 1. Flood events and flood damages reported worldwide, 1980-2014

1.A. Number of flood events **1.B. Flood damages**



Source: EM-DAT, 2016.

Floods are a major issue in many regions of the world (IPCC, 2012; Ahern et al., 2005). During the period 2000-2014 floods accounted for an average of 50% of the natural disasters worldwide (Guha-Sapir et al., 2015). However, the absolute and relative exposure to floods varies considerably between regions. For the period 2000-2014, Asia is the region which has been most affected by flooding in terms of number of flood events (39%). It is also the region with the greatest number of individuals affected by flooding with around 94% of the total affected population. However, Europe is also largely affected by flooding. Although it is the fourth region most affected by flooding (below Asia, Africa and the Americas) and the number of flood victims in the region represent less than 1% of the total affected population, it is the second region with the highest value of flood damages (23%), just below Asia. Total flood damages in Europe accounted for over US$ 4 billion in 2014. Averaged over 2000 to 2014 flood damages in the United Kingdom (UK) accounted for 43% of total flood damages in Europe.

In the UK flood risk is a significant policy issue. After a relatively dry period, the Easter river floods in 1998 generated renewed interest in the management of flood risk (Lamond, Proverbs and Hammond, 2010; Bye and Horner, 1998). This was a historical flood with a scale and extent that broke records set by the 1947 Great Floods, causing damages of over £350m. This interest was further reinforced by widespread flooding across much of England during autumn 2000 with an estimated cost of the order of £1.0bn (EA, 2001), and the summer floods in 2007 where over 55,000 properties were flooded causing total damages of around £3.2bn (EA, 2010). Following the 2007 floods, the UK Government invited Sir Michael Pitt to conduct an independent review on the response to the flood event for England and Wales; this report was published by June 2008 (Pitt, 2008). The report consists of an assessment of what happened during the flood emergency and a total of 92 recommendations to improve the response to flood events and management of flood risk. Recommendations cover a range of topics from prediction and warning of flooding, to emergency management, resilience and recovery. A total of £60 million for the period 2008 – 2011 was allocated to implement the recommendations (DEFRA, 2009).

In 2009 the Environment Agency (EA) published the first national assessment of flood risk for England and Wales (EA, 2009a, 2009b). The assessments emphasises the importance of understanding the national and spatial dimension of flood risk in the UK. The final report of the Government's Response to Sir Michael Pitt's Review was published by the Department for Environment, Food and Rural Affairs (DEFRA) in 2012 (DEFRA, 2012). This report highlights the actions undertaken by the Government in response to the recommendations included in the Pitt Review (Pitt, 2008). By 2012, 43 recommendations were fully implemented, 40 more were implemented with ongoing work continuing and 6 were on track of completion by a particular date[1]. Among the most notable contributions we can mention an update of the legislative framework through the Flood Risk Regulation 2009 and the Flood and Water Management Act 2010; together they provide a more comprehensive management of flood risk for people, homes and business.

The National Flood Emergency Framework was published in 2010 and the National Flood and Coastal Erosion Risk Management Strategy in 2011. The 2010 Comprehensive Spending Review for England (2011-12 to 2014-15) provided a total of £2.17 billion in central government funding for the building and maintenance of new and existing flood defences, which represents an average expenditure of £542.5 million per year (Bennett and Hartwell-Naguib 2014). Important actions were also undertaken for prediction and

[1] The remaining three recommendations where categorized as not completely implemented, not now taken forward or not for the Government (see DEFRA, 2012).

warning. The First UK Climate Change Risk Assessment was published in 2012, significant resources were allocated to the Met Office to improve its forecasting of severe weather events and the Flood Forecasting Centre (FFC) was established (DEFRA, 2012).

Despite the actions taken to manage flood risk and an increasing amount of resources allocated to prevention and warning (DEFRA, 2012; EA, 2009a, 2009b), flooding remains a serious problem throughout the country. In 2012, several floods occurred across the country resulting in an estimated cost to the UK economy of close to £600m (Met Office and JBA, 2012; EA, 2013). During the winter 2013/2014 extreme weather conditions caused widespread flooding in the south of England leading to total economic damages of £1.3bn; the greatest proportion of these damages correspond to residential properties (Met Office, 2014; EA, 2016). More recently, storms Desmond and Eva caused severe flooding during December 2015-January 2016 in the north of England with flood damages estimated on the order of £1.3bn (Met Office, 2016; ABI, 2016). After the most recent flood crises, Helm (2016) has called for a radical rethink and restructuring of the UK Government’s approach to flood defences; one which puts the economic valuation of flood risk on a sound economic basis.

It is estimated that as of 2014 a total of 2.8 million residential properties in England are exposed to some level of risk, 25% of them are properties exposed to the highest level of risk (75-year return period or greater). The expected direct annual damages to residential properties amounts to £270m (Sayers et al., 2015). Moreover, flood risk is expected to increase as a consequence of climate change. The projections of future flood risk for the UK Climate Change Risk Assessment 2017 suggest that for a scenario assuming no population growth the number of properties in England exposed to the highest level of risk could increase between 43 and 130% in 2080, with an increase in direct annual damages between 47 and 470%. This represents expected annual damages in the range of £397m to £1.5bn by the end of the century (Sayers et al., 2015). This increase is only due to changing weather conditions and different climate change scenarios. If we consider the effect of population growth, new developments will add to future costs of flooding. The UK Committee on Climate Change (2015) points out that each year 4,600 new homes are built in areas exposed to significant flood risk, almost 50% of these correspond to properties at the highest level of risk.

In this thesis we contribute to the debate on the economic valuation of flood risk in the UK from a household perspective using a non-market valuation approach from the housing market. The prevalence of flooding together with the continuous development on floodplains and the expected increase in flood risk due to climate change highlight the importance of understanding the implications of flooding to households.

Economic theory suggests that residential housing markets provide a way to estimate consumer's willingness to pay (WTP) to reduce flood risk. If a property is subject to frequent flooding the owner may incur substantial repair costs and additional associated flood losses. All these future costs might easily exceed the cost of buying an equivalent property outside the flood risk area. Therefore, in a housing market with flood risk, individuals will bid up the price of properties that reduce the chances of being flooded. The resulting price differential between properties inside and outside the floodplain reveals an individual's WTP for flood protection and can be interpreted as a measure of the benefits associated with a reduction in flood risk. Throughout the three chapters that comprise this thesis we investigate the capitalisation of flood risk in property prices and the economic benefits of flood protection to English households.

In the first chapter we investigate whether flood risk is capitalised in property prices by means of a meta-analysis. Numerous authors have explored the price differential for floodplain location on property prices for both coastal and inland areas. The results however, are somewhat variable and in several cases the findings suggest the existence of a price premium rather than a discount. Given the broad heterogeneity in results, it is not possible to conclude to what extent (if any) flood risk is capitalised into property prices by simply reviewing existing studies. The objective of our meta-analysis is to summarise and explore the wide study-to-study variation among empirical results and to provide a useful figure to guide policy decisions.

The results suggest that there are marked differences in the capitalisation of flood risk across different types of flooding. For properties exposed to fluvial flood risk, floodplain location is associated with a price discount on the order of 5%. The level of risk and the flooding history in the location are especially important in determining the extent of the discount. Our findings support the idea that recent experience with flooding provides new information to homeowners to update their subjective perception of flood risk. The discount is greater immediately after a flood, but then decreases as time elapses. For properties exposed to coastal flood risk, floodplain location is associated with a price premium. However, this effect is likely to be driven by biased results due to a high correlation between flood risk and coastal amenities.

For the second and third chapters we use a repeat-sales specification of a hedonic model to investigate the capitalisation of flood defences and the effect of flooding on the price of properties in England. For this purpose, we exploit big data on property prices in England and high resolution GIS data available from government agencies. Our final dataset includes information on over 12 million individual property transactions, representing about 4.8 million houses with at least one repeat-sale during the period 1995-2014. By looking at two sales of the same property, we avoid the use cross-sectional approach prevalent in the existing literature, which for identification requires controlling for a large number or factors (some of them non-observable) potentially influencing house prices.

In the second chapter we estimate the economic benefits of flood protection in England. The current methodology for assessing the benefits of flood protection in the UK follows a damage cost approach. The resulting figures reflect the costs of flooding rather than the economic value of risk reduction. This approach favors the construction of projects that provide the maximum standard of protection at the least cost. It does not consider individual’s preferences towards different flood alleviation strategies, nor does it incorporate the potential negative externalities of flood defences in the valuation process. Helm (2016) argues that this methodology does not represent a sensible approach to determine the allocation of resources. In this chapter, we suggest the use of the WTP as an economic measure of value to guide the allocation of resources for flood protection.

In particular, we are interested in measuring the capitalisation of flood defences into the price of properties. For this purpose, we merged our dataset containing information on property prices with high resolution GIS data from the UK National Flood and Coastal Defence Database (NFCDD) which indicates the location and main characteristics of flood defences in England. To the best of our knowledge, this is the first empirical contribution that uses difference-in-difference (DID) approach to measure the ex-post economic benefits of structural flood protection. The results indicate that the extent to which the benefits of flood protection capitalise in the price of properties depends mainly on the characteristics of the defence, the type of property and the type of flood risk. We highlight the existence of negative externalities associated with the environmental disruption of flood protection that, under certain circumstances, can result in a reduction of property prices. These potential negative impacts are not currently considered for the allocation of funding to flood relief projects. The results suggest that the use of the current methodology to estimate the benefits of flood protection results in a misallocation of resources. Our results provide an alternative for deciding how much to spend, and what and where to spend it.

Finally, in the third chapter we estimate the effect of a flood on the price of properties in England and provide some insight in the post-flood recovery of prices. This is a relevant topic in England where flooding represents an increasing threat to households and new developments continue to be constructed in the floodplain. Authors such as Lamond, Proverbs and Hammond (2010) and recent media articles by Brignall and Jones (2016) document the fear of homeowners that flooding will lead to a decrease in value of their major asset. Unlike most of the previous hedonic applications that analyse the effect of a flood on the price of properties in the floodplain, we focus on the evolution of the price of properties in areas recorded as having been inundated. Our analysis goes far beyond the scale of existing empirical studies which focus on a single or multiple sites, conducting a comprehensive analysis considering all individual flood events on records in England between 1995-2014.

In this chapter, we merge our database containing information on property prices with high resolution GIS data from the EA delineating the area affected by flooding for each individual flood event during the period of analysis. We use a DID specification to measure the change in the price of properties affected by flooding, and we exploit the panel data structure of our data to track the evolution of prices after a flood. The results suggest that, after a flood, there is a decrease in the price of affected properties. The discount is associated with flood damages and the information effect of a flood on affected properties. The extent of the discount depends mainly on the type of property and the characteristics of the flood. The discount is, however, transitory and prices recover as time elapses and individuals invest in repairing flood damages and the memory of the event fades. The results provide useful policy guidance to identify the longer term welfare impact of flooding on households.

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Chapter 1

Is flood risk capitalised into property values? A meta-analysis approach from the housing market

N.B. During the preparation of this Thesis, previous versions of this chapter were submitted for presentation at the following conferences. In some cases these had been made public as part of the conference proceedings. When this is the case I include the link to the corresponding webpage.

- June, 2015. Annual Conference of the European Association of Environmental and Resource Economists (EAERE), Helsinki, Finland. [http://www.webmeets.com/files/papers/eaere/2015/618/Meta_Analysis_FloodRisk_Helsinki.pdf]

- September, 2014. Meta-Analysis of Economic Research Network, MAER-Net 2014 Colloquium, Athens, Greece. [http://slideplayer.com/slide/5270735/] [http://metaanalysis2014.econ.uoa.gr/papers.html]

- July, 2014. EAERE-FEEM-VIU European Summer School on the Economics of Adaptation to Climate Change, Venice, Italy.

- April, 2014. Midlands Regional Doctoral Colloquium, University of Nottingham, United Kingdom.

Abstract

Economic theory suggests that benefits of flood risk reduction are reflected in the price differential of comparable properties located within and outside a floodplain. Empirical evidence suggests this differential ranges anywhere between -75% – +61%. This chapter shows the results of a meta-analysis on the price differential for floodplain location. The objective is to summarize and explore the wide study-to-study variation among empirical results and to provide a useful figure to guide policy decisions. The final meta-sample includes 37 studies and 364 point estimates. The results suggest there are important differences across different types of flooding. Estimates for river regions vary anywhere from -7% to +1%, depending on the level of risk and the time with respect to the previous flood. The results of the meta-regression analysis indicate that the dependent variable is highly sensitive to differences in the context of the study. In all cases the coefficients support the idea that the effect of a flood on property prices diminishes as time elapses. The results for coastal regions suggest that properties in the floodplain are sold at higher prices; this effect is likely to be driven by biased results due to a high correlation between flood risk and amenity benefits from proximity to coast. Although there is some evidence of publication selection in specific areas of the flood risk literature this does not appear to affect the main conclusions.

Keywords: Flood Risk, Meta-analysis, Meta-regression, Hedonic Valuation

JEL Code: Q51, Q54, R21

1.1 Introduction

Floods are the leading cause of natural disaster related deaths worldwide (CRED, 2012). During the last 15 years the frequency and intensity of floods has risen rapidly, and this trend is expected to continue as a consequence of climate change (IPCC, 2012; UNISDR, 2011; Visser et al., 2012). This increase in the number of floods has been accompanied by an increase in related damage costs. Estimated economic losses in 2012 exceeded US $19 billion globally, and by 2050 are expected to exceed US $1 trillion annually (Munich Re, 2013; The World Bank 2013). As a result, flood risk is now a significant policy issue.

It is a generally held view that it is not technically feasible, nor economically affordable to prevent all properties from flooding (EA, 2009a, 2009b). Attention has been devoted to the issue of resource allocation for flood risk reduction. Economic analysis of flood management measures is useful since it can be used to guide policy decisions regarding the choice of flood risk reduction measures by comparing the benefits and costs of each alternative, and identifying the measure which offers the greatest net benefits. This allows scare resources allocated to disaster management to be used as efficiently as possible. Under these circumstances a critical question is, what are the benefits from flood risk reduction?

Economic theory suggests that residential housing markets provide a way to estimate consumer’s willingness to pay (WTP) to reduce flood risk. In an efficient housing market prices of properties located within a floodplain should be lower than observationally equivalent housing units located outside. This price differential can be interpreted as a measure of benefits for living in an area with lower risk. Following this reasoning, several authors have measured the effect of floodplain location on property prices, their results range from a discount of 75% to a premium of 61%. In not a few cases the findings are contradictory regarding the direction of the impact of flood risk and how the price schedule evolves after a flood in regions with different levels of risk. Therefore, from the literature available it is difficult to conclude what is the impact of flood risk on property prices.

In this chapter, we present the results of a meta-analysis on the relative price differential for floodplain location. The objective is to summarize and explore the wide study-to-study variation among empirical results to provide a useful figure that can be used as a measure of the benefits from flood risk reduction and guide policy decisions. There is one previous meta-analysis on this topic by Daniel, Florax and Rietveld (2009a). The authors use a meta-sample consisting of 19 studies and 117 point estimates, and focus only in the use of meta-regression analysis to explore the heterogeneity in previous results considering a set of 18 moderator variables accounting for differences in the space-time features of studies, study design and control variables included in primary studies. However, we believe that the understanding of factors driving the heterogeneity in the results can be improved. The recent debate in the economics of flood risk emphasises that individuals poorly integrate risk into their decisions; however, recent experience with flooding raises perception of risk and the associated price differential in the housing market. Authors such as Bin and Landry (2013) and Atreya, Ferreira and Kriesel (2013) find evidence indicating that the information effect of flood events diminishes as time elapses; it is not clear, however, the functional form of this process and how it operates in regions with different level of risk.

We believe that differences in flood risk perception play an important role in determining the heterogeneity in previous results.

The contributions of this meta-analysis are manifold. First, it extends the literature survey by providing an up-to-date literature review and extending the quantitative analysis with a meta-sample consisting of 38 studies published between 1987 and 2013, with a total of 364 point estimates; that is doubling the number of studies considered in the previous meta-analysis, and more than trebling the number of point estimates. Second, it adds more content to the analysis by considering important theoretical differences among estimates from primary studies with different econometric specifications. Third, it deepens the analysis by exploring the distribution of effect sizes considering different sources of flooding and different levels of risk, and by using meta-analysis techniques to help to provide a common measure of the property price differential for floodplain location under different circumstances. Fourth, it expands the previous study by using meta-regression analysis to explore the heterogeneity of point estimates by different sources of flood risk, different levels of risk and different econometric specifications. Fifth, it contributes to the recent debate on flood risk capitalisation and flood risk perception by including moderator variables to account for differences in flood risk perception, among regions and through time. Finally, it considers additional statistical tests exploring the existence of publication bias in the flood risk literature.

The results of the meta-analysis suggest that there are important differences across different types of flooding. Estimates for river regions vary anywhere from -7% to +1%, depending on the level of risk and the time with respect to the previous flood. The evidence supports the widespread idea that recent floods provide new information to homeowners to update their flood risk perception; however, pre-flood information available appears to play a role in determining the extent of the update. The results of the meta-regression analysis indicate that the dependent variable is highly sensitive to differences in the context of the study. In all cases the coefficients support the idea that the effect of a flood on property prices diminishes as time elapses. There is very little evidence from studies analysing the impact of flood risk in coastal properties; thus no meaningful conclusions can be drawn for these regions. In any case, the results suggest that properties exposed to coastal flood risk are sold at higher prices than those outside the risk area; this result is likely to be driven by biased results due to a high correlation between flood risk and benefits from proximity to coast.

The remainder of the chapter is divided as follows. Section 1.2 outlines the theoretical framework of the hedonic model to describe the impact of flood risk on property prices. Section 1.3 describes the evolution of the empirical evidence and the different applications of the hedonic framework to the flood risk literature. Section 1.4 presents a meta-analysis of the percentage change in house prices per unit of change in the probability of flooding. This section includes: a) the definition of the relationship of interest; b) a systematic literature review describing the collection and coding of relevant studies and; c) meta-analysis and meta-regression analysis results. Section 1.5 addresses the issue of publication bias in the flood risk literature, and section 1.6 concludes.

1.2 The Theoretical model

Flooding imposes costs on all sectors of societies including households. Economic theory suggests that residential housing markets provide a way to estimate consumer’s WTP to reduce flood risk. This idea is based on an early preposition by Ridker and Henning (1967) who suggest that if costs derived from housing rise (e.g. if additional maintenance and cleaning costs are required), the property will be discounted in the market to reflect people's evaluation of these changes. Therefore, price of houses located within a floodplain should be lower than equivalent houses located outside floodplains. The observed price differential reveals the WTP for different lower levels of flood risk (Holway and Burby, 1990).

After the characterization of the hedonic price function (HPF) by Rosen (1974), the hedonic price model (HPM) has been the preferred framework to describe the effect of flood risk on property prices. The HPF allows us to describe the price of a quality differentiated commodity as a function of its various quality attributes. Residential properties are composite goods with a variety of attributes; therefore the price of the property is assumed to represent the value of the collection of these attributes (Bin and Kruse, 2006). In this way, observing how property values change as the level of specific attributes changes, ceteris paribus, allow us to estimate the contribution to the total value attributable to each characteristic (Bin and Kruse, 2006; Atreya and Ferreira, 2011).

The objective of this section is to describe the theoretical framework of the hedonic model that describes the impact of flood risk on property prices. Section 1.2.1 describes the standard hedonic price model, and section 1.2.2 introduces flood risk and uncertainty using an expected utility framework. Sections 1.2.3 through 1.2.5 expands the model to consider different aspects such as the role of flood insurance, information, and the presence of amenity values correlated with location and the level of risk.

1.2.1 The Basic Hedonic Model

Following Rosen's (1974) proposition of the hedonic price function, let $\boldsymbol{S}$ represent a set of structural characteristics of a house such as age, number of bathrooms and lot size; $\boldsymbol{N}$ the neighborhood/locational characteristics such as crime rate, distance to central business centre or to a major motorway, and $\boldsymbol{E}$ environmental characteristics such as the level of pollution. Define $Z = \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{E}$. Then, the HPF describing the price of a property, P, might be written as:

$$P = P(Z) \tag{1}$$

Prices are assumed to be market clearing, given the inventory of housing choices and their characteristics. The housing market is assumed to be in equilibrium which requires that individuals optimize their residential choice based on the prices of alternative locations. It is assumed that homebuyers are able to adjust the different levels of each characteristic by moving their residence; no transaction costs are considered.

The marginal implicit price for Z in the market is given by ${}^{\partial P}\!/_{\partial Z}$, i.e. the increase in expenditure on a house required to obtain a house with one more unit of Z. Households are assumed to derive utility from Z, as well as from a numerarie commodity, Q, representing all other consumption goods with the price implicitly scaled to 1. Thus, the utility function of a household can be represented as:

$$U(Z, Q) \tag{2}$$

where $U(\cdot)$ is assumed to be bounded, increasing, and strictly concave in all arguments. The rational consumer will choose to live in a house with a level of Z that maximizes his utility, subject to a budget constraint given by:

$$M = P(Z) + Q \tag{3}$$

where M is total income. Thus, the first order condition for optimization is given by:

$$\frac{\partial P}{\partial Z} = \frac{\partial U / \partial Z}{\partial U / \partial Q} \tag{4}$$

Equation (4) shows that the optimal choice of a house is characterized by a level of Z such that the marginal rate of substitution between Z and the composite commodity, i.e. the marginal WTP for additional units of Z, equals the implicit price of Z in the market.

Since the work by Rosen (1974) many studies have applied the HPM to estimate the marginal WTP of individuals for specific housing characteristics; the valuation of environmental attributes has received special attention. For example, Wolverton (1997) estimates the amenity value associated with scenic view in Tucson, Arizona, US; Garrod and Willis (1992) focus on the value of woodlands in the UK; Tapsuwan et al. (2009) study the value of wetlands in a city in Western Australia; Nelson (2010) focuses on the value of proximity to lake and ski recreation areas at Deep Creek Lake, Maryland, US, and Gibbons, Mourato, and Resende (2014) estimate the value of proximity to habitats and natural areas in various cities of the UK, to name but a few. The impact of disamenities on property prices has also been considered; some examples include Smith and Deyak (1975) who estimate the effect of air pollution in the US, Zabel and Kiel (2000) do a similar exercise for four different cities; authors such as Lake et al. (2000) and Espey and Lopez (2000) focus on the effect of noise pollution and Ham, Maddison, and Elliott (2013) study the impact of landfill disamenities.

1.2.2 Uncertainty and flood risk

The HPM has also been applied to estimate the impact of hazards on property values. For instance, Bernknopf, Brookshire, and Thayer (1990) and Beron et al. (1997) focus on earthquake and volcanic hazards; the effect of hazardous waste and superfund sites is analysed by authors such as Clark and Allison (1999) and McCluskey and Rausser (2001); wildfire hazard is considered by Donovan, Champ, and Butry (2007).

MacDonald, Murdoch, and White (1987) were probably the first authors to provide a theoretical framework for the application of HPM to estimate the WTP for a reduction in the probability of flooding. Their model is based on the application of the expected utility framework to the HPM by Brookshire et al. (1985) and the option price literature on supply uncertainty described by Smith (1985). The rational consumer will choose to live in a location which maximizes his expected utility. Flood risk is considered a characteristic of properties, and when individuals decide a location where to live this decision often includes the level of risk they face (Bin, Kruse, and Landry, 2008; MacDonald, Murdoch, and White, 1987). Since there is a potential loss associated with flood risk, individuals will incorporate this into his choice.

The model we describe in this section is based on MacDonald, Murdoch, and White (1987), Bin et al. (2008), Kousky (2010) and Bin and Landry (2013). Formally, we can redefine the HPF (1) to consider explicitly the property risk factors of the house. Following Hallstrom and Smith (2005), let the subjective probability of flooding, i.e. the homeowner's subjective assessment of flood risk, be a function $p(i, r)$ of the set of information, i, the individual holds about flood risk in the location of the property, and r which represents the site attributes related to flood risk, this could be locational characteristics such as proximity to water bodies or elevation. It is important to distinguish the subjective assessment of the probability of flooding, p, from the objective measure of flood risk, π. This distinction implies three important things; first, that the perceived risk is not necessarily equal to the objective risk; second, that changes in the objective risk are not necessarily perceived; and third, that changes in the perceived risk do not necessarily arise from changes in the objective risk. In areas where flood risk disclosure is mandatory or public information about flood risk is available, the set of information, i, might include the objective probability of flooding, π.

Let the HPF be given by the following equation:

$$P = P\big(Z, r, p(i, r)\big) \tag{5}$$

Therefore, P is exogenous to individual buyers and sellers, but reflects subjective risk perception $p(i, r)$. Following Brookshire et al. (1985) the model uses an expected utility framework that incorporates risk factors associated with a property. The utility function of individuals is given by equation (2), and the household's decision is modeled using the following state dependent utility function:

$$EU = p(i, r) \cdot U^{F}[Z, r, Q] + \big(1 - p(i, r)\big) \cdot U^{NF}[Z, r, Q] \tag{6}$$

$U^{F}(\cdot)$ is the utility of the homeowner in a state where a flood occurs and $U^{NF}(\cdot)$ is the utility of the homeowner when there is no-flood. The budget constraint for the individual in state F (with perceived probability $p(i, r)$) and NF (with perceived probability $\big(1 - p(i, r)\big)$) is given by equations (7) and (8), respectively.

$$F: \quad M = P\big(Z, r, p(i, r)\big) + Q + L(r) \tag{7}$$

$$NF: \; M = P\big(Z, r, p(i, r)\big) + Q \tag{8}$$

Note from equations (7) and (8) that the level of consumption of Q is different across states, in particular $Q^F < Q^{NF}$. Both, the level of utility and the marginal utility of income may change with the state. The conditional loss $L(r) \in (0, \bar{S})$, is a function of the locational risk characteristics of the house, r, and reflects the magnitude of the loss should state F occurs; $\bar{S}$ represents the structure replacement cost of the property. Notice that budget constraint (8) is the same as (2) where no flood risk is considered. Thus, the occurrence of a flood is associated with a potential monetary loss $L(r)$.

The rational consumer will choose to live in a location which maximizes his expected utility subject to the budget constraint. If a property is subject to frequently substantial flooding, the owner may incur substantial repair costs and additional associated losses; alleviating strategies include constructing flood-proofing structures and engaging in environmental flood control practices. All these future costs might easily exceed the cost of buying an equivalent property outside the flood risk area (Bin and Kruse, 2006; Lamond, 2012; MacDonald, Murdoch, and White, 1987; Zimmerman, 1979). Consumers will locate within a floodplain if they are compensated for accepting the potential loss (MacDonald, Murdoch, and White, 1987). Intuitively this means that flood risk is capitalised into property prices.

Formally, maximizing expected utility (6), with respect to the subjective probability of flooding, p, subject to the homeowner's budget constraint, and dividing by the expected marginal utility of income yields:

$$\frac{\partial P}{\partial p} = \frac{U^F - U^{NF}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \tag{9}$$

Equation (9) is the coefficient on the risk variables estimated in hedonic regressions. It indicates that the marginal implicit hedonic price for flood risk reflects the incremental utility difference across states; dividing by the expected marginal utility of income produces a measure of marginal WTP. This implicit price can be used to estimate welfare effects of marginal changes in the independent variable (Bin et al., 2008; Kousky, 2010; MacDonald, Murdoch, and White, 1987).

To see why, following MacDonald, Murdoch, and White (1987) and Smith (1985), consider σ to be a reduction to p. The Option Price (OP) is defined as the maximum WTP for an improvement in the chance of the desirable state, NF, holding expected utility constant, and can be expressed as:

$$\begin{aligned}(p(i,r) - \sigma) \cdot U^F[Z,r,Q - OP] + (1 - p(i,r) + \sigma) \cdot U^{NF}[Z,r,Q - OP] \\ = p(i,r) \cdot U^F[Z,r,Q] + \left(1 - p(i,r)\right) \cdot U^{NF}[Z,r,Q]\end{aligned} \tag{10}$$

Therefore, the marginal WTP for reducing the probability of a flood can be expressed as the change in OP due to a reduction in the probability of flooding (σ). From equation (10) and assuming constant expected utility we get:

$$\frac{\partial OP}{\partial \sigma} = \frac{U^{NF} - U^F}{(p(i,r) - \sigma)\frac{\partial U^F}{\partial Q} + (1 - p(i,r) + \sigma)\frac{\partial U^{NF}}{\partial Q}} \tag{11}$$

Thus, in a housing market with flood risk, the locations that improve the chances of state NF will get bid up, ceteris paribus. Notice from equations (9) and (11) that:

$$\frac{\partial P}{\partial p} = -\frac{\partial OP}{\partial \sigma}\ , \ \text{for } \sigma = 0 \tag{12}$$

Therefore, the marginal WTP for a reduction of p whilst remaining indifferent is captured by the sales price differential resulting in housing markets as consumers bid for locations with lower p. This justifies interpreting the coefficients from hedonic regressions as estimates of the amount of compensation a homeowner requires, through a lower property price, to move into a riskier area. Some examples of applications of the hedonic price model to valuation of flood hazard include MacDonald, Murdoch, and White (1987), Speyrer and Ragas (1991), Harrison, Smersh, and Schwartz (2001) and Bin and Kruse (2006).

1.2.3 The role of flood insurance

In locations where flood insurance is available individuals can decide to buy an insurance policy to avoid the risk of potential financial loss. MacDonald, Murdoch, and White (1987) include a variation of the initial model to reflect the influence of flood hazard, which, more recently, has been adapted by Bin and Landry (2013) to include some recent developments in the flood risk literature. Throughout this subsection I follow closely the description by the latter.

Those individuals who decide to buy flood insurance policy are assumed to change an unknown loss into a known payment. The insurance cover on the property is given by $C \in (0, \bar{S})$, the known insurance payment (premium) is $I(\pi(r), C)$ which is assumed to be a function of the objective probability of flooding $\pi(r)$ rather than $p(i, r)$, i.e. flood insurances is assumed to be risk based, and a function of the level of cover on the property.

Household's decision is modeled using the same state dependent utility function as in equation (6). The budget constraint for the individual in state FI (flood with insurance policy) and NFI (no flood with insurance policy) is given by equations (13) and (14), respectively:

$$FI: \quad M = P\big(Z, r, p(i,r)\big) + Q + L(r) + I(\pi(r), C) - C \tag{13}$$

$$NFI: \; M = P\big(Z, r, p(i,r)\big) + Q + I(\pi(r), C) \tag{14}$$

That is, whenever the individual decides to buy an insurance policy we also need to subtract the cost of insurance from total income, and add the compensation from the insurer should state FI occurs. If the payment from the insurer in state FI is perceived to be equal to the loss, $L = C$, then the level of consumption of Q will be the same across states. For those who decide not to buy flood insurance, the budget constraint is still given by equations (7) or (8), depending on the state of the individual.

The OP for the individual who decides to buy insurance policy is defined by equation (15), an expression similar to (10) but where states F and NF are replaced by FI and NFI, respectively, to reflect the costs of insurance and the potential compensation. From equation (15), and assuming constant expected utility, we can derive the expression for the marginal WTP for a reduction σ in the probability of flooding in equation (16).

$$\begin{aligned}(p(i,r) - \sigma) \cdot U^{FI}[Z, r, Q - OP] + (1 - p(i,r) + \sigma) \cdot U^{NFI}[Z, r, Q - OP] \\ = p(i,r) \cdot U^{FI}[Z, r, Q] + \big(1 - p(i,r)\big) \cdot U^{NFI}[Z, r, Q]\end{aligned} \tag{15}$$

$$\frac{\partial OP}{\partial \sigma} = \frac{U^{NFI} - U^{FI}}{(p(i,r) - \sigma)\dfrac{\partial U^{F}}{\partial Q} + (1 - p(i,r) + \sigma)\dfrac{\partial U^{NF}}{\partial Q}} \tag{16}$$

Notice that the denominator in (16) is the same to that in (11). Maximizing expected utility (6) with respect to p, subject to the budget constraint in (13) and (14), yields:

$$\frac{\partial P}{\partial p} = \frac{U^{FI} - U^{NFI}}{p(i,r)\frac{\partial U^{F}}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} - \frac{\frac{\partial I}{\partial \pi}}{p(i,r)\frac{\partial U^{F}}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \qquad (17)$$

Therefore, notice from equations (16) and (17) that for the individual who decides to buy an insurance policy:

$$\frac{\partial P}{\partial p} = -\frac{\partial OP}{\partial \sigma} - \frac{\partial I}{\partial \pi}\ , \text{ for } \sigma = 0 \qquad (18)$$

that is, the marginal implicit hedonic price for a change in a risk factor that affects the probability of a loss, π, is the sum of the OP for residual risk and the marginal insurance cost (Bin and Landry, 2013).

MacDonald, Murdoch, and White (1987) note that if the payment from the insurer in state FI is perceived to be equal to the loss from flooding ($C = L$) such that the utility function is state independent, then:

$$U^{FI} = U^{NFI}; \qquad \frac{\partial OP}{\partial \sigma} = 0; \qquad \frac{\partial P}{\partial p} = -\frac{\partial I}{\partial \pi}$$

Under these specific circumstances the sales price differential is determined by the change in insurance cost resulting from changes in the probability of flooding. This reasoning has led to the use of the estimated present value cost of future insurance premiums as a proxy for the benefits of flood prevention schemes in countries such as the UK (Crichton, 2005). However, evidence suggests that the PV of insurance payments is less than the property price discount for living in an area prone to flooding (see for example MacDonald, Murdoch and White, 1987; Speyrer and Ragas, 1991; Bin, Kruse and Landry, 2008 and Atreya and Ferreira, 2011). If the payment from the insurer is perceived to be less than the loss from flooding ($L > C$), then:

$$U^{FI} < U^{NFI}; \qquad \frac{\partial OP}{\partial \sigma} > 0; \qquad \frac{\partial P}{\partial p} > -\frac{\partial I}{\partial \pi}$$

Under these circumstances the individual will be WTP to increase the probability of the desired state (NFI), regardless of the change in insurance cost. Therefore, if the individual purchases insurance the WTP for a reduction of π is dependent upon the perceived difference between the loss from flooding and the payment from the insurance company should state FI occurs (MacDonald, Murdoch, and White, 1987). This difference arises due to the existence of non-insurable costs associated with flooding, including disruption of normal life and loss of items with sentimental value, psychological stress to residents and hassle and deprivation of being displaced. Insurance leads only to a mitigation of financial losses associated to flood risk rather than an elimination of the risk (Harrison, Smersh, and Schwartz, 2001). The HPF capitalises insurance cost and residual risk of non-insurable losses (Bin and Landry, 2013).

1.2.4 Location, risk and amenities

Depending on the perceived loss and its probability of occurring, individuals can decide to self-insure against flood risk and associated damages by choosing to live in a different location with lower risk, paying the associated price differential (Bin and Kruse, 2006; Lamond, 2012; MacDonald, Murdoch, and White, 1987; Zimmerman, 1979). Different locations have a different level of attributes associated to flood risk, r. The HPF is given by equation (5). We assume that households choose a property with a level of r so as to maximize expected utility (6), subject to the budget constraint given by (7) and (8), such that:

$$\frac{\partial P}{\partial r} = \frac{\frac{\partial p}{\partial r}\left(U^F - U^{NF}\right)}{p(i,r)\frac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\frac{\partial U^{NF}}{\partial Q}} - \frac{p\frac{\partial U^F}{\partial Q}\cdot\frac{\partial L}{\partial r}}{p(i,r)\frac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\frac{\partial U^{NF}}{\partial Q}} + \frac{p\frac{\partial U^F}{\partial r} + (1-p)\frac{\partial U^{NF}}{\partial r}}{p(i,r)\frac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\frac{\partial U^{NF}}{\partial Q}} \tag{19}$$

Equation (19) is composed of three terms: the risk discount, or implicit price of risk, multiplied by how a change in location alters the subjective probability of a flood; the effect of location on losses and the direct effect of location on utility (for simplicity flood insurance is not considered). If we interpret r as a locational attribute associated to flood risk such as proximity to coast or a river, then we would expect that changes in r would lead to a change in flood risk. However, Carbone, Hallstrom, and Smith (2006) pointed out that proximity to water is also closely related to the existence of amenity values. Therefore, the variable r might represent not only attributes related to flood risk, but also other desirable attributes related to proximity to water.

Carbone, Hallstrom, and Smith (2006) emphasize the difficulty of the behavioural interpretation of equation (19), as it can reflect a composite of any risk changes along with any other contributions that amenities of proximity to water bodies make to individuals well-being aside from risk (third term in equation (19)). In some cases, it is reasonable to expect that locations associated with a higher flood risk may have other desirable attributes such as improved access for recreation and ocean view, which often command a premium large enough to offset the price reduction due to flood risk.

1.2.5 The role of information

The effect of an information shock is described by Carbone, Hallstrom, and Smith (2006) and Kousky (2010). The HPF is given by equation (5). The decision of the individual is modeled using the expected utility framework described in equation (6), where utility depends on the state of the individual F (loss) or NF (no-loss) and the conditional budget constraint is given by equations (7) and (8), respectively. Maximizing expected utility subject to the individual's budget constraint and solving for the partial derivative of the HPF with respect to the new information, i, yields:

$$\frac{\partial P}{\partial i} = \frac{\frac{\partial p}{\partial i}\left(U^F - U^{NF}\right)}{p(i,r)\frac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\frac{\partial U^{NF}}{\partial Q}} \tag{20}$$

Thus, the marginal effect of information is to change the perceived probability of a flood. Equation (20) multiplies the *ex-ante* discount (9) by the change in the subjective probability of flooding due to an information update, to get an expression for the effect of new information on property values. The change in subjective probability is converted to a monetary trade-off. Equation (20) does not consider changes in insurance terms due to information, an expression considering this is provided by equation (4) in Carbone, Hallstrom, and Smith (2006).

Dividing both sides of equation (20) by $\partial p/\partial i$ gives:

$$\left.\frac{\partial P}{\partial i}\middle/\frac{\partial p}{\partial i}\right. = \frac{U^F - U^{NF}}{p(i,r)\frac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\frac{\partial U^{NF}}{\partial Q}} \tag{21}$$

Which can be interpreted as the *ex ante* incremental option price an individual would be WTP for a home that is located so as to reduce the risk of damage and disruption from flooding (Carbone, Hallstrom, and Smith, 2006).

1.3 Empirical applications

Several empirical studies address the issue of floodplain location and its capitalisation in property prices using hedonic applications. In general, it is typically assumed that the HPF (5) can take the following additive representation:

$$P_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \phi p_i + \varepsilon_i \tag{22}$$

Where i denotes a specific house; j represents specific structural, neighborhood/locational and environmental characteristics of house i; P, Z, r and p are defined as in equation (5) and β_0, β_j, γ and ϕ are estimated coefficients; note ϕ is the coefficient on the risk variable as denoted in (9). ε_i is the house specific error term to which the usual assumptions apply $\varepsilon_i \sim N(0, \sigma^2 I)$.

A continuous variable of flood risk, p, is generally non observable, modifications often depend on the proxy variables used to measure flood risk. Barnard (1978) suggests the use of property elevation as a proxy to determine the level of risk. Other authors such as Shilling, Benjamin, and Sirmans (1985) and Speyrer and Ragas (1991) use measures based on insurance costs, and Tobin and Montz (1994) suggest the use of actual flood depth to capture the level of risk. However, some of this information is rarely available for researchers and the use of insurance costs have some limitations as some countries have subsidized flood insurance schemes. Furthermore, the inclusion of insurance cost in hedonic regressions can cause problems related to endogeneity, as the cost of insurance is likely to be determined by property specific variables, locational variables and personal details (Lamond, Proverbs, and Antwi, 2007b). Instead, a common alternative has been the use of a dummy variable, FP_i, to distinguish those properties located in a floodplain at different levels of risk.

One important consideration is that the appropriate functional form of the HPF has not been specified on theoretical grounds, as it reflects influences of both, supply and demand (Halvorsen and Pollakowski, 1981; Rosen, 1974). The only restriction has been that the first derivative with respect to environmental characteristic be negative if the characteristic is a *bad*, and vice-versa if it is a *good* (Atreya and Ferreira, 2012b; Halstead, Bouvier, and Hansen, 1997). Most of the studies use the natural log of the sale price as the dependent variable (semi-log); other specifications such as linear and Box-Cox transformations have also been used (see for example MacDonald et al., 1990; Harrison, Smersh and Schwartz, 2001; Bin and Kruse, 2006 for the use of different functional forms).

A key difference arises between studies which measure the effect of flood risk location using a standard hedonic model (see for example MacDonald, Murdoch and White, 1987; Donnelly, 1989; Speyrer and Ragas, 1991; Bin, 2004; Bin and Kruse, 2006; Lamond and Proverbs, 2006; Rambaldi et al.,2012; Meldrum, 2013) and those who focus in identifying the effect of new information about flood risk and how this is capitalised in property prices of floodplain designated properties using a Difference-in-difference (DID) approach; within this last category we can identify studies analysing the information effect of major flood events (see for example Bin and Polasky, 2004; Kousky, 2010; Atreya and Ferreira, 2011; Atreya and Ferreira, 2012a, 2012b; Atreya, Ferreira and Kriesel, 2012, 2013; Bin and Landry, 2013) and studies examining the information effect of changes in regulations, risk disclosure or flood risk designation maps (see for example Troy and Romm 2004; Pope 2008; Samarasinghe and Sharp, 2010).

Geographically, the evidence has been largely confined to the United States (US) after the implementation of the National Flood Insurance Program (NFIP) in 1968 and further amendments in 1973, 1982, 1994 and 2004, and the occurrence of several major flood events across the country. The studies have focused mainly in four States: North Carolina (Bin, 2004; Bin et al., 2008; Bin and Kruse, 2006; Bin, Kruse, and Landry, 2008; Bin and Landry, 2013; Bin and Polasky, 2004; Dei-Tutu and Bin, 2002; Pope, 2008), Georgia (Atreya and Ferreira, 2011, 2012a, 2012b; Atreya, Ferreira, and Kriesel, 2012, 2013), Louisiana (MacDonald, Murdoch, and White, 1987; MacDonald et al., 1990; Shilling, Benjamin, and Sirmans, 1985; Speyrer and Ragas, 1991; Turnbull, Zahirovic, and Mothorpe, 2013) and Florida (Carbone, Hallstrom, and Smith, 2006; Hallstrom and Smith, 2005; Harrison, Smersh, and Schwartz, 2001; Morgan, 2007); although there are also studies for Alabama, California, Colorado, Minnesota, Missouri, North Dakota, Texas and Wisconsin. Studies outside the US have been carried out in The Netherlands (Daniel, Florax, and Rietveld, 2007, 2009b), United Kingdom (Lamond and Proverbs, 2006), New Zealand (Samarasinghe and Sharp, 2010) and Australia (Rambaldi et al., 2012).

This section presents a review of the literature on the economics of flood risk using hedonic applications. The exposition is divided in two: first, we discuss the evidence provided by these studies which measures the effect of flood risk location on property prices and then we focus on studies which identify the effect of new information on property prices. We place special emphasis on describing the different econometric applications.

1.3.1 The standard HPM regression

Empirical application using a standard HPM regression can be generalised with the following expression:

$$lnP_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \theta_1 FP100_i + \theta_2 FP500_i + \varepsilon_i \tag{23}$$

where the dependent variable is the natural logarithm of the sales price; Z includes variables such as the age of the house, number of bathrooms, number of bedrooms, square feet, among other important locational and structural characteristics of the house; r is usually represented by the euclidian distance to the nearest water body; $FP100$ and $FP500$ are dummy variables identifying location in a flood prone area, the former takes a value of one if the house is located within a floodplain with an annual 1% probability of flooding (henceforth referred as 100-year floodplain) whereas the latter identifies properties located in a floodplain with a 0.2% annual probability of flooding (henceforth referred as 500-year floodplain). Estimated coefficients $\hat{\theta}_i$ are interpreted as the relative price differential for floodplain location at different levels of risk.

During the last years great attention has been devoted to the issue of spatial dependence in hedonic models, which refers to the interdependence among house sales prices due to common proximity. Carbone, Hallstrom, and Smith (2006) pointed out the potential correlation between spatially delineated risks and other unobserved characteristics of the locations. Sale prices tend to cluster in space as houses in a neighborhood share similar location amenities or disamenities (such as flood risk and proximity to coast) or because they have similar structural characteristics due to location or time of construction (Bin et al., 2008).

To address this issue authors such as Daniel, Florax, and Rietveld (2007), Bin, Kruse, and Landry (2008), Bin et al. (2008), Posey and Rogers (2010), Rambaldi et al. (2012) and Bin and Landry (2013) estimate different variations of spatial hedonic regressions which can be generalized with the following equation:

$$lnP_i = \beta_0 + \rho W_i lnP_i + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \theta_1 FP100_i + \theta_2 FP500_i + (I - \lambda W_i)^{-1} \varepsilon_i \quad (24)$$

This general model nests two different types of spatial processes which can be derived by putting restrictions on the parameters ρ and λ, where W represents a spatial weights matrix. The spatial lag model is obtained in the case where $\rho \neq 0$ and $\lambda = 0$, this model assumes that the spatially weighted sum of neighborhood housing prices enters as an explanatory variable in the specification of the hedonic price function; it has been applied by authors such as Bin et al. (2008) and Posey and Rogers (2010). The spatial autoregressive error model corresponds to the case where $\rho = 0$ and $\lambda \neq 0$, it assumes that the price at any location is a function of the local characteristics but also of omitted variables in the hedonic equation that vary spatially; it has been applied by Bin, Kruse, and Landry (2008) and Rambaldi et al. (2012), among others.

As a result of this literature review, a total of 30 studies have been identified where the authors report results from regressions using the standard hedonic approach (some details of these studies can be consulted in table A1.1 of the annex). [1] In general, most studies agree that properties located within a floodplain are sold at an average discount of between 6 and 7% with respect to those properties outside the floodplain; however, there are a number of studies (12) which report results suggesting a positive effect of flood risk on property prices with an average premium of the same magnitude. Both, the discount and the premium, are generally larger for properties located in the 100-year floodplain with an average discount around 7% and an average premium of 10%. For properties located in the 500-year floodplain the average discount is around 5% and the average premium around 4%.

The full set of results range between a price discount of 42% by Bin and Landry (2013) to a premium of 61% by Bin and Kruse (2006). Bin and Landry (2013) examine the change in implicit flood risk prices after Hurricane Floyd (1999) using a sample of 3,360 properties in Pitt County, North Carolina, US, for the period 2002-2008. The authors use a spatial lag model and present results for eight different regressions which differ mainly in the level of risk (dummy variable for floodplain location – no distinction of risk – and dummy variable for 100-year and 500-year floodplain – separately), and the functional form of the variable they use to measure the time with respect to the previous flood. Their results suggest a price differential ranging between -42% – +6% for properties located in the 100-year floodplain; the functional form of the variable they use to measure the time with respect to the previous flood varies across specifications. Bin and Kruse (2006) examine the price of 4,342 properties in Carteret County, North Carolina, US, that were sold during the period 2000-2004. They use a standard hedonic model and present the results for three different regressions focusing in three different regions (mainland, Outer Banks[2] and both). The

[1] Some studies report results using both, standard hedonic regressions and DID hedonic models.
[2] The Outer Banks is a 200-mile long string of narrow barrier islands off the coast of North Carolina.

authors distinguish three categories of flood risk: 500-year floodplain, 100-year floodplain and 100-year floodplain with additional vulnerability to wave action.[3] Their results range between -10% – +61%, the former correspond to properties located in a 500-year floodplain in the Outer Banks and the latter to properties in mainland located within the 100-year floodplain with additional vulnerability to wave action. The authors associate these findings to the existence of substantial amenity values of proximity to coastal water, which exceed the perceived and real costs of flood risk. Interestingly, note that both locations, Pitt County and Carteret County, are within the same State in the US, only 110 Km apart from each other, [4] and the results correspond to similar time periods.

Floodplains are spatially delineated areas that would naturally be affected by flooding should a river or lake rise above its banks, or high tides and stormy seas cause flooding in coastal areas. As expected, the location of flood risk areas and the level of risk are closely related with proximity to water; which in turn might be related to desirable attributes. Authors such as Hallstrom and Smith (2005), Bin and Kruse (2006), Carbone, Hallstrom, and Smith (2006) and Bin, Kruse, and Landry (2008) argue that when there are opposite effects correlated with variables that are usually used as proxy for flood risk (proximity to water body or dummy variable for floodplain location) it is difficult to disentangle the value of risk. Thus, if not all amenity values correlated with flood risk are accounted for, the effect of these is consigned to the error term and the identification of θ_i is compromised due to endogeneity, as there then exist confounder factors associated with proximity to water. In this case, estimates of risk value tend to be biased downwards or even positive.

[3] As defined by the US Federal Emergency Management Agency (FEMA).
[4] Corresponds to the great circle distance between coordinates 34° 44' 00'' N, 76° 46' 00'' W for Carteret County and 35° 35' 24'' N, 77° 22' 48'' W for Pitt County.

Bin et al. (2008) estimate the implicit price of flood risk using data for four beach communities along the Atlantic Coast of New Hanover County in North Carolina, US, during the period 1995-2002. The authors estimate a spatial lag model and include a three-dimensional measure of ocean viewscape (accounting for natural topography and buildings) varying independently of risk classification to control for amenity values; they also include proximity to the nearest beach as a control variable. They use a dummy variable identifying properties located in a 100-year floodplain as a proxy for flood risk. Their results indicate a property discount for floodplain location between 11 and 17% for a spatial and linear specification, respectively. Based on these results, the authors conclude that the variables they use were successful in isolating risk factors from spatial amenities. Kousky (2010) also points out the importance of considering the possible existence of other disamenities associated with proximity to water bodies; [5] however, to the best of our knowledge this is not something that has been specifically considered in the flood risk literature.

Authors such as MacDonald, Murdoch, and White (1987) and MacDonald et al. (1990) estimate a Box-Cox (1964) transformation of the selling price of properties located in Monroe, Louisiana, US. Their results indicate that houses in the 100-year floodplain are sold at significantly lower prices than an otherwise similar house located outside of a floodplain; the discount is not linear in price and ranges from 6 to 10%; below average price homes are discounted relatively more than above average ones. Dei-Tutu and Bin (2002) found similar results for a sample of properties located in Pitt County, North Carolina, US.

[5] The author mentions the case of the Missouri River across St. Louis County, Missouri, US, which one of the homeowners refers to as a "*mosquito infested swamp*" (p. 405).

Meldrum (2013) examines the implicit price of floodplain location across different property types – standalone homes and condominiums – sold in Boulder County, Colorado, US, between 1995 and 2010. The dataset includes observations for 40,101 standalone homes, and 8,604 condominiums. The author uses a dummy variable to distinguish properties located in the 100-year floodplain. For a specification where different types of properties are not distinguished the results suggests that properties in the floodplain are discounted by about 2%. However, when the effect is allowed to vary across property types the results indicate that it is condominiums that are discounted from 6 to 10% compared to similar condominiums not in a designated flood area. No significant price differential is observed for standalone homes. The author suggests that, in this case, the presence of a floodplain discount for condominiums but not for standalone homes is due to information asymmetries about costs of insurance across property types, and not due to a higher valuation of risk. To the best of our knowledge this is the only study allowing for differences in the implicit price of risk across property types.

1.3.2 Difference-in-difference (DID) HPM regression

Bin and Polasky (2004) observed that previous studies which estimated the implicit price of flood risk and found a large discount of between 4 and 12% were all in areas that had experienced recent flooding (Donnelly, 1989; MacDonald, Murdoch, and White, 1987; Shilling, Benjamin, and Sirmans, 1985; Speyrer and Ragas, 1991); however, the study of Harrison, Smersh, and Schwartz (2001) which found a discount of between 1 and 3% was somewhat unusually in a location that had not experienced any major flooding in the recent past. This led the authors to propose that recent experience with flooding raises the perception of flood risk and the associated discount for living in a floodplain. This argument follows from prospect theory which suggests that people poorly integrate risk into their decisions, especially when the risk is high consequence and low probability such as natural disasters (Camerer and Kunreuther, 1989; Kunreuther, 1976, 1996; Kunreuther and Slovic, 1978; McDaniels, Kamlet, and Fischer, 1992; Slovic, 1987; Smith, 1986). Authors such as Hallstrom and Smith (2005), Kousky (2010), Atreya and Ferreira (2011a, 2012b) and Bin and Landry (2013) argue that since floods are low probability events (floodplains are delineated as 1% or 0.2% annual probability of flooding), individuals often neglect the associated risk, π. However, recent experience with flooding provides new information to individuals to update their subjective assessment of risk, $p(i, r)$, which causes a change in the price of floodplain property.

Since Bin and Polasky (2004), there has been a growing body of research examining the effect of new information about flood risk and how this is capitalised into property prices of floodplain-designated properties using a Difference-in-difference (DID) approach. The strategy for identification relies on the occurrence of natural events as a source of exogenous variation in the explanatory variable by introducing a temporal element to the analysis by the use of a before-after approach. These natural events are usually changes or spatial variation in rules governing behaviour, which are assumed to satisfy the randomness criterion (Rosenzweig and Wolpin, 2000). The vast majority of DID HPM applications in the flood risk literature use the occurrence of a flood event (or hurricane) as a source of exogenous variation to identify the information effect on property prices. However, Harrison, Smersh, and Schwartz (2001), Troy and Romm (2004) and Pope (2008), look at the information effect of changes in regulations for properties in the floodplain; and Samarasinghe and Sharp (2010) evaluate the effect of floodplain zoning. Hallstrom and Smith (2005) suggest that changes in information can also be due to media coverage and education programs, amongst others.

Authors such as Meyer (1995), Rosenzweig and Wolpin (2000) and Carbone, Hallstrom, and Smith (2006) emphasise that the use of weather events as an identification strategy does not guarantee a random treatment; as it is clear from equations (19) and (20) flood hazard is a spatially delineated risk such that the probability of occurrence of a flood and the amount of losses is highly related to location and individuals' preferences towards risk and other environmental amenities. Therefore, the application of DID models in the flood risk literature has been denoted as *quasi-experimental* (quasi-random) *approach*, where control is not guaranteed to meet the standards of a completely random assignment (Carbone, Hallstrom, and Smith, 2006; Meyer, 1995).[6]

Following Meyer (1995), Carbone, Hallstrom, and Smith (2006) and Parmeter and Pope (2012), there are two dimensions distinguishing the structure of a quasi-experiment: the group assignment for each unit (house) in the study, i.e. inside or outside a floodplain, and the timing (t) of the potential outcome that is observed for each unit. The price P_{it} designates the outcome we observe for each house, i. Therefore there exists two potential prices P_{i0} and P_{i1} for the before and after treatment effect. Carbone, Hallstrom and Smith (2006) argue that combining temporal variation in risk perceptions with spatial variation in risk characteristics can also help to avoid the endogeneity problems discussed earlier.

Hedonic studies using a DID approach can be distinguished according to the kind of data they use. The most common approach is to model property prices as a pooled cross-section over time, i.e. the prices of houses at different points in time do not correspond to sales of the same property. Housing sales of the same region are observed over time and

[6] As Meyer (1995) and Carbone, Hallstrom and Smith (2006) pointed out, in economics natural experiments are usually induced by policy changes, government randomization, or other events which examine outcome measures for observations in treatment groups and comparisons groups that are not randomly assigned.

unobserved heterogeneity is controlled for using region or neighbourhood level fixed effects (Parmeter and Pope, 2012). The second approach is known as the repeat-sales model. It uses actual panel data by considering sale prices of the same houses that has been sold multiple times over a given time period in which some of the houses experienced an environmental change which is not uniform across properties; a flood event can be regarded as one of such changes. Below, we describe these two applications and discuss the evidence.

Pooled Cross-Section over time

Empirical applications of the DID framework using pooled data of cross-section over time can be described using the general regression model in equation (25) which assumes a linear HPF specification as in (22). The treatment group is distinguished by floodplain location ($FP100_i$ or $FP500_i$) and the treatment refers to the occurrence of a flood. The timing is the date of the sale in relation to the flood event ($Flood_i$) (for studies analysing the information effect of policy changes the timing is given with respect to the date in which the new policy was implemented).

$$\begin{aligned} lnP_{it} &= \beta_0 + \theta_1 FP100_i + \theta_2 FP500_i + \alpha Flood_i + \psi_1(Flood_i \times FP100_i) \\ &\quad + \psi_2(Flood_i \times FP500_i) + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \varepsilon_{it} \end{aligned} \tag{25}$$

The variables Z and r are observable sources of heterogeneity and have the same interpretation as in equation (23); ε_{it} captures unobservable sources of heterogeneity which vary with the property, and the usual *iid* assumptions apply. The variable $Flood$ is a dummy variable equal to one if the sale happened after the flood event of interest and $FP100$ and $FP500$ are dummy variable which takes the value of one if the house is located within a 100-year or 500-year floodplain, respectively. The parameter θ_i represents the group effect, i.e. the pre-flood relative price differential between the control group (no floodplain location) and the treatment group (100-year and/or 500-year floodplain location); α captures the time effect, i.e. the relative price difference for all properties that were sold after the flood; and ψ_i represents the treatment response, i.e. the incremental effect due to information conveyed by the flood (treatment) in known risky locations (floodplains). That is,

$$\hat{\psi}_1 = \left(\overline{lnP_1^{FP100}} - \overline{lnP_0^{FP100}}\right) - \left(\overline{lnP_1} - \overline{lnP_0}\right) \tag{26}$$

By introducing separate variables to control for different levels of risk it is possible to analyse how new information about flood risk is capitalised at different levels of risk. A similar expression applies for $\hat{\psi}_2$ in the 500-year floodplain. The key assumption for identification is that $E[\varepsilon_{it}|Flood_i] = 0$, for $t = 0, 1$ (before and after the flood).

In this case, it is possible to obtain an expression for the post-flood price differential for properties located in the floodplain Θ_i, which is defined as the sum of two terms: the pre-flood price differential (θ_i), plus the incremental effect due to an update of flood risk perception for properties within known risky locations (ψ_i), as it appears in equation (27).

$$\Theta_i = \theta_i + \psi_i \quad ; \quad \text{for } i = 1, 2 \text{ for FP100 and FP500, respectively.} \tag{27}$$

Recent applications of the DID HPF approach to the flood risk literature focus on the issue of potential correlation between spatially delineated risks and unobserved characteristics, and the exogeneity assumption $E[\varepsilon_{it}|Flood_i] = 0$ of the treatment variable for the identification of ψ_i. In particular, authors such as Atreya and Ferreira (2012a), Atreya, Ferreira and Kriesel (2012, 2013), Meldrum (2013) and Bin and Landry (2013) estimate a spatial specification of the DID HPM; these applications can be generalized using the following equation:

$$
\begin{aligned}
lnP_{it} = \beta_0 + \rho W_i lnP_i + \theta_1 FP100_i + \theta_2 FP500_i + \alpha Flood_i + \psi_1 (Flood_i \times FP100_i) \\
+\psi_2 (Flood_i \times FP500_i) + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + (I - \lambda W_i)^{-1} \varepsilon_{it}
\end{aligned}
\tag{28}
$$

Equation (28) includes two different types of spatial process models which can be derived by putting restrictions on the parameters ρ and λ. Meldrum (2013) and Bin and Landry (2013) estimate a spatial lag model which is obtained in the case where $\rho \neq 0$ and $\lambda = 0$; as in equation (24) W represents a spatial weights matrix. On the other hand, authors such as Atreya and Ferreira (2012c), Atreya and Ferreira (2012a) and Atreya, Ferreira, and Kriesel (2012) estimate a Spatial Autoregressive Model with Autoregressive Disturbances (SARAR) (Anselin and Florax, 1995), this model is obtained in the case where $\rho \neq 0$ and $\lambda \neq 0$. Spatial interactions in the dependent variable are modeled with the spatial lag structure, with spatial weights W, and the error term assumes a spatially weighted error structure accounting for unobserved spatial correlation.

A shortcoming of this approach is the amount of information it requires, since information on all the major structural and locational characteristics (Z_i and r_i) influencing the value of a house must be included in the regression to ensure unbiased estimates (Palmquist, 1982, 2005). A focus of debate has been the existence of unobserved, time invariant, omitted variables causing econometric issues due to spatial autocorrelation that hinders estimation of the hedonic price model (Bin and Polasky, 2004; Hallstrom and Smith, 2005). Hallstrom and Smith (2005) and Carbone, Hallstrom, and Smith (2006) argue that the hedonic model cannot isolate the effects of new information even considering transactions before and after a flood event. For these reasons authors such as Hallstrom and Smith (2005), Kousky (2010) and Lamond, Proverbs, and Antwi (2007a) have suggested the use of the repeat-sales model.

Repeat-sales model

The repeat-sales model uses actual panel data by considering sale prices of the same houses that have been sold multiple times over a given time period in which some of the houses experienced an environmental change which is not uniform across properties. This model can be derived from the hedonic price model, and it is used to remove unobservable, time-invariant characteristics of a property from the specification of the hedonic model (Kousky, 2010; Palmquist, 1982, 2005). Palmquist (1982) argue that between the sales of a house there are changes in some characteristics such as age, environmental quality and the general real state price level; however other characteristics of the house (structural and locational) remain the same. Therefore, by considering two sales of the same property it is possible to recover estimates for the effect of those aspects of home's location that change over time.

Among the flood risk literature, the specification of the repeat-sales model to assess the effects of new information on property prices assumes that the effect of a flood event as new information is to introduce a constant differential between homes located within a floodplain, and those which are not (Hallstrom and Smith, 2005). Here we present the basic theoretical framework of the repeat-sales model. The exposition follows closely that of Palmquist (1982, 2005) and Kousky (2010).

Formally, let Z_i again represent the set of structural, locational and environmental characteristics; r_i the site attributes related to flood risk and C_i the set of unobserved characteristics for house i. All these variables are assumed to remain unchanged between the two sales period, $t = 0, 1$. Thus, the time of the first sale is denoted by 0 and that of the second sale by 1. The variable age represents the age of the structure at the time of sale (for 0 or 1). As in equation (25), $FP100$ and $FP500$ are dummy variables which takes the value of one if the house is located within a 100-year and 500-year floodplain, respectively, and the variable $Flood_i$ is a dummy variable equal to one if the sale happened after the flood event of interest ($t = 1$). Therefore, following Palmquist (1982) the price of property i in year t is given by:

$$P_{it} = B_t\, g(Z_i, r_i, C_i)\, exp(\gamma_1 FP100_i \times Flood_{it}) exp(\gamma_2 FP500_i)\, exp(\gamma_2 Flood_{it}) \quad (29)$$
$$exp(\gamma_3 age_{it})\, exp(\varepsilon_{it})$$

where B_t denotes the real estate price index and γ's are parameters to be estimated. ε_{it} represents an idiosyncratic error term for which the usual *iid* assumptions apply. As the repeat-sales model requires at least two sales for each property, for house i there is an earlier sale in year s ($t = 0$) for which the price is explained by an equation similar to (29). Dividing the former by the latter and assuming structural, locational, and neighbourhood characteristics (Z_i, r_i, C_i) are constant over the period of analysis, as well as the parameters of the hedonic price function, the term $g(Z_i, r_i, C_i)$ drops out of the equation such that unobservables, C_i, are no longer a concern. Following Palmquist (1982) it is also possible to drop the age variable as it is perfectly collinear with the price index and an estimation of depreciation is not of interest in this case (Kousky, 2010). Taking the natural logarithm of the remaining expression yields the repeat-sales model specification in equation (30).

$$\Delta ln(P_i) = \beta_1(FP100_i \times Bracket_i) + \beta_2(FP500_i \times Bracket_i) + \beta_3 Bracket_i + \beta_4 Year_1 + \beta_5 Year_0 + \Delta e_i \tag{30}$$

Notice that after dividing expression (29) at $t = 1$ by that at $t = 0$ the term identifying post-flood sales, $Flood_i$, now represents a term identifying sales that *bracket* the flood, i.e. those for which the first sale is before the flood and the second one after.[7] The interaction term $FP100_i \times Bracket_i$ and $FP500_i \times Bracket_i$ identifies those properties within the floodplain, at different levels of risk, with sales that *bracket* the flood. The natural logarithm of B (in equation (29)) takes the form of coefficients on dummy variables taking on the year of the sale (Palmquist, 2005). Therefore, assuming there are no other changes in observable variables that contribute to price differences and that unobservables, represented by $(e_{i1} - e_{i0})$, are not correlated with the effect being measured, then $\hat{\beta}_1$ can be expressed as

$$\hat{\beta}_1 = \left(\overline{lnP_1^{FP100}} - \overline{lnP_0^{FP100}}\right) - \left(\overline{lnP_1} - \overline{lnP_0}\right) \tag{31}$$

in which the coefficient on the environmental variable, β_1, represents the marginal effect of changes in environmental attributes on property values in relative terms, i.e. the panel data equivalent of $\hat{\psi}_1$ in equation (25) (Kousky, 2010; Palmquist, 1982). A similar expression applies for $\hat{\beta}_2$ in the 500-year floodplain. Notice that in this case it is not possible to recover an expression for the pre-flood and/or post-flood price differential for floodplain location. The only information we get is how new information, due to environmental changes, is capitalised in known risky locations with different levels of risk.

[7] If the flood occurred before the time of the first sale (s), it also takes place before the second sale (t) and $Flood_{it} - Flood_{is} = 0$, implying $Bracket_{its} = 0$. When both sales were before the flood the variable is also zero, and it is impossible for the flood to be before the first sale and not before the second. The only way for $Flood_{it} - Flood_{is}$ to be equal 1, i.e. $Bracket_{its} = 1$, is when the two sales *bracket* the flood date.

Although the repeat-sales model deals with the possible omitted variable bias, it brings with it additional complications. The sample is restricted to properties that have been sold more than once, thus is not a random sample and usually a small fraction of the full data set. It also assumes that real estate depreciates at a geometric rate and that risk has a linear effect on the natural logarithm of property price (Kousky, 2010; Palmquist, 1982, 2005).

Evidence

Based on early empirical observations, studies by Tobin and Newton (1986) and Montz and Tobin (1988) describe different dynamics that house prices might experience following a flood event. The authors suggest that negative aspects of flood hazard are capitalised into property prices to an extent that varies spatially and temporally depending on the frequency, severity and spatial characteristics of flood events, and that a recovery process of house prices might follow depending on various socio-economic criteria along with the prevailing flood conditions.

Tobin and Newton (1986) propose four different price profiles which are shown in figure 1.1; the timing of flood events is characterized by vertical dotted lines. Figure 1.1.A depicts the evolution of house prices in a location with rare flood events; the flood has an initial impact reducing property prices but after a period of time prices recover to levels at or near to those prevailing prior to the event. Figure 1.1.B represents the situation of an area subject to regular flooding. In this case people are aware of flood risk in their community (this might also happen due to disclosure policies), the effects of floods are already capitalised into property prices and recent floods provide no new information; the market does not have sufficient time to recover before the occurrence of a subsequent flood. Lamond and Proverbs (2006) argue that in this case a DID study focusing on an individual flood event would reveal no information effect. Figure 1.1.C shows a situation in which floods are less frequent than in figure 1.1.B such that the market has the ability to recover before a new flood occurs. In figure 1.1.C the occurrence of a catastrophic flood provides new information about flood risk for a community and permanently changes resident's expectations; damage could be so great as to preclude any noticeable recovery in property prices.

Figure 1.1 Tobin and Newton (1986): Price dynamics after a flood event

Figure 1.1.A

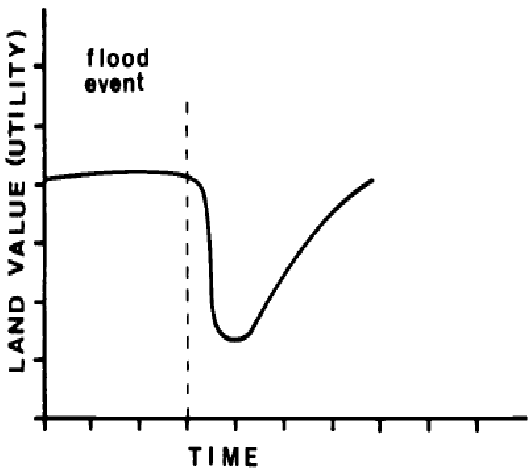


Figure 1.1.B

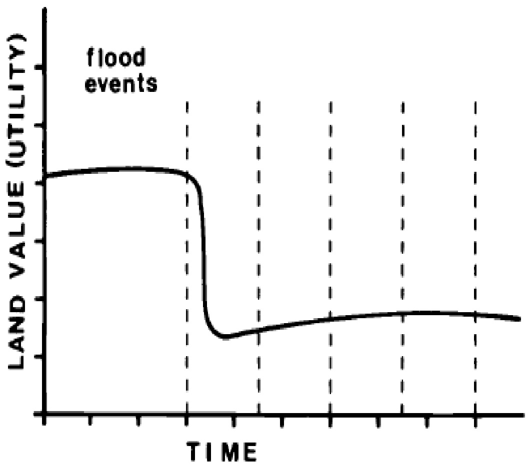


Figure 1.1.C

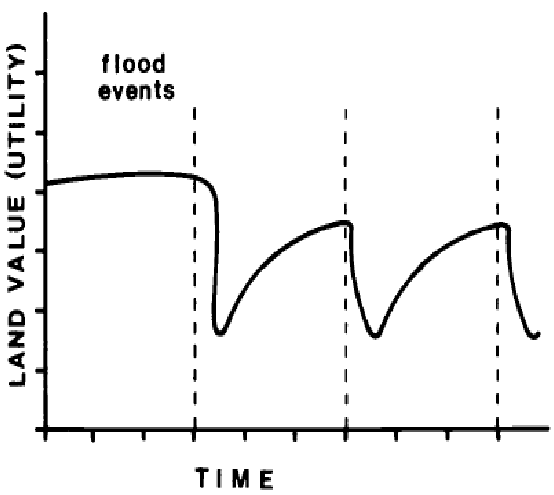
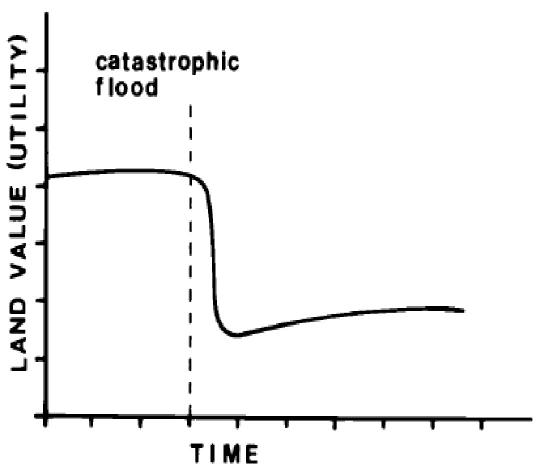


Figure 1.1.D



Source: Tobin and Newton (1986).

Thus, it is possible to identify two main areas of research for application of hedonic DID models in the flood risk literature: studies which focus on examining the effect of new information about flood risk and how this is capitalised in prices of properties within the floodplain (see for example Bin and Polasky, 2004; Troy and Romm, 2004; Kousky, 2010; Atreya and Ferreira 2012a, 2012c), and those which additionally explore the persistence of this information effect over time (see for example Atreya and Ferrieria 2012a, 2012c, Atreya, Ferreira and Kriesel, 2013; Bin and Landry, 2013).

The literature suggests that the average price discount for floodplain location before a flood is about 1%. The results however, range between a discount of 20% by Atreya and Ferreira (2012a) and a premium of 32% by Morgan (2007). Dividing the estimates by different levels of risk we get that location in a 100-year floodplain before a flood is associated with an average discount of 3%, however, location in a 500-year floodplain under the same circumstances is associated with an average premium of the same magnitude.

There is general agreement that prices of properties within a floodplain decline after a flood event, the evidence suggesting an average reduction of around 15%. This evidence is consistent with the idea that recent experience of flooding raises the perception of flood risk and the associated discount for living in a floodplain (Bin and Polasky, 2004). However, there is no agreement on how the information update operates at different levels of risk. For instance, Kousky (2010) examines the change in the price differential for floodplain location for properties in St. Louis County, Missouri, US, after a flood in 1993 on the Missouri and Mississippi rivers, using data for 424,727 properties that were sold during the period 1979-2006. The results suggest that before the flood properties in the

100-year floodplain were significantly discounted, on average, by about 3%, whereas no significant price differential was observed for properties located in the 500-year floodplain. After the flood, property prices in the 100-year floodplain did not change significantly, but prices of properties in the 500-year floodplain experienced a significant decline of 2%. The author associates these results to pre-flood differences in information available about flood risk to homeowners among floodplains with different levels of risk. Kousky (2010) points out that in the US, sellers of houses at the highest level of risk (100-year floodplain) have to provide to prospective buyers a Natural Hazard Disclosure Statement (NHDS) prior to transaction. In this way potential buyers are aware of the risk they face. Nonetheless, this disclosure clause is not applicable for properties within 500-year floodplains. Thus, the results indicate that little updating after the flood occurs in areas that had some prior knowledge of flood risk (100-year floodplain), but significant updating occurred where no prior capitalisation of flood risk into property prices had taken place (500-year floodplain).

Bin and Landry (2013) explore the change in implicit flood risk prices after Hurricane Fran (1996) and Floyd (1999) using a sample of 8,159 properties in Pitt County, North Carolina, US, for the period 1992-2008. Their results suggest that it is properties in the 100-year floodplain the ones which experience a significant discount between 8 and 12% after a major flood, while properties in the 500-year floodplain did not experience significant changes. Atreya, Ferreira, and Kriesel (2013) find similar results but with a significant price decline between 28 and 48% for properties located in the 100-year floodplain after a major flood in Dougherty County, Georgia, US.

Following a flood event the discount in properties is expected to be large as homeowners are also likely to have experienced flood damages. Hallstrom and Smith (2005) argue that estimates of $\hat{\psi}_i$ from DID HPM regressions also capture the effect of flood damages and how repairs and reconstruction after the flood might have affected property prices. In general, empirical applications have not included variables to control for property damages as this information is rarely available. Exceptions include two studies by Atreya and Ferreira (2012a, 2012c).[8] The authors examine the change in implicit flood risk prices in the city of Albany, Georgia, US, after a major flood in 1994, using data for 3,005 properties sold during the period 1985-2010. They use simulated inundation maps to construct a variable to identify those properties that were flooded during the event to tease out the information effect of the flood from potential reconstruction or other inundation-related costs. Atreya and Ferreira (2012a) use a standard DID hedonic model, whereas Atreya and Ferreira (2012c) controls for possible spatial autocorrelation by using a DID SARAR specification; the results are, however, similar. Both studies agree that properties located within the floodplain (no distinction is made between 100-year and 500-year floodplain) and also in the inundated area were significantly discounted by 48% after the flood; however, for those properties within the floodplain and where no inundation damage occurred after the flood, Atreya and Ferreira (2012a) found no significant price differential, whereas Atreya and Ferreira (2012c) found a significant 6% premium. The authors conclude that the post-flood discount is mainly driven from an inundation effect rather than an informational effect. They conclude that not accounting for whether properties in the floodplains are also in the inundated area may overestimate the information effect of the flood.

[8] Another exception is by Carbone, Hallstrom and Smith (2006), who test two variables to control for flood damages using a repeat-sales model. The first variable relies on a database published by the Miami Herald in December 1992 with data of a damage assessment by housing subdivision conducted by the US National Oceanic and Atmospheric Administration (NOAA). The second variable uses geo-coded map of the storm's path and the winds map, to estimate a band where storm damages were most likely.

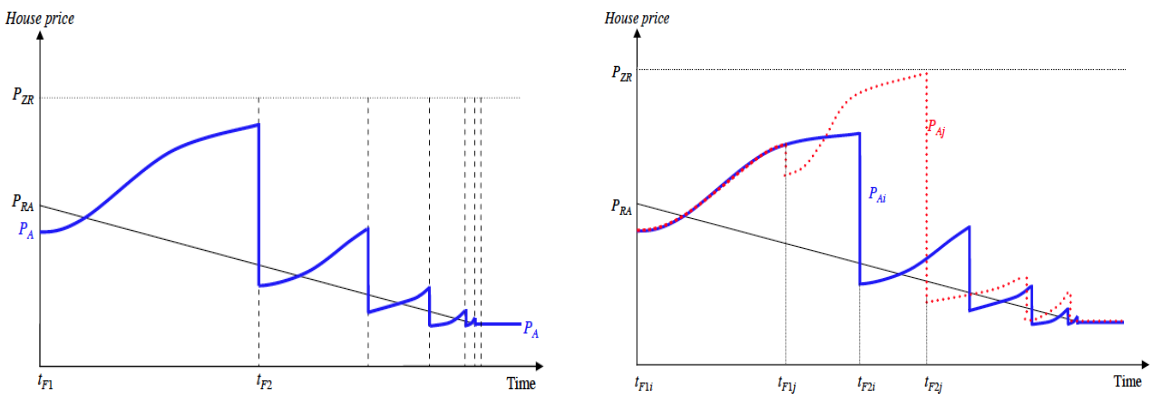
Alternatively, Hallstrom and Smith (2005) suggest the use of a "*near-miss*" location to identify the pure information effect conveyed by extreme weather events. They evaluate whether the prices of properties known to be in risky locations adjusted to the information provided by Hurricane Andrew, a record setting hurricane that hits Florida, US, in 1992. The identification strategy involves the use of a DID HPM regression focusing the analysis on Lee County, Florida, a location which was far enough that residents did not experience structural damage, but close enough to hypothesise that they might have noticed the potential risk and adjust their behaviour to the new information. Results suggest that prices of properties located in a flood risk area declined significantly after the occurrence of Andrew by an amount anywhere between 7 to 28%. The authors suggest that the most likely explanation is an updating of homeowner's risk perceptions and conclude that people learn from comparable circumstances.

Another area of research has been to explore the effect of changes in regulations for floodplain designated areas. Troy and Romm (2004) and Pope (2008) examine flood risk disclosure policies in the US across different levels of risk. The former focuses on the implementation of the 1998 California Natural Hazard Disclosure Law (AB 1195), and the later in the implementation of the 1995 North Carolina General Statute 47E, known as the "Residential Property Disclosure Act". In general, both policies require owners of properties in the 100-year floodplain to provide prospective buyers with a property disclosure statement prior to closing. Troy and Romm (2004) use a dummy variable to identify properties located in the 100-year floodplain; Pope (2008) also identifies properties located in the 500-year floodplain. Both studies found no significant price discount for floodplain location before the implementation of the law, regardless of the level of risk. However, after implementation results agree in that properties in the 100-year floodplain were discounted between 4 and 5%. Pope (2008) found no significant discount for properties located in the 500-year floodplain after the implementation of the law. Harrison, Smersh, and Schwartz (2001) found a significant 1% discount for properties in the 100-year floodplain before the implementation of the 1994 National Flood Insurance Reform Act in Alachua County, Florida, US; however, after the reform they found no significant change in prices. Samarasinghe and Sharp (2010) found that before maps outlining flood-hazard boundaries were made available in North Shore City, New Zealand, properties in the floodplain were sold at a discount close to 6%; however after the maps become available prices were 4% higher for those properties in the floodplain. Although there is little evidence available, it is reasonable to believe that the effect of changes in regulations highly depends on the nature of the policy, as well as other underlying factors that facilitate the enforcement of new policies or dissemination of information.

More recently, Pryce, Chen, and Galster (2011) build on the price dynamics proposed by Tobin and Newton (1986) and Montz and Tobin (1988), and suggest that agents suffer from *myopia* and *amnesia* regarding flood risk, in that they discount information of past flood events and anticipated future events. In the case of future events (*myopia*) the discount is assumed to rise progressively as the event becomes less imminent. In the case of past events (*amnesia*) the discount rises progressively as people tend to forget about the risk of flooding with the passage of time. According to the authors, these effects make perceived flood risk, $p(i, r)$, differ from objective risk, π. Following the idea of the availability heuristic in risk perception by Tversky and Kahneman (1973), the authors suggest that recent flood experiences raises the perception of risk, i.e. people estimate the frequency or probability of an event by the ease with which instances of associations can be brought to mind (Atreya and Ferreira, 2012a, 2012c). Thus, they argue that *myopia* and *amnesia* will diminish in the housing market as flood events become more frequent due to the effect of climate change and information becoming broadly available due to communication technologies. Furthermore, they suggest that the observed house prices and risk-adjusted prices will converge in an idiosyncratic way, contingent on the sequence of flood experiences in each region (Pryce, Chen, and Galster, 2011). These ideas are depicted in the house price dynamics shown in figure 1.2; P_{ZR} represents the price of a house with zero flood risk; P_{RA} represents the fully risk-adjusted price of the property in locations where there is non-zero flood risk, P_A represents the actual observed price of the property in the market (blue line in figure 1.2). Figure 1.2.A depicts a situation characterized by climate change, where there are increasingly frequent floods and *myopia* and *amnesia* are present in the housing market, it also illustrates the convergence of observed home prices and risk adjusted prices. Figure 1.2.B illustrates the idea of an idiosyncratic convergence path of observed home prices to risk-adjusted prices in two different regions, i (blue) and j (red), contingent on the sequence of flood experiences; these two regions are assumed to be identical except for the timing and frequency of prior flood events.

Figure 1.2. Pryce, Chen and Galster (2011): Price dynamics after a flood, with increasingly frequent floods

Figure 1.2.A **Figure 1.2.B**



Note: t_{F1}, t_{F2}, t_{F3} and t_{F4} refer to the timing of flood incident.

Source: Pryce, Chen and Galster, (2011).

To the best of our knowledge, there are only two studies exploring the effect of subsequent floods on the implicit price of flood risk. Daniel, Florax, and Rietveld (2009b) explore changes in the implicit price of flood risk following two subsequent floods (1993 and 1995) in an area prone to flooding along the Meus River in the Netherlands. The authors use a sample of 9,505 properties sold during the period 1990-2004. Before the first flood the authors found no significant price differential between the properties inside and outside the floodplain; after the first flood they found a negative, but not significant, price discount close to 5%; after the second flood properties were significantly discounted by about 9%. On the other hand, Bin and Landry (2013) examine the changes in implicit price of flood risk across areas with different level of risk in Pitt County, North Carolina, US, following flood events due to Hurricane Fran (1996) and Floyd (1999); they use a sample of 4,799 properties in Pitt County, North Carolina, US, for the period 1992-2002. Their results suggest that before the first flood prices of properties in the floodplain were not significantly different from those outside, regardless of the level of risk; however, after the first flood prices of properties in the 100-year floodplain declined by about 9%, and 13% after the second flood. For properties in the 500-year floodplain the authors do not observe a significant price differential after the floods. Although this evidence seems to suggest a price pattern similar to the one suggested by Pryce, Chen, and Galster (2011) in figure 1.2.A, it is important to highlight that neither Daniel, Florax, and Rietveld (2009b) nor Bin and Landry (2013) include variables to test the existence of a decay in the implicit price of risk between the two floods, and the larger and significant discount after the second flood might well be due to specific characteristics of the second event, such as intensity, affected area, or media coverage, to name but a few.

There are few studies exploring the persistence of the information effect of flood events over time; in general, these studies include a time trend variable interacting with the dummy variable identifying post-flood sales to capture the evolution of prices within the floodplain after a flood. Atreya and Ferreira (2012a) and Atreya, Ferreira, and Kriesel (2012) include a linear trend to test for the decay of the discount after a major flood event in 1994 in Dougherty County, Georgia, US. The authors find evidence of a significant decay of the information effect. The time persistence appears to be different across regions with different levels of risk. The results suggest that for properties in the 100-year floodplain the discount vanishes after 7 years, while in the 500-year floodplain it lasts longer and might take up to 15 years to disappear.

Bin and Landry (2013) point out that a linear specification is not ideal as any positive trend eventually results in large positive coefficients associated with floodplain location. Bin and Landry (2013) and Atreya, Ferreira, and Kriesel (2013) test different functional forms for the time decay including a linear time trend, $f(t) = t$, and nonlinear natural logarithm, $f(t) = ln(t)$; ratio, $f(t) = (t - 1)/t$; and square root, $f(t) = Sqrt(t)$. Bin and Landry (2013) find that the post-flood discount in Pitt County, North Carolina, US, vanishes 5 to 6 years after Hurricane Floyd (1999), although the authors do not distinguish floodplains at different levels of risk. Atreya, Ferreira, and Kriesel (2013) suggest that the discount disappears after 6 to 8 years in the 100-year floodplain; no significant decay was found for properties in the 500-year floodplain, although no significant post-flood discount was found either. The persistence of the post-flood discount is similar across different functional forms of the time variable; however, the size of the post-flood implicit price of risk varies greatly across specifications. Estimates by Bin and Landry (2013) vary gradually from a post-flood discount of 6 to 22% across linear, natural logarithm and ratio specifications, whereas those by Atreya, Ferreira, and Kriesel (2013) vary in the same fashion from 28 to 41%. The model using the ratio functional form imposes an extreme amount of curvature, which implies a large flood zone discount immediately after the flood. The use of the natural logarithm is less extreme in this respect. To the best of our knowledge, there is no study exploring the persistence of the information effect due to changes in regulations.

1.4 Meta-analysis

Several previous studies have employed different variants of hedonic econometric regressions to estimate the percentage price differential for floodplain location. Evidence suggests that this differential ranges from a price discount of 75% suggested by Atreya, Ferreira, and Kriesel (2013), to a premium of 61% estimated by Bin and Kruse (2006). As can be inferred from the literature review, estimates might vary depending on several things such as the area of study, the context in which the prices are analysed, the econometric technique, the functional form of the hedonic price function, housing characteristics included in the regression, among others. In not a few cases the findings are contradictory regarding the direction of the impact of flood risk and how the price schedule evolves after a flood in regions with different levels of risk. Given this broad heterogeneity in results, it is difficult to conclude to what extent (if any) flood risk location is capitalised in property prices. The use of meta-analysis techniques has proven to be useful to summarise, present key findings and identify possible factors driving the heterogeneity in results of a well-defined class of empirical studies.

In general, the term ‘meta-analysis’ refers to the use of statistical analysis to synthesise empirical findings. Traditional narrative literature reviews are useful in summarizing economic theories and identifying potential areas of research, however they have been criticised for being subjective as the sample of studies examined is based on the author's whim, and can dismiss certain studies in a subjective and selective manner (Chalmers, 1991; Stanley, 2001; Stanley and Jarrell, 1989). Glass (1976) first introduced the term meta-analysis which he defined as the *analysis of analyses*, consisting of the systematic statistical analysis of evidence across empirical studies. The purpose is to provide a more formal and objective process of reviewing empirical literature using objective procedures for the selection and analysis of studies, such that results can be independently evaluated and replicated (Stanley, 2001).

The use of meta-analysis in economics was introduced by Stanley and Jarrell in 1989, and since then it has been a growing field, especially in environmental economics (Smith and Pattanayak, 2002). The authors proposed what is called meta-regression analysis (MRA), as *the regression analysis of regression analyses,* which consists of studying the process that produce empirical economic results as though they were any other social scientific phenomenon. The idea is that in an area where multiple independent studies have been conducted on a particular subject, the results can be statistically combined to gain more insight; at the same time, the enlarged sample size generates more explanatory power than the mere listing of individual results (Pang, Drummond, and Song, 1999; Smith and Pattanayak, 2002; Stanley, 2001).

Guidelines have been proposed for carrying out a meta-analysis study, examples of these are those by The Cochrane Collaboration (1996) and Deeks, Glanville, and Sheldon (1996) for the area of medical research. Stanley et al. (2013) published the first reporting guidelines for meta-regression analysis in economics. It is possible to identify four basic steps to perform a meta-analysis (DeCoster, 2009):

1.1 Define the theoretical relationship of interest.
1.2 Collect the population of studies that provide data on the relationship.
1.3 Code the studies and compute effect sizes.
1.4 Examine the distribution of effect sizes and analyse the impact of moderating variables.

To the best of our knowledge there is only one previous meta-analysis on the price differential for floodplain location; this is due to Daniel, Florax, and Rietveld (2009a). The authors use a meta-sample consisting of 19 studies and 117 point estimates and focus only in the use of meta-regression analysis techniques to explore the causes for variation in previous results considering a set of 18 moderator variables accounting for differences in the space-time features of studies, study design and control variables included in primary studies. However, we believe that the understanding of factors driving the heterogeneity in the results can be improved. The recent debate in the economics of flood risk emphasises that individuals poorly integrate risk into their decisions; however, recent experience with flooding raises the perception of risk and the associated price differential in the housing market. Authors such as Bin and Landry (2013) and Atreya, Ferreira, and Kriesel (2013) find evidence indicating that the information effect of flood events diminishes as time elapses; however, there is no clear sign as to how this process operates at regions with different levels of risk and the functional form of the recovery. Pryce, Chen, and Galster (2011) suggest that the path of the price schedule following a flood is contingent on the sequence of flood experiences in each region. We believe that differences in flood risk perception play an important role in determining the heterogeneity in previous results. This has been entirely ignored in the aforementioned meta-analysis. Furthermore, important theoretical distinctions have to be considered.

This section shows the results of a meta-analysis on the estimated relative price differential for floodplain location following the four steps defined by Stanley et al. (2013). The contributions of this meta-analysis are multiple. First, it extends the literature survey by providing an up-to-date literature review and extending the quantitative analysis with a meta-sample consisting of 37 studies published between 1987 and 2013, with a total of 349 point estimates; that is doubling the number of studies considered in the previous meta-analysis, and more than trebling the number of point estimates. Second, it adds more content to the analysis by considering important theoretical differences among estimates from primary studies with different econometric specifications. Third, it deepens the analysis by exploring the distribution of effect sizes considering different sources of flooding and different levels of risk, and by using meta-analysis techniques to help to provide a common measure of the property price differential for floodplain location under different circumstances. Fourth, it expands the previous study by using meta-regression analysis to explore the heterogeneity of point estimates by different sources of flood risk, different levels of risk and different econometric specifications. Fifth, it contributes to the recent debate on flood risk capitalisation and flood risk perception by including moderator variables to account for differences in flood risk perception, among regions and through time. Finally, it considers additional statistical tests exploring the existence of publication bias in the flood risk literature.

The remaining of this section is divided as follows. Section 1.4.1 defines the theoretical relationship of interest and highlights the theoretical difference between estimates from studies with different econometric specifications. Section 1.4.2 presents the systematic review of literature for this meta-analysis. Section 1.4.3 describes the meta-sample and section 1.4.4 analyses the distribution of effect sizes and presents the results of the meta-analysis and meta-regression analysis.

1.4.1 Define the theoretical relationship of interest

Empirical applications of the HPM in the flood risk literature focus in two main areas, those studies trying to identify the marginal implicit hedonic price for flood risk location, and those which focus on identifying the marginal value for the information induced effect by exogenous events, mainly floods. These relationships correspond to equations (9) and (20) in section 1.2, respectively, and are given by:

1. Marginal implicit price of flood risk
$$\frac{\partial P}{\partial p} = \frac{U^F - U^{NF}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \qquad (32)$$

2. Marginal value for the information induced change in risk
$$\frac{\partial P}{\partial i} = \frac{\frac{\partial p}{\partial i}(U^F - U^{NF})}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \qquad (33)$$

The main theoretical relationship of interest is the marginal implicit price for flood risk defined in equation (32). Notice, however, that the two expressions above are related. The variable p denotes the subjective probability of flooding, i.e. flood risk perception, and is defined as a function $p(i,r)$, where i represents the set of information the individual holds about flood risk in the location of the property, and r represents the site attributes related to flood risk. The second expression, (33), indicates that the marginal effect of new information is to change the perceived probability of a flood, and evidence suggests that the occurrence of flood events provides additional information about flood risk in a particular location. Therefore estimates from standard hedonic models and pre-flood estimates from DID models, θ_i, are determined, in part, by the prevailing information about flood risk in the location of interest at the time the transactions in the housing market took place; this includes the historical frequency, severity and spatial characteristics of previous flood events, among other important information. That is, these estimates are post-flood price differentials for floodplain location in the sense that they include information of previous floods taking place at the location of interest, although not during the specific period of the sample. The time with respect to the previous flood will vary for different locations and different time periods, and there is evidence that suggests that the information effect diminishes over time.

The use of DID models allows us to identify the extent to which prices in a floodplain vary after the occurrence of a particular flood event; this effect is given by the expression (33) above, which is the coefficient ψ_i we obtain from DID applications. In this case the post-flood price differential for floodplain location would be given by the following expression:

$$\frac{\partial P}{\partial p} = \frac{U^F - U^{NF}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} + \frac{\frac{\partial p}{\partial i}\left(U^F - U^{NF}\right)}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \qquad (34)$$

That is, the pre-flood price differential for floodplain location, plus the marginal value of the information induced change in risk. This effect is given by the coefficient Θ_i defined in equation (27). Therefore, this meta-analysis also collects information on the theoretical relationship given in equation (33), as it is used to determine the post-flood price differential for floodplain location from DID specifications.

There are two main differences to highlight between θ_i and Θ_i. First, estimates of Θ_i allow us to separate the value of the information induced change in risk conveyed by the most recent flood event in a specific location during the period of analysis, whereas estimates of

θ_i already contain this information and is not possible to separate it. The second difference is probably the time elapsed since the previous flood event; since estimates of ψ_i from DID models are based on prices of properties that are sold in the aftermath of a flood, it is likely that for estimates of θ_i the time with respect to the previous flood event is longer than for estimates of Θ_i. This distinction is important as there is evidence which suggests that the information effect of a flood decays over time. Otherwise, it is important to highlight that both estimates provide information on the same theoretical relationship of interest.

1.4.2 Collect the population of studies that provide data on the relationship

The essential step of a comprehensive meta-analysis is to undertake a systematic literature review. The author should do all efforts to identify as many studies as possible related to the topic of interest, published and unpublished, as a way of reducing potential biases introduced by any non-random selection of studies; rules of inclusion and exclusion should be made explicit (H. Doucouliagos and Ulubaşoğlu, 2008; Stanley, 2001). Unlike traditional literature reviews, systematic reviews are more objective and reliable by systematically locating, appraising and synthesizing evidence form scientific studies (Deeks, Glanville, and Sheldon, 1996; H. Doucouliagos and Ulubaşoğlu, 2008; Pang, Drummond, and Song, 1999).

For this purpose, this meta-analysis involves a comprehensive computer search of relevant databases and careful study of references. Based on the theoretical review of literature a list of keywords was identified; these can be divided into four groups: 1) type of environmental event; 2) words describing the risk of the event and; 3) words related with houses and properties and 4) words related to values and prices. This list is presented in table 1.1.

Table 1.1. Keywords for computer search

Group 1	Group 2	Group 3	Group 4
Flood	Risk	Property	Values
Flooding	Hazard	Residential	Sales
Hurricanes	Threat	Housing	Prices
Inundation		Real Estate	
		Market	
		Land	
		Households	
		House	

Source: Own elaboration.

Once the relevant keywords have been identified, different combinations of these were tested to get a combination that retrieves a reasonably large number of studies that contain the relevant literature on the topic, while being able to examine all the results to identify the ones that are potentially useful for the meta-analysis. The use of *Boolean* operators such as the words AND or OR, parentheses and wildcards (*) are useful to expand or narrow the search. The search was undertaken in English as the main language for dissemination of academic research. The combination of words used for this meta-analysis is presented below:

(Flood* OR Hurricane* OR Inundat*) AND (Propert* OR Resident* OR Hous* OR "Real Estate")

This combination contains words from group 1 and group 3 in table 1.1; including words from another group resulted in a considerable decrease of the results which might leave important pieces of research out. The use of the wildcard character * allows us to expand the results of the search by replacing letters or sequence of letters. Thus searching for the word *Flood** will retrieve results such as *Flood*, *Floods*, *Flooding*, *Floodplain*, and so on.

We examine relevant databases of studies, journals, economic research and dissertations. Some databases such as the Social Science Research Network (SSRN) do not allow the use of Boolean operators or wildcards in advance searches. In this case we use different combinations of the words included in the main search. Other databases such as ProQuest retrieve too many results such that words from group 4 in table 1.1 were used to narrow the search. A chronological summary of the literature review is presented in table 1.2. The last column of *saved studies for further research* includes those studies that can be potentially included in the meta-analysis, but further research is needed to take a decision. This column does not duplicate papers found in previous databases.

Table 1.2. Chronological summary of literature review

Database	Date	Total of Entries	Saved for further research
EconLit	18/04/2013	365	59
Social Science Citation Index and Conference Proceedings Citation Index	24/04/2013	249	34
IngentaConnect	25/04/2013	982	12
Environmental Valuation Reference Inventory	30/04/2013	228	11
AGRICOLA. US National Agricultural Library Catalog	02/05/2013	143	0
SSRN	02/05/2013	285	16
ProQuest	03/05/2013	3,776	32
Total		**6,028**	**164**

Source: Own elaboration.

More than 6,000 entries from different electronic databases were reviewed and 164 studies were kept for further research. An update of the literature review was done during May

2014 to ensure most recent studies were included.[9] The rules for inclusion of studies are similar to those by Daniel, Florax, and Rietveld (2009a), namely:

(i) Estimates have to be determined using an econometric specification of a hedonic price function, either standard HPM or DID HPM (see section 1.3).
(ii) Estimate can be expressed, eventually after recalculation, as a percentage of the average price of the house.
(iii) The risk of flooding is captured by a dummy, where the dummy reflects the location within a 100-year or 500-year floodplain.
(iv) Repeated studies are not included. For studies that have become available in more than one version with the same results only the most up-to-date version is recorded.

We set these rules with the objective of having a final meta-sample which includes studies with a range of applications but sufficiently homogeneous such that estimates can be comparable and meaningful conclusions could be drawn from the meta-analysis. These rules, however, imply some evidence is not included. The first rule explicitly excludes studies with estimates obtained by comparing average sale prices within and outside a floodplain, such as Zimmerman (1979) or Babcock and Mitchell (1980); studies comparing appreciation trends, such as Eves (2002) or Lamond, Proverbs, and Hammond (2010); and studies using repeat-sales models, such as Lamond and Proverbs (2006) and Carbone, Hallstrom, and Smith (2006). The second rule implies the exclusion of studies providing monetary estimates of price change for floodplain location without information on the average house price such as Holway and Burby (1990). The third rule excludes studies such as Barnard (1978), Shilling, Benjamin, and Sirmans (1985) and Tobin and Montz (1994) who use elevation, the cost of flood insurance or flood depth, respectively, as a proxy for flood risk. It also excludes the study by Atreya and Ferreira (2012b) who use a dummy variable to identify properties located within a floodplain regardless of the level of

[9] This exercise resulted in the inclusion of four studies that become available during 2013, see details in table 1.3 and table A1.1.

risk, as well as some results from the studies by Bin, Kruse, and Landry (2008) and Bin and Landry (2013) from regressions where the level of risk is not distinguished. The fourth rule ensures that each study in the final meta-sample is unique.

1.4.3 Code the studies and compute effect sizes

The final meta-sample includes a total of 37 studies and 349 point estimates, this means almost doubling the number of studies considered by Daniel, Florax, and Rietveld (2009a) and more than trebling the number of point estimates. The date of publication of studies is between 1987 and 2013. The availability of empirical evidence is geographically confined to the United States contributing with 33 studies across 12 different States. The sample also includes studies for Australia, The Netherlands, New Zealand and United Kingdom (see table 1.3 below).

Once we select the studies for the meta-analysis, their main characteristics and results have to be coded. From studies using a standard HPF, generalized in equations (23) and (24), the coefficient of interest is $\hat{\theta}_i$, which represents the relative price differential for floodplain location at different levels of risk.

Although all studies in the meta-sample use a similar variable to control for flood risk, the functional form of the hedonic price function is not the same; therefore some of the observations are not expressed in the same units and adjustments have to be done. The effect size of interest for this meta-analysis is the relative price differential for floodplain location, following the same notation as Daniel, Florax, and Rietveld (2009a), this is referred as T, with associated standard errors s_T. Most studies use a semi-loglinear specification as in equation (35) below, where lnP_i denotes the natural logarithm of the selling price of house i, F represents a dummy variable equal to one if the property is located in a floodplain, Z represents the set of all other house specific characteristics j and ε_i is the house specific error term which is assumed $\varepsilon_i \sim N(0, \sigma^2 I)$. In this case, the effect size T and the standard errors s_T are considered to be the coefficient θ and the standard error s_θ as recorded from the primary studies.[10] Studies by Donnelly (1989), Bialaszewski and Newsome (1990), Speyrer and Ragas (1991), US Army Corps of Engineers (1998), Harrison, Smersh, and Schwartz (2001) and Shultz and Fridgen (2001) report estimates from linear specifications as in equation (36); in this case $T = \theta/\bar{P}$ and $s_T = s_\theta/\bar{P}$, where $\bar{P}$ is the sample mean of the selling price.

$$lnP_i = \beta_0 + \theta F_i + \textstyle\sum_{j=1} \beta_j Z_{ij} + \varepsilon_i \tag{35}$$

$$P_i = \beta_0 + \theta F_i + \textstyle\sum_{j=1} \beta_j Z_{ij} + \varepsilon_i \tag{36}$$

$$\frac{P_i^\lambda - 1}{\lambda} = \beta_0 + \theta F_i + \textstyle\sum_{j=1} \beta_j Z_{ij} + \varepsilon_i \tag{37}$$

Studies by MacDonald, Murdoch, and White (1987), MacDonald et al. (1990), Dei-Tutu and Bin (2002) and Bin (2004) report estimates using a Box-Cox specification as in equation (37); in this case $T = \theta \bar{\bar{P}}^{1-\hat{\lambda}}$, where $\bar{\bar{P}}$ represents the mean estimated selling price and $\hat{\lambda}$ is the estimated non-linearity parameter. Notice that, in this case, the effect size, T, is a function of two random parameters, therefore the standard errors, s_T, cannot easily be computed from the parameters reported in primary studies; following Daniel, Florax, and Rietveld (2009a), these have been approximated using the Delta method, as in equation (38).

[10] Notice that, formally, in the case of a dummy variable in a semi-log specification the marginal effect should be adjusted to $e^\theta - 1$ (Halvorsen and Palmquist, 1980). However, following Daniel, Florax, and Rietveld (2009a) adjustments are not taken into account given the small magnitude of the coefficients.

$$s_T = \sqrt{\left(\frac{\partial T}{\partial \lambda}\right)^2 \sigma_\lambda^2 + \left(\frac{\partial T}{\partial \theta}\right)^2 \sigma_\theta^2 + 2\left(\frac{\partial T}{\partial \lambda}\right)\left(\frac{\partial T}{\partial \theta}\right) r_{\theta\lambda}\sigma_\theta\sigma_\lambda} \tag{38}$$

Where σ_i represents the standard error of parameters λ and θ, respectively, and $r_{\theta\lambda}$ is its correlation coefficient. For studies such as MacDonald, Murdoch, and White (1987) and MacDonald et al. (1990) which do not provide an estimate of σ_λ, we approximate this using a standard error of $\lambda/2$ as in Daniel, Florax, and Rietveld (2009a); this makes λ significantly different from zero at the 5% significance level. Since an estimate of $r_{\theta\lambda}$ is generally unavailable, we assume a value of ±0.9 depending on whether $(\partial T/\partial\theta)(\partial T/\partial\lambda)$ is positive or negative, respectively, in order to have conservative standard errors.

All studies using a hedonic DID model, generalised in equations (25) and (28), assume a semi-loglinear specification. From these models it is possible to recover estimates for the pre-flood and post-flood relative price differential for floodplain location. In the case of pre-flood estimates $T = \theta$, with standard errors $s_T = s_\theta$, as recorded from primary studies. For post-flood estimates $T = \Theta$, as defined in equation (27); therefore, we have to collect information on two coefficients: the pre-flood relative price differential for floodplain location, $\hat{\theta}_i$ and the incremental effect due to information conveyed by the flood in known risky locations, $\hat{\psi}_i$. Since T is given by a linear combination of two parameters, the standard errors have to be estimated using the following formula:

$$s_T = \sqrt{\sigma_\theta^2 + \sigma_\psi^2 + 2r_{\theta\psi}\sigma_\theta\sigma_\psi} \tag{39}$$

Again, σ_i represents the standard error of parameters θ and ψ, respectively, and $r_{\theta\psi}$ is the corresponding correlation coefficient. Since the latter is generally unavailable, a value of 0.9 has been assumed to keep standard errors conservative. We do not include evidence from repeat-sales models in the analysis, as equation (30) makes clear that from these specifications it is only possible to recover an estimate of $\hat{\psi}_i$ and therefore is not possible to compute the coefficient of interest.

All estimates included in the analysis are based on actual transaction data, i.e. selling price. We exclude 13 estimates by US Army Corps of Engineers (1998) based on appraised values.[11] For studies using a spatial lag model only, we collect only the 'pure' effect of flood risk location (i.e. the pre-dynamic effect), and spatial spillovers due to prices of nearby properties are not considered; studies dealt with thus include Daniel, Florax, and Rietveld (2007), Bin et al. (2008), Posey and Rogers (2010), Atreya and Ferreira (2012a), Atreya and Ferreira (2012c), Atreya, Ferreira, and Kriesel (2012), Atreya, Ferreira, and Kriesel (2013) and Meldrum (2013).[12]

The number of observations collected from each primary study varies widely, ranging from studies such as Donnelly (1989), Shilling, Benjamin, and Sirmans (1985), Bialaszewski and Newsome (1990), Dei-Tutu and Bin (2002) and Rambaldi et al. (2012) contributing with one observation each, up to studies such as Atreya, Ferreira, and Kriesel (2013) and Kousky (2010), that contribute with 40 and 46 observations, respectively. Table 1.3 shows a summary of the studies and the effect sizes that were computed.

It is important to note that the mean effect sizes that we report in table 1.3 corresponds to the relative price differential for floodplain location (100, 500-year floodplain or both) and have not been adjusted for different levels of risk. Daniel, Florax, and Rietveld (2009a) standardised the effect sizes (and corresponding standard errors) to account for differences in the level of risk and report them as $T^{*} = T \times (1/\omega \times 100)^{-1}$, where T represents the unstandardised effect size and ω the recurrence interval of the floodplain, for instance 100

[11] These were, however, included in the meta-analysis by Daniel, Florax and Rietveld (2009a).
[12] See equations (24) and (28) in section 1.3 for details on the specification of the spatial lag model.

or 500-year. However, such a transformation assumes the relative price differential for floodplain location is linear in risk and applying it to the effect sizes led, in some cases, to unrealistic figures.[13] Therefore, we do not standardise the effect sizes prior to the analysis, instead we explore differences arising due to different levels of risk as part of the meta-analysis.

Most studies follow the definition of flood zones by the US Federal Emergency Management Agency (FEMA) under the National Flood Insurance Program (NFIP) and analyse the implicit price of flood risk for areas defined as Special Flood Hazard Area (SFHA). SFHAs are areas regarded to have a 1% probability (or higher) of being flooded in any single year, also known as 100-year floodplains; these areas are subdivided in Flood Zones with categories V and A, the former usually correspond to first-row, beach-front properties with additional hazards due to storm-induced velocity wave action, and the latter usually describes zones subject to rising waters. Other studies also consider areas of moderate flood hazard which are classified as zones B or X by the FEMA and are designated between the limits of the 100-year floodplain and the 0.2% annual probability of flooding, also known as 500-year floodplain. Studies by US Army Corps of Engineers (1998), Bin, Kruse, and Landry (2008) and Bin and Landry (2013) include regressions where a dummy variable is use to indicate floodplain location in either 100-year or 500-year floodplain without proper distinction; these estimates have been excluded from the final meta-sample. Estimates by US Army Corps of Engineers (1998) corresponding to 10, 25, and 50-year floodplain have been considered within the 100-year floodplain, as this is the highest flood hazard area considered by the FEMA. Estimates by Bartosova et al. (1999) for 200, 300 and 400-year floodplain have been classified as being within the 500-year floodplain. For estimates outside the US similar flood zones are distinguished.

[13] For instance, Atreya and Ferreira (2012a) reports the effect size which represents the highest price discount for location in a 500-year floodplain of -0.34. Applying the standardisation procedure proposed by Daniel, Florax and Rietveld (2009a) would imply $T^* = -0.34 \times (1/500 \times 100)^{-1} = -1.7$, i.e. an estimated discount of 170% of the price of the house for being located in a 100-year floodplain, which results implausible.

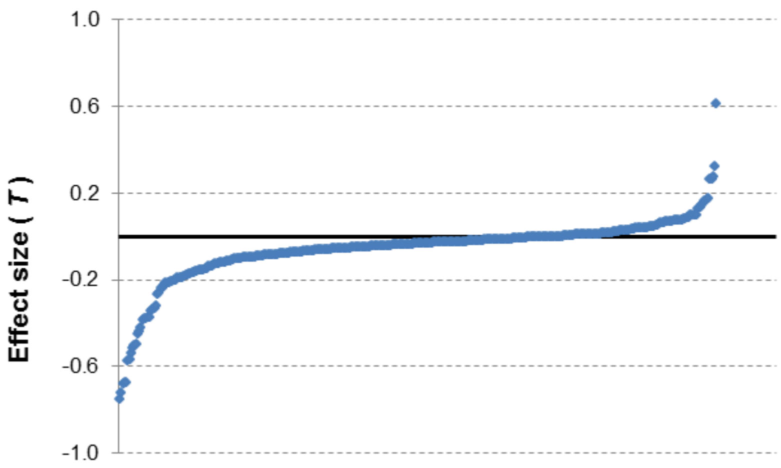
Table 1.3. Summary of studies included in the meta-sample

ID	Authors	Year	Country[1]	Location	Flood risk (floodplain)	No. Obs.	Effect size (*T*) Mean	S.D.	Min.	Max.
1	MacDonald, Murdoch and White[a]	1987	US	Louisiana	100	2	-0.077	0.014	-0.086	-0.067
2	Skantz and Strickland[a]	1987	US	Texas	100	8	-0.025	0.019	-0.056	-0.012
3	Donnelly[a]	1989	US	Wisconsin	100	1	-0.121	-	-	-
4	Shilling, Sirmans and Benjamin[a]	1989	US	Louisiana	100	1	-0.076	-	-	-
5	Bialszewski and Newsome[a]	1990	US	Alabama	100	1	0.000	-	-	-
6	MacDonald et al.[a]	1990	US	Louisiana	100	2	-0.100	0.024	-0.117	-0.083
7	Speyrer and Ragas[a]	1991	US	Louisiana	100	4	-0.098	0.073	-0.204	-0.042
8	US Army Corps of Engineers[a]	1998	US	Texas	100	14	-0.029	0.083	-0.268	0.080
9	Bartosova et al.[a]	1999	US	Wisconsin	100 and 500	7	-0.016	0.074	-0.078	0.144
10	Harrison, Smersh and Schwartz[a]	2001	US	Florida	100	4	-0.025	0.013	-0.041	-0.014
11	Shultz and Fridgen[a]	2001	US	ND and MI [2]	100 and 500	4	-0.032	0.073	-0.102	0.031
12	Troy	2001	US	California	100	20	0.024	0.022	-0.017	0.061
13	Dei-Tutu and Bin[a]	2002	US	North Carolina	100	1	-0.062	-	-	-
14	Bin	2004	US	North Carolina	100	4	-0.062	0.015	-0.076	-0.044
15	Bin and Polasky[a]	2004	US	North Carolina	100	3	-0.060	0.023	-0.084	-0.038
16	Troy and Romm[a]	2004	US	California	100	2	-0.011	0.030	-0.032	0.009
17	Hallstrom and Smith[a]	2005	US	Florida	100	8	0.066	0.118	-0.113	0.173
18	Bin and Kruse[a]	2006	US	North Carolina	100 and 500	9	0.107	0.235	-0.103	0.610
19	Lamond and Proverbs	2006	UK	North Yorkshire	100	2	-0.175	0.005	-0.178	-0.171
20	Daniel, Florax and Rietveld	2007	NL	Meuse River	100	15	-0.026	0.042	-0.064	0.066
21	Morgan	2007	US	Florida	100	3	0.254	0.080	0.165	0.321
22	Bin et al.[a]	2008	US	North Carolina	100	2	-0.139	0.037	-0.165	-0.113
23	Bin, Kruse and Landry[a]	2008	US	North Carolina	100 and 500	6	-0.054	0.028	-0.078	-0.010
24	Pope[a]	2008	US	North Carolina	100 and 500	22	-0.002	0.025	-0.045	0.038
25	Daniel, Florax and Rietveld	2009	NL	Meuse River	100	4	-0.049	0.041	-0.086	0.005
26	Kousky	2010	US	Missouri	100 and 500	46	-0.024	0.017	-0.073	0.008
27	Samarasinghe and Sharp	2010	NZ	Auckland	100	4	-0.040	0.025	-0.064	-0.014
28	Posey and Rogers	2010	US	Missouri	100	2	-0.082	0.023	-0.098	-0.066
29	Atreya and Ferreira	2011	US	Georgia	100 and 500	6	-0.134	0.143	-0.375	0.042
30	Rambaldi et al.	2012	AU	Queensland	100	1	-0.013	-	-	-
31	Atreya and Ferreira	2012c	US	Georgia	100	20	-0.187	0.245	-0.722	0.127
32	Atreya and Ferreira	2012a	US	Georgia	100 and 500	18	-0.174	0.195	-0.677	0.102
33	Atreya, Ferreira and Kriesel	2012	US	Georgia	100 and 500	22	-0.084	0.163	-0.382	0.100
34	Atreya, Ferreira and Kriesel	2013	US	Georgia	100 and 500	40	-0.164	0.226	-0.753	0.087
35	Bin and Landry	2013	US	North Carolina	100 and 500	18	-0.093	0.101	-0.423	0.041
36	Meldrum	2013	US	Colorado	100	21	-0.038	0.040	-0.096	0.010
37	Turnbull, Zahirovic and Mothorpe	2013	US	Louisiana	100 and 500	10	-0.006	0.016	-0.023	0.014
	Overall					**349**	**-0.059**	**0.147**	**-0.753**	**0.610**

Notes: [1] AU = Australia, NL = The Netherlands, NZ = New Zealand, UK = United Kingdom, US = United States.
[2] ND = North Dakota, MI = Minnesota.
[a] Studies included in the previous meta-analysis by Daniel, Florax and Rietveld (2009a).

There is general agreement in that prices of properties in a flood prone area are lower than those of equivalent houses outside; a total of 33 studies, out of 37, estimate a mean negative price effect of flood risk location on property prices. Evidence suggests that properties located in a floodplain are discounted, on average, by 5.9%; however, there is great within-study and between-study variability as highlighted by the columns reporting the standard deviation (SD) of the effect sizes, as well as their minimum (Min.) and maximum (Max) values. Estimates range from a price discount of 75% suggested by Atreya, Ferreira, and Kriesel (2013), to a price premium of 61% by Bin and Kruse (2006). Figure 1.3 shows the 349 effect sizes included in the meta-sample. Given the broad heterogeneity in results, it is difficult to conclude to what extent (if any) flood risk location is capitalised in property prices. Nonetheless, it is important to remember that the effect sizes represent different levels of risk, and that other characteristics of the study and the location of interest are not accounted for. The following sections explore the wide heterogeneity in results.

Figure 1.3. Meta-sample: Relative price differential for floodplain location



Source: Own elaboration based on results from primary studies.

Finally, although all studies included in the meta-sample by Daniel, Florax, and Rietveld (2009a) are represented in our meta-analysis, the number of point estimates collected from each study is not always the same; some of the differences require special mention. As noted earlier, 13 point estimates by US Army Corps of Engineers (1998) based on appraised values are not included. This meta-analysis includes three additional estimates by Bin and Kruse (2006) associated with locations within a 100-year floodplain with additional vulnerability to wave action, one of the flood zone subdivisions within SFHAs as specified by the US FEMA.[14] For those studies using a Box-Cox specification the effect sizes have been computed based on the estimated sales prices at the average values of the characteristics of the properties in the sample of the studies; as a result the final meta-sample only includes two estimates by MacDonald, Murdoch, and White (1987) and MacDonald et al. (1990) and only one from Dei-Tutu and Bin (2002).[15]

1.4.4 Examine the distribution of effect sizes and the impact of moderating variables

The point estimates that we collect for this meta-analysis come from primary studies that vary in many aspects. The objective of this section is to present the statistical analysis of evidence across empirical studies. The analysis is divided in three sections. Section 1.4.4.1 examines the distribution of effect sizes, and section 1.4.4.2 presents summary statistics for the price differential on property prices for floodplain location and examines the heterogeneity of previous results using a meta-regression analysis to assess the impact of moderating variables. Throughout the analysis we emphasise the theoretical, methodological and contextual differences among primary studies.

1.4.4.1 Examine the distribution of effect sizes

Figure 1.4 shows the distribution of the 349 effect sizes included in the meta-sample. 70% of the observations suggest that properties located in the floodplain are sold at lower prices than comparable properties not in flood risk region; the remaining observations suggest prices of properties in the floodplain are higher. The mean of the distribution is about -0.06, and the distribution peaks around -0.02. Ninety percent of the observations lie between -0.37 and +0.09. However, the effect sizes correspond to different levels of risk

[14] Daniel, Florax and Rietveld (2009a) do not provide a specific explanation for the exclusion of the estimates by Bin and Kruse (2006).

[15] Daniel, Florax and Rietveld (2009a) include six estimates by MacDonald, Murdoch and White (1987) and MacDonald et al. (1990) and three by Dei-Tutu and Bin (2002). They compute the effect sizes based on estimated sales prices resulting from assuming hypothetical values of the characteristics of a house, for three different types of houses: below average, average and above average properties.

and come from primary studies which vary in several aspects. Figures 1.5 through 1.7 show the distribution of effect sizes grouping the estimates by different characteristics such as the level of risk, type of flood risk and methodology. The main descriptive statistics of the distributions appear in table 1.4.

Figure 1.4. Effect size: Distribution density plot

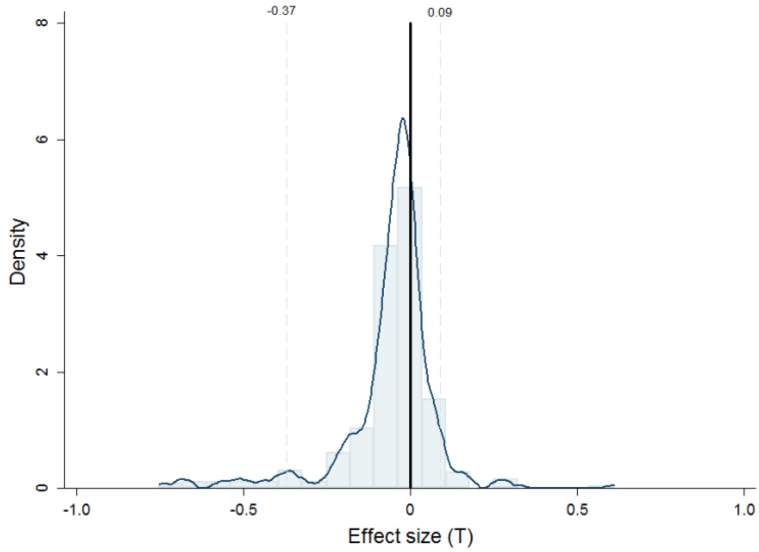


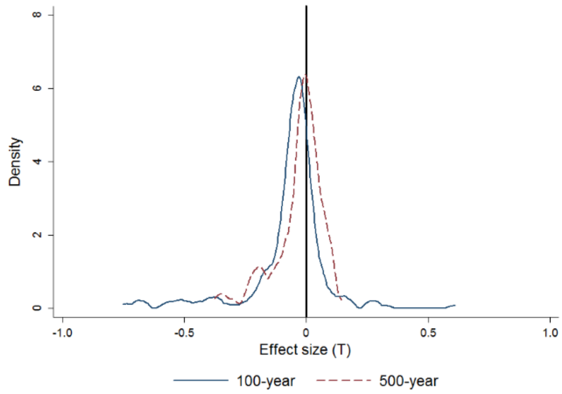
Figure 1.5.A shows the distribution of effect sizes by level of risk. Out of the total 349 effect sizes, 256 correspond to estimates for properties in a 100-year floodplain (1% annual probability of flooding) and 93 correspond to estimates for properties in a 500-year floodplain (0.2% annual probability of flooding). As expected, the distribution of estimates from properties in the 100-year floodplain has a larger mean discount, compared to the properties in the 500-year floodplain, and is also the one which shows the most extreme values in the left-tail of the distribution. Nevertheless, it is also the distribution that shows the highest premiums and the most extreme values in the right-tail. As Bin and Kruse (2006) and Bin et al. (2008) suggest, it might be that high positive values for properties in the 100-year floodplain correspond to locations where proximity to water is also associated to important amenity values, such as coastal regions.

To examine this possibility figure 1.5.B shows the effect sizes divided by the type of floods they represent, river flooding (fluvial) or coastal flooding. Both types possess different characteristics and their potential impacts are also different. The former are likely to be a result of heavy rain events whereas the latter are usually a result of storm surges created by storms like hurricanes and tropical cyclones. The distributions are skewed in opposite directions; the one for river flooding shows the highest discounts with a mean around -7%, whereas that for coastal flooding shows the highest premiums with a mean around 3%; both distributions nonetheless have a negative mode. Figures 1.5.C and 1.5.D explore the distribution of effect sizes for river and coastal flood risk by different levels of risk. In both cases largest negative values and fatter left tails correspond to regions with higher flood risk. Coastal flood risk is associated with smaller discounts and higher premiums. It is possible to conclude that extreme values in opposite tails of the distributions of 100-year and 500-year floodplain in figure 1.5.A correspond to flood risk from different sources. This pattern is likely to reflect the difficulties of isolating the value of risk in coastal regions where proximity to water is highly correlated with coastal amenities such as, waterfrontage and proximity to beach.

The two-sample Kolmogorov-Smirnov (K-S) distance statistic is also reported below each pair of distributions. This statistic is commonly used to compare two empirical distributions under the null hypothesis that the samples are drawn from the same distribution. Rejection of the null is regarded as evidence indicating the two distributions are statistically different, i.e. the samples are drawn from two different populations. Values of the K-S statistic in figure 1.5 suggest a significant difference between the distributions of estimates from different levels of risk and different sources of flooding, something which requires further research.

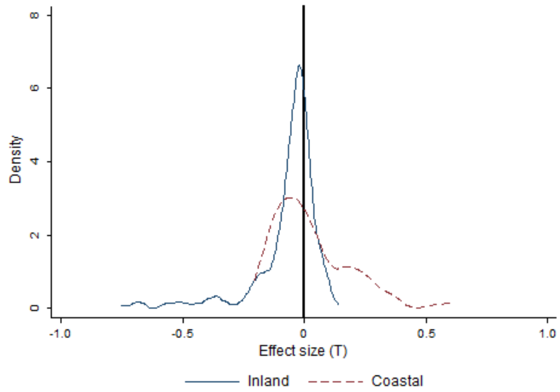
Figure 1.5. Effect size: Distribution density plots for different levels of risk and different types of flooding

Figure 1.5.A. 100 and 500-year



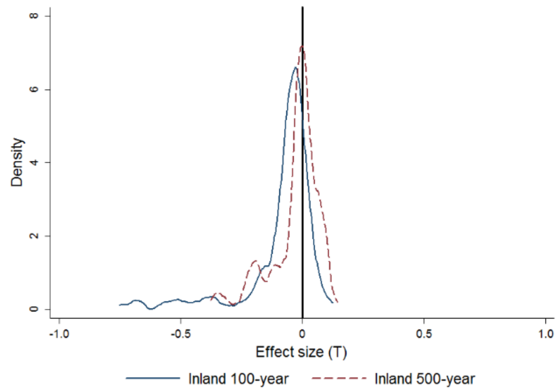
K-S: 0.25***

Figure 1.5.B. River and Coastal



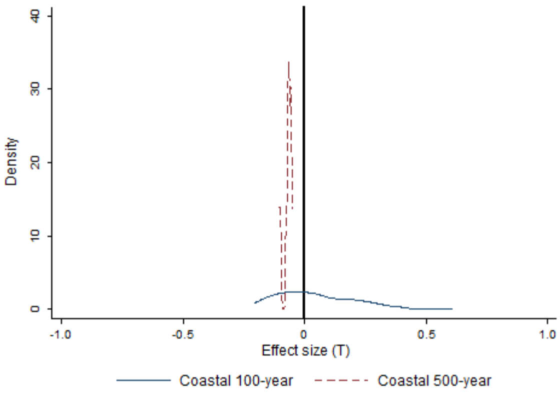
K-S: 0.29***

Figure 1.5.C. River: 100 and 500-year



K-S: 0.32***

Figure 1.5.D. Coastal: 100 and 500-year



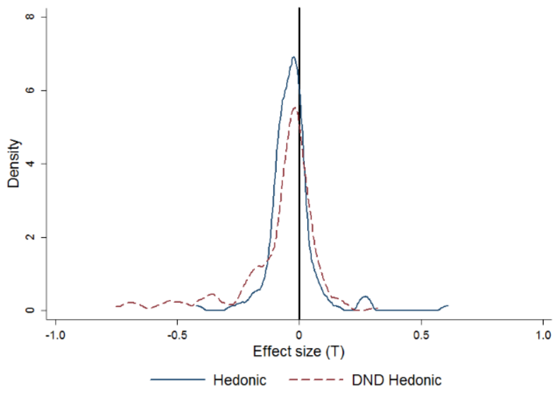
K-S: 0.60**

Notes: K-S represents the two-sample Kolmogorov-Smirnov statistic. H0: the samples are drawn from the same population. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Empirical studies also differ in the theoretical relationship of interest they estimate and, consequently, the econometric approach they use. Figure 1.6.A shows the distribution of effect sizes according to the corresponding methodology. The distribution of estimates using standard hedonic models shows the largest premiums, whereas that of estimates using a DID model shows the largest discounts. As shown in figure 1.6.B, these large discounts correspond to post-flood estimates, in this case the discount is expected to be large as the risk has become salient and homeowners might have experienced flood damages. This evidence is consistent with the idea that recent experience with flooding raises perception of risk; although, as Hallstrom and Smith (2005) and Atreya and Ferreira (2012a) point out, the large negative values of post-flood estimates might also be due to storm damages when these are not properly accounted for elsewhere. In both cases the K-S statistic suggests that the distributions come from different populations.

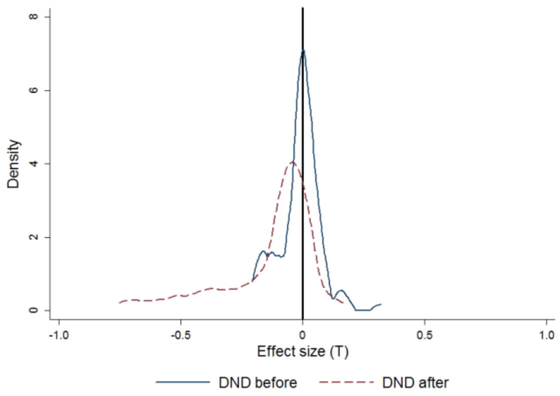
Figure 1.6. Effect size: Distribution density plots by methodologies and timing with respect to flood event

Figure 1.6.A Standard and DID hedonic



K-S: 0.18***

Figure 1.6.B DID: before and after



K-S: 0.44***

Notes: K-S represents the two-sample Kolmogorov-Smirnov statistic. H0: the samples are drawn from the same population. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

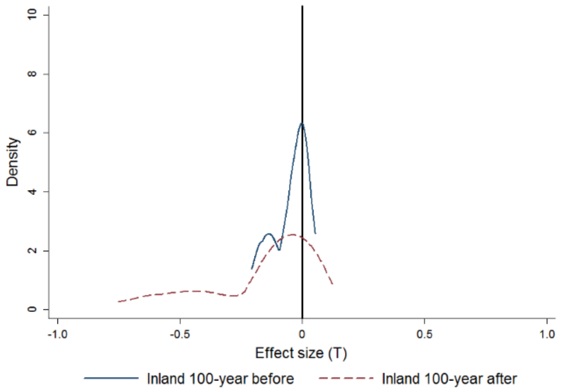
In order to explore further the evidence from DID hedonic models, figure 1.7 shows the distribution of effect sizes with respect to the time of the flood event, by different types of flooding and by different levels of risk. Figures 1.7.A and 1.7.B refers to river flood risk for properties in the 100-year and 500-year floodplain, respectively. There seems to be some pre-flood capitalisation of risk for properties in the 100-year floodplain; however, properties in the 500-year floodplain do not seem to be discounted before a flood. In both cases, the occurrence of a flood seems to raise the perception of risk. The mean value of the distribution for properties in the 100-year floodplain goes from a pre-flood discount of 5% to a post-flood discount around 17%, whereas for properties in the 500-year floodplain it goes from a 3% pre-flood premium to a 11% post-flood discount. Notice the change in the mean value is greater for those properties in the 500-year floodplain. Kousky (2010) suggests that differences in the capitalisation of risk after a flood event might arise due to information issues. Individuals in the 100-year floodplain tend to be more aware about the level of risk they face (this might be due to risk disclosure policies), thus the occurrence of a flood might not imply such an information update as it might be for individuals in the 500-year floodplain, which tend to have none or little information about the risk until it is brought to mind by flooding experiences. As Carbone, Hallstrom, and Smith (2006) suggests, in some cases the occurrence of a flood for individuals in the 100-year floodplain might simply be a realization from a known probability distribution, in which case no flood risk update is expected (see for example Kousky, 2010).

It might also be the case of post-flood estimates being higher than pre-flood ones. As it appears in figure 1.7.A, some post-flood values in the right tail of the distribution imply greater premiums than pre-flood estimates. Montz (1992) and Tobin and Montz (1994) suggest that this pattern could be a result of improvements in housing conditions due to repairs and/or investment to improve house quality after a flood.

The meta-sample includes only three studies applying a DID approach to estimate the implicit price of coastal flood risk, namely Hallstrom and Smith (2005), Morgan (2007) and Samarasinghe and Sharp (2010). Figure 1.7.C shows the distribution of the effect sizes collected from these studies, all of them focus in properties in the 100-year floodplain. These estimates are consistent with Hallstrom and Smith (2005), Bin and Kruse (2006) and Bin et al. (2008), which emphasise the difficulty of identifying the implicit price of flood risk in coastal regions due to the presence of confounder amenity values. Although the evidence suggests important pre-flood and post-flood premiums for location in a floodplain near to the coast, in all cases the occurrence of a flood decreases the associated premium (in some cases it becomes negative).

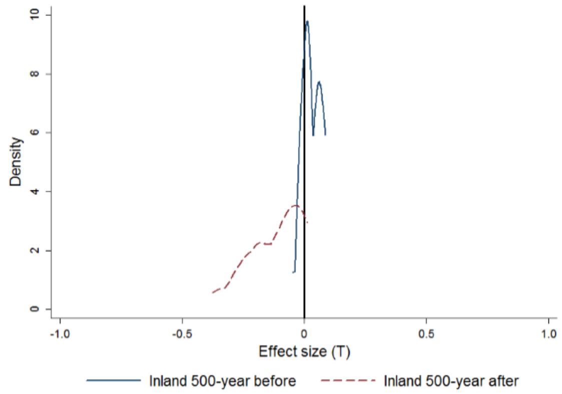
Figure 1.7. Effect size: Distribution density plots for estimates using DID models, by different type of flood risk, level of risk and timing with respect to flood event

Figure 1.7.A River flooding 100-year



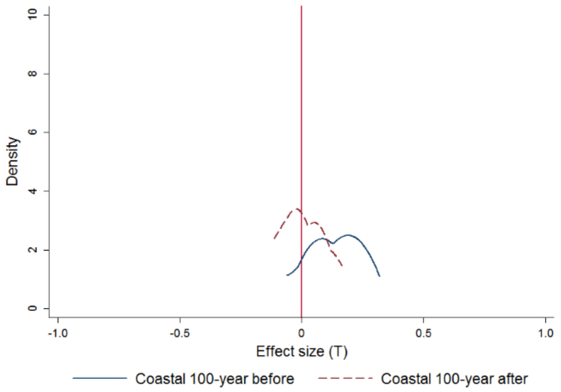
K-S: 0.42***

Figure 1.7.B River flooding 500-year



K-S: 0.84***

Figure 1.7.C Coastal flooding 100-year



K-S: 0.57

Notes: K-S represents the two-sample Kolmogorov-Smirnov statistic. H0: the samples are drawn from the same population. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Summarising, estimates for properties located within a 100-year floodplain show a greater discount than those for properties located in a 500-year floodplain. There seems to be a difference in the capitalisation of flood risk in river and coastal properties; the evidence highlights the difficulty of isolating the implicit price of risk in coastal regions where proximity is also associated to important benefits. In general, post-flood estimates imply a higher discounts, this is the case across regions with different levels of risk and different types of flooding. This evidence supports the widespread idea that recent floods provide new information to homeowners to update their flood risk perception; however, pre-flood information available appears to play a role in determining the extent of the update.

Table 1.4. Effect size: Summary statistic for point estimates grouped by different categories

No.	Grouped by								Num. Obs.	Mean	Mode	S.D.	Min	Max	90% Interval
	100 year	500 year	River	Coastal	Hedonic	DID Hedonic	Before	After							
1	●								256	-0.07	-0.02	0.16	-0.75	0.61	[-0.44; 0.10]
2		●							93	-0.03	-0.02	0.10	-0.37	0.14	[-0.21; 0.09]
3			●						314	-0.07	-0.02	0.14	-0.75	0.14	[-0.38; 0.07]
4				●					35	0.03	-0.06	0.16	-0.20	0.61	[-0.16; 0.32]
5	●		●						226	-0.08	-0.04	0.15	-0.75	0.13	[-0.45; 0.04]
6		●	●						88	-0.03	-0.02	0.10	-0.37	0.14	[-0.21; 0.09]
7	●			●					30	0.05	-0.06	0.17	-0.20	0.61	[-0.16; 0.32]
8		●		●					5	-0.07	-0.06	0.02	-0.10	-0.05	[-0.10; -0.05]
9					●				138	-0.03	-0.01	0.10	-0.42	0.61	[-0.16; 0.08]
10						●			211	-0.08	-0.02	0.17	-0.75	0.32	[-0.50; 0.08]
11						●	●		101	-0.01	0.00	0.09	-0.21	0.32	[-0.17; 0.09]
12						●		●	110	-0.14	-0.05	0.20	-0.75	0.16	[-0.57; 0.07]
13	●		●			●	●		63	-0.05	-0.03	0.07	-0.21	0.05	[-0.19; 0.04]
14	●		●			●		●	71	-0.17	-0.04	0.23	-0.75	0.13	[-0.68; 0.07]
15		●	●			●	●		31	0.03	0.00	0.04	-0.05	0.09	[-0.04; 0.08]
16		●	●			●		●	32	-0.11	-0.02	0.11	-0.37	0.01	[-0.34; 0.01]
17	●			●		●	●		7	0.12	0.16	0.14	-0.06	0.32	[-0.06; 0.32]
18	●			●		●		●	7	0.00	-0.11	0.10	-0.11	-0.16	[-0.11; 0.16]
Full Sample									349	-0.06	-0.02	0.15	-0.75	0.61	[-0.37; 0.09]

Source: Own elaboration based on results from primary studies.

Finally, it is important to be cautious when interpreting this evidence. As we subdivided the meta-sample for the analysis, the number of observations of the different groups markedly decreases; this is especially true for estimates from coastal regions. Furthermore, although analysing the distribution of effect sizes is useful to have a general overview of the meta-sample and to explore its variability, this analysis is rather limited. When comparing distributions it is only possible to control for one single aspect, for instance the level of risk, the type of flooding or the timing with respect to a flood event; however all other characteristics of the studies are allowed to vary and therefore no conclusions can be drawn. Section 1.4.4.2 presents the results of a meta-regression analysis, which allow us to explore the drivers of heterogeneity in the results from primary studies, while controlling for other multiple attributes that might cause the effect sizes to vary.

1.4.4.2 Meta-analysis

The objective of this meta-analysis is to gain more insight from information of multiple studies using a weighted average to summarise and combine the results. There are two popular models used for this purpose the fixed-effect model and the random-effects model. In both cases weights are usually assigned using the inverse of the error variance so that more weight is assigned to more precise studies, i.e. those which carry more information. The crucial difference between these two models lies in the assumptions they use to define the error variance.

In the fixed-effect model it is assumed that all studies included in the meta-analysis share a common true effect size, differences in observed effects arise only due to sampling error, i.e. if the sample size for each of the studies were infinite the observed effect for all cases would be the same as the true effect size. However because studies commonly differ in implementation and underlying population, among others, the assumption of the fixed-effect model is often implausible. The random-effects model allows the true effect size to differ from study to study. It assumes a distribution of true effect sizes, and the goal is to estimate the mean of the distribution, i.e. if it were possible to implement an infinite number of studies the true effect size of these studies would be distributed around some mean. Equations (40.a) and (40.b) shows the observed effect size T, as defined above, for any study i under the fixed-effect and random-effects model, respectively:

Fixed-effect		**Random-effects**	
$T_i = \eta + \xi_i$	(40.a)	$T_i = \mu + \varphi_i + \xi_i$	(40.b)

where η represents the common true effect size that all studies share in the fixed-effect model; μ is the mean of the distribution of true effect sizes that all studies share in the random-effects model (grand mean); ξ_i is the difference between the true mean of study i (η_i) and its observed mean (T_i), i.e. $\xi_i = T_i - \eta_i$ for both models, and φ_i is the difference between the grand mean of the random-effects model (μ) and true mean (η_i) for study i, i.e. $\varphi_i = \eta_i - \mu$. Thus in the case of the random-effects model there are two sources of variation: true variation in effect sizes (φ_i) and sampling error (ξ_i).

At this point the difference between the fixed-effect and random-effects model when using the inverse of the error variance as a weighting scheme should be evident. Under the fixed-effect model the overall study variance is simply the within-study variance (σ_i^2), whereas for the random-effects model it has two components: the within study error variance (σ_i^2) and the between-study variance (τ^2), that is the variance of the distribution of true effect sizes. Therefore, the weights (W_i) assigned to each study under the fixed-effect model and random-effects model are given by:

Fixed-effect		**Random-effects**	
$W_i = \frac{1}{\sigma_i^2}$	(41.a)	$W_i = \frac{1}{\sigma_i^2 + \tau^2}$	(41.b)

The implication is that, whenever $\tau^2 \neq 0$, relative weights assigned to each study are more balanced under the random-effects model. However, it is important to bear in mind that we are estimating two different parameters. In the fixed-effect model we estimate the common effect size (η) in the studies that are observed, whereas in the random-effects model is the mean of a hypothetical population of studies (μ), which includes studies that are not observed.

A common practice in meta-analysis literature is to use the results of the heterogeneity test to select the more appropriate model: random-effects or fixed-effect. Here the term heterogeneity is understood as the variation in the true effect sizes. The main statistic for this purpose is the Q-statistic (Cochran, 1954), defined as:

$$Q = \sum_{i=1}^{k} W_i (T_i - \eta)^2 \tag{42}$$

where W_i is the weighting factor for the ith study assuming a fixed-effect model ($1/\sigma_i^2$), T_i is the study effect size, η is the combined effect under the fixed-effect model and k is the number of studies. Thus the Q-statistic represents the observed weighted sum of squares (WSS) which reflects the total dispersion. Notice that the expected value of Q under the assumptions of the fixed-effect model (all the variation is due to sampling error) is simply the degrees of freedom ($df = k - 1$, where k represents the number of studies), since Q is a standardized measure and the expected value does not depend on the metric of the effect size. The difference:

$$Q - df \tag{43}$$

represents the excess variation, i.e. that attributed to differences in the true effects from study to study.

The heterogeneity test consists of testing the assumption of heterogeneity in effects using the statistic Q and df. The null hypothesis is that all studies share a common effect size.

Under the null Q follows a central χ^2 distribution with $k-1$ degrees of freedom. Thus, a rejection of the null is usually interpreted as evidence for the random-effects model. However, Borenstein et al. (2009) emphasises that the selection of the appropriate model should be based on our understanding of whether or not all studies share a common effect size and not on the outcome of the Q-statistic as it often has poor power, especially when dealing with small samples.

Another common measure of dispersion is the I^2 statistic. This was proposed by Higgins et al. (2003) and describes the ratio of excess dispersion to total dispersion, i.e. what proportion of the observed variance is real. The I^2 statistic is given by:

$$I^2 = \left(\frac{Q - df}{Q}\right) \times 100 \tag{44}$$

where Q and df are defined as in equations (42) and (43). A value of I^2 close to zero suggests that almost all observed variance is due to sampling error, which means that there is little, or nothing, to explain. On the other hand, a large value of I^2 is interpreted as evidence of real variation and supports the use of meta-regression analysis to identify possible causes. Higgins et al. (2003) suggest that values on the order of 25%, 50% and 75% can be considered as an indicator of low, moderate and high variation, respectively; no critical value is proposed.

In our case, as in most meta-analysis in economics, the assumptions of the fixed-effect model seems implausible. Table 1.5 reports the summary statistics obtained with the random-effects meta-analysis over the 349 effect sizes and different subgroups according to the level of risk, the type of risk and the econometric technique for estimation. The table also reports the 90% confidence interval, the between study variance τ^2, the Q-statistic and the I^2. However, this approach treats each observation as a separate study, which results in more weight assigned to studies reporting more than one outcome. To address this issue, table 1.5 also shows the meta-analysis summary statistics using another popular weighting scheme; assigning weights according to the sample size considered for each study. The weight assigned to each observation corresponds to the average sample size of each study, divided by the number of estimates that the study provides to the final meta-sample. In this way, studies are assigned more weight based on the total information that they contain and not because of providing a higher number of estimates. Thus, we prefer the interpretation of results using the later approach.

Notice that the summary effect sizes for the sub-sample of estimates in the 100-year floodplain suggests a price premium of 3%. However, it is possible to see that this average premium is driven by properties in coastal regions. If we subdivide the sample according to different type of flooding, for properties subject to river flooding in the 100-year floodplain the summary statistic suggests a discount of around 5%, whereas for properties in coastal regions at the same level of risk the results suggest a premium around 14%.

For properties in river regions in the 100-year floodplain there appears to be a significant discount of around 3%, even if we focus only on evidence from DID models before a flood. After a flood the associated discount in this region increases close to 7%. The summary statistic for houses in river regions in the 500-year floodplain suggests that before a flood the price differential is not significantly different from zero; however, after a flood there is a discount close to 6%. Therefore, unlike authors such as Kousky (2010) and Bin and Landry (2013) which found contrasting results suggesting that it is either properties in the 500-year floodplain or properties in the 100-year floodplain that are significantly discounted after a flood, our results considering evidence from multiple studies suggest this is true at both levels of risk. Furthermore, although the discount is greater in areas with higher risk, notice that the average decline of prices after a flood is greater in 500-year floodplains (6%) than in 100-year floodplains (4%). This result supports the idea by Kousky (2010) that significant updating occurs in areas where no prior capitalisation of flood risk into property prices has yet taken place.

Table 1.5. Meta-analysis: Summary statistics, random-effects and sample size weights

Sample	Random-Effects						Sample size weights			
	N	Summary Statistic[1]	90% Conf. Interval	τ^2	Q-Stat[2]	I^2	Summary Statistic[1]	90% Conf. Interval	Q-Stat[2]	I^2
All	**349**	**-0.025*****	**[-0.032; -0.018]**	**0.0029**	**5543.9*****	**93.5**	**-0.027*****	**[-0.032; -0.022]**	**6277.9*****	**94.2**
500 year	93	-0.001	[-0.006; 0.005]	0.0001	133.3***	31.0	-0.020**	[-0.040; -0.000]	385.5***	76.1
100 year	256	-0.033***	[-0.042; -0.023]	0.0039	5300.7***	95.2	0.031***	[0.024; 0.039]	7675.1***	96.7
River	314	-0.023***	[-0.028; -0.019]	0.0008	1739.3***	81.3	-0.037***	[-0.042; -0.032]	2704.5***	87.9
River 100-year	226	-0.032***	[-0.038; -0.026]	0.0010	1417.5***	84.1	-0.051***	[-0.058; -0.044]	2691.0***	91.6
DID River 100-year BF	63	-0.017***	[-0.028; -0.006]	0.0010	237.8***	73.1	-0.031***	[-0.041; -0.021]	417.9***	84.7
DID River 100-year AF	71	-0.076***	[-0.097; -0.055]	0.0037	215.0***	67.4	-0.069***	[-0.087; -0.050]	252.0***	72.2
River 500-year	88	0.003	[-0.002; 0.007]	0.0000	103.9	16.2	-0.021***	[-0.032; -0.009]	390.76***	77.7
DID River 500-year BF	31	0.005	[-0.003; 0.013]	0.0000	15.0	0.0	0.003	[-0.009; 0.015]	15.32	0.0
DID River 500-year AF	32	-0.025***	[-0.041; -0.009]	0.0000	14.36	0.0	-0.059***	[-0.087; -0.030]	31.84	2.6
Coast	35	0.024	[-0.034; 0.083]	0.0308	2226.9***	98.4	0.134***	[0.122; 0.147]	2228.8***	98.4
Coast 100 year	30	0.046	[-0.018; 0.110]	0.0297	1811.1***	98.4	0.141***	[0.129; 0.154]	1827.2***	98.4
DID Coast 100-year BF	7	0.118	[-0.030; 0.265]	0.0391	841.3***	99.3	0.261***	[0.248; 0.273]	1060.2***	99.4
DID Coast 100-year AF	7	0.016	[-0.072; 0.105]	0.0110	43.02***	86.1	0.116***	[0.083; 0.149]	50.22***	88.1
Coast 500-year	5	-0.066***	[-0.092; -0.040]	0.0000	1.35	0.0	-0.069***	[-0.098; -0.040]	1.41	0.0
Hedonic	138	-0.027***	[-0.027; -0.019]	0.0020	2989.3***	95.2	-0.022***	[-0.026; -0.017]	3128.0***	95.4
DID Hedonic	211	-0.031***	[-0.044; -0.017]	0.0065	2377.0***	90.8	-0.019***	[-0.029; -0.009]	2726.5***	92.0
DID Hedonic BF	101	-0.002	[-0.021; 0.016]	0.0068	1929.2***	94.5	0.009*	[-0.000; 0.018]	1979.0***	94.6
DID Hedonic AF	110	-0.057***	[-0.073; -0.040]	0.0036	331.1***	66.2	-0.047***	[-0.065; -0.028]	357.8***	68.7

Notes: [1] H0: the summary effect size is not statistically different from zero. [2] H0: all studies in the sample share a common effect size.
*, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.
BF= Before flood event, AF= After flood event.

There is very little evidence looking at the implicit price of flood risk in coastal regions, most of it corresponds to properties in 100-year floodplains. The results suggest that prices in these regions are higher than those outside the floodplain; this is even if we look only at post-flood estimates. In general the premium ranges anywhere between 11 to 26%. As authors such as Hallstrom and Smith (2005), Bin and Kruse (2006), and Bin, Kruse, and

Landry (2008) suggests, these results are likely to arise due to the existence of high positive amenity values associated with proximity to coast. When no amenity values correlated with flood risk are accounted for, the effect of these is consigned to the error term and the identification of the coefficient on the risk variable is compromised due to endogeneity. The occurrence of floods appears to have a negative effect on property prices, in the sense that they reduce the associated premium. For properties in the 500-year floodplain the results indicate a significant 7% discount; nevertheless, only two studies, Bin and Kruse (2006) and Bin, Kruse, and Landry (2008), look at these area of risk and both focus on the same region over the same period of time. The meta-sample does not include estimates from DID models in coastal regions in the 500-year floodplain.

Grouping the effect sizes according to the econometric approach they use, i.e. standard hedonic and DID hedonic models, yields similar results. Both methodologies suggest a price discount around 2%. Evidence from DID models post flood suggests flood events cause individuals to update flood risk perception.

There are two important things to mention related to the statistics describing the dispersion of results in table 1.5, the Q-statistic and the I^2. First, note that estimates from 500-year floodplains, regardless of the type of flooding, show very little total dispersion as given by the Q-static; the I^2 statistic suggests that only a very small fraction of this dispersion (in some cases it is even zero) is not due to sample error. These results indicate that for estimates form the 500-year floodplain there is very little variation to explain. At the other extreme, we have estimates from coastal regions. These contribute very few observations, which, however, seem to have a high amount of total dispersion. A value of the I^2 greater than 98% suggests that most of this dispersion is due to factors other than sample error.

In general, there appear to be three major factors causing a great deal of heterogeneity in the results and which deserve further analysis. First, differences in the level of risk; results suggest that properties in the highest area of risk are significantly discounted with respect to comparable properties outside the floodplain. Second, differences in the type of risk; results from coastal regions highlight the difficulty of isolating the value of risk in areas where proximity to water is also associated with important benefits, this is the case even when considering post-flood evidence. Finally, differences in the context of the area of study; results suggest higher discounts and smaller premiums in regions that have been recently affected by flooding. These sources of heterogeneity, among others, are explored with a meta-regression analysis in the following section.

a) Meta-regression analysis

The objective of a meta-regression analysis is to study the process that produces empirical economic results as though they were any other social scientific phenomenon (Stanley and Jarrell, 1989). In practice, it consists on identifying specific variables or circumstances causing excess dispersion (real variation) in the results, i.e. variation apart to that due to sampling error.

The full database consists of a total of 50 variables that were collected from each study; these variables describe important information on specific characteristics of each study. However, it is not possible to include them all in the meta-regression; many of them are correlated and in some cases the information is not available for all the studies. Our final model includes a set of 18 moderator variables which can be divided in six groups and are described in table 1.6. The first group refers to variables to control for changes in flood risk perception over time. Authors such as Hallstrom and Smith (2005), Atreya and Ferreira (2012a, 2012c), Atreya, Ferreira and Kriesel (2012, 2013) and Bin and Landry (2013) found evidence indicating that the price differential for floodplain location increases after a flood, but then it decreases as time elapses. Therefore, following previous findings we hypothesise that the time with respect to the previous flood in each location is important in explaining the heterogeneity in empirical results. To control for this we include a time variable *mnths* taking the value of the number of months since the major previous flood in the location of each study. In cases where the date of the previous flood was available from the study, this was just collected and the number of months was then calculated considering the median sample year of each study. For studies where the information on the previous flood was not available, this was obtained from historical records available online on major floods and storms. Notice that for studies using a DID approach, the time with respect to the previous flood for pre-flood estimates is different to that for post-flood estimates.

The second group of moderator variables controls for differences in the level of risk. We include a dummy variable to distinguish effect sizes corresponding to properties in the 100-year floodplain (*100year*); the omitted category corresponds to effect sizes from 500-year floodplains.

Table 1.6. Description of the variables included in the meta-regression model

Variable	Description
Flood risk perception	
mnths	Number of months since the previous flood.
Flood risk level	
100year	Dummy variable = 1, if the effect size refers to 100-year floodplain.
Context of the study	
lav_feet	Natural logarithm of the average square feet of the properties per study.
lavprice_2010	Natural logarithm of the average price of the properties per study in 2010 US dollars.
flooded	Dummy variable = 1, if the effect size refers to flooded properties.
scnd_flood	Dummy variable = 1, if the effect size refers to a second flood.
dd_after	Dummy variable=1, if the effect size corresponds to a post-flood DID estimate.
dd_afterlaw	Dummy variable = 1, if the effect size is from a DID model after a change in a regulation for floodplain designated areas.
coast	Dummy variable = 1, if the study area has a coastline.
Control variables of study	
amenity	Dummy variable = 1, if the study includes variables to control for amenity value of proximity to river, lake or coast.
real_p	Dummy variable = 1, if the study convert prices to constant measure before estimation.
Characteristics of econometric model	
linear	Dummy variable = 1, if the effect size corresponds to a linear specification of a hedonic price function.
Box-Cox	Dummy variable = 1, if the study specifies a semi-logarithmic specification of a hedonic price function.
spatial	Dummy variable = 1, if the effect size corresponds to a spatial econometric model.
dd_hpm	Dummy variable = 1, if the effect size corresponds to a DID specification (either before or after).
Characteristics of the study	
published	Dummy variable = 1, if the primary study is from a refereed journal.
med_sampleyear	Median sample year of the primary study.
time_span	Time span of the data covered in the primary studies.

Source: Own elaboration.

The third set of moderators refers to variables accounting for the context in which different studies take place. It includes the natural logarithm of the average square feet of the properties of each primary study (*lav_feet*) to control for differences in the type of houses in each region, and the natural logarithm of the average price of a property in 2010 US dollars (*lavprice_2010*) as a proxy for personal income of the households and to control for income differences across studies. As Hallstrom and Smith (2005) and Carbone, Hallstrom, and Smith (2006) point out, after a flood the discount in properties is expected to be large as homeowners are likely to have experienced flood damages; thus, we include a dummy variable to control for effect sizes from studies that explicitly specify that the estimated coefficient corresponds to flooded properties (*flooded*). Following Pryce, Chen, and

Galster (2011), we expect a higher discount for properties in the floodplain after a second subsequent flood (*scnd_flood*). We also include a dummy variable (*dd_afterlaw*) to identify effect sizes from studies looking at the price differential for floodplain location after changes in regulations and a dummy variable (*coast*) to distinguish effect sizes from coastal and river regions.

The fourth group of moderator variables consists of two dummy variables that signal the inclusion of specific control variables in primary studies. The first one (*amenity*) takes the value of one for studies which include variables to control for the amenity value of proximity to water. As mentioned before, if the amenity values correlated with flood risk are not accounted for, we expect estimates of risk value to be biased downwards or even positive. The second dummy variable (*real_p*) identifies studies using constant house prices to control for time variation. The fifth set of moderators refers to differences in the econometric model from primary studies. Two dummy variables (*linear* and B*ox-Cox*) account for differences in the functional form of the hedonic price function; the omitted category corresponds to studies assuming a semi-log functional form, i.e. studies using the natural logarithm of house prices as dependent variable. A dummy variable (*spatial*) distinguishes the use of spatial econometric techniques and the variable *dd_hpm* takes the value of one for estimates from DID hedonic models, either before or after.

The final group of moderator variables control for specific characteristics of the primary studies. As a proxy for quality of the study, we include a dummy variable (*published*) which takes the value of unity to distinguish studies published in refereed journals from those published as dissertations, working papers or conference proceedings. The median sample year of the primary studies (*med_sampleyear*) is included to identify any significant trend in the valuation of flood risk; the time span (*time_span*) of each study is also included. Table 1.7 show the summary statistics for the variables included in the meta-regression analysis.

Table 1.7. Summary statistics

Variable	No. Obs.	Mean	St. dev.	Min.	Max
Dependent variable					
Effect size (T)	349	-0.059	0.145	-0.754	0.610
Flood risk perception					
mnths	349	144.4	175.7	3.0	840.0
Flood risk level					
100year	349	0.703	0.457	0	1
Context of the study					
lav_feet	349	7.425	0.249	6.558	8.051
lavprice_2010	349	11.861	0.557	9.191	12.956
flooded	349	0.025	0.155	0	1
scnd_flood	349	0.033	0.179	0	1
dd_after	349	0.329	0.471	0	1
dd_afterlaw	349	0.074	0.262	0	1
Coast	349	0.102	0.303	0	1
Control variables of study					
amenity	349	0.876	0.330	0	1
real_p	349	0.667	0.472	0	1
Characteristics of econometric model					
linear	349	0.071	0.258	0	1
Box-Cox	349	0.019	0.137	0	1
spatial	349	0.343	0.475	0	1
dd_hpm	349	0.593	0.492	0	1
Characteristics of the study					
published	349	0.580	0.494	0	1
med_sampleyear	349	1995.1	6.464	1978	2006
time_span	349	7.173	6.416	1	40

Source: Own elaboration.

The assumptions and algebraic representation of the meta-regression model with random-effects is similar to that described in equation (40.b). However, in this case we replace the common true mean μ, by the conditional mean $\sum_{k=1}^{m} \beta_k X_k$. The objective is to estimate μ as a function of a set of m explanatory variables X and a vector β of associated parameters. The random-effects meta-regression model is represented as follows:

$$T_i = \sum_{k=1}^{m} \beta_k X_k + \varphi_i + \xi_i \tag{45}$$

where T_i represents the observed mean from each study i, and ξ_i and φ_i represent the within and between study variation, respectively. The usual assumptions on the error terms, $\xi_i \sim iid(0, \sigma_i^2)$ and $\varphi_i \sim iid(0,\ \tau^2)$, apply. The within study variance σ_i^2 is known, and is taken from primary studies. The between study variance τ^2 is an unknown term common to all studies, and is usually estimated using an iterative maximum likelihood process. The weights assigned to each observation are given by $W_i = {}^{1}/_{(\sigma_i^2 + \tau^2)}$.

The previous met-regression analysis by Daniel, Florax, and Rietveld (2009a) present their results using three different alternative weighting schemes. First they apply a random-effects meta-regression model (mixed-effects) where weights are assigned as stated above; second, they estimate an unweighted model using Huber-White standard errors which are robust to heteroscedasticity and correlation among effect sizes sampled form the same primary study; and finally they present the results using inverse variance weights, as in a fixed-effect model, with Huber-White standard errors. However, all of these models treat each entry as a separate study, with the resulting aforementioned problem of assigning more weight to studies which contribute more observations to the meta-sample. This might represent an important problem with a meta-sample like the one by Daniel, Florax, and Rietveld (2009a) where some studies contribute with more than 20 observations.

Authors such as Stanley and Doucouliagos (2013) suggest that, in many cases, weighted least squares performs better than conventional random-effects meta-regression; however, this does not address the issue of overrepresentation of studies with more than one estimate. To mitigate this issue we show the results of a meta-regression model assigning weights according to the sample size considered for each study. The weight assigned to each observation corresponds to the average sample size of each study, divided by the number of estimates that the study contributes to the final meta-sample. In this case the regression model looks as follows:

$$T_i\sqrt{\bar{N}_{j,i}/n_j} = \sum_{k=1}^{m} \beta_k X_k \sqrt{\bar{N}_{j,i}/n_j} + e_i\sqrt{\bar{N}_{j,i}/n_j} \tag{46}$$

where $\bar{N}_{j,i}$ represents the average sample size of *j*th study, from which the *i*th effect size has been collected, and n_j is the total number of observations from the *j*th study to the total meta-sample. In this way, the studies are assigned more weight because of the total information that they contain and not because of providing a higher number of estimates. A downside of this approach is that it does not fully exploit all available information because it estimates the variances rather than using the information on the estimated standard errors available from primary studies. However, Lewis and Linzer (2005) show that the use of heteroscedastic consistent standard errors yields good results. Therefore, when presenting the results of the meta-regression analysis using the weighting scheme in equation (46), we report standard errors using the Huber-White variance estimator (Huber, 1967; White, 1980) which, as stated before, accounts for heteroscedasticity and cluster correlation among effect sizes sampled from the same primary study (Williams, 2000).

Recent studies by Bin and Landry (2013) and Atreya, Ferreira, and Kriesel (2013) try to characterise the recovery process of prices after a flood for their specific region of analysis by considering different functional forms of the time variable. Following these authors, we run separate regressions considering four different functional forms for the variable *mnths* which controls for differences in flood risk perception over time: a linear specification

($f(mnths) = mnths$), and the nonlinear natural logarithm ($f(mnths) = \ln(mnths)$); ratio ($f(mnths) = (mnths - 1)/mnths$); and square root ($f(mnths) = Sqrt(mnths)$). In this case, it is possible to exploit the meta-regression approach to test this hypothesis considering the occurrence of many different flood events, over a broad range of regions. Atreya, Ferreira, and Kriesel (2013) also test for differences in the recovery process across regions with different level of risk, and conclude that this effect is only significant for properties in the 100-year floodplain; whereas for properties in the 500-year floodplain they found no significant recovery, although no significant post-flood discount was found either. To test for differences in the recovery process across regions with different level of risk the meta-regression model includes interaction of the time variable (*mnths*) with the dummy variable distinguishing different levels of risk, that is: *mnths*100year* (the omitted category is the 500-year floodplain).

Finally, Tobin and Newton (1986) and Pryce, Chen, and Galster (2011) emphasise that the extent to which flood risk is capitalised in property prices and the characteristics of the recovery of prices after a flood, depend on prevalent social and economic conditions in the specific area of study, as well as the history of flooding in the location. The effect sizes in the meta-sample show a wide geographical variability. Most studies are drawn from the United States, contributing with 33 studies across 12 different States (see table 1.3 for details). The sample also includes studies for Australia, The Netherlands, New Zealand and United Kingdom. Therefore, besides the variables listed in table 1.7, the final regression models also include regional fixed effects to control for various regional differences that might be reflected in the results of primary studies.

The results of the meta-regression analysis appear in table 1.8. The first set of results (columns (1) through (4)) correspond to results using random-effects meta-regression weights, with different functional forms of the *mnths* variable; the second set of results (columns (5) through (8)) assigns weights according to the average sample size of each study and reports Huber-White standard errors, robust to heteroscedasticity and correlation among effect sizes from the same primary study (Williams, 2000).

The coefficient on the *mnths* variable (β_1) is highly significant. This coefficient gives information regarding the marginal decay of the discount for properties in the 500-year floodplain. The results are robust across all different specifications of the time variable and different weighting schemes. In particular, as the number of months elapsed since the last flood in each location increases, the estimated property price discount for floodplain location tends to be significantly lower. For properties in the 100-year floodplain, the coefficient on the interaction variable *mnths*100year* (β_2) indicates that the discounts decreases at a lower pace for these properties which are exposed to more frequent and more severe flooding. The marginal decay of the discount for properties at this level of risk is given by the sum of the coefficients $\beta_1 + \beta_2$, which is positive in all cases. This differentiated effect across regions with different levels of risk is robust across different specifications of the time variable, except the one assuming a ratio functional form ($f(mnths) = (mnths - 1)/mnths$).

Thus, unlike Atreya, Ferreira, and Kriesel (2013) who found that the price discount, and its corresponding decay, is only significant for properties in the 100-year floodplain, the results of our meta-regression analysis considering a broad range of locations with different flooding history suggest that this effect its true for properties at both levels of risk, 100 and 500-year floodplain, and that the decay is significantly faster for properties in the lower risk area. Bin and Landry (2013) found the price discount after a flood decreases as time passes, however the authors did not distinguish regions at different levels of risk.

Interestingly, once we controlled for differences in flood risk perception over time, among regions with different levels of risk, differences in the level of risk, given by the variable *100year* in table 1.8, are not consistently significant across different specifications of the time variable and do not have the expected sign. However, when running the meta-regression without the set of variables controlling for differences in flood risk perception across time, then the variable *100year* is consistently significant and has a negative sign with a coefficient between -0.035 and -0.040. We suggest this is because individuals respond to external factors and circumstances altering the perception of risk, and not spatially delineated risk areas. Floodplains are usually defined in a discrete manner in terms of the recurrence interval as 100-year or 500-year, meaning there is a respective 1% or 0.2% annual probability of flooding. However, these are areas with various levels of risk which decrease rapidly as distance from the water body increases and elevation rises (Bartosova et al., 1999). In general, we would expect a 1% annual probability of flooding for properties at the edge of the 100-year floodplain; however, for properties within the same area, at the edge of a water body, we would expect a higher risk. Likewise, we do not expect flood risk to change discretely from a 1% annual probability of flooding to a 0.2% probability as we cross the border of the 100-year floodplain and move into the 500-year floodplain.

In this respect, it is important to highlight a clear inconsistency between theory and empirical evidence. Since the application of the hedonic price model (HPM) to the flood risk literature by MacDonald, Murdoch, and White (1987), the authors specify that individuals maximize expected utility considering the subjective probability of flooding, i.e. homeowner's subjective assessment of the probability of flooding. This distinction has been broadly supported in further theoretical representations by authors such as Hallstrom and Smith (2005), Carbone, Hallstrom, and Smith (2006), Bin et al. (2008), Bin, Kruse, and Landry (2008), Kousky (2010) and Bin and Landry (2013). However, empirical applications have constantly used a proxy variable for flood risk based on an objective measure of risk (dummy variable for floodplain location), and that, as stated before, do not accurately reflect the various levels of risk within the floodplain. This is an issue that has been overlooked in the flood risk literature. Although we recognize the difficulties involved in defining a subjective measure of risk, no attempts have been identified in the hedonic literature for its implementation. Results in table 1.8 seem to suggest that the broad range of results from previous studies might be majorly influenced by differences in flood risk perception rather than objective risk.

Table 1.8. Meta-regression results: Random-effects and sample size weights

Variables	Random-effects weights				Sample size weights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000582***	0.0688***	1.301***	0.0161***	0.000473***	0.0668***	1.187***	0.0150***
	(8.26e-05)	(0.00981)	(0.319)	(0.00213)	(7.46e-05)	(0.00970)	(0.333)	(0.00199)
mnths*100year	-0.000404***	-0.0367***	-0.235	-0.00976***	-0.000298***	-0.0290***	-0.117	-0.00862***
	(7.58e-05)	(0.00912)	(0.334)	(0.00189)	(7.10e-05)	(0.0101)	(0.370)	(0.00188)
Flood risk level								
100year	0.0144	0.131***	0.198	0.0652***	0.0100	0.104**	0.0800	0.0656***
	(0.0124)	(0.0416)	(0.329)	(0.0209)	(0.0106)	(0.0483)	(0.366)	(0.0221)
Context of the study								
lav_feet	0.0471**	0.0600***	0.0666***	0.0516**	-0.00787	0.0201	0.0146	0.00405
	(0.0207)	(0.0204)	(0.0201)	(0.0205)	(0.0369)	(0.0351)	(0.0342)	(0.0363)
lavprice_2010	0.0243	0.0183	0.0168	0.0217	0.0101	-0.00755	0.00836	-0.00421
	(0.0177)	(0.0175)	(0.0175)	(0.0175)	(0.0537)	(0.0523)	(0.0534)	(0.0528)
flooded	-0.0324	-0.0290	-0.0392	-0.0230	-0.0422	-0.0223	-0.0230	-0.0303
	(0.0348)	(0.0338)	(0.0330)	(0.0345)	(0.0614)	(0.0629)	(0.0625)	(0.0627)
scnd_flood	0.0442*	0.0214	-0.00414	0.0380	0.0109	-0.0240	-0.0598*	0.000823
	(0.0243)	(0.0233)	(0.0235)	(0.0236)	(0.0313)	(0.0323)	(0.0334)	(0.0315)
dd_after	-0.0480**	-0.0415**	-0.0479**	-0.0408**	-0.0390	-0.0147	-0.00918	-0.0234
	(0.0198)	(0.0195)	(0.0192)	(0.0196)	(0.0277)	(0.0269)	(0.0283)	(0.0273)
dd_after*100year	-0.0223	-0.00453	0.00766	-0.0152	-0.0134	-0.00845	0.0101	-0.0195**
	(0.0178)	(0.0176)	(0.0174)	(0.0177)	(0.0109)	(0.00860)	(0.00822)	(0.00963)
dd_afterlaw	0.0368**	0.0276	0.0303*	0.0287	0.0532**	0.0381	0.0163	0.0478*
	(0.0175)	(0.0173)	(0.0170)	(0.0174)	(0.0269)	(0.0245)	(0.0230)	(0.0263)
coast	0.0227	0.0209	0.0178	0.0221	0.0393	0.0328	0.0253	0.0386
	(0.0144)	(0.0142)	(0.0141)	(0.0143)	(0.0322)	(0.0300)	(0.0315)	(0.0306)
Control variables of study								
amenity	-0.00860	-0.0152	-0.00266	-0.0137	-0.0106	-0.00964	-0.00790	-0.00830
	(0.0166)	(0.0163)	(0.0160)	(0.0165)	(0.0227)	(0.0208)	(0.0205)	(0.0224)
real_p	-0.00892	0.00386	0.0161	-0.00540	0.0402	0.0766**	0.0806***	0.0538*
	(0.0161)	(0.0161)	(0.0159)	(0.0160)	(0.0291)	(0.0308)	(0.0299)	(0.0297)
Characteristics of econometric model								
linear	-0.0859***	-0.101***	-0.0960***	-0.0942***	-0.178***	-0.179***	-0.186***	-0.178***
	(0.0190)	(0.0188)	(0.0186)	(0.0189)	(0.0494)	(0.0458)	(0.0461)	(0.0478)
Box-Cox	-0.0236	-0.0305	-0.0318	-0.0281	-0.0317	-0.0356	-0.0212	-0.0389
	(0.0249)	(0.0245)	(0.0242)	(0.0246)	(0.0275)	(0.0263)	(0.0264)	(0.0264)
spatial	-0.0120	-0.00574	-0.00476	-0.00951	-0.00408	0.000624	0.00316	-0.00235
	(0.00989)	(0.00969)	(0.00959)	(0.00975)	(0.0145)	(0.0133)	(0.0133)	(0.0140)
dd_hpm	0.0229***	0.0181**	0.0187**	0.0198**	0.0183**	0.0106	0.00953	0.0148**
	(0.00826)	(0.00812)	(0.00795)	(0.00819)	(0.00747)	(0.00679)	(0.00662)	(0.00723)

(Continued)

Table 1.8. Continue

Characteristics of the study								
published	-0.000309	-0.00222	-0.00997	7.47e-05	-0.0102	-0.0159	-0.0161	-0.0125
	(0.0133)	(0.0130)	(0.0129)	(0.0131)	(0.0175)	(0.0167)	(0.0155)	(0.0172)
med_sampleyear	0.00386***	0.00382***	0.00232**	0.00424***	0.00291	0.00202	-0.000942	0.00308
	(0.000959)	(0.000936)	(0.000919)	(0.000951)	(0.00194)	(0.00195)	(0.00205)	(0.00196)
time_span	0.00150	0.000907	0.000539	0.00106	0.00532***	0.00127	0.00141	0.00314
	(0.00116)	(0.00115)	(0.00113)	(0.00115)	(0.00205)	(0.00196)	(0.00180)	(0.00204)
Regional fixed effects[1]								
louisiana	0.126***	0.144***	0.0926***	0.152***	0.163***	0.251***	0.167***	0.227***
	(0.0327)	(0.0327)	(0.0298)	(0.0337)	(0.0562)	(0.0634)	(0.0549)	(0.0616)
n_carolina	0.105***	0.0985***	0.0546**	0.114***	0.170***	0.166***	0.107***	0.183***
	(0.0245)	(0.0233)	(0.0218)	(0.0244)	(0.0371)	(0.0359)	(0.0326)	(0.0374)
texas	0.223***	0.222***	0.177***	0.237***	0.352***	0.337***	0.276***	0.358***
	(0.0306)	(0.0295)	(0.0277)	(0.0307)	(0.0521)	(0.0506)	(0.0481)	(0.0524)
wisconsin	0.185***	0.173***	0.117***	0.193***	0.202***	0.183***	0.112**	0.211***
	(0.0319)	(0.0305)	(0.0293)	(0.0316)	(0.0603)	(0.0593)	(0.0566)	(0.0600)
alabama	0.276***	0.278***	0.237***	0.290***	0.446***	0.438***	0.373***	0.458***
	(0.0537)	(0.0526)	(0.0514)	(0.0534)	(0.0585)	(0.0564)	(0.0514)	(0.0587)
florida	0.251***	0.246***	0.227***	0.255***	0.367***	0.372***	0.335***	0.380***
	(0.0307)	(0.0301)	(0.0295)	(0.0305)	(0.0552)	(0.0542)	(0.0525)	(0.0552)
california	0.163***	0.180***	0.136***	0.183***	0.237***	0.274***	0.210***	0.267***
	(0.0292)	(0.0292)	(0.0265)	(0.0298)	(0.0519)	(0.0537)	(0.0499)	(0.0533)
missouri	0.116***	0.0867***	0.0508***	0.113***	0.126***	0.102***	0.0409	0.132***
	(0.0205)	(0.0186)	(0.0183)	(0.0198)	(0.0405)	(0.0366)	(0.0343)	(0.0398)
colorado	0.0303	0.0117	0.0116	0.0196	0.0269	0.0329	0.0320	0.0355
	(0.0249)	(0.0244)	(0.0243)	(0.0246)	(0.0574)	(0.0549)	(0.0558)	(0.0559)
minesota	0.185***	0.183***	0.182***	0.185***	0.361***	0.359***	0.359***	0.361***
	(0.0359)	(0.0355)	(0.0348)	(0.0356)	(0.0621)	(0.0595)	(0.0644)	(0.0596)
nl	0.0712**	0.0780***	0.0723**	0.0742**	0.194***	0.224***	0.188***	0.216***
	(0.0301)	(0.0295)	(0.0292)	(0.0296)	(0.0575)	(0.0576)	(0.0557)	(0.0572)
uk	-0.0268	0.00923	0.0183	-0.00650	0.0662	0.124**	0.0915*	0.0983*
	(0.0482)	(0.0490)	(0.0482)	(0.0485)	(0.0452)	(0.0548)	(0.0516)	(0.0500)
aus	0.0411	0.0426	0.0425	0.0499	-0.0109	0.123	0.0766	0.0719
	(0.0744)	(0.0733)	(0.0726)	(0.0737)	(0.116)	(0.118)	(0.113)	(0.117)
nz	0.0197	0.00338	-0.0337	0.0220	0.0904	0.0726	0.0339	0.0954
	(0.0384)	(0.0372)	(0.0364)	(0.0379)	(0.0724)	(0.0673)	(0.0688)	(0.0698)
Constant	-8.518***	-8.681***	-6.676***	-9.359***	-6.144*	-4.579	0.362	-6.489*
	(1.886)	(1.844)	(1.848)	(1.874)	(3.588)	(3.621)	(3.773)	(3.649)
Observations	349	349	349	349	349	349	349	349
τ^2	0.00102	0.000979	0.000915	0.00102				
I^2	0.727	0.704	0.685	0.721				
R^2					0.685	0.697	0.692	0.695
Adj. R^2					0.651	0.664	0.659	0.661

Note: [1] The omitted region is Georgia, US.

The dependent variable is the effect size T. Standard errors in parentheses; for results using sample size weights they correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Regarding the characteristics of the econometric model, studies using a *linear* form of the selling price of properties as a dependent variable tend to obtain significantly greater discounts than studies using a *Box-Cox* transformation or a natural logarithm functional form.

Variables controlling for differences in the context of primary studies such as *lav_feet* and *dd_after* are only significant under the random-effects scheme. The same is true for the variable *dd_hpm* controlling for characteristics of the econometric model, and the variable *med_sampleyear* controlling for differences in characteristics of the study. Some of these variables are also significant in the meta-regression analysis by Daniel, Florax, and Rietveld (2009a). However, for models in which studies with a greater number of observations are not overrepresented these variables are no longer significant. This indicates that results of the former meta-regression analysis might not accurately represent the vast set of research on the economics of flood risk due to overrepresentation of studies such as Pope (2008) and US Army Corps of Engineers (1998) providing over 20 observations to their final meta-sample. Thus the importance of providing the second set of results (columns (5) through (8)) where this is accounted for.

The former meta-regression analysis by Daniel, Florax, and Rietveld (2009a) considers only studies for the US without including regional fixed effects. Results in table 1.8 indicate that most of the dummy variables controlling for regional differences are highly significant; especially regarding regional differences within the US. This result is robust across different weighting schemes and different functional forms of the time variable. Before including regional fixed effects, variables such as *lavprice_2010*, *flooded*, *coast*, *amenity*, *real_p*, and *spatial* are also significant for the set of regressions applying random-effects weights; in the case of regressions using weights according to sample size it is only the variables *coast*, *real_p*, and *spatial* that are significant. The results can be consulted in table A1.2 of the appendix. Some of these variables are included in the former meta-regression analysis with significant coefficients. Our results suggest that after including regional fixed effects these are no longer significant. Thus, we believe that regional dummies control for regional differences in flood risk perception (due to different flooding history), along with other social, geographical and housing market conditions. Including the regional dummies significantly improves the goodness of fit of the meta-regressions.

The analysis of the distribution of effect sizes in section 1.4.4.1 reveals an interesting difference between estimates focusing on flood risk from different sources. We consider the possibility that the heterogeneity in the results from studies focusing on river or coastal flood risk might be driven by different underlying factors. Table 1.9 shows the results of separate meta-regression analyses for estimates of inland and coastal regions. Due to the aforementioned reasons this table only shows the results of regressions assigning weights according to the sample size of each study, whilst including regional fixed effects. Regression results using the random-effects weighting scheme and regional fixed effects can be consulted in table A1.3 of the appendix.

For the sample focusing on effect sizes from river regions the results in table 1.9 are similar to those shown in table 1.8; i.e. as the time since the last flood increases the estimated price discount for floodplain location decreases, this decay is slower for properties in the 100-year floodplain. The results are robust across different specifications of the time variable, except for the one assuming a ratio functional form, as in table 1.8.

Considering the set of variables controlling for differences in the context of primary studies, the variable *lav_feet* is the only one which is significant across all specifications of the time variable. The positive coefficient indicates that the price discount for floodplain location is lower for studies focusing on average bigger houses; i.e. the monetary discount due to flood risk location, relative to price of the property, is smaller for bigger houses. The variable *lavprice_2010* controls for differences in the average price of properties; although, as mentioned before, once we control for regional differences this variable is not significant anymore, its consistently negative coefficient, for properties in river regions, together with the coefficient of the variable *lav_feet* represents an interesting relationship between the relative price discount for floodplain location and difference in size and price of the properties. Results suggests that the relative price discount is smaller for bigger houses; however if the price of the property increases, i.e. if the properties are more valuable, the discount tends to increase. This may indicate that individuals who purchase higher priced homes (in river regions) face a greater potential loss, should flooding occur; this includes non-insurable losses.

Results for river regions in table 1.9 also suggest that studies using a *linear* form of the selling price of properties as a dependent variable tend to obtain significantly greater discounts than studies using a B*ox-Cox* transformation or a natural logarithm functional form. Regional fixed effects are also highly significant. This is consistent with results in table 1.8.

Five moderator variables (*flooded*, *scnd_flood*, B*ox-Xox*, *dd_after*100year* and *published*) are dropped from the meta-regression on estimates from coastal regions; this is because there are only 35 observations from eight primary studies focusing on these regions, all of them are *published* studies, and none of them distinguishes *flooded* properties, or study two consecutive floods (*scnd_flood*), or use a B*ox-Cox* transformation for the dependent variable. In the case of the variable *dd_after*100year*, this is dropped because, as we noted in tables 1.4 and 1.5, all studies using a DID approach in coastal regions focus on 100-year floodplains, therefore this variable is perfectly collinear with the variable *dd_after*; as a result, in this case the coefficients on the latter corresponds to properties in the 100-year floodplain. Out of the total 15 regions represented in the meta-sample only five are located on the coast, therefore most of the regional fixed effects have also been dropped; in this case the omitted region is North Carolina, US.

In general, we believe that there are two important challenges in interpreting the results of the meta-regression analysis on coastal estimates and drawing meaningful conclusions. The first one, and most important, is the problem of endogeneity on effect sizes due to the existence of confounder factors associated with proximity to water. This problem has been documented by authors such as Hallstrom and Smith (2005), Bin and Kruse (2006), Bin et al. (2008) and Bin, Kruse, and Landry (2008), where only the latter two authors claim successfully to identify the effect of flood risk on prices of coastal properties. This is an important issue because in the presence of endogeneity the coefficient on the risk variable on primary studies does not identify the relationship of interest; in this case the coefficients are likely to be biased downwards due to the existence of amenity values from proximity to water. Therefore it is important to be careful with the interpretation of the set of results for coastal flood risk in table 1.9, as the dependent variable might not accurately be interpreted as the relative price differential for floodplain location. Although this problem might also be present on estimates from river regions, the literature is oddly only concerned about this issue when dealing with coastal flood risk. The second problem is related to the sample size; there are few studies looking at the relative price differential for floodplain location on coastal areas and the meta-regression includes 19 moderator variables, which results in very few degrees of freedom for estimation.

Table 1.9. Meta-regression results by type of flood risk: Including regional fixed effects, sample size weights

Variables	River flood risk				Coastal flood risk			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000477***	0.0655***	1.187***	0.0152***	-0.00153	0.0433*	2.399	-0.00332
	(7.40e-05)	(0.0100)	(0.332)	(0.00196)	(0.00138)	(0.0226)	(1.482)	(0.0107)
mnths*100year	-0.000267***	-0.0319***	-0.226	-0.00844***	0.00381**	0.188**	6.298*	0.0555**
	(6.95e-05)	(0.0109)	(0.374)	(0.00191)	(0.00176)	(0.0842)	(3.136)	(0.0238)
Flood risk level								
100year	0.00418	0.118**	0.187	0.0634***	-0.00625	-0.520**	-5.938*	-0.191*
	(0.00970)	(0.0526)	(0.370)	(0.0224)	(0.0638)	(0.231)	(2.956)	(0.0937)
Context of the study								
lav_feet	0.0778***	0.102***	0.0915***	0.0944***	-0.474	-0.603	-0.575	-0.563
	(0.0271)	(0.0264)	(0.0252)	(0.0272)	(0.335)	(0.359)	(0.398)	(0.331)
lavprice_2010	-0.00642	-0.0179	-0.00134	-0.0231	0.118	-0.00534	-0.0890	0.0795
	(0.0584)	(0.0585)	(0.0585)	(0.0587)	(0.210)	(0.162)	(0.178)	(0.178)
flooded	-0.0255	-0.0187	-0.0196	-0.0176	-	-	-	-
	(0.0580)	(0.0591)	(0.0580)	(0.0593)				
scnd_flood	-0.00180	-0.0367	-0.0691**	-0.0144	-	-	-	-
	(0.0251)	(0.0250)	(0.0276)	(0.0247)				
dd_after	-0.0122	0.0113	0.0150	0.00503	-0.445***	0.00473	0.476	-0.274***
	(0.0259)	(0.0257)	(0.0276)	(0.0251)	(0.0711)	(0.0863)	(0.314)	(0.0253)
dd_after*100year	0.000703	-0.00178	0.0177**	-0.00871	-	-	-	-
	(0.00937)	(0.00781)	(0.00754)	(0.00798)				
dd_afterlaw	0.00377	-0.00687	-0.0255	-0.00154	0.474***	0.0141	-0.449	0.296***
	(0.0246)	(0.0229)	(0.0216)	(0.0237)	(0.0756)	(0.0958)	(0.322)	(0.0234)
coast	-	-	-	-	-	-	-	-
Control variables of study								
amenity	-0.00824	-0.00514	-0.00725	-0.00485	0.0104	-0.0288	-0.0416	-0.00768
	(0.0173)	(0.0182)	(0.0149)	(0.0201)	(0.0629)	(0.0420)	(0.0405)	(0.0518)
real_p	-0.0877***	-0.0510*	-0.0405	-0.0753***	-0.994***	-0.379*	0.375	-0.798***
	(0.0209)	(0.0264)	(0.0290)	(0.0228)	(0.285)	(0.184)	(0.340)	(0.229)
Characteristics of econometric model								
linear	-0.158***	-0.152**	-0.140**	-0.167***	-0.0916**	-0.0916**	-0.0916**	-0.0916**
	(0.0581)	(0.0598)	(0.0610)	(0.0605)	(0.0373)	(0.0369)	(0.0388)	(0.0367)
Box-Cox	0.00982	0.00379	0.0173	0.00214	-	-	-	-
	(0.0244)	(0.0268)	(0.0279)	(0.0249)				
spatial	0.0112	0.0139	0.0169	0.0120	-0.0526	0.0112	0.0205	-0.0183
	(0.0109)	(0.0100)	(0.0104)	(0.0104)	(0.0863)	(0.0375)	(0.0303)	(0.0624)
dd_hpm	0.00798	0.00222	0.00117	0.00502	0.130***	-0.121	-0.466*	0.0320
	(0.00526)	(0.00562)	(0.00561)	(0.00530)	(0.00988)	(0.0912)	(0.265)	(0.0283)

(Continued)

Table 1.9. Continue

Characteristics of the study								
published	-0.0156	-0.0211	-0.0207	-0.0187	-	-	-	-
	(0.0164)	(0.0158)	(0.0152)	(0.0160)				
med_sampleyear	0.000783	-0.000145	-0.00287	0.000822	0.100***	0.0203***	0.0994*	0.0728***
	(0.00181)	(0.00185)	(0.00200)	(0.00181)	(0.0219)	(0.00499)	(0.0563)	(0.0146)
time_span	0.00330	-2.50e-05	0.000368	0.000973	0.0134***	-0.0393	-0.153*	-0.00489
	(0.00203)	(0.00193)	(0.00188)	(0.00195)	(0.00398)	(0.0233)	(0.0788)	(0.00887)
Regional fixed effects[1]								
louisiana	0.0758	0.143***	0.0669	0.139**	1.295***	0.695***	-0.139	1.113***
	(0.0506)	(0.0542)	(0.0492)	(0.0539)	(0.358)	(0.159)	(0.291)	(0.250)
n_carolina	0.132***	0.115***	0.0629*	0.140***	-	-	-	-
	(0.0348)	(0.0329)	(0.0325)	(0.0348)				
texas	0.202***	0.178***	0.114***	0.207***	-	-	-	-
	(0.0405)	(0.0373)	(0.0383)	(0.0407)				
wisconsin	0.251***	0.222***	0.149***	0.263***	-	-	-	-
	(0.0460)	(0.0416)	(0.0396)	(0.0454)				
alabama	0.316***	0.295***	0.220***	0.332***	-	-	-	-
	(0.0567)	(0.0503)	(0.0528)	(0.0550)				
florida	0.242***	0.238***	0.187***	0.262***	0.139	0.346***	0.636***	0.226**
	(0.0564)	(0.0504)	(0.0522)	(0.0543)	(0.111)	(0.0553)	(0.161)	(0.0836)
california	0.159***	0.178***	0.125***	0.185***	-	-	-	-
	(0.0489)	(0.0482)	(0.0469)	(0.0499)				
missouri	0.152***	0.118***	0.0577	0.157***	-	-	-	-
	(0.0427)	(0.0383)	(0.0370)	(0.0412)				
colorado	0.0859	0.0882	0.0807	0.102*	-	-	-	-
	(0.0609)	(0.0607)	(0.0586)	(0.0610)				
minesota	0.237***	0.222***	0.210***	0.242***	-	-	-	-
	(0.0595)	(0.0545)	(0.0591)	(0.0585)				
nl	0.0840	0.111**	0.0813	0.110**	-	-	-	-
	(0.0529)	(0.0512)	(0.0501)	(0.0527)				
uk	0.00692	0.0487	0.0206	0.0376	-	-	-	-
	(0.0358)	(0.0451)	(0.0446)	(0.0407)				
aus	-	-	-	-	-0.778***	0.822	4.432*	-0.275
					(0.219)	(0.640)	(2.340)	(0.271)
nz	-	-	-	-	-0.671***	-0.214**	0.288	-0.505***
					(0.176)	(0.0830)	(0.244)	(0.128)
Constant	-2.215	-0.618	3.869	-2.314	-197.4***	-35.83***	202.1*	-141.7***
	(3.279)	(3.373)	(3.597)	(3.298)	(43.88)	(12.25)	(114.9)	(28.46)
Observations	314	314	314	314	35	35	35	35
R^2	0.607	0.608	0.598	0.617	0.892	0.904	0.902	0.900
Adj. R^2	0.564	0.565	0.554	0.575	0.771	0.796	0.791	0.788
Rmse	0.0448	0.0447	0.0452	0.0441	0.0773	0.0730	0.0738	0.0744

Note: [1] The omitted region for the meta-regression on river and coastal estimates is Georgia, US, and North Carolina, US, respectively. The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Considering the aforementioned issues, effect sizes focusing on coastal flood risk indicate that the time with respect to the previous flood is not significant to explain heterogeneity of estimates from studies focusing in the 500-year floodplain; however, for those focusing on properties in the 100-year floodplain there is a significant decay across all specifications of the time variable. Similar to results for river regions, regression results for coastal regions suggest that using a *linear* functional form of the dependent variable tend to obtain significantly greater discounts than studies using a natural logarithm (there are no studies using B*ox-Cox* transformation for coastal regions). In this case the variable *med_sampleyear* has a positive sign and is consistently significant for all specifications of the time variable. This means that studies analysing a more recent sample of properties in coastal regions tend to find smaller discounts (or greater premiums) for properties located in the floodplain. This result indicates a systematic positive trend in the estimated risk assessments of previous studies which could be due to a relative appreciation of the amenity values of living close to the sea. Regional fixed effects are also significant in explaining the heterogeneity of effect sizes for the sub-sample of coastal regions. Variables related to the risk level, the context of the study or control variables included in primary studies are not significant. More research is needed on the effect of flood risk on property prices in coastal regions.

A final set of results focus on the sub-sample of effect sizes according to the different econometric approach used in primary studies: standard hedonic or DID hedonic models. As highlighted before, the former set of studies look to document the existence of a price differential for floodplain location, whereas the latter also allow us to determine whether this differential changes following named flood events. Thus, columns (1) through (4) of table 1.10 show the regression results on estimates from primary studies using a standard hedonic approach and assuming different functional forms of the time variable; columns (5) through (8) do the same for estimates on studies using a DID approach.

For the results focusing on effect sizes from standard hedonic models, the time variable reveals similar results as before; its coefficient suggests that as the time since the last flood increases, the estimated price discount for floodplain location decreases, the decay is slower for properties exposed to more severe flooding. These results are robust across different specifications of the time variable. From the set of variables controlling for the context of primary studies, the variables *lav_feet* and *coast* have a positive sign and are both significant across all specifications of the time variable. As before, the former indicates that the price discount for floodplain location is lower for studies focusing on average bigger houses. The coefficient on the *coast* variable indicates that results from primary studies on coastal regions estimate a lower price discount for floodplain location. This result is as expected, considering the already discussed issue of endogeneity. Although this coefficient is positive in previous sets of regressions, it is only significant for the sub-sample of effect sizes from studies using standard hedonic models. The coefficient on the variable *real_p* suggests that primary studies which convert nominal house prices to real prices before estimation find greater discounts. Although in most cases this variable has a negative sign, the result is consistently significant across all forms of the time variable only for this set of results. As in previous results, the coefficient on the *linear* variable suggests that primary studies using a linear functional form of the dependent variable tend to estimates greater discounts than those using a *Box-Cox* transformation or the natural logarithm. Again, some of the regional fixed-effects appear to be highly significant.

Table 1.10. Meta-regression results by different econometric approach: Including regional fixed effects, sample size weights

Variables	Standard hedonic models				DID hedonic models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000274***	0.0547**	1.796**	0.0105***	0.000644***	0.0500***	0.852**	0.0147***
	(6.51e-05)	(0.0215)	(0.804)	(0.00286)	(0.000137)	(0.0140)	(0.343)	(0.00328)
mnths*100year	-9.54e-05**	-0.0254***	-1.229**	-0.00396***	-0.000642***	-0.0321*	-0.169	-0.0134***
	(4.11e-05)	(0.00938)	(0.554)	(0.00131)	(0.000118)	(0.0174)	(0.431)	(0.00338)
Flood risk level								
100year	-0.00842	0.0995**	1.193**	0.0238	0.0634***	0.117	0.124	0.127***
	(0.00622)	(0.0452)	(0.548)	(0.0151)	(0.0184)	(0.0885)	(0.429)	(0.0429)
Context of the study								
lav_feet	0.112***	0.132***	0.120***	0.126***	-0.0980	0.0460	0.0904	-0.0425
	(0.0287)	(0.0320)	(0.0298)	(0.0298)	(0.222)	(0.242)	(0.248)	(0.230)
lavprice_2010	-0.00919	-0.0484	-0.0350	-0.0330	-0.0171	-0.0650	-0.121	-0.0194
	(0.0533)	(0.0583)	(0.0560)	(0.0545)	(0.255)	(0.266)	(0.297)	(0.248)
flooded	0.0207	0.0489	0.0128	0.0509	-0.0343	-0.0149	-0.00473	-0.0284
	(0.0344)	(0.0455)	(0.0315)	(0.0413)	(0.0668)	(0.0694)	(0.0711)	(0.0678)
scnd_flood	-	-	-	-	-0.0442	-0.0502	-0.0754**	-0.0419
					(0.0324)	(0.0315)	(0.0357)	(0.0303)
dd_after	-	-	-	-	-0.0850**	-0.0914***	-0.0927***	-0.0790**
					(0.0349)	(0.0349)	(0.0344)	(0.0369)
dd_after*100year	-	-	-	-	-0.0361***	-0.00331	0.0239**	-0.0352***
					(0.0107)	(0.0146)	(0.00951)	(0.0128)
dd_afterlaw	-	-	-	-	0.0819***	0.0693***	0.0516**	0.0764***
					(0.0269)	(0.0253)	(0.0232)	(0.0278)
coast	0.124***	0.130***	0.128***	0.129***	0.122	0.138	0.200	0.103
	(0.0404)	(0.0412)	(0.0397)	(0.0413)	(0.349)	(0.356)	(0.404)	(0.332)
Control variables of study								
amenity	0.0129	0.00104	-0.00179	0.00892	-0.100	-0.206	-0.261	-0.137
	(0.0199)	(0.0201)	(0.0169)	(0.0209)	(0.262)	(0.281)	(0.298)	(0.265)
real_p	-0.115***	-0.111***	-0.113***	-0.114***	-0.0318	-0.0419	-0.0566	-0.0373
	(0.0353)	(0.0386)	(0.0367)	(0.0375)	(0.111)	(0.118)	(0.126)	(0.111)
Characteristics of econometric model								
linear	-0.269***	-0.269***	-0.264***	-0.272***	-0.188*	-0.208**	-0.208*	-0.207**
	(0.0468)	(0.0455)	(0.0459)	(0.0462)	(0.104)	(0.102)	(0.115)	(0.0977)
Box-Cox	0.0457	0.0303	0.0357	0.0355	-	-	-	-
	(0.0370)	(0.0413)	(0.0397)	(0.0388)				
spatial	0.00742	0.0109	0.0144	0.00778	0.0203	0.0171	0.0142	0.0206
	(0.0124)	(0.0113)	(0.0103)	(0.0123)	(0.0220)	(0.0234)	(0.0235)	(0.0224)
dd_hpm	-	-	-	-	-	-	-	-

(Continued)

Table 1.10. Continue

Characteristics of the study								
published	0.00599	-0.0149	-0.0152	-0.00454	-0.00353	-0.00705	-0.00738	-0.00384
	(0.0274)	(0.0262)	(0.0277)	(0.0249)	(0.0166)	(0.0184)	(0.0176)	(0.0176)
med_sampleyear	0.00262	0.00491	0.00322	0.00430	0.00768***	0.00676***	0.00466*	0.00744***
	(0.00264)	(0.00335)	(0.00280)	(0.00294)	(0.00235)	(0.00234)	(0.00246)	(0.00244)
time_span	0.00367*	0.00365	0.00489**	0.00314	0.00718**	0.00416*	0.00391*	0.00583*
	(0.00210)	(0.00229)	(0.00204)	(0.00225)	(0.00296)	(0.00241)	(0.00203)	(0.00309)
Regional fixed effects[1]								
Louisiana	-0.0646	-0.0520	-0.148*	-0.0223	-	-	-	-
	(0.0900)	(0.111)	(0.0836)	(0.103)				
n_carolina	-0.00743	-0.00653	-0.0710	0.0181	0.203**	0.155**	0.135	0.174**
	(0.0659)	(0.0773)	(0.0584)	(0.0736)	(0.0851)	(0.0784)	(0.0914)	(0.0753)
Texas	0.214**	0.163**	0.0934	0.217***	0.203	0.0428	-0.0933	0.141
	(0.0833)	(0.0674)	(0.0630)	(0.0777)	(0.382)	(0.417)	(0.442)	(0.391)
Wisconsin	0.213***	0.197***	0.122**	0.235***	-	-	-	-
	(0.0635)	(0.0658)	(0.0473)	(0.0677)				
Alabama	0.338***	0.324***	0.246***	0.363***	-	-	-	-
	(0.0738)	(0.0771)	(0.0573)	(0.0789)				
Florida	0.259***	0.234***	0.171***	0.272***	0.219	0.0947	-0.00633	0.185
	(0.0755)	(0.0733)	(0.0626)	(0.0766)	(0.436)	(0.463)	(0.501)	(0.434)
California	0.0710	0.0865	0.00963	0.106	0.172	0.196	0.219	0.159
	(0.0678)	(0.0889)	(0.0634)	(0.0802)	(0.187)	(0.189)	(0.218)	(0.174)
Missouri	0.0686	0.0588	-0.00766	0.0918	0.151*	0.137*	0.115	0.142*
	(0.0655)	(0.0731)	(0.0529)	(0.0718)	(0.0828)	(0.0817)	(0.0893)	(0.0779)
Colorado	0.00570	-0.0221	-0.0520	0.00366	-	-	-	-
	(0.0622)	(0.0589)	(0.0587)	(0.0599)				
Minesota	0.238***	0.212***	0.174***	0.243***	-	-	-	-
	(0.0767)	(0.0660)	(0.0615)	(0.0721)				
Nl	-0.105	-0.120	-0.164**	-0.0963	0.217	0.220	0.253	0.194
	(0.0698)	(0.0760)	(0.0681)	(0.0733)	(0.187)	(0.189)	(0.217)	(0.175)
Uk	-0.0996	-0.0849	-0.151*	-0.0678	-	-	-	-
	(0.0737)	(0.0970)	(0.0787)	(0.0859)				
Aus	-0.281**	-0.268*	-0.361**	-0.239	-	-	-	-
	(0.140)	(0.158)	(0.139)	(0.150)				
Nz	-	-	-	-	-	-	-	-
Constant	-6.016	-10.43	-8.585	-9.246	-14.53***	-13.19**	-9.176	-14.45***
	(4.963)	(6.406)	(5.757)	(5.575)	(5.164)	(5.156)	(5.709)	(5.285)
Observations	138	138	138	138	211	211	211	211
R^2	0.861	0.855	0.847	0.861	0.800	0.786	0.784	0.795
Adj. R^2	0.825	0.818	0.808	0.825	0.774	0.759	0.756	0.769
Rmse	0.0347	0.0354	0.0364	0.0348	0.0456	0.0471	0.0473	0.0461

Note: [1] The omitted region is Georgia, US.

The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

For the sub-sample of effect sizes from studies using DID hedonic models the results look slightly different. As before, the set of variables controlling for flood risk perception across time are highly significant and suggest that as the time with respect to the previous flood increases, the price discount for floodplain location decreases; again this effect is slower for those properties exposed to more frequent and more severe flooding. The variable *dd_after* has a negative sign and is highly significant across all specifications of the time variable. The coefficient (β_8) suggests that effect sizes after the event of interest from studies using a DID approach estimate a price differential for floodplain location which is about 8 to 9% lower than it was before the event; this change might be due to an update of flood risk perception, but also due to damages resulting from a flood. The results on the variable *dd_after*100year* are not consistent across different specifications of the time variable, therefore there is no clear evidence to suggest that this effect is different for areas with different level of risk.

The majority of studies using a DID approach focus on investigating the effect of a flood event on property prices, however authors such as Harrison, Smersh, and Schwartz (2001), Troy and Romm (2004), Pope (2008) focus on analysing the effect of changes in regulations on prices of properties in the floodplain. We hypothesise that some of the heterogeneity in the results from primary studies using a DID approach might be due to studies focusing on different type of events, i.e. floods or changes in regulations. To test this hypothesis we also include the variable *dd_afterlaw* which takes the value of unity to identify effect sizes from primary studies using a DID approach after changes in regulations affecting properties in a floodplain designated area. The negative coefficient β_8 corresponds to results from primary studies after a flood. The coefficient on the variable *dd_afterlaw* (β_{10}) is positive and highly significant across all functional forms of the time variable, indicating that the effect of changes in regulation is less negative than the effect of a flood event. In this case the effect of changes in regulations is given by the sum of $\beta_8 + \beta_{10}$, which is negative between 0 and 4% across all specifications of the time variable; i.e. both the occurrence of a flood and the specific changes in regulations which have been analysed increase the price differential for floodplain location, although the effect is less pronounced, almost negligible depending on the functional form of the time variable, for changes in regulations.

The coefficient on the *linear* variable, as before, indicates that primary studies using a linear functional form of the dependent variable tend to report greater discounts for floodplain location than studies using the natural logarithm. The coefficient on the variable *med_sampleyear* is positive and significant across all functional forms of the time variable. It has the opposite sign than the one suggested by Daniel, Florax, and Rietveld (2009a); the authors interpreted their results as a time trend towards primary studies estimating greater discounts due to an amplified concern about risk, implying that modern societies are more risk averse. Regarding these contrasting results it is important to consider three things; first, the results presented in this chapter, in general, include more evidence than the former meta-analysis; second, the results suggest that this positive effect is only significant for effect-sizes from studies using a DID approach; and third, the meta-regression model in this chapter includes more variables to control for time effects than in the previous meta-analysis. In this case the positive sign of the coefficient of *med_sampleyear* indicates that more recent studies tend to estimate smaller discounts. We suggest that this effect might be due to general pressure on the house market pushing the prices of properties up (especially in the US), net out the effect of flood events, and a relative appreciation of the amenity value of proximity to water. Although during 2008 there was a global crisis triggered by the US housing market after a steep decline in house prices, only four studies using a DID approach (Atreya and Ferreira, 2011, 2012a, 2012c; Atreya, Ferreira, and Kriesel, 2012) use a sample beyond this period. All other studies consider houses sold before this period, which is characterised by a boom in house prices in countries such as Australia, Canada, China, France, India, Ireland, Italy, Korea, Russia, Spain, the UK and the US, since the late 90's (Shiller, 2007).

The coefficient on the *time_span* variable is also positive and statistically significant across all functional forms of the time variable. In this case the coefficient has the same sign and similar magnitude to the one reported by Daniel, Florax, and Rietveld (2009a), however the authors suggest that the positive coefficient on this variable does not have a meaning in itself and link the interpretation of this coefficient to the negative time trend they find with the variable *med_sampleyear*. We suggest a different hypothesis. In general, the regression results in tables 1.8, 1.9 and 1.10 suggest that the heterogeneity in the results of primary studies is highly sensitive to the time with respect to the previous flood. The results indicate that in the aftermath of a flood, primary studies tend to estimate higher discounts for properties located in the floodplain; this discount then decreases as time passes by. We believe that the positive sign of the variable *time_span* is because as the time span of the sample of properties after a flood increases, the sample will include houses sold longer time after a flood, and therefore with a lower discount. Thus, as the time span of the sample in primary studies increases, it is likely that the studies will estimate lower average discounts as they include properties which have been sold at lower discounts.

Interestingly, unlike previous regressions on different sub-samples, for the sub-sample of studies using a DID approach the regional fixed-effects are not significant. In this case the heterogeneity seems to be mostly driven by the before and after effect, and changes in perception on flood risk as time elapses, regardless of the region of study.

Finally, a question which has been of interest among recent studies using a DID approach is the persistence of the price discount for floodplain location after a flood. Previous studies which provide estimates to address this question are Atreya and Ferreira (2011), Atreya, Ferreira, and Kriesel (2012), Atreya and Ferreira (2012a), Atreya, Ferreira, and Kriesel (2013) and Bin and Landry (2013); the studies conclude that it takes between 5 to 14 years for the post-flood discount to vanish. The results vary depending on the region of study, the level of risk and the functional form of the time variable, among others. Available evidence agrees that this effect is true for properties in the 100-year floodplain; however, there is no agreement upon its existence for properties in the 500-year floodplain or the relative speed of the process with respect to properties in the 100-year floodplain. For instance, Atreya and Ferreira (2011) and Atreya and Ferreira (2012a) suggest the post-flood discount vanishes faster for properties in the 500-year floodplain, whereas Atreya, Ferreira, and Kriesel (2012) suggest it is the other way around. Atreya, Ferreira, and Kriesel (2013) found no significant post-flood discount for properties in the 500-year floodplain; no significant discount decay was found either. Bin and Landry (2013) did not differentiate between properties at different levels of risk.

Bin and Landry (2013) and Atreya, Ferreira, and Kriesel (2013) are the only two studies which have measured the degree to which the effect of the flood on property prices recedes over time across different functional forms of the time variable. The former did not include variables to distinguish the effect for properties at different levels of risk, whereas the latter does for properties at 100 and 500-year floodplain. Their results suggest that the time when the post-flood discount vanishes is similar across different specifications of the time variable. Bin and Landry (2013) suggest it disappears after 5 to 6 years, whereas Atreya, Ferreira, and Kriesel (2013) suggest it does after 4 to 9 years, with no significant results for properties in the 500-year floodplain. However, the size of the discount they estimate immediately after the flood varies depending on how the time effect is specified. Bin and Landry (2013) suggest an immediate discount of 6%, 12% and 23% for linear, logarithm and ratio functional forms, respectively, whereas Atreya, Ferreira, and Kriesel (2013) suggest 38%, 44%, 50% and 57% for linear, logarithm, ratio and square root functional forms respectively[16]. This suggests that the speed at which the flood discount diminishes varies across different functional forms, and in general is faster for non-linear specifications.

Although there are five studies which address the issue of the persistence of the post-flood discount in flood risk areas, only two different flood events, across three different regions, are represented. Atreya, Ferreira and Kriesel (2012, 2013) focus on the effect of flooding due to tropical storm Alberto during 1994 in Dougherty County, Georgia, US. Atreya and Ferreira (2011, 2012a, 2012c) focus on the effect of the same flood in the city of Albany, Georgia, US; the city of Albany is the county seat[17] of Dougherty County, therefore some of the observations in the studies by Atreya and Ferreira are also included in the studies by Atreya, Ferreira and Kriesel. Bin and Landry (2013) focus in the effect of flooding due to Hurricane Floyd during 1999 in Pitt County, North Carolina, US. It is important to note that both, tropical storm Alberto and Hurricane Floyd, are considered among the worst flooding disasters in US history. The Albany Herald (2014) considers the 1994 flood as the worst disaster to ever hit Southwest Georgia, whereas the US Federal Emergency

[16] Bin and Landry (2013) focus on the effect of Hurricane Floyd in 1999 using a sample for the period 2002-2008, therefore the corresponding figures are for three years after the flood (2002).
[17] A county seat is the administrative centre of a county.

Management Agency (2000) considered Hurricane Floyd as the worst modern disaster in North Carolina by 1999.

The results of the meta-regression analysis allow us to study the average persistence of the average post-flood price discount for floodplain location, considering evidence from floods with different characteristics, across different regions, with different functional forms of the time variable. Results of table 1.9 from the set of regressions for estimates from coastal regions are not considered in this analysis; important flaws with effect-sizes from coastal regions have already been mentioned. For the case of effect sizes from river regions, results in table 1.5 using sample size weights suggests that the average post-flood discount for properties in the 100-year floodplain is 6.9%, whereas for properties in the 500-year floodplain is 5.9%. Taking these figures as a reference, the average persistence of the post-flood price discount for floodplain location (x) is calculated for different functional forms of the time variable using the formulas below, where, as before, β_1 and β_2 refer to the coefficients on the variable *mnths* and *mnths*100year*, respectively.

Table 1.11. Calculation of the persistence of the price discount for floodplain location, for different functional forms of the time variable

Functional form	500-year	100-year
$mnths$	$x = \frac{0.059}{\beta_1}$	$x = \frac{0.069}{\beta_1 + \beta_2}$
$\ln(mnths)$	$x = e^{\frac{0.059}{\beta_1}}$	$x = e^{\frac{0.069}{\beta_1 + \beta_2}}$
$\frac{(mnths - 1)}{mnths}$	$x = -\frac{1}{\frac{0.059}{\beta_1} - 1}$	$x = -\frac{1}{\frac{0.069}{\beta_1 + \beta_2} - 1}$
$Sqrt(mnths)$	$x = \left(\frac{0.059}{\beta_1}\right)^2$	$x = \left(\frac{0.069}{\beta_1 + \beta_2}\right)^2$

Source: Own elaboration.

After calculation the result for x is divided by twelve to express the persistence of the floodplain discount in the number of years, as previous studies do. Table 1.12 shows the results for all the set of regressions in table 1.8, 1.9 and 1.10 (except those for coastal regions). For most of the results in which the time variable takes a ratio functional form, only the coefficient β_1 is used to estimate the persistence of the risk discount, as when applying this functional form the decay of the discount is not significantly different across different levels of risk. However, differences in post-flood discounts across different levels of risk are considered; i.e. 5.9% and 6.9% for the 500 and 100-year floodplains, respectively. The only exception is for the results with the sub-sample of effect sizes from standard hedonic models in table 1.10; in this case, the decay for properties in the 100-year floodplain for the specification using a ratio functional form of the time variable is calculated using $\beta_1 + \beta_2$, since results suggest that the speed of the decay is significantly different at different levels of risk.

Table 1.12. Persistence of the price discount for floodplain location across different functional forms of the time variable

Set of results		Risk level	Functional form[1,2]			
			$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Table 1.8	Random-effects weights	500-year	8.45	0.20	0.09	1.12
		100-year	32.30	0.72	0.09	9.87
	Sample size weights	500-year	10.39	0.20	0.09	1.29
		100-year	32.86	0.52	0.09	9.75
Table 1.9	River flood Risk	500-year	10.31	0.21	0.09	1.26
		100-year	27.38	0.65	0.09	8.68
Table 1.10	Standard hedonic models	500-year	17.94	0.25	0.09	2.63
		100-year	32.19	0.88	0.09	9.28
	DID hedonic models	500-year	7.63	0.27	0.09	1.34
		100-year	2875	3.93	0.09	235

Note: [1] Results are expressed in number of years.
[2] A discount of 5.9% and 6.9% is assumed for properties in the 500 and 100-year floodplain, respectively

The estimated persistence of the post-flood discount for different functional forms of the time variable is consistent across results from different sub-samples in table 1.8, 1.9 and

1.10, except for those of the sub-sample on effect sizes from DID hedonic models which suggest that the discount takes much longer to vanish than for any other sub-sample of effect sizes. We believe this is due to a problem with the construction of the time variable (*mnths*). Before including the variable *mnths* in the results on table 1.8 and 1.9, the variables *dd_after* and *dd_hpm*, controlling for the before and after effect of effect sizes from DID hedonic models, were significant; however, once the variable *mnths* is included, these two variables are no longer significant. This is due to collinearity, since the *mnths* variable also captures the before and after effect. For effect sizes after a flood, the number of months elapsed since the previous flood is smaller than for effect sizes before a flood. The average number of months with respect to the previous flood for DID effect sizes before a flood is 250 (21 years), whereas for effect sizes after a flood is 30 (2-3 years). Thus, the results of the meta-regression seem to suggest that the variable *mnths* is also controlling for the before and after effect. As we commented before, all effect sizes are after a flood in the sense that in all cases there has been a previous flood event back on time; thus the main difference is merely the amount of time that has elapsed since the previous flood.

However, when we focus only on effect sizes from DID hedonic models the meta-regression results in table 1.10 indicate that both, the variable *mnths* and the variable *dd_after*, are highly significant. It seems that, in this case, the before and after effect is so strong that the variable *mnths* does not perfectly control for the before and after effect, such that the variable *dd_after* is significant even after including the variable *mnths*; this results in coefficients for the interaction variable *mnths*100year* suggesting that the decay of the post-flood discount for properties in the 100-year floodplain is too slow. We suggest this is due to the use of average values for the construction of the time variable. For instance, consider a DID study with a sample from 1992 to 2000, where there is a flood during 1996 and the previous flood in that location was in 1986. For the pre-flood effect-size the variable *mnths* takes the value of 96; i.e. six years from 1986 to 1991 (times twelve), plus the average number of months from 1992 to 1995; i.e. 24. For the post-flood effect-size it takes the value of 24; i.e. the average number of months between 1997 and 2000.

Therefore, we estimate again the meta-regression model for the sub-sample of effect sizes from DID hedonic models excluding the variables *dd_after* and *dd_after*100year*, the results appear in table A1.7 of the appendix. Table 1.13 shows the results for the persistence of the post-flood discount using the new coefficients. For properties in the 500-year floodplain, the results are similar to those in table 1.12, and for properties in the 100-year floodplain the results are now consistent with those obtained for different sub-samples of the dependent variable. [18]

Table 1.13. Persistence of the price discount for floodplain location across different functional forms of the time variable
*(Variables dd_after and dd_after*100yearare not included in meta-regression models)*

Set of results		Risk level	Functional form[1,2,3]			
			$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Table A1.7	DID hedonic models	500-year	7.85	0.22	0.09	1.29
		100-year	50.00	0.73	0.09	17.22

Note: [1] The results are based on the coefficients of the meta-regression models in table A1.7 of the appendix.
[2] Results are expressed in number of years.
[3] A discount of 5.9% and 6.9% is assumed for properties in the 500 and 100-year floodplain, respectively.

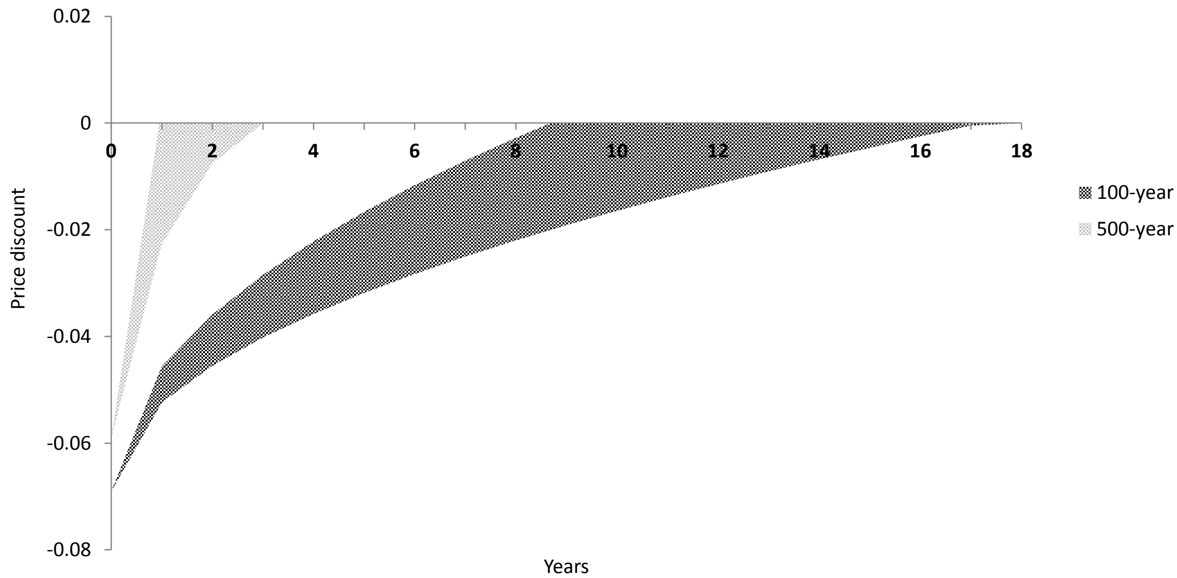
The speed at which the post-flood discount diminishes varies across different functional forms, and it is faster for non-linear specifications. This is consistent with the results by Bin and Landry (2013) and Atreya, Ferreira, and Kriesel (2013). The R^2 statistic of the

[18] The results of the meta-regression models for the sub-samples in tables 1.8 and 1.9 were also estimated excluding the variables *dd_after* and *dd_after*100year*, together with the corresponding persistence of the post-flood discount. The results are similar to those found previously and can be consulted in tables A1.5, A1.6 and A1.8 of the appendix.

meta-regression models in tables 1.8, 1.9, and 1.10 suggest that the functional forms of the time variable that best fit the data are square root, natural logarithm and linear; in general, the ratio functional form does not perform well. As Bin and Landry (2013) suggest, we believe that assuming a logarithmic functional form imposes too much curvature on the decay process, resulting in estimates indicating that the post-flood discount disappears in less than one year after a flood, which seems implausible as most evidence has documented significant discounts for floodplain location after more than one year after a flood. We also agree in that assuming a linear functional form can eventually result in large positive values for floodplain location after a considerable amount of time which is not credible. Therefore, the preferred model for interpretation is the one using the square root of the time variable as we believe is the one that provides more plausible results.

Figure 1.8 shows that the evolution of the post-flood discount for properties located in floodplains at different levels of risk, assuming that the discount decreases in a non-linear way following the square root of the number of months since the flood event ($f(mnths) = Sqrt(mnths)$). The results suggest that in 100-year floodplains (black shaded area), where properties are exposed to more frequent and more severe flooding, the discount can take between 9 to 17 years to disappear. This is longer than the period of 6 to 8 years estimated by Atreya, Ferreira, and Kriesel (2013). A similar effect is true for properties in 500-year floodplains (grey shaded area); in this case the post-flood discount is much less persistent, taking around 1 to 3 years.

Figure 1.8. Evolution of the post-flood discount for properties in the 100 and 500-year floodplain: across different functional forms of the time variable



Source: Own elaboration based on results from the econometric model.

As suggested by Tobin and Newton (1986) and Pryce, Chen, and Galster (2011), the size of the post-flood discount, as well as the characteristics of the recovery of prices, are likely to depend on the history of flooding in the location, together with the prevalent social and economic conditions.

1.5 Publication bias

So far, when using the meta-analysis techniques in section 1.4.1.2 we have implicitly assumed that the collection of effect sizes from primary studies is a representative sample, and inference has been drawn based on their weighted average. The possibility of sample selection bias has not been considered. In the meta-analysis literature this can arise due to a preference of researchers and/or reviewers to report and publish only statistically significant results, or coefficients with the sign or direction suggested by economic theory. This process of publication selection is known as publication bias or the "*file drawer* *problem*" (Rosenthal, 1978, 1979), referring to the fact that studies which find no significant results or an effect with an unexpected coefficient will be difficult to get published, and therefore, tend to remain in the file drawer. If the sample of observations included in the meta-analysis is truncated, then any average, weighted or simple, will lead to biased estimates; this is also true for meta-analysis using popular weighting schemes such as fixed and random-effects. In general, with the presence of publication bias averages of effect sizes will be biased upwards in magnitude and, hence, subject to faulty inference (Card and Krueger, 1995; De Long and Lang, 1992; C. Doucouliagos, Stanley, and Giles, 2012; Stanley, 2005; Stanley, Jarrell, and Doucouliagos, 2010).

Since the work by De Long and Lang (1992), publication bias is recognized as an important issue in empirical economics. Card and Krueger (1995) identify three potential sources of publication selection in economics (Stanley, 2005):

1. Reviewers and editors might be predisposed to accept papers consistent with conventional economic theory.
2. Researchers might use the presence of a conventionally expected result as criterion for model selection.
3. A general predisposition to treat statistically significant results more favourably.

We tried to mitigate this issue by performing a comprehensive systematic literature review on the issue of flood risk and property prices, and by including evidence from working papers, dissertations and any other published reports that were found, whether significant or not and regardless of the direction of the effect. Furthermore, the use of a weighting scheme assigning more weight to larger studies, which are acknowledged to contain more information, is known to minimize the variance of the weighted average. However, as mentioned above, publication bias might arise from different sources, and these strategies might remove some, but not all, of the potential publication bias (Stanley, 2005).

The objective of this section is to answer three questions: Is there publication selection in the flood risk literature? If so, to what extent are the results of the meta-analysis affected by this issue? Is there any significant empirical effect beyond publication bias?

1.5.1 Identifying publication bias

Publication bias is the result of selective sampling. The meta-analysis literature identifies two types of publication bias:

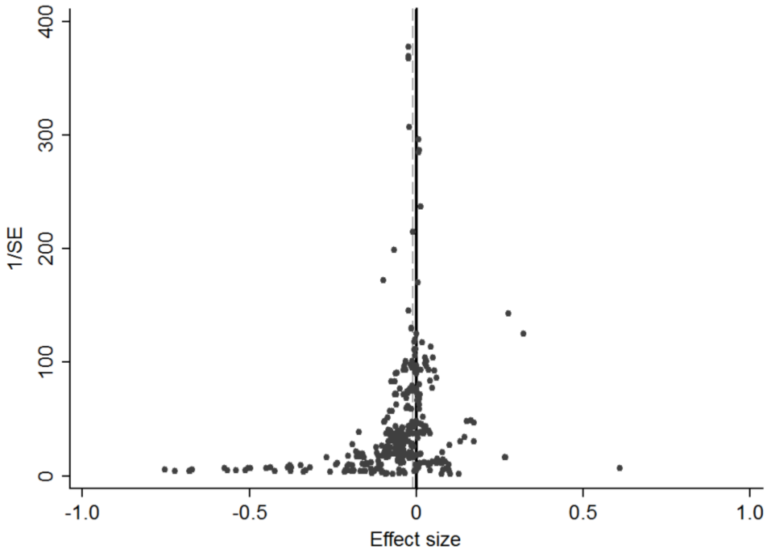
- **Type I.** Directional: Publication selection favours a particular direction of the effect, e.g. positive or negative effect.
- **Type II.** Statistically significance: Publication selection favours significant findings, irrespective of their direction.

The most commonly used method to detect publication bias is an informal, visual, examination of a funnel plot; however, since visual examination is always vulnerable to subjective interpretation statistical tests based on meta-regression analysis (MRA) have become popular to identify this issue. Section 1.5.1.1 below relies on the use of graphical techniques for the identification of publication bias. Section 1.5.1.2 verifies these findings using MRA techniques.

1.5.1.1 Funnel Graphs and Galbraith Plots

Funnel graphs are used to visually identify type I publication bias. A funnel graph is a scatter diagram of a measure of precision of effect sizes versus the non-standardised effect size. The former is usually represented by the inverse of the standard error ($1/SE_i$) and the latter generally corresponds to elasticities, regression coefficients or correlation coefficients. Figure 1.9 shows the funnel plot for the 349 effect sizes included in the meta-sample. The vertical axis measures precision as the inverse of the standard error, and the horizontal axis the magnitude of the effect size defined as the relative price differential for floodplain location. The dark vertical line at the centre of the plot represents a zero effect.

Figure 1.9. Funnel plot: Relative price differential for floodplain location, full sample



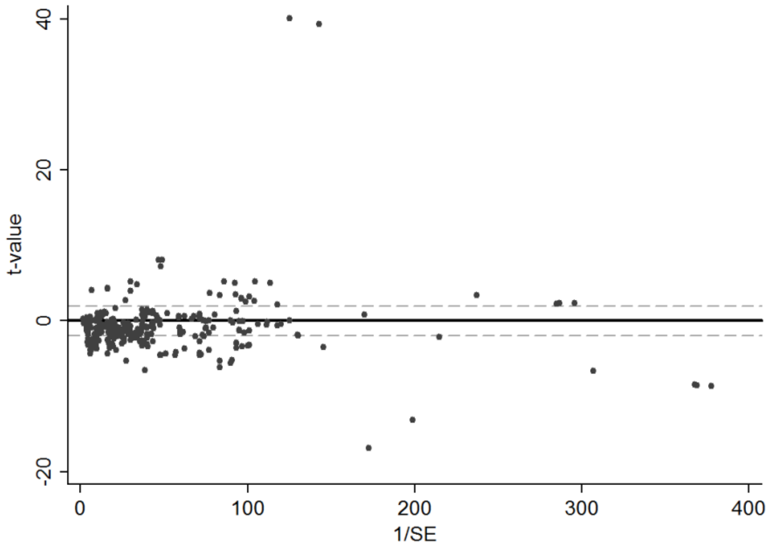
Source: Own elaboration based on effect sizes from primary studies.

In the absence of publication selection this plot is expected to show an inverted funnel shape, where effect sizes vary randomly and symmetrically around the true effect size, regardless of its magnitude. This expected shape is dictated by the existence of heteroscedasticty; less precise effect sizes from small-sample studies will be spread out at the bottom of the plot, and will become thinner at the top with more precise effect sizes (Stanley, 2005). Therefore, the existence of publication bias is assessed by looking at the symmetry (or asymmetry) of the plot.

A visual inspection of figure 1.9 suggests that the plot is overweighted on the left side, which suggest the existence of type I publication bias with a tendency to report negative impacts of flood risk on property prices. As the precision of effect sizes increases the plot seems to centre around a value close to 0; this can be confirmed by averaging the top effect sizes of the graph (those with a value for $1/Se_i > 250$), which results in a value close to -0.01, which is represented by the vertical grey dashed line in figure 1.10. Notice this value is less negative than the value suggested by the full-sample summary statistic of the meta-analysis in table 1.5; i.e. the true effect of flood risk on property prices might be actually less than initially thought. Comparing this result to the value of -0.059 of the simple average for the full sample would indicate a publication bias of a magnitude around 0.049. That is, the publication selection of large negative coefficients is likely to result in an inflated summary statistic around 5% larger than what it might actually be. A problem with this approach is that our meta-sample includes studies which contribute with more than one observation to the final sample; therefore the visual inspection of the funnel plot in figure 1.9 is likely to be biased due to the overrepresentation of some studies. It might be that we observed an asymmetric funnel only because studies which find negative coefficients report results for several regression models, for instance using different specifications or a different sub-sample. To illustrate this issue it is important to note that the average of the top observations in figure 1.9 with a value of $1/Se_i > 250$ includes only effect sizes from the study by Turnbull, Zahirovic, and Mothorpe (2013).

Type II publication bias arises from the selection of statistically significant results, regardless of their direction. This type of publication bias can be visually investigated using Galbraith plots (Stanley, 2005). A Galbraith plot is a scatter diagram of standardised effect versus precision (Galbraith, 1988). In practice, it is a funnel plot rotated 90° and adjusted to remove its heteroscedasticity. Figure 1.10 shows the Galbraith plot for the 349 effect sizes included in the meta-sample. The vertical axis measures the standardised effect size which is given by dividing each observation by its corresponding standard error ($effect_i/SE_i$), i.e. the *t*-statistic. Precision on the vertical axis is measured as before by the inverse of the standard error. The horizontal dashed lines represent the critical value of the t-statistic for large samples which can be approximated at ±1.96.

Figure 1.10. Funnel plot: Relative price differential for floodplain location, full sample



Source: Own elaboration based on effect sizes from primary studies.

Type II selection causes excess variation; this results in large t-values being over-reported (Stanley, 2005). In the case of no genuine effect of flood risk location on property prices we would expect the points to be randomly distributed around 0, with no systematic relation to precision and with only 5% of effect sizes with a t-value exceeding ±1.96. However, we find that 112 of 349 (32%) effect sizes report a *t*-value greater, in magnitude, than the associated critical value with a 5% significance level. Note that again, the issue of overrepresentation of studies contributing with more than one effect size might lead to misleading conclusions. In this case, the 112 effect sizes reporting a significant effect represent 31 out of the 37 studies (84%) included in the meta-analysis; that is 31 of the studies report at least one coefficient indicating a significant effect of flood risk location on property prices, regardless of the direction of the effect. This might reflect selection for statistical significant results, the existence of genuine heterogeneity in the price differential for floodplain location, or both. In itself, the presence of such excess variation does not bias the magnitude of the combined summary statistic resulting from the meta-analysis, as type I publication selection does. Nevertheless, (Stanley, 2005) argues that type II publication selection can explain why most meta-analyses in economics find excess variation. Therefore, an important question is: is there a genuine effect of flood risk location on property prices beyond publication bias? This question will be addressed further in this section.

An additional problem of determining the presence of publication bias using a graphical approach is that visual interpretation is subjective; therefore statistical tests have been developed to assess this issue in a more objective way. The following section relies on MRA to test for the asymmetry of the funnel plot and to correct effect sizes for publication bias.

1.5.1.2 Meta-regression analysis (MRA)

The use of MRA has become a popular way to identify publication bias by testing funnel plot asymmetry. Card and Krueger (1995) were probably the first authors to implement this approach in economics to examine the existence of an employment effect of minimum wages. Further, authors such as Ashenfelter, Harmon, and Oosterbeek (1999), Gorg and Strobl (2001), Stanley (2005) and C. Doucouliagos, Stanley, and Giles (2012) implement a similar approach.

In its simplest form a MRA for modelling publication selection takes the form of a linear regression between the reported effect sizes from primary studies and its standard error, as in equation (47).

$$effect_i = \beta_0 + \beta_1 Se_i + \varepsilon_i \tag{47}$$

When there is no publication selection, effect sizes should vary randomly around β_0, independently of the standard error. β_0 is regarded as the underlying true effect size, after controlling for the presence of publication bias. This is because as the study's sample size increases, we expect Se_i to become smaller approaching 0 as the sample goes to infinity. Therefore, with large samples we expect the reported effect to approach β_0. Thus, large samples are expected to be less affected by publication bias (Macaskill, Walter, and Irwig, 2001; Stanley, 2005; Sutton et al., 2000).

Meta-regression model (47) is generally not estimated because estimation errors ε_i will be heterosedastic as primary studies use different sample sizes and modelling variations. Therefore a variation of equation (47) is usually used to obtain efficient estimates with corrected standard errors; this implies dividing the equation by the estimated standard errors Se_i, which results in equation (48).

$$t_i = \beta_1 + \beta_0(1/Se_i) + e_i \tag{48}$$

Where the dependent variable $effect_i/Se_i$ represents the corresponding *t*-value, t_i, for effect size i, and the independent variable is now $1/Se_i$. Note that the intercept and slope coefficients are now reversed. As Egger et al. (1997) suggests, a conventional *t*-test on the intercept of equation (48), β_1, is a test for publication bias, and its sign indicates the direction of the bias. Stanley (2005) showed that this procedure filters out both types of publication bias.

Table 1.14 reports the meta-regression results for equation (48). Column 1 shows the results considering the full sample of effect sizes included in the meta-analysis; Huber-White robust standard errors are reported to correct for possible heteroscedasticity. A conventional t-test on the coefficient of the intercept, β_1, reveals significant publication bias in the flood risk literature towards reporting negative impacts of flood risk on property prices. Furthermore, the coefficient β_0 suggests that the effect of flood risk on property prices might not be different from 0. However, the coefficients of column 1 weight all effect sizes as if they were independent studies which, as with the funnel plot, results in overrepresentation of studies contributing with more than one observation. To accommodate this issue we proceed in the same way as in equation (46) of the MRA of the previous section, i.e. assigning weights according to the total sample size of each study divided by the number of estimates that the study provides to the final meta-sample. Column 2 shows the results for the full sample, and columns 3 through 8 report the coefficients for the different sub-samples that we analysed throughout the chapter.

Table 1.14. Meta-regression: Funnel Asymmetry Test

		Sample size weights						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Full Sample**	**Full Sample**	**100 year**	**500 year**	**River**	**Coast**	**Hedonic**	**DID Hedonic**
$1/Se_i$ (β_0)	-0.000974	-0.0304	-0.0325*	0.00870***	-0.0414***	0.363***	-0.0271	0.0821
	(0.00710)	(0.0206)	(0.0184)	(0.00164)	(0.0157)	(0.0255)	(0.0262)	(0.0661)
Constant (β_1)	-0.675***	0.719	0.378	-0.980***	0.455	-10.15***	0.959	-3.920
	(0.209)	(0.751)	(0.615)	(0.122)	(0.630)	(1.170)	(1.394)	(2.500)
t $\alpha = 0.10$	[0.000]***	[0.169]	[0.269]	[0.000]***	[0.235]	[0.000]***	[0.246]	[0.059]*
Observations	349	349	256	93	314	35	138	211
R-squared	0.000	0.065	0.079	0.278	0.338	0.929	0.025	0.160
Rmse	3.947	7.757	7.715	0.832	3.956	5.004	10.99	5.515

Note: The dependent variable corresponds to the standardised effect size, i.e. the corresponding t-value. Standard errors in parentheses correspond to Huber-White robust standard errors. The numbers in brackets correspond to the p-value for the one-tail t-test. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Once we account for the overrepresentation of studies with multiple estimates, the results in column 2 indicate that there is no evidence of publication bias in the flood risk literature taken as a whole. Egger et al. (1997) suggest that the statistical power of this test is limited and therefore propose to base evidence of asymmetry on a one tail t-test with $p < 0.1$; the results of this test are shown in brackets in table 1.14. Again, the results reveal no evidence of publication bias. Note, however, that the coefficient β_0 is not statistically different form 0, which suggest that the effect of flood risk on property prices is not significant beyond publication bias. The results in columns 3 through 8 lead to different conclusions depending on the sub-sample we consider; however, these do not appear to change the conclusions from the meta-analysis in section 1.4.4.2. In general, there is evidence of publication selection of studies reporting results for properties in 500-year floodplains and coastal regions; in both cases this bias operates in a negative direction, i.e. towards reporting impacts of flood risk greater in magnitude than it might actually be. After filtering out publication bias, there appear to be a negative impact of flood risk between 3 – 4% on properties in 100-year floodplains and for those properties subject to river flooding. On the other hand, flood risk does not seem to be capitalised in properties within 500-year floodplains; the coefficient β_0 suggest prices for these properties are about 1% higher compared to those outside the floodplain. For properties in coastal regions floodplain location seems to raise the value of the property around 36%, although, as discussed above, it is more likely that this value is associated with amenity values of proximity to coastal water.

Therefore, publication bias in the flood risk literature might be explained by a tendency of reviewers or researchers to under-report positive coefficients for the implicit price of flood risk. These results might appear as not intuitively or economically appealing, hence authors may be less likely to submit these findings or referees and editors may favour the publication of sought-for negative coefficients. Nevertheless this is only significant for the sub-sample of effect sizes from properties in 500-year floodplains and coastal regions.

1.6 Conclusions

Theory suggests that residential housing markets provide a way to estimate the benefits from flood risk reduction. The use of hedonic pricing models has been especially popular to this purpose. Empirical evidence suggests that properties within a flood risk area are sold at differential price ranging anywhere between -75 - +61%, with respect to properties outside the floodplain. In not a few cases the findings are contradictory regarding the direction of the impact of flood risk and how the price schedule evolves after a flood in regions with different levels of risk. The chapter shows the results of a meta-analysis on the relative price differential for floodplain location. The objective of this meta-analysis is to answer two questions: what is the price differential for floodplain location and what determines the variability in empirical results?

The results of the meta-analysis suggest there are important differences across different types of flooding. Estimates for river regions vary anywhere from -7% to +1%, depending on the level of risk and the time with respect to the previous flood. In these regions, location within a 100-year floodplain is associated with a 5% discount; however after a flood the discount increases to about 7%. There seems to be little awareness of flood risk in 500-year floodplains. In these regions prices appear to be insignificantly different compared to properties outside the floodplain; however, after a flood properties are significantly discounted by about 6%. This evidence supports the widespread idea that recent floods provide new information to homeowners to update their flood risk perception; however, pre-flood information available appears to play a role in determining the extent of the update. There is very little usable evidence from studies analysing the impact of flood risk on coastal properties; thus no meaningful conclusions can be drawn for these regions. In any case, the results suggest that properties exposed to coastal flood risk are sold at higher prices than those outside the risk area; this result is likely to be driven by biased results due to a high correlation between flood risk and benefits from proximity to coast. It is important that future efforts to identify the price effect of flood risk in these regions focus on mitigating this issue.

The results of the meta-regression analysis indicate that the dependent variable is highly sensitive to differences in the context of study. In all cases the coefficients support the idea that the effect of a flood on property prices diminishes as time elapses. Unlike previous studies which suggest this effect is only true for properties within the highest area of risk, our results suggest it is also true for properties in the 500-year floodplain, although less persistent. In 100-year floodplains the discount can take between 9 to 17 years to disappear, whereas in 500-year floodplains it might only last around 1 to 3 years. Thus, the discount is more persistent in properties exposed to more frequent and more severe flooding. Interestingly, once we control for differences in flood risk perception, differences in the level of risk are not significant. We interpret this as evidence that individuals respond to differences in flood risk perception, rather than to the location in spatially designated regions with different level of risk; although the availability of information regarding the objective level of risk might play a role in determining flood risk perception, as well as previous flood experiences.

Although efforts have been made to consider as much evidence as possible, it is important to recognise that the geographical scope of the meta-analysis, and therefore the generalization of results, is hindered by the lack of research outside the US. Out of 37 studies in the meta-sample only five correspond to other countries than the US. Thus, it is likely that the conclusions of the meta-analysis are only applicable to the US, and that the observed price discount and time to recovery are highly determined by US flood policies. Even within the US the evidence is confined only to 12 States. Therefore, more research is needed to understand the dynamics of the housing market in the presence of flood risk under different social, geographical and political circumstances.

Other areas for future research emerge for this meta-analysis. Although the theoretical model for the impact of flood risk on property prices suggests that the price differential arises due to differences in flood risk perception, so far all the evidence is based on studies using a proxy variable for flood risk based on an objective measure of risk. This approach suggests that the price differential in property prices will vary as you move across the border of the 100-year floodplain into the 500-year floodplain. However, the results from the meta-regression analysis suggest it is regional and temporal differences in flood risk perception that drives the heterogeneity of results, rather than differences in spatially delineated flood risk areas. Therefore, efforts should be directed to include variables accounting for differences in the perceived level of risk in hedonic models. Several questions arise from this difference between objective and perceived flood risk: Is there any significant effect of spatially delineated risk on property prices once flood risk perception has been accounted for? To what extent is objective risk perceived? Are reductions in objective risk perceived and capitalised in property prices? How does perception of flood risk diminish as we move far away and to higher altitudes from the source of risk? All these questions remain areas of future research.

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Appendix

Table A1.1. Main characteristics of the studies included in the meta-sample

Study ID[1]	Author	Year	Estimation period	Year last flooded[2]	Flood risk (floodplain)	Average sample	Hedonic specification	Functional form of dependent variable	Econometric model	Notes
1	MacDonald, Murdoch and White [a]	1987	Jan 1985 – Mar 1985	1983	100	139	Standard	Box-Cox	OLS	
2	Skantz and Strickland [a]	1987	Jul 1977 – Jul 1981	1975	100	176	Standard/DID	Semi-log	OLS	
3	Donnelly [a]	1989	Jan 1984 – Dec 1985	1981	100	334	Standard	Linear	OLS	
4	Shilling, Sirmans and Benjamin [a]	1989	Dec 1982 – Feb 1984	1973	100	114	Standard	Semi-log	OLS	
5	Bialszewski and Newsome [a]	1990	1987 – 1989	1983	100	93	Standard	Linear	OLS	
6	MacDonald et al. [a]	1990	Jan 1988 – Jul 1988	1983	100	183	Standard	Box-Cox	OLS	
7	Speyrer and Ragas [a]	1991	1971 – 1986	1969	100	999	Standard	Linear/Semi-log	OLS	
8	US Army Corps of Engineers [a]	1998	Apr 1988 – Mar 1993	1981	100	344	Standard	Linear	OLS	13 flood events during 1974 and 1986, the most destructive in 1981.
9	Bartosova et al. [a]	1999	Jan 1995 – Jul 1998	1986	100 and 500	1,431	Standard	Semi-log	OLS	
10	Harrison, Smersh and Schwartz [a]	2001	1980 – 1997	1964	100	22,411	Standard/DID	Linear	OLS	
11	Shultz and Fridgen [a]	2001	Jan 1995 – Aug 1998	1969	100 and 500	3,783	Standard	Linear	OLS	
12	Troy	2001	Dec 1996 – Jan 2000	1996	100	15,716	Standard/DID	Semi-log	OLS/WLS	Before and after the implementation of the 1998 California Natural Hazard Disclosure Law
13	Dei-Tutu and Bin [a]	2002	Jan 1998 – Jun 2002	1996	100	5,122	Standard	Box-Cox	OLS	
14	Bin	2004	Jul 2000 – Jun 2002	1999	100	1,397	Standard	Semi-log	OLS	
15	Bin and Polasky [a]	2004	Jul 1992 – Jun 2002	1991/1999	100	8,375	Standard/DID	Semi-log	OLS	Before and after Hurricane Floyd in 1999.
16	Troy and Romm [a]	2004	Dec 1996 – Jan 2000	1996	100	21,693	DID	Semi-log	WLS	Before and after the implementation of the 1998 California Natural Hazard Disclosure Law.
17	Hallstrom and Smith [a]	2005	1982 – 2000	1960/1992	100	5,212	DID	Semi-log	OLS	
18	Bin and Kruse [a]	2006	Sept 2000 – Sept 2004	1995	100 and 500	2,895	Standard	Semi-log	OLS	Minor flood in 1999.
19	Lamond and Proverbs	2006	2000 – 2005	2000	100	159	Standard	Semi-log	OLS	
20	Daniel, Florax and Rietveld	2007	1990 – 2004	1926/1993/1995	100	9,505	Standard/DID	Semi-log	OLS/Spatial	Before and after floods along the Meuse River in 1993 and 1995.
21	Morgan	2007	Jan 2000 – Feb 2006	1998/2004	100	20,882	Standard/DID	Semi-log	OLS	Before and after Hurricane Ivan in 2004. Ivan was the 4th Hurricane to hit Florida in 2004.

(Continued)

Table A1.1 Continue

Study ID[1]	Author	Year	Estimation period	Year last flooded[2]	Flood risk (floodplain)	Average sample	Hedonic specification	Functional form of dependent variable	Econometric model	Notes
22	Bin et al. [a]	2008	1995 – 2002	1991	100	990	Standard	Semi-log	OLS/Spatial	
23	Bin, Kruse and Landry [a]	2008	Sept 2000 – Sept 2004	1999	100 and 500	3,106	Standard	Semi-log	Spatial	
24	Pope [a]	2008	Jan 1995 – Sept 1996	1989	100 and 500	9,349	Standard/DID	Semi-log	OLS	Before and after Residential Property Disclosure Act in 1995.
25	Daniel, Florax and Rietveld	2009	1990 – 2004	1926/1993/1995	100	9,505	Standard/DID	Semi-log	OLS	Before and after floods along the Meuse River in 1993 and 1995.
26	Kousky	2010	1979 – 2006	1973/1993	100 and 500	291,831	Standard/DID	Semi-log	OLS	Before and after flood in 1993 along the Mississippi-Missouri River.
27	Samarasinghe and Sharp	2010	2006	2001	100	2,241	DID	Semi-log	OLS/Spatial	Before and after publication of maps outlining flood-hazard boundaries.
28	Posey and Rogers	2010	2000	1997	100	69,022	Standard	Semi-log	OLS/Spatial	
29	Atreya and Ferreira	2011	1985 – 2010	1959/1994	100 and 500	15,650	Standard/DID	Semi-log	OLS	Before and after Tropical Storm Alberto in 1994.
30	Rambaldi et al.	2012	1970 – 2010	1931	100	3,944	Standard	Semi-log	Spatial	
31	Atreya and Ferreira	2012c	1985 – 2010	1959/1994	100	3,005	DID	Semi-log	OLS/Spatial	Before and after Tropical Storm Alberto in 1994.
32	Atreya and Ferreira	2012a	1985 – 2010	1959/1994	100 and 500	9,958	DID	Semi-log	OLS/Spatial	Before and after Tropical Storm Alberto in 1994.
33	Atreya, Ferreira and Kriesel	2012	1985 – 2010	1959/1994	100 and 500	10,348	Standard/DID	Semi-log	OLS/Spatial	Before and after Tropical Storm Alberto in 1994.
34	Atreya, Ferreira and Kriesel	2013	1985 – 2004	1959/1994	100 and 500	8,042	DID	Semi-log	Spatial	Before and after Tropical Storm Alberto in 1994.
35	Bin and Landry	2013	1992 – 2008	1992/1996/1999	100 and 500	4,080	Standard/DID	Semi-log	Spatial	Before and after Hurricane Fran 1996 and Floyd 1999.
36	Meldrum	2013	1995 – 2010	1974	100	25,512	Standard	Semi-log	OLS/Spatial	
37	Turnbull, Zahirovic and Mothorpe	2013	1984 – 2005	1983	100 and 500	22,351	Standard	Semi-log	OLS/Spatial	

Notes: [1] Corresponds to the same ID as in table 1.3.
[2] For studies using a DID approach before and after a flood the dates correspond to the year of the previous flood for the pre-flood and post-flood sample.
[a] Studies included in the previous meta-analysis by Daniel, Florax and Rietveld (2009a).

Table A1.2. Meta-regression results: Random-effects and sample size weights
(*no regional fixed effects*)

Variables	Random-effects weights				Sample size weights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000400***	0.0586***	1.285***	0.0116***	0.000387***	0.0672***	1.367***	0.0132***
	(8.28e-05)	(0.0108)	(0.334)	(0.00219)	(7.70e-05)	(0.0122)	(0.385)	(0.00253)
mnths*100year	-0.000323***	-0.0383***	-0.159	-0.00882***	-0.000268***	-0.0424***	-0.371	-0.00943***
	(8.35e-05)	(0.0109)	(0.356)	(0.00219)	(8.18e-05)	(0.0128)	(0.404)	(0.00264)
Flood risk level								
100year	0.00115	0.131***	0.116	0.0511**	0.00284	0.165***	0.329	0.0724**
	(0.0158)	(0.0508)	(0.351)	(0.0258)	(0.0146)	(0.0624)	(0.400)	(0.0320)
Context of the study								
lav_feet	0.0398*	0.0526***	0.0662***	0.0436**	0.00796	0.0342	0.0437	0.0161
	(0.0204)	(0.0199)	(0.0193)	(0.0202)	(0.0291)	(0.0285)	(0.0280)	(0.0289)
lavprice_2010	0.0494***	0.0357***	0.0299**	0.0436***	0.0439	0.00588	0.00203	0.0274
	(0.0130)	(0.0129)	(0.0126)	(0.0129)	(0.0335)	(0.0334)	(0.0337)	(0.0330)
flooded	-0.103***	-0.0947**	-0.0617*	-0.102***	-0.0955*	-0.0775	-0.0341	-0.0927*
	(0.0391)	(0.0382)	(0.0370)	(0.0387)	(0.0496)	(0.0531)	(0.0579)	(0.0507)
scnd_flood	0.0328	0.0152	-0.0222	0.0279	0.0632	0.0368	-0.00960	0.0565
	(0.0273)	(0.0268)	(0.0265)	(0.0270)	(0.0388)	(0.0370)	(0.0366)	(0.0383)
dd_after	-0.0345	-0.0298	-0.0322	-0.0299	-0.0483	-0.0377	-0.0411	-0.0379
	(0.0226)	(0.0221)	(0.0212)	(0.0225)	(0.0323)	(0.0286)	(0.0266)	(0.0306)
dd_after*100year	-0.0211	-0.00649	0.0234	-0.0190	0.000614	-0.00516	0.0201*	-0.0102
	(0.0228)	(0.0226)	(0.0217)	(0.0228)	(0.0163)	(0.0129)	(0.0113)	(0.0146)
dd_afterlaw	0.0273	0.0189	0.00634	0.0234	0.0414	0.0409	0.0234	0.0415
	(0.0195)	(0.0192)	(0.0187)	(0.0194)	(0.0306)	(0.0290)	(0.0272)	(0.0301)
coast	0.0526***	0.0584***	0.0572***	0.0555***	0.152***	0.160***	0.173***	0.154***
	(0.0136)	(0.0133)	(0.0128)	(0.0135)	(0.0465)	(0.0434)	(0.0424)	(0.0453)
Control variables of study								
amenity	-0.0558***	-0.0625***	-0.0539***	-0.0594***	-0.0325	-0.0386	-0.0322	-0.0350
	(0.0136)	(0.0134)	(0.0128)	(0.0135)	(0.0292)	(0.0276)	(0.0263)	(0.0287)
real_p	-0.0340***	-0.0481***	-0.0374***	-0.0419***	-0.0251*	-0.0540***	-0.0438***	-0.0400***
	(0.0108)	(0.0111)	(0.0100)	(0.0111)	(0.0129)	(0.0126)	(0.0123)	(0.0127)
Characteristics of econometric model								
linear	-0.0196	-0.0468**	-0.0442**	-0.0325*	-0.0125	-0.0588**	-0.0449	-0.0347
	(0.0194)	(0.0199)	(0.0187)	(0.0196)	(0.0286)	(0.0283)	(0.0275)	(0.0286)
Box-Cox	-0.0254	-0.0193	-0.0220	-0.0230	0.0349	0.0323	0.0174	0.0356
	(0.0275)	(0.0270)	(0.0260)	(0.0273)	(0.0355)	(0.0301)	(0.0297)	(0.0331)
spatial	-0.0580***	-0.0521***	-0.0381***	-0.0570***	-0.0639**	-0.0529**	-0.0394*	-0.0606**
	(0.0113)	(0.0104)	(0.00989)	(0.0109)	(0.0286)	(0.0257)	(0.0232)	(0.0277)
dd_hpm	0.0280***	0.0187*	0.0195**	0.0234**	0.0329**	0.0252*	0.0259**	0.0291**
	(0.0105)	(0.0105)	(0.00985)	(0.0106)	(0.0146)	(0.0134)	(0.0130)	(0.0142)

(Continued)

Table A1.2. Continue

Characteristics of the study								
published	-0.00490	-0.00883	-0.0262***	-0.00462	0.0369*	0.0228	-0.0126	0.0365**
	(0.0115)	(0.0106)	(0.0101)	(0.0111)	(0.0203)	(0.0151)	(0.0146)	(0.0184)
med_sampleyear	0.00127	0.00181**	0.000723	0.00166*	0.00234	0.00329	0.00123	0.00305
	(0.000915)	(0.000908)	(0.000851)	(0.000917)	(0.00198)	(0.00202)	(0.00185)	(0.00202)
time_span	0.00179**	0.000947	0.000293	0.00145*	0.00315*	0.00150	0.000432	0.00258
	(0.000761)	(0.000775)	(0.000727)	(0.000775)	(0.00185)	(0.00173)	(0.00149)	(0.00186)
Constant	-3.412*	-4.597***	-3.460**	-4.204**	-5.337	-7.157*	-4.086	-6.675*
	(1.765)	(1.759)	(1.705)	(1.769)	(3.704)	(3.775)	(3.509)	(3.785)
Observations	349	349	349	349	349	349	349	349
τ^2	0.00248	0.00243	0.00236	0.00245				
I^2	0.886	0.886	0.883	0.886				
R^2					0.475	0.512	0.526	0.493
Adj. R^2					0.443	0.483	0.497	0.462
Rmse					0.0661	0.0637	0.0628	0.0650

Note: The dependent variable is the effect size T. Standard errors in parentheses; for results using sample size weights they correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.3. Meta-regression results by type of flood risk: Including regional fixed effects, random-effects weights

Variables	River flood risk				Coastal flood risk			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000412***	0.0407***	1.001***	0.0102***	-0.000758	0.0347	1.480	0.00184
	(6.30e-05)	(0.00664)	(0.241)	(0.00152)	(0.00223)	(0.0951)	(3.340)	(0.0288)
mnths*100year	-0.000222***	-0.0110**	-0.124	-0.00378***	0.00278	0.140	4.744	0.0410
	(5.53e-05)	(0.00520)	(0.235)	(0.00119)	(0.00222)	(0.0892)	(3.049)	(0.0280)
Flood risk level								
100year	-0.00979	0.0165	0.0919	0.00357	-0.0115	-0.401	-4.484	-0.153
	(0.00697)	(0.0227)	(0.230)	(0.0119)	(0.120)	(0.335)	(2.958)	(0.195)
Context of the study								
lav_feet	0.0763***	0.0812***	0.0766***	0.0804***	-0.494	-0.535	-0.525	-0.524
	(0.0142)	(0.0141)	(0.0137)	(0.0142)	(0.822)	(0.850)	(0.885)	(0.822)
lavprice_2010	0.0133	0.0140	0.0197	0.0118	0.185	0.1000	0.0597	0.151
	(0.0164)	(0.0163)	(0.0162)	(0.0163)	(0.168)	(0.167)	(0.173)	(0.164)
flooded	0.0116	0.00677	-0.0173	0.0208	-	-	-	-
	(0.0211)	(0.0204)	(0.0189)	(0.0213)				
scnd_flood	0.0320*	0.0192	0.00103	0.0305*	-	-	-	-
	(0.0179)	(0.0175)	(0.0173)	(0.0176)				
dd_after	-0.0109	-0.0156	-0.00708	-0.0145	-0.408**	-0.102	0.179	-0.271
	(0.0137)	(0.0136)	(0.0134)	(0.0136)	(0.181)	(0.237)	(0.354)	(0.192)
dd_after*100year	-0.00306	0.0101	0.00901	0.00548	-	-	-	-
	(0.0125)	(0.0127)	(0.0124)	(0.0126)				
dd_afterlaw	-0.00796	-0.00122	-0.00168	-0.00617	0.439**	0.126	-0.147	0.297
	(0.0120)	(0.0120)	(0.0118)	(0.0120)	(0.203)	(0.260)	(0.372)	(0.215)
coast	-	-	-	-	-	-	-	-
Control variables of study								
amenity	0.0147*	0.0131*	0.0130*	0.0141*	-0.0149	-0.0503	-0.0579	-0.0334
	(0.00807)	(0.00792)	(0.00720)	(0.00814)	(0.0859)	(0.0918)	(0.0975)	(0.0867)
real_p	-0.0567***	-0.0338***	-0.0240*	-0.0474***	-0.947	-0.455	0.0136	-0.747
	(0.0121)	(0.0125)	(0.0125)	(0.0122)	(0.567)	(0.555)	(0.630)	(0.545)
Characteristics of econometric model								
linear	-0.0231	-0.0453**	-0.0226	-0.0410**	-0.0834	-0.0845	-0.0851	-0.0838
	(0.0186)	(0.0194)	(0.0181)	(0.0192)	(0.0974)	(0.101)	(0.105)	(0.0974)
Box-Cox	0.00304	-0.00175	-0.00387	0.000563	-	-	-	-
	(0.0156)	(0.0155)	(0.0151)	(0.0155)				
spatial	0.00942	0.0113**	0.0139**	0.00962*	-0.0108	0.0247	0.0240	0.0114
	(0.00578)	(0.00570)	(0.00541)	(0.00578)	(0.0671)	(0.0784)	(0.0842)	(0.0714)
dd_hpm	0.00757*	0.00714*	0.00790**	0.00689	0.127	-0.0414	-0.260	0.0520
	(0.00418)	(0.00414)	(0.00397)	(0.00418)	(0.140)	(0.178)	(0.267)	(0.150)

(Continued)

Table A1.3. Continue

Characteristics of the study								
published	-0.00559	-0.00821	-0.0129	-0.00590	-	-	-	-
	(0.00876)	(0.00869)	(0.00850)	(0.00872)				
med_sampleyear	0.000454	0.000725	-0.00102	0.00111	0.0910***	0.0272	-0.0535	0.0655**
	(0.000745)	(0.000754)	(0.000691)	(0.000769)	(0.0311)	(0.0275)	(0.0551)	(0.0263)
time_span	0.00117	0.000800	0.00133*	0.000740	0.0153	-0.0239	-0.103	0.000706
	(0.000710)	(0.000710)	(0.000682)	(0.000714)	(0.0181)	(0.0267)	(0.0618)	(0.0197)
Regional fixed effects[1]								
louisiana	0.0902***	0.110***	0.0656***	0.116***	1.243**	0.712**	0.143	1.042**
	(0.0227)	(0.0239)	(0.0210)	(0.0241)	(0.458)	(0.330)	(0.330)	(0.393)
n_carolina	0.105***	0.102***	0.0751***	0.114***	-	-	-	-
	(0.0173)	(0.0171)	(0.0155)	(0.0178)				
texas	0.143***	0.161***	0.106***	0.170***	-	-	-	-
	(0.0227)	(0.0239)	(0.0198)	(0.0245)				
wisconsin	0.211***	0.193***	0.148***	0.216***	-	-	-	-
	(0.0248)	(0.0239)	(0.0227)	(0.0249)				
alabama	0.185***	0.208***	0.148***	0.217***	-	-	-	-
	(0.0402)	(0.0412)	(0.0383)	(0.0414)				
florida	0.123***	0.144***	0.102***	0.146***	0.199	0.340	0.535*	0.262
	(0.0266)	(0.0276)	(0.0253)	(0.0276)	(0.172)	(0.195)	(0.260)	(0.177)
california	0.152***	0.163***	0.127***	0.169***	-	-	-	-
	(0.0204)	(0.0210)	(0.0185)	(0.0214)				
missouri	0.117***	0.0926***	0.0566***	0.117***	-	-	-	-
	(0.0162)	(0.0150)	(0.0145)	(0.0160)				
colorado	0.0672***	0.0436**	0.0440**	0.0524**	-	-	-	-
	(0.0202)	(0.0204)	(0.0201)	(0.0202)				
minesota	0.111***	0.130***	0.112***	0.127***	-	-	-	-
	(0.0247)	(0.0256)	(0.0239)	(0.0254)				
nl	0.0173	0.0275	0.0239	0.0217	-	-	-	-
	(0.0212)	(0.0211)	(0.0209)	(0.0210)				
uk	0.00222	0.0401	0.0389	0.0267	-	-	-	-
	(0.0327)	(0.0345)	(0.0337)	(0.0336)				
aus	-	-	-	-	-0.855	0.374	2.876	-0.423
					(0.698)	(0.854)	(1.852)	(0.705)
nz	-	-	-	-	-0.610**	-0.276	0.0330	-0.466*
					(0.253)	(0.254)	(0.334)	(0.239)
Constant	-1.772	-2.487*	0.166	-3.143**	-179.9**	-51.36	109.2	-128.5**
	(1.433)	(1.461)	(1.366)	(1.489)	(62.44)	(55.33)	(109.5)	(52.79)
Observations	314	314	314	314	35	35	35	35
τ^2	0.000106	9.89e-05	7.70e-05	0.000110	0.00497	0.00607	0.00695	0.00523
I^2	0.293	0.282	0.255	0.286	0.745	0.772	0.783	0.756

Note: [1] The omitted region for the meta-regression on river and coastal estimates is Georgia, US, and North Carolina, US, respectively.
The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.4. Meta-regression results by different econometric approach: Including regional fixed effects, random-effects weights

Variables	Standard hedonic models (1) $mnths$	(2) $\ln(mnths)$	(3) $\frac{(mnths-1)}{mnths}$	(4) $Sqrt(mnths)$	DID hedonic models (5) $mnths$	(6) $\ln(mnths)$	(7) $\frac{(mnths-1)}{mnths}$	(8) $Sqrt(mnths)$
Flood risk perception								
mnths	0.000480***	0.0500***	1.598**	0.0133***	0.000571***	0.0591***	0.673*	0.0141***
	(0.000157)	(0.0162)	(0.732)	(0.00391)	(9.72e-05)	(0.0123)	(0.352)	(0.00250)
mnths*100year	-0.000152	-0.0179	-0.691	-0.00448	-0.000476***	-0.0336***	0.279	-0.0100***
	(0.000128)	(0.0142)	(0.732)	(0.00312)	(9.07e-05)	(0.0116)	(0.360)	(0.00229)
Flood risk level								
100year	-0.00534	0.0580	0.659	0.0225	0.0331**	0.129**	-0.308	0.0818***
	(0.0163)	(0.0595)	(0.716)	(0.0291)	(0.0142)	(0.0564)	(0.357)	(0.0270)
Context of the study								
lav_feet	0.103***	0.112***	0.106***	0.111***	-0.0212	-0.0107	-0.000986	-0.0177
	(0.0255)	(0.0252)	(0.0246)	(0.0255)	(0.0834)	(0.0803)	(0.0780)	(0.0832)
lavprice_2010	0.00141	-0.00545	-0.00242	-0.00453	0.108	0.0835	0.0570	0.102
	(0.0211)	(0.0213)	(0.0213)	(0.0211)	(0.126)	(0.124)	(0.123)	(0.126)
flooded	0.0725	0.0574	0.0302	0.0819	-0.0242	-0.0246	-0.0261	-0.0220
	(0.0586)	(0.0537)	(0.0509)	(0.0575)	(0.0394)	(0.0388)	(0.0385)	(0.0393)
scnd_flood	-	-	-	-	0.00351	-0.00536	-0.0288	0.00443
					(0.0206)	(0.0184)	(0.0181)	(0.0197)
dd_after	-	-	-	-	-0.0512**	-0.0446**	-0.0478**	-0.0463**
					(0.0217)	(0.0220)	(0.0213)	(0.0221)
dd_after*100year	-	-	-	-	-0.0246*	-0.00783	0.0125	-0.0201
					(0.0144)	(0.0148)	(0.0133)	(0.0149)
dd_afterlaw	-	-	-	-	0.0437***	0.0334**	0.0303**	0.0379**
					(0.0153)	(0.0152)	(0.0149)	(0.0155)
coast	0.0675***	0.0663***	0.0603***	0.0698***	-0.0664	-0.0480	-0.0304	-0.0617
	(0.0214)	(0.0208)	(0.0207)	(0.0211)	(0.180)	(0.177)	(0.175)	(0.180)
Control variables of study								
amenity	0.00892	0.00122	-0.000744	0.00475	-0.187*	-0.180*	-0.175*	-0.185*
	(0.0193)	(0.0188)	(0.0188)	(0.0190)	(0.106)	(0.103)	(0.101)	(0.106)
real_p	-0.0323	-0.0291	-0.0195	-0.0349	-0.0513	-0.0209	-0.00432	-0.0407
	(0.0293)	(0.0284)	(0.0283)	(0.0288)	(0.0491)	(0.0485)	(0.0478)	(0.0492)
Characteristics of econometric model								
linear	-0.140***	-0.145***	-0.139***	-0.147***	-0.375***	-0.356***	-0.346***	-0.368***
	(0.0289)	(0.0283)	(0.0279)	(0.0287)	(0.0642)	(0.0641)	(0.0632)	(0.0645)
Box-Cox	0.0118	0.0159	0.0117	0.0154	-	-	-	-
	(0.0328)	(0.0321)	(0.0320)	(0.0323)				
spatial	-0.0123	-0.00366	-0.00283	-0.00727	0.0252**	0.0161	0.0122	0.0218*
	(0.0129)	(0.0126)	(0.0125)	(0.0127)	(0.0126)	(0.0125)	(0.0122)	(0.0127)
dd_hpm	-	-	-	-	-	-	-	-

(Continued)

Table A1.4. Continue

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Characteristics of the study								
published	-0.0221	-0.0260	-0.0366	-0.0222	0.00786	0.00557	0.00316	0.00786
	(0.0261)	(0.0253)	(0.0255)	(0.0256)	(0.0114)	(0.0109)	(0.0106)	(0.0113)
med_sampleyear	0.00407***	0.00410***	0.00280**	0.00467***	0.00494***	0.00419***	0.00201	0.00497***
	(0.00155)	(0.00149)	(0.00141)	(0.00156)	(0.00145)	(0.00142)	(0.00147)	(0.00144)
time_span	0.00147	0.00222	0.00307**	0.00153	0.00849***	0.00565***	0.00481**	0.00723***
	(0.00160)	(0.00151)	(0.00150)	(0.00156)	(0.00193)	(0.00203)	(0.00202)	(0.00200)
Regional fixed effects[1]								
louisiana	0.152*	0.0720	0.0195	0.134*	-	-	-	-
	(0.0806)	(0.0625)	(0.0577)	(0.0721)				
n_carolina	0.110	0.0365	0.00653	0.0868	0.0881	0.102*	0.0874*	0.0966*
	(0.0720)	(0.0567)	(0.0543)	(0.0636)	(0.0537)	(0.0539)	(0.0526)	(0.0541)
texas	0.303***	0.207***	0.159***	0.272***	0.0389	0.0539	-0.00127	0.0537
	(0.0728)	(0.0530)	(0.0500)	(0.0622)	(0.159)	(0.155)	(0.151)	(0.159)
wisconsin	0.271***	0.190***	0.137***	0.252***	-	-	-	-
	(0.0737)	(0.0544)	(0.0494)	(0.0646)				
alabama	0.386***	0.301***	0.256***	0.363***	-	-	-	-
	(0.0918)	(0.0758)	(0.0727)	(0.0835)				
florida	0.334***	0.257***	0.226***	0.307***	0.254	0.253	0.236	0.255
	(0.0742)	(0.0605)	(0.0588)	(0.0663)	(0.190)	(0.186)	(0.183)	(0.190)
california	0.204***	0.146**	0.105*	0.193***	0.0540	0.102	0.108	0.0738
	(0.0746)	(0.0600)	(0.0552)	(0.0678)	(0.100)	(0.101)	(0.0988)	(0.101)
missouri	0.173**	0.0790	0.0415	0.140**	0.0663	0.0601	0.0347	0.0684
	(0.0678)	(0.0486)	(0.0461)	(0.0571)	(0.0446)	(0.0435)	(0.0425)	(0.0447)
colorado	0.0437	-0.0183	-0.0262	0.0104	-	-	-	-
	(0.0488)	(0.0433)	(0.0436)	(0.0443)				
minesota	0.268***	0.194***	0.188***	0.233***	-	-	-	-
	(0.0739)	(0.0626)	(0.0621)	(0.0665)				
nl	0.0259	-0.0432	-0.0535	-0.00989	-0.0219	0.0190	0.0586	-0.0136
	(0.0631)	(0.0559)	(0.0558)	(0.0576)	(0.0998)	(0.0991)	(0.0985)	(0.0997)
uk	0.0560	0.0106	0.000287	0.0456	-	-	-	-
	(0.0873)	(0.0775)	(0.0775)	(0.0820)				
aus	0.0195	-0.0796	-0.110	-0.0217	-	-	-	-
	(0.107)	(0.0976)	(0.0977)	(0.101)				
nz	-	-	-	-	-	-	-	-
Constant	-9.090***	-9.216***	-7.955***	-10.34***	-10.96***	-9.467***	-5.240	-11.05***
	(3.050)	(2.942)	(2.966)	(3.084)	(3.202)	(3.161)	(3.240)	(3.196)
Observations	138	138	138	138	211	211	211	211
τ^2	0.000794	0.000692	0.000629	0.000756	6.61e-05	3.85e-05	2.04e-05	6.41e-05
I^2	0.753	0.731	0.721	0.744	0	0.00631	0	0.00591

Note: [1] The omitted region is Georgia, US.

The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.5. Meta-regression results: Random-effects and sample size weights
(*excluding variables dd_after and dd_after*100year*)

Variables	Random-effects weights				Sample size weights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-}{mnths}$	$Sqrt(mnths$
Flood risk perception								
mnths	0.000638***	0.0759***	1.412***	0.0179***	0.000470***	0.0671***	1.215***	0.0148***
	(8.24e-05)	(0.00964)	(0.318)	(0.00209)	(7.33e-05)	(0.00964)	(0.331)	(0.00197)
mnths*100year	-0.000397***	-0.0371***	-0.206	-0.00979***	-0.000271***	-0.0267***	-0.157	-0.00746***
	(7.54e-05)	(0.00908)	(0.331)	(0.00187)	(6.64e-05)	(0.00959)	(0.366)	(0.00177)
Flood risk level								
100year	0.00975	0.132***	0.171	0.0633***	0.00251	0.0902**	0.123	0.0469**
	(0.0117)	(0.0408)	(0.325)	(0.0201)	(0.0101)	(0.0453)	(0.361)	(0.0203)
Context of the study								
lav_feet	0.0266	0.0483**	0.0544***	0.0370*	-0.0361	0.0101	0.0131	-0.0155
	(0.0211)	(0.0203)	(0.0200)	(0.0205)	(0.0357)	(0.0331)	(0.0323)	(0.0346)
lavprice_2010	0.0439**	0.0307*	0.0302*	0.0363**	0.0570	0.00975	0.0101	0.0307
	(0.0174)	(0.0170)	(0.0170)	(0.0171)	(0.0450)	(0.0426)	(0.0427)	(0.0436)
flooded	-0.0227	-0.0216	-0.0348	-0.0124	-0.0432	-0.0204	-0.0225	-0.0288
	(0.0361)	(0.0342)	(0.0335)	(0.0351)	(0.0578)	(0.0612)	(0.0617)	(0.0600)
scnd_flood	0.0254	0.00568	-0.0214	0.0227	-0.000331	-0.0308	-0.0583**	-0.00920
	(0.0247)	(0.0229)	(0.0226)	(0.0236)	(0.0236)	(0.0273)	(0.0285)	(0.0250)
dd_after	-	-	-	-	-	-	-	-
dd_after*100year	-	-	-	-	-	-	-	-
dd_afterlaw	-0.0234**	-0.0108	-0.00411	-0.0184	0.0159	0.0222	0.0171	0.0181
	(0.0116)	(0.0113)	(0.0112)	(0.0113)	(0.0194)	(0.0153)	(0.0112)	(0.0182)
coast	0.0183	0.0174	0.0139	0.0185	0.0286	0.0280	0.0249	0.0299
	(0.0150)	(0.0144)	(0.0142)	(0.0146)	(0.0320)	(0.0295)	(0.0301)	(0.0304)
Control variables of study								
amenity	-0.0242	-0.0254	-0.0104	-0.0260	-0.0249	-0.0151	-0.00794	-0.0191
	(0.0172)	(0.0164)	(0.0162)	(0.0167)	(0.0245)	(0.0209)	(0.0203)	(0.0227)
real_p	-0.00458	0.0100	0.0233	-0.000665	0.0539*	0.0842***	0.0826***	0.0657**
	(0.0167)	(0.0162)	(0.0160)	(0.0163)	(0.0310)	(0.0309)	(0.0274)	(0.0315)
Characteristics of econometric model								
linear	-0.0770***	-0.0981***	-0.0926***	-0.0895***	-0.177***	-0.179***	-0.186***	-0.177***
	(0.0197)	(0.0192)	(0.0188)	(0.0193)	(0.0532)	(0.0470)	(0.0462)	(0.0505)
Box-Cox	-0.0192	-0.0310	-0.0336	-0.0267	-0.0162	-0.0290	-0.0222	-0.0257
	(0.0259)	(0.0249)	(0.0246)	(0.0252)	(0.0245)	(0.0253)	(0.0243)	(0.0246)
spatial	-0.0107	-0.00374	-0.00260	-0.00803	-0.00201	0.00153	0.00330	-0.000792
	(0.0103)	(0.00985)	(0.00974)	(0.01000)	(0.0137)	(0.0128)	(0.0131)	(0.0133)
dd_hpm	0.0120	0.0101	0.0111	0.0108	0.0129	0.00831	0.00924	0.0105
	(0.00823)	(0.00783)	(0.00769)	(0.00797)	(0.00798)	(0.00728)	(0.00675)	(0.00787)

(Continued)

Table A1.5. Continue

Characteristics of the study								
published	-0.00349	-0.00527	-0.0145	-0.00242	-0.00905	-0.0160	-0.0161	-0.0118
	(0.0137)	(0.0131)	(0.0129)	(0.0133)	(0.0180)	(0.0168)	(0.0155)	(0.0176)
med_sampleyear	0.00158**	0.00227***	0.000527	0.00258***	-2.84e-05	0.000843	-0.00120***	0.000980*
	(0.000786)	(0.000760)	(0.000688)	(0.000795)	(0.000447)	(0.000518)	(0.000445)	(0.00050)
time_span	0.00276**	0.00152	0.00115	0.00183	0.00574***	0.00117	0.00136	0.00326
	(0.00118)	(0.00116)	(0.00113)	(0.00117)	(0.00204)	(0.00201)	(0.00181)	(0.00205)
Regional fixed effects[1]								
louisiana	0.133***	0.155***	0.0936***	0.167***	0.173***	0.262***	0.170***	0.239***
	(0.0339)	(0.0328)	(0.0302)	(0.0341)	(0.0585)	(0.0663)	(0.0538)	(0.0653)
n_carolina	0.142***	0.123***	0.0706***	0.146***	0.180***	0.172***	0.108***	0.192***
	(0.0237)	(0.0220)	(0.0212)	(0.0230)	(0.0389)	(0.0375)	(0.0328)	(0.0396)
texas	0.218***	0.221***	0.167***	0.238***	0.363***	0.343***	0.277***	0.370***
	(0.0318)	(0.0300)	(0.0280)	(0.0314)	(0.0585)	(0.0524)	(0.0474)	(0.0570)
wisconsin	0.190***	0.175***	0.111***	0.202***	0.188***	0.179***	0.112**	0.201***
	(0.0329)	(0.0308)	(0.0295)	(0.0321)	(0.0609)	(0.0598)	(0.0560)	(0.0610)
alabama	0.271***	0.277***	0.228***	0.291***	0.439***	0.438***	0.373***	0.456***
	(0.0559)	(0.0535)	(0.0522)	(0.0546)	(0.0619)	(0.0579)	(0.0503)	(0.0622)
florida	0.255***	0.252***	0.230***	0.262***	0.370***	0.377***	0.337***	0.384***
	(0.0318)	(0.0304)	(0.0298)	(0.0310)	(0.0601)	(0.0569)	(0.0524)	(0.0600)
california	0.190***	0.202***	0.147***	0.210***	0.230***	0.276***	0.211***	0.266***
	(0.0296)	(0.0287)	(0.0266)	(0.0295)	(0.0524)	(0.0552)	(0.0497)	(0.0546)
missouri	0.108***	0.0777***	0.0357**	0.108***	0.105***	0.0950***	0.0399	0.118***
	(0.0210)	(0.0186)	(0.0178)	(0.0200)	(0.0377)	(0.0339)	(0.0308)	(0.0374)
colorado	0.0237	0.00569	0.00577	0.0133	0.00950	0.0282	0.0322	0.0213
	(0.0257)	(0.0246)	(0.0245)	(0.0249)	(0.0587)	(0.0552)	(0.0555)	(0.0568)
minesota	0.203***	0.199***	0.195***	0.202***	0.387***	0.372***	0.363***	0.381***
	(0.0370)	(0.0357)	(0.0350)	(0.0361)	(0.0700)	(0.0638)	(0.0645)	(0.0664)
nl	0.0575*	0.0734**	0.0663**	0.0664**	0.160***	0.214***	0.188***	0.192***
	(0.0310)	(0.0298)	(0.0295)	(0.0301)	(0.0535)	(0.0562)	(0.0539)	(0.0547)
uk	-0.00210	0.0345	0.0380	0.0202	0.0711	0.133**	0.0923*	0.108**
	(0.0497)	(0.0488)	(0.0481)	(0.0489)	(0.0458)	(0.0557)	(0.0503)	(0.0515)
aus	-0.00641	0.0166	0.0139	0.0203	-0.0530	0.119	0.0772	0.0484
	(0.0763)	(0.0739)	(0.0730)	(0.0747)	(0.114)	(0.119)	(0.112)	(0.118)
nz	0.0702*	0.0337	-0.0105	0.0621*	0.0924	0.0747	0.0346	0.0971
	(0.0382)	(0.0363)	(0.0361)	(0.0370)	(0.0752)	(0.0687)	(0.0691)	(0.0719)
Constant	-4.065***	-5.684***	-3.275**	-6.147***	-0.627	-2.366**	0.843	-2.572**
	(1.558)	(1.517)	(1.452)	(1.580)	(0.951)	(1.065)	(1.021)	(1.046)
Observations	349	349	349	349	349	349	349	349
τ^2	0.00117	0.00106	0.000984	0.00113				
I^2	0.743	0.715	0.691	0.735				
R^2					0.679	0.696	0.692	0.690
Adj. R^2					0.646	0.665	0.660	0.658

Note: [1] The omitted region is Georgia, US.

The dependent variable is the effect size T. Standard errors in parentheses; for results using sample size weights they correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.6. Meta-regression results by type of flood risk: Including regional fixed effects, sample size weights
(*excluding variables dd_after and dd_after*100year*)

Variables	River flood risk				Coastal flood risk			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000481***	0.0644***	1.184***	0.0148***	-0.00195	0.0421	-0.666	-0.00428
	(7.47e-05)	(0.00976)	(0.329)	(0.00195)	(0.00237)	(0.0283)	(1.799)	(0.0173)
mnths*100year	-0.000269***	-0.0314***	-0.305	-0.00791***	0.00201	0.187**	4.169**	0.0470*
	(6.81e-05)	(0.0101)	(0.371)	(0.00181)	(0.00228)	(0.0673)	(1.960)	(0.0245)
Flood risk level								
100year	0.00474	0.114**	0.270	0.0547***	0.0281	-0.517**	-3.891**	-0.156
	(0.0101)	(0.0480)	(0.366)	(0.0209)	(0.0775)	(0.179)	(1.836)	(0.101)
Context of the study								
lav_feet	0.0687***	0.109***	0.111***	0.0933***	0.144	-0.598*	-0.237	-0.319
	(0.0233)	(0.0224)	(0.0211)	(0.0229)	(0.832)	(0.326)	(0.507)	(0.448)
lavprice_2010	0.00728	-0.0286	-0.0305	-0.0202	-0.257	-0.00576	-0.113	-0.0752
	(0.0445)	(0.0448)	(0.0425)	(0.0452)	(0.281)	(0.163)	(0.213)	(0.194)
flooded	-0.0257	-0.0191	-0.0202	-0.0173	-	-	-	-
	(0.0571)	(0.0594)	(0.0593)	(0.0591)				
scnd_flood	-0.00430	-0.0343	-0.0561**	-0.0155	-	-	-	-
	(0.0213)	(0.0227)	(0.0243)	(0.0219)				
dd_after	-	-	-	-	-	-	-	-
dd_after*100year	-	-	-	-	-	-	-	-
dd_afterlaw	0.00377	-0.00687	-0.0255	-0.00154	0.0426	0.0190	0.0366	0.0261
	(0.0246)	(0.0229)	(0.0216)	(0.0237)	(0.107)	(0.0128)	(0.0483)	(0.0377)
coast	-	-	-	-	-	-	-	-
Control variables of study								
amenity	-0.00992	-0.00400	-0.00319	-0.00532	0.0122	-0.0284	-0.00567	-0.00828
	(0.0176)	(0.0180)	(0.0151)	(0.0188)	(0.0644)	(0.0462)	(0.0533)	(0.0503)
real_p	-0.0823***	-0.0562**	-0.0528**	-0.0747***	0.537	-0.381*	0.0344	-0.0337
	(0.0190)	(0.0254)	(0.0241)	(0.0221)	(0.494)	(0.187)	(0.267)	(0.401)
Characteristics of econometric model								
linear	-0.148***	-0.160***	-0.166***	-0.163***	-0.0916	-0.0916**	-0.0916	-0.0916*
	(0.0543)	(0.0541)	(0.0521)	(0.0549)	(0.0860)	(0.0359)	(0.0535)	(0.0473)
Box-Cox	0.0128	0.00171	0.00829	0.00402	-	-	-	-
	(0.0212)	(0.0233)	(0.0230)	(0.0221)				
spatial	0.0116	0.0136	0.0159	0.0121	-0.156	0.00995	-0.0740	-0.0577
	(0.0108)	(0.0100)	(0.0105)	(0.0103)	(0.116)	(0.0550)	(0.0855)	(0.0826)
dd_hpm	0.00705	0.00305	0.00318	0.00488	0.0182	-0.117***	-0.0855**	-0.0748
	(0.00544)	(0.00574)	(0.00567)	(0.00559)	(0.0684)	(0.0286)	(0.0366)	(0.0797)

(Continued)

Table A1.6. Continue

Characteristics of the study								
published	-0.0155	-0.0211	-0.0208	-0.0185	-	-	-	-
	(0.0163)	(0.0157)	(0.0152)	(0.0160)				
med_sampleyear	1.89e-05	0.000510	-0.00131***	0.000857*	-0.0122	0.0208***	-0.0145**	0.0182
	(0.000398)	(0.000485)	(0.000404)	(0.000473)	(0.0252)	(0.00714)	(0.00596)	(0.0273)
time_span	0.00336*	2.33e-05	0.000396	0.00104	0.0127	-0.0386***	-0.0446**	-0.0122
	(0.00201)	(0.00193)	(0.00185)	(0.00195)	(0.0145)	(0.0107)	(0.0173)	(0.0189)
Regional fixed effects[1]								
louisiana	0.0812	0.136**	0.0551	0.137**	-0.329	0.693***	0.0539	0.474
	(0.0521)	(0.0564)	(0.0483)	(0.0567)	(0.544)	(0.149)	(0.209)	(0.480)
n_carolina	0.134***	0.112***	0.0580*	0.139***	-	-	-	-
	(0.0367)	(0.0349)	(0.0326)	(0.0368)				
texas	0.202***	0.177***	0.117***	0.207***	-	-	-	-
	(0.0413)	(0.0366)	(0.0367)	(0.0399)				
wisconsin	0.245***	0.227***	0.168***	0.260***	-	-	-	-
	(0.0433)	(0.0392)	(0.0371)	(0.0425)				
alabama	0.307***	0.302***	0.244***	0.329***	-	-	-	-
	(0.0513)	(0.0433)	(0.0447)	(0.0483)				
florida	0.236***	0.242***	0.203***	0.258***	0.113	0.343***	0.289**	0.244**
	(0.0549)	(0.0468)	(0.0482)	(0.0513)	(0.156)	(0.0777)	(0.115)	(0.108)
california	0.156***	0.179***	0.130***	0.185***	-	-	-	-
	(0.0466)	(0.0469)	(0.0445)	(0.0480)				
missouri	0.147***	0.122***	0.0717**	0.156***	-	-	-	-
	(0.0379)	(0.0339)	(0.0321)	(0.0370)				
colorado	0.0804	0.0916	0.0921	0.0979*	-	-	-	-
	(0.0583)	(0.0578)	(0.0565)	(0.0581)				
minesota	0.235***	0.223***	0.219***	0.238***	-	-	-	-
	(0.0601)	(0.0525)	(0.0563)	(0.0560)				
nl	0.0757	0.117**	0.0989**	0.107**	-	-	-	-
	(0.0472)	(0.0460)	(0.0452)	(0.0473)				
uk	0.00962	0.0449	0.0119	0.0379	-	-	-	-
	(0.0362)	(0.0459)	(0.0429)	(0.0418)				
aus	-	-	-	-	0.0418	0.805**	1.398**	0.262
					(0.654)	(0.339)	(0.630)	(0.591)
nz	-	-	-	-	0.108	-0.217**	-0.0586	-0.110
					(0.211)	(0.0876)	(0.105)	(0.176)
Constant	-0.791	-1.840*	0.954	-2.404**	26.01	-36.87**	32.88**	-33.14
	(0.904)	(1.048)	(0.955)	(1.025)	(51.20)	(13.04)	(12.65)	(54.07)
Observations	314	314	314	314	35	35	35	35
R^2	0.607	0.608	0.594	0.617	0.801	0.904	0.880	0.838
Adj. R^2	0.566	0.568	0.552	0.578	0.602	0.808	0.760	0.675
Rmse	0.0446	0.0445	0.0453	0.0440	0.102	0.0708	0.0791	0.0921

Note: [1] The omitted region for the meta-regression on river and coastal estimates is Georgia, US, and North Carolina, US, respectively. The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.7. Meta-regression results by different econometric approach: Including regional fixed effects, sample size weights
(*excluding variables dd_after and dd_after*100year*)

Variables	Standard hedonic models				DID hedonic models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$	$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Flood risk perception								
mnths	0.000274***	0.0547**	1.796**	0.0105***	0.000626***	0.0619***	1.132***	0.0150***
	(6.51e-05)	(0.0215)	(0.804)	(0.00286)	(0.000120)	(0.0120)	(0.334)	(0.00272)
mnths*100year	-9.54e-05**	-0.0254***	-1.229**	-0.00396***	-0.000511***	-0.0302**	-0.234	-0.0102***
	(4.11e-05)	(0.00938)	(0.554)	(0.00131)	(9.90e-05)	(0.0134)	(0.414)	(0.00257)
Flood risk level								
100year	-0.00842	0.0995**	1.193**	0.0238	0.0301**	0.107*	0.200	0.0753**
	(0.00622)	(0.0452)	(0.548)	(0.0151)	(0.0147)	(0.0641)	(0.410)	(0.0297)
Context of the study								
lav_feet	0.112***	0.132***	0.120***	0.126***	-0.0854	0.0484	0.0894	-0.0249
	(0.0287)	(0.0320)	(0.0298)	(0.0298)	(0.225)	(0.242)	(0.251)	(0.231)
lavprice_2010	-0.00919	-0.0484	-0.0350	-0.0330	-0.0434	-0.0856	-0.128	-0.0551
	(0.0533)	(0.0583)	(0.0560)	(0.0545)	(0.256)	(0.269)	(0.303)	(0.253)
flooded	0.0207	0.0489	0.0128	0.0509	-0.0556	-0.0255	-0.0122	-0.0424
	(0.0344)	(0.0455)	(0.0315)	(0.0413)	(0.0617)	(0.0661)	(0.0683)	(0.0636)
scnd_flood	-	-	-	-	-0.0332	-0.0511*	-0.0790***	-0.0355
					(0.0243)	(0.0266)	(0.0303)	(0.0241)
dd_after	-	-	-	-	-	-	-	-
dd_after*100year	-	-	-	-	-	-	-	-
dd_afterlaw	-	-	-	-	0.00292	0.00570	0.00260	0.00289
					(0.0197)	(0.0164)	(0.0133)	(0.0186)
coast	0.124***	0.130***	0.128***	0.129***	0.283	0.252	0.269	0.263
	(0.0404)	(0.0412)	(0.0397)	(0.0413)	(0.349)	(0.359)	(0.409)	(0.339)
Control variables of study								
amenity	0.0129	0.00104	-0.00179	0.00892	-0.243	-0.286	-0.318	-0.264
	(0.0199)	(0.0201)	(0.0169)	(0.0209)	(0.271)	(0.281)	(0.298)	(0.272)
real_p	-0.115***	-0.111***	-0.113***	-0.114***	-0.0585	-0.0388	-0.0518	-0.0534
	(0.0353)	(0.0386)	(0.0367)	(0.0375)	(0.115)	(0.118)	(0.126)	(0.114)
Characteristics of econometric model								
linear	-0.269***	-0.269***	-0.264***	-0.272***	-0.131	-0.152	-0.181	-0.141
	(0.0468)	(0.0455)	(0.0459)	(0.0462)	(0.116)	(0.111)	(0.121)	(0.111)
Box-Cox	0.0457	0.0303	0.0357	0.0355	-	-	-	-
	(0.0370)	(0.0413)	(0.0397)	(0.0388)				
spatial	0.00742	0.0109	0.0144	0.00778	0.00853	0.00736	0.00819	0.00873
	(0.0124)	(0.0113)	(0.0103)	(0.0123)	(0.0208)	(0.0228)	(0.0235)	(0.0215)
dd_hpm	-	-	-	-	-	-	-	-

(Continued)

Table A1.7. Continue

Characteristics of the study								
published	0.00599	-0.0149	-0.0152	-0.00454	-0.00553	-0.0111	-0.00951	-0.00765
	(0.0274)	(0.0262)	(0.0277)	(0.0249)	(0.0191)	(0.0189)	(0.0174)	(0.0193)
med_sampleyear	0.00262	0.00491	0.00322	0.00430	0.000405	0.000444	-0.00120***	0.000784
	(0.00264)	(0.00335)	(0.00280)	(0.00294)	(0.000480)	(0.000445)	(0.000313)	(0.000503)
time_span	0.00367*	0.00365	0.00489**	0.00314	0.00632*	0.000649	0.00101	0.00363
	(0.00210)	(0.00229)	(0.00204)	(0.00225)	(0.00337)	(0.00301)	(0.00250)	(0.00318)
Regional fixed effects[1]								
Louisiana	-0.0646	-0.0520	-0.148*	-0.0223	-	-	-	-
	(0.0900)	(0.111)	(0.0836)	(0.103)				
n_carolina	-0.00743	-0.00653	-0.0710	0.0181	0.232***	0.184**	0.139	0.211***
	(0.0659)	(0.0773)	(0.0584)	(0.0736)	(0.0820)	(0.0805)	(0.0949)	(0.0770)
texas	0.214**	0.163**	0.0934	0.217***	-0.0619	-0.124	-0.249	-0.0845
	(0.0833)	(0.0674)	(0.0630)	(0.0777)	(0.388)	(0.410)	(0.433)	(0.393)
wisconsin	0.213***	0.197***	0.122**	0.235***	-	-	-	-
	(0.0635)	(0.0658)	(0.0473)	(0.0677)				
alabama	0.338***	0.324***	0.246***	0.363***	-	-	-	-
	(0.0738)	(0.0771)	(0.0573)	(0.0789)				
florida	0.259***	0.234***	0.171***	0.272***	0.00190	-0.0308	-0.0947	-0.0109
	(0.0755)	(0.0733)	(0.0626)	(0.0766)	(0.442)	(0.462)	(0.502)	(0.440)
california	0.0710	0.0865	0.00963	0.106	0.239	0.267	0.249	0.245
	(0.0678)	(0.0889)	(0.0634)	(0.0802)	(0.184)	(0.193)	(0.224)	(0.179)
missouri	0.0686	0.0588	-0.00766	0.0918	0.147*	0.145*	0.107	0.152*
	(0.0655)	(0.0731)	(0.0529)	(0.0718)	(0.0874)	(0.0846)	(0.0932)	(0.0835)
colorado	0.00570	-0.0221	-0.0520	0.00366	-	-	-	-
	(0.0622)	(0.0589)	(0.0587)	(0.0599)				
minesota	0.238***	0.212***	0.174***	0.243***	-	-	-	-
	(0.0767)	(0.0660)	(0.0615)	(0.0721)				
nl	-0.105	-0.120	-0.164**	-0.0963	0.201	0.231	0.248	0.202
	(0.0698)	(0.0760)	(0.0681)	(0.0733)	(0.181)	(0.195)	(0.226)	(0.179)
uk	-0.0996	-0.0849	-0.151*	-0.0678	-	-	-	-
	(0.0737)	(0.0970)	(0.0787)	(0.0859)				
aus	-0.281**	-0.268*	-0.361**	-0.239	-	-	-	-
	(0.140)	(0.158)	(0.139)	(0.150)				
nz	-	-	-	-	-	-	-	-
Constant	-6.016	-10.43	-8.585	-9.246	0.333	-0.348	2.362	-0.770
	(4.963)	(6.406)	(5.757)	(5.575)	(2.142)	(2.309)	(2.638)	(2.150)
Observations	138	138	138	138	211	211	211	211
R^2	0.861	0.855	0.847	0.861	0.776	0.776	0.776	0.775
Adj. R^2	0.825	0.818	0.808	0.825	0.749	0.750	0.749	0.749
Rmse	0.0347	0.0354	0.0364	0.0348	0.0480	0.0479	0.0480	0.0480

Note: [1] The omitted region is Georgia, US.

The dependent variable is the effect size T. Standard errors in parentheses correspond to Huber-White robust standard errors. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

Table A1.8. Persistence of the price discount for floodplain location across different functional forms of the time variable

*(Variables dd_after and dd_after*100yearare not included in meta-regression models)*

Set of results		Risk level	Functional form[1,2,3]			
			$mnths$	$\ln(mnths)$	$\frac{(mnths-1)}{mnths}$	$Sqrt(mnths)$
Table A1.5	Random-effects weights	500-year	7.71	0.18	0.09	0.91
		100-year	23.86	0.49	0.09	6.03
	Sample size weights	500-year	10.46	0.20	0.09	1.32
		100-year	28.89	0.46	0.09	7.36
Table A1.6	River flood Risk	500-year	10.22	0.21	0.09	1.32
		100-year	27.12	0.67	0.09	8.36
Table A1.7	Standard hedonic models	500-year	17.94	0.25	0.09	2.63
		100-year	32.19	0.88	0.09	9.28
	DID hedonic models	500-year	7.85	0.22	0.09	1.29
		100-year	50.00	0.73	0.09	17.22

Note: [1] The results are based on the coefficients of the meta-regression models in tables A1.5, A1.6 and A1.7 of the appendix; these regressions does not include the variables *dd_after* and *dd_after*100year*.

[2] Results are expressed in number of years.

[3] A discount of 5.9% and 6.9% is assumed for properties in the 500 and 100-year floodplain, respectively.

Chapter 2

Assessing the economic benefits of structural flood protection: A repeat sales approach from the English housing market

N.B. During the preparation of this Thesis, previous versions of this chapter were submitted for presentation at the following conferences. In some cases these had been made public as part of the conference proceedings. When this is the case I include the link to the corresponding webpage:

- June, 2016. 22nd Annual Conference of the European Association of Environmental and Resource Economists (EAERE). Zurich, Switzerland.
[http://www.webmeets.com/files/papers/EAERE/2016/879/UK_Flood_Defences_Repeat_sales.pdf]

- June, 2016. 4th Workshop On Non-Market Valuation (WONV4). National Research Institute of Science and Technology for Environment and Agriculture (IRSTEA). Bordeaux, France.
[http://www.wonv.fr/program]
[https://drive.google.com/file/d/0B6ZZlm-PlyMwNGtjVmcwYjdmZ190czlNUllXVVQxZm5iYjJz/view]

- June, 2016. Annual Conference of the Association of Environmental and Resource Economists (AERE). Colorado, United States.
[http://academiccommons.webmeets.com/AERE/2016/m/viewpaper.asp?pid=181]

- June, 2016. 4th Canadian PhD and Early Career Workshop in Environmental Economics. Ottawa, Canada.

- June, 2015. Midlands Regional Doctoral Colloquium, University of Birmingham, United Kingdom.

- April, 2015. EEEM Workshop on the Economics and Management of Flood Risk, University of Birmingham, United Kingdom.

Abstract

We use a repeat-sales model to identify the price effect of flood defences that were constructed in England between 1995 and 2014. To the best of our knowledge, this is the first study to use a difference-in-differences hedonic price framework to assess the economic benefits from constructing structural flood defences. The final dataset includes information on over 12 million individual property transactions, which represent about 4.8 million houses with at least one repeat-sale. This database is merged with GIS data containing the spatial location and main characteristics of a total of 1,666 flood defences that were constructed in England during the period of analysis, representing 553 km of defences. The results suggest that flood defences capitalise on property prices at a rate that ranges between 1% and 13%, depending on the level of risk, the type of risk and the type of property; for a median-priced house in 2014 these represent £2,000 to £30,000. However, for the case of rural properties and flats, the construction of defences results in significant negative impacts that range from a price discount of -1% to -9% (-£3,000 to -£10,000). These negative impacts are not currently considered for the purpose of funding allocation and can result in overinvestment in locations where defences might not be desirable.

Keywords: Flood risk, flood defences, housing prices, repeat-sales, hedonic valuation

JEL Code: Q51, R21, D12

2.1 Introduction

During the last 15 years the United Kingdom (UK) has experienced an increasing number of floods which have been accompanied by an increase in related damage costs over time. In England and Wales, the responsibility for policy and strategy on flood and coastal erosion risk management (FCERM) lies on the Department for Environment, Food and Rural Affairs (Defra) and the Environment Agency (EA). Historically, the construction of flood defences has been the traditional method of protecting low-lying communities against flooding, and although current UK strategies for FCERM place emphasis on alternative means for reducing or mitigating flood risk, floodwalls and embankments are expected to remain one of the most important means of protecting communities against flooding for the foreseeable future (Ackers, Rickard, and Gill 2009).

The primary function of these structures is to contain floodwaters and hence to reduce the probability of flooding in the defended area. However, flood defences are costly to build and require management and maintenance to ensure they remain serviceable. In England, the 2010 Comprehensive Spending Review (2011-12 to 2014-15) provided a total of £2.17 billion in central government funding for the building and maintenance of new and existing flood and coastal risk management assets, which represents an average expenditure of £542.5 million per year (Bennett and Hartwell-Naguib 2014). The EA *2014 Long-term investment scenarios for flood and coastal erosion risk management* (EA, 2014) report suggests that a real increase in public investment to the tune of £870 million per year will be needed by 2040. This level of investment represents a real increase of around 60% on the average yearly funding for the period 2011-12 to 2014-15.

It is generally agreed that it is not technically feasible, nor economically affordable to prevent all properties from flooding (EA, 2009; Ackers, Rickard, and Gill, 2009). Considerable attention has therefore been devoted to the issue of an efficient and fair allocation of resources for FCERM. Currently, Defra allocates funding to FCERM capital projects through the Flood and Coastal Resilience Partnership Funding (FCRPF) following a system of local/national cost-sharing. This ‘partnership funding’ operates on a formula basis to determine the amount of funding to be allocated to each project as Flood Defence Grant-in-Aid (FDGiA). The amount of grant available for each project is determined according to its economic, social and environmental benefits with a principle of ‘payment for outcomes’ (Defra, 2011; EA, 2014a; Penning-Rowsell and Pardoe, 2012; Penning-Rowsell et al., 2014). Under this scheme, the government quantifies the benefits delivered by a project considering four outcome measures (social, economic and environmental), and determines the total FDGiA funding available for the project by evaluating the outcomes at different payment rates. The outcomes and payment rates are defined by Defra (2011). Despite Defra’s funding allocation measures now includes a broader range of ‘outcome measures’ (social, economic and environmental), it is the economic impact of floods that still mainly drives policy and expenditure decisions. A benefit-cost ratio of at least 5 to 1 has been set for household protection schemes, and of 18 to 1 for non-household economic assets (Defra, 2011; UK Parliament, 2013; Penning-Rowsell, 2015). Two important questions are then: how benefits are identified, defined and measured and, given those benefits, how funding to FCERM schemes should be allocated.

Not surprisingly, given the political and economic importance of flooding and flood risk, there is a substantial body of research on the economic valuation of flood risk. Some studies try to identify the economic value, defined as the willingness to pay (WTP), of the natural flood protection services of different ecosystems, including coastal, using a varied set of market and non-market valuation techniques including the contingent valuation method (CVM), choice experiments, the hedonic price model and alternative replacement costs (King and Lester 1995, Bateman and Langford 1997, Leschine, Wellman, and Green 1997, Bateman et al. 2001, Ming et al. 2007, Polyzos and Minetos 2007, Filatova, Parker, and Veen 2011, Gibbons, Mourato, and Resende 2014). Other studies focus on the potential macroeconomic impact of flooding (Benson and Clay 2000, Pelling, Özerdem, and Barakat 2002, Hallegatte et al. 2013, Ward et al. 2013, Winsemius et al. 2013, Jongman et al. 2014) or try to assess the WTP for flood risk reduction to homeowners based on the price comparison of comparable properties located in floodplains at different levels of risk (Bin and Polasky 2004, Bin and Kruse 2006, Lamond and Proverbs 2006, Kousky 2010, Atreya, Ferreira, and Kriesel 2013, Bin and Landry 2013). The value of non-structural protection measures (Holway and Burby 1990, Troy and Romm 2004, Samarasinghe and Sharp 2010, Ball et al. 2012, Meyer, Priest, and Kuhlicke 2012, Dachary-Bernard, Rambonilaza, and Lemarié-Boutry 2014) and the determinants of private flood mitigation measures have also been explored (Bramley and Bowker 2002, Kazmierczak and Bichard 2010, Kreibich, Christenberger, and Schwarze 2011, Bichard and Thurairajah 2014, Osberghaus 2015).

Existing studies that focus on the economic benefits of constructing structural flood protection can be classified in three types: (1) averted future impacts (AFI) use different flooding scenarios and depth/damage data to construct loss/probability curves within a benefit-cost analysis framework (Oliveri and Santoro 2000, Brouwer and Van Ek 2004, Sheng et al. 2005, Blonn, Throneburg, and Grabowy 2010, Jongman et al. 2012); (2) stated preference methods (SPM) assess the WTP for the construction of flood defences using contingent scenarios (Koutrakis et al. 2011, Brouwer et al. 2009, Zhai and Suzuki 2008, Phillips 2011, Veronesi et al. 2014); and (3) hedonic price models (HPM) make a cross-sectional comparison of property prices across locations with different levels of risk, where some of these locations have been protected against flooding (Damianos and Shabman 1976, Miyata and Abe 1994, Dorfman, Keeler, and Kriesel 1996, Lee and Li 2009). The AFI method represents the current standard approach for assessing the economic benefits of flood alleviation schemes (Smith 1994, Merz et al. 2010), whereas the SPM is used for academic research purposes or to complement the non-market benefits to include in AFI studies (Penning-Rowsell et al. 2014); both are ex-ante evaluations that rely on the use of hypothetical scenarios. Existing studies using HPM take place once a structural flood protection is in place, and therefore the risk-reducing intervention they evaluate is a shift in household location to places with higher/lower flood risk (as other studies comparing the prices of properties inside or outside the floodplain do) and not the capitalisation of the construction of the flood relief project in the properties that were protected.

Despite the increasingly large amounts of money invested every year for the maintenance and construction of structural flood protection, and evidence that suggest that not all anticipated benefits of flood alleviation schemes are realised (Penning-Rowsell and Pardoe 2012a), there is a surprising lack of research on the ex-post evaluation of the economic benefits delivered by these projects. In general, much more attention is given to the assessment of flood hazard, and no efforts have been undertaken to evaluate whether individual households experience the benefits anticipated by the AFI methodology on which grounds financial resources are allocated (Merz et al. 2010). The significant investment, together with the prevalence of flooding and an expected future increase in flood risk due to climate change, provides the motivation for this paper.

The contributions of this chapter are numerous. To the best of our knowledge this is the first study to use a difference-in-differences (DID) hedonic price framework to measure the ex-post economic benefits to households form the construction of structural flood defences.[1] We avoid using the cross-sectional approach prevalent in the existing literature, which for identification requires controlling for a large number or factors (some of them non-observable) potentially impacting house prices. Instead, we follow a repeat-sales specification to look at the capitalisation of the flood relief project between two sales of the same property. Furthermore, this analysis goes beyond the scale of usual empirical studies which focus on a single or multiple sites, by conducting a comprehensive analysis of the benefits of all structural flood protection projects undertaken in England during the period 1995-2014. The sample includes information on over 12 million individual property transactions, which represent about 4.8 million houses with at least one repeat-sale during the period of analysis. We analyse the construction of a total of 1,666 flood defences, equivalent to 553km.

Briefly, the results suggest that the benefits from the construction of flood defences are capitalised into the price of properties at a rate that ranges between 1% and 13%, depending on the level of risk, the type of risk and the type of property. For a median-priced house in 2014 this represents £2,000 to £30,000. For the case of fluvial flood risk the results are surprisingly in line with the official estimates for funding allocation

[1] Existing literature was searched via a systematic literature review using the following keywords: (flood* OR inundation) AND (defense OR defence OR protection OR control OR embankment OR wall) AND (house OR property OR land OR residential OR real estate OR hedonic) AND (price OR value OR benefit). The search was undertaken in English as the main language for dissemination of academic research. The following seven relevant databases of studies, journals, economic research and dissertations were examined during the period from the 25th of March – 3rd of April 2015: EconLit, Social Science Citation Index and Conference Proceedings Citation Index, Social Science Research Netwrok, Ingenta Connect, ProQuest, Environmental Valuation Reference Inventory and AGRICOLA US National Agricultural Library. More than 4,000 entries were reviewed. Further details of the systematic literature review are available from the author upon request.

suggested by Defra. On the other hand, Defra appear to underestimate the willingness to pay of coastal householders for flood protection. The evidence also suggests significant negative impacts of flood defences that range from a price discount of -1% to -9% (-£3,000 to -£10,000) for properties which are not directly affected by floods (flats), and in locations were defences may result in loss of significant amenity values (rural areas). These negative impacts are not currently considered by Defra for the purpose of funding allocation and can result in overinvestment in locations where defences might not be desirable.

The remainder of the paper is organized as follows. Section 2.2 presents the literature review on the different methodologies to quantify the benefits of flood risk reduction, with special emphasis on existing hedonic applications. Section 2.3 specifies the theoretical model that describes the effect of flood defences on property prices. Section 2.4 describes the identification strategy using a repeat-sales model. Section 2.5 presents the dataset. Section 2.6 shows the empirical results, and section 2.7 provides an interpretation of the results. Section 2.8 analyses the policy implications and section 2.9 concludes. Robustness tests are presented in section A2.1 of the appendix.

2.2 Literature Review

In general, the benefits of flood alleviation schemes for the housing sector are defined as the sum of averted future flood damages on households that result from projects to reduce the frequency of flooding (probability) and/or the impact of flooding to households (Penning-Rowsell et al. 2014). Thus, the question of identifying the benefits of flood risk reduction has been reduced to assessing the potential damages of future flood events, with different frequencies and intensities, which would occur should the project not be implemented.

Flood damages are customarily classified as direct or indirect, and by whether they are tangible and intangible. Direct residential flood damages result from the physical contact of flood water with damageable property (building fabric and inventory), whereas indirect flood losses refer to the additional costs induced by direct impacts and can occur outside the time and space of the flood event. The classification of damages as tangible or intangible usually depends on whether or not they can be assessed in monetary values (Merz et al. 2010, Penning-Rowsell et al. 2014). Table 2.1 exemplifies the classification of flood damages to residential property and households. Notice that this classification might differ among different authors (Jonkman et al. 2008).

The identification and quantification of averted future flood impacts is the current standard approach to assess the economic benefits to households of flood alleviation schemes (Merz et al. 2010). In general, the main inputs to estimate future flood damages with this method are: (1) a hazard assessment detailing the probability of future flood events to be averted, and (2) a vulnerability assessment with information on the damage that would have been caused by those floods (Penning-Rowsell et al. 2014). The former requires hydrographic data and hydraulic simulations for the area to be protected; the latter requires information on the expected damages (direct and indirect) caused by floods of different intensities. With these data it is possible to construct depth/damage and loss/probability relationships to calculate the weighted annual average damages to households (WAAD) (Penning-Rowsell et al. 2014).

Table 2.1. Classification of flood damages to residential property and households

	Tangible	**Intangible**
Direct	- Damage to building fabric, - Damage to household inventory items, - Clean-up costs, - etc…	- Hassle and deprivation of being displaced, - Loss of items with sentimental value, - Damage to physical and/or mental health, - etc…
Indirect	- Disruption to households due to flood damage, - Temporary evacuation costs, - Loss of utility services, - Loss of income/earnings, - etc…	- Worry about future flooding, - Loss of trust in authorities and services, - etc…

Source: Adapted with information from Penning-Rowsell et al., 2014 and Merz et al., 2010.

Different countries, including Australia, Czech Republic, Germany, Netherlands, United Kingdom (UK) and United States (US), have developed sophisticated models to assess potential flood damages based on the AFI method, although with some important differences (Messner and Meyer 2006, Merz et al. 2010, Walliman et al. 2012). These differences include: the use of different hydraulic simulation models (with different parameters and different resolution), spatial and temporal scales (e.g. micro-, macro- or meso-scale), damage categories considered (e.g. direct and indirect, tangible or intangible), the degree of detail, the application of evaluation principles (e.g. the use of replacement values, depreciated values or economic values), the vulnerability assumptions of building fabric and inventory items, and the type of data they use for economic valuation (e.g. historical or simulated) (Messner and Meyer 2006, Merz et al. 2010, Penning-Rowsell et al. 2014).

Although the AFI method is widely applied for the economic assessment of flood damages, it is subject to important criticisms. It relies on hypothetical flooding scenarios and a diverse set of assumptions on the vulnerability and extent of the flood damage to property and its contents; the method is not based on observed behaviour and therefore no post-flood damage, repair or replacement choices are considered. Instead, it assumes that the occupant would make the repairs or replacements suggested by the analyst, with an equivalent time horizon, risk attitude, and discount rate (Shabman and Stephenson 1996). Thus, the AFI method implies that averted future damages to real property is the only argument in the utility function of the floodplain occupant; it does not consider that individuals make decisions in a context of varying levels of perceived risk, socio-economic constraints, and with different attitudes towards risk or preferences for ex-ante or ex-post alleviation measures (Shabman and Stephenson 1996, Zhai and Ikeda 2006).

Authors such as Shabman and Stephenson (1996) and Braden and Johnston (2004) argue that the sum of AFI of flooding represents an indirect benefit measure, where repair and replacement costs are a proxy for the commodity of interest which is flood risk reduction. Therefore, the values obtained with this method reflect the costs of flooding, rather than the economic value of hazard reduction. Braden and Johnston (2004) and Kind (2014) argue that the willingness to pay (WTP) is the correct economic measure of value to guide the allocation of public funds. WTP is linked to the concept of utility, and it might be higher or lower than the expected value of the monetary risk reduction as it is based on individuals' preferences and alternatives.

Penning-Rowsell et al. (2014) highlights that the AFI methodology assumes that the most efficient flood alleviation scheme, as far as protected households are concerned, is the one which provides the maximum protection at the minimum cost. In this sense, flood alleviation projects always seek to achieve the maximum standard of protection that can be justified or afforded. However, authors such as Penning-Rowsell and Fordham (1994), Zhai et al. (2006), Phillips (2011) highlight that individuals are prepared to live with flood risk. Zhai et al. (2006) use a CVM survey to investigate flood risk acceptability and evacuation behaviour in Central Japan; they found that individuals who accept flood risk below certain level of damage and frequency have a lower WTP for flood risk control. Phillips (2011) uses a choice experiment to investigate the welfare impact of coastal flood defences on Buffalo beach in Whitianga, New Zealand. The author concludes that residents were willing to pay $20 NZD per year (2010 prices) to remove an existing floodwall due to its negative impacts on visual amenity, biodiversity and recreational values. Penning-Rowsell and Fordham (1994) interview riverside residents (where flood hazard is highest) in the Lower Thames catchment, UK, and conclude that about 34% of those interviewed were prepared to live with a 20% annual probability of flooding in exchange for the location being left undisturbed by flood risk management engineering structures; this figure rises to 94% for residents willing to live with a 0.5% annual flooding probability. Penning-Rowsell et al. (2014) concludes that there appears to be a trade-off for households between flood protection and amenity loss.

Diverse modifications to the AFI method have been suggested to address, to different extents, these criticisms. [2] However, Shabman and Stephenson (1996) and Braden and

[2] For instance, Penning-Rowsell et al. (2014) suggest to incorporate the intangible impacts of flooding to the appraisal process by considering a WTP value to avoid stress and health effects caused by flooding obtained from contingent valuation studies, or by complementing damage estimation with Multi-Criteria Analysis (weighting and scoring). They suggest the use of 'economic values' by deducting taxes to market repair/replacement costs and assuming a 50% depreciation to all damaged items, and to account for social vulnerability by identifying depth/damage curves for occupants with different income levels. They also suggest to account for averting behaviour by adding a set of assumptions regarding the share of movable contents that could be protected upon the issue of a flood warning, or the share of houses that install property-level protection, and the effectiveness of such protections, etc. However, all these modifications add

Johnston (2004) conclude that the AFI method represents a useful damage assessment technique for having a compelling, appealing and understandable investment logic, and not for being considered an accurate or comprehensive measure of the economic benefits of flood alleviation schemes.

Stated preference methods (SPM) are used as an alternative to estimate the WTP for the implementation of flood alleviation schemes. For instance, Koutrakis et al. (2011) use the CVM to estimate the WTP for coastal defence systems in different regions of the Mediterranean area. Brouwer et al. (2009) use the same methodology to assess the WTP for the construction of an embankment to protect the sub-district of Homna, Bangladesh, against flooding. Zhai and Suzuki (2008) and Veronesi et al. (2014) use choice experiment models to assess the WTP for flood defence schemes. The former evaluates the WTP of residents from the Chinese coastal area of Tianjin to reduce the risk of flooding. The latter focus on the WTP of Swiss households to reduce intangible impacts (ecological and health) of wastewater flooding. Although these methods, especially the CVM, have received considerable support for the benefit estimation of changes in the level of provision of public goods, their use in the flood risk literature has been somehow restricted to academic research or to complement non-marketable benefits of AFI estimates (see for example Penning-Rowsell et al., 2014).

Aside from the ability of these methods to yield a comprehensive estimate of the economic benefits of the construction of flood alleviation schemes, a characteristic of both the AFI and SPM, is that their results represent an ex-ante assessment of the benefits of the implementation of a project, i.e. the estimates rely on hypothetical scenarios and no post-

a set of assumptions to the damage assessment procedure that, in many cases, lack a solid basis and are left to the discretion of the analyst.

flood repair choices or post-project benefits are observed. Ward, Moel and Aerts (2011) and Penning-Rowsell et al. (2014) argue that the application of the AFI method can be subject to significant errors that can be categorised as: (1) systematic errors which relate to a misunderstanding of the appraisal process, and (2) measurement errors which can arise at any stage of the appraisal process and consist of errors on the assumptions or simulations required for the application of the methodology.

Authors such as Thompson, Wigg and Parker (1991) and Penning-Rowsell and Pardoe (2012b) highlight that in many situations not all anticipated benefits of flood alleviation schemes are realised. The former do a post-project appraisal of seven urban flood protection schemes completed during 1960-1987 in England and Wales and conclude that at least in four cases the ex-post standard of protection of the project was lower than previously anticipated. The latter focus on the distribution of the tangible economic impacts of three case studies of engineering-oriented flood alleviation schemes in England. The authors conclude that in at least two cases the intended benefits failed to live up to expectations and that the beneficiaries are likely to be less numerous than forecasted in the Project Appraisal Template (PAR). In one case (The Lyth Valley, Cumbria) this overestimation of benefits in the pre-appraisal report is of such a magnitude that the scheme would not have been promoted based on the observed post-project benefits.

Despite this evidence and the increasingly large amounts of money invested every year for the maintenance and construction of structural flood protection, there is a surprising lack of research on the ex-post evaluation of the economic benefits delivered by flood alleviation projects. In general, ex-post evaluations focus on the assessment of flood hazard. They look at the engineering design or try to re-assess the standard of protection of the project for maintenance purposes, for example, to determine the timing and implementation of a follow-up project (heighten or strengthen of defences). In some cases, the ex-post evaluations are followed by a review of the cost-benefit analysis. However, these only update the different levels of expected flooding in the benefited area (based on the ex-post standard of protection of the project) and use the same depth/damage and loss/probability assumptions used in the ex-ante project appraisal (see for example Ramirez et al., 1988; Thompson, Wigg and Parker, 1991; Zhu et al., 2007; Penning-Rowsell et al., 2014). To the best of our knowledge, no efforts have been undertaken to evaluate whether individual households experience the benefits anticipated by the AFI methodology.

There are a handful of studies which try to identify the ex-post economic benefits (WTP) to households from the construction of flood defences. These studies carry out a HPM including locations that have been benefited by the construction of a flood relief project.[3] Two early studies look at the prices of residential land. Damianos and Shabman (1976) use a HPM to identify the flood risk reduction benefits of the construction of the Claytor Lake Dam in Virginia, US. The project was finished in 1947; the authors use a before and after approach looking at the sale price of 25 floodplain residential lots (11 before and 14 after) sold during the period 1931-1974. The treatment effect is identified using a dummy variable taking the value unity for those observations sold after the construction of the project. The results suggest that the price of those lots sold after the construction of the project were $439 US (1967 prices) higher than those sold before. Thompson and Stoevener (1983) estimate the benefits of the construction of the Sutherlin Creek Watershed Project concluded in 1970, in Oregon, US. The authors use a before and after HPM approach to identify the pre and post-project price differential of residential lot

[3] The studies by Miyata and Abe (1994) and Dorfman, Keeler and Kriesel (1996) are not considered in this description. Although the authors use HPMs to estimate the benefits of the construction of flood defences, their results are based on the simulation of the construction of a flood defence via changes in independent variables defining flood risk and therefore do not evaluate the ex-post benefits of the construction of a defence.

values located inside an outside the floodplain. They estimate two separate equations for the pre and post-project period looking at prices in 1962 and 1978 respectively. The equations use different specifications and focus on different samples (48 and 78 observations for the pre and post-project equations respectively). In both cases the dependent variable is the estimated value of residential land based on appraised property values reported in records of the Douglas County. The authors conclude, after accounting for inflation, that the construction of the project resulted in a reduction of the price differential for floodplain location equivalent to $735 US (1978 prices).

A more recent study by Lee and Li (2009) uses a HPM to estimate the benefits of the construction of different types of detention basin design for flood control. The authors focus on two communities in College Station, Texas, US. Two different detention pond designs are analysed: (1) a uniuse flood control detention basin (UDB) in Woodcreek subdivision solely for flood control, and (2) a multi-use detention basin (MDB) in Edelweiss Estates subdivision with multi-functional benefits that incorporates sports, recreation and stormwater management. The authors use separate HPM regressions with a sample size of 156 and 72 residential properties for the UDB and MDB, respectively, with different, *ad hoc*, functional form and specification. In both cases the data on property prices correspond to appraised values from the County office. The results are based on a 2006 cross-section comparison of property prices with different levels of flood risk (measured as the distance to the respective detention pond). Therefore their sample only include observations after the construction of the flood relief projects. For the UDB the authors conclude that the distance with respect to the pond does not have a significant influence on property prices, however those properties with direct view to the UDB experience a significant discount on the order of 3.5% ($4,950 US in 2006 prices). The results for the MDB suggest that the residential property values decrease by $164.82 US (in 2006 prices) per 10m away from the basin. The effect is only significant within a distance of 274m around the pond. This means that prices of properties next to the basin are about 4.1% ($4,516 US in 2006 prices) higher. This price premium decreases as houses are located further away from the pond and disappears after 274m. The authors conclude that the different results are driven by amenity/disamenity differences associated with the two different designs of the detention basins. They argue that issues related to the construction of UDBs such as maintenance problems, safety issues, and visual disamenity, outweigh the flood risk reduction benefits associated with them. In contrast, for MDBs the benefits of the multiple functions (mainly recreational) would result in higher property prices.

Therefore, previous studies using HPM to estimate the benefits of the construction of flood defences suffer several flaws and/or limitations. For instance, in all cases the studies use estimated or appraised values of land/property prices and therefore might not appropriately reflect the transaction decisions and flood risk perception of individuals. The three studies use very small samples, ranging from 25 to 156 observations. Furthermore, although the studies by Damianos and Shabman (1976) and Thompson and Stoevener (1983) use a before and after approach, the development of the econometric methods does not allow them to control for time and treatment effects. The risk reducing intervention suggested by Lee and Li (2009) consists of a shift in household location to places with higher/lower flood risk (further away from the detention pond) and not on quantifying the capitalisation of the construction of the flood relief project in the properties that were protected. Finally, in all cases the results rely on the cross-section comparison of comparable property prices over time, in which case the correct identification of the policy effect requires controlling for a large number of other factors potentially impacting house prices.

This chapter tries to address these issues and to contribute to filling the literature gap on the ex-post evaluation of the economic benefits to households from the construction of flood defences. We use a difference-in-differences (DID) hedonic price framework to identify the capitalisation of flood alleviation schemes into the price of properties impacted by the project. In this way, we avoid the use of the cross-sectional approach prevalent in the existing literature, which for identification requires one to control for a large number or factors (some of them non-observable) potentially impacting house prices. Instead, we follow a repeat-sales specification where the sale price of the same property is observed before and after the construction of a flood alleviation scheme. This identification strategy allow us to observe the ex-post household decisions in the housing market. The analysis goes beyond the scale of usual empirical studies which focus on a single site or multiple sites, to conduct a comprehensive analysis of the benefits of all structural flood protection projects undertaken in England during the period 1995-2014. The sample includes information on over 12 million individual property transactions, which includes about 4.8 million houses with at least one repeat-sale during the period of analysis. Our analysis focuses on the construction of a total of 1,666 structural flood alleviation projects, equivalent to 553 km of defences. The remainder of the chapter describes the theoretical development of the HPM, the identification strategy and the empirical results.

2.3 The Hedonic Model for Flood Risk Valuation

Economic theory suggests that residential housing markets provide a means of estimating the benefits of flood risk reduction. Early research by Ridker and Henning (1967) suggests that if costs derived from housing rise (e.g. if additional maintenance and cleaning costs are required), the price of the property will be discounted in the market to reflect people's evaluation of these changes. This price differential can be interpreted as a measure of benefits for living in an area with lower risk. Therefore, the price of houses located within a floodplain should be lower than equivalent houses located outside floodplains. The observed price differential reveals the (marginal) WTP for different lower levels of flood risk .

Hedonic pricing models have been an especially popular way to estimate the WTP for flood risk reduction. The hedonic price function (HPF) describes the price of a quality-differentiated commodity as a function of its multiple attributes. When an individual decides where to live this decision should include the level of flood risk they face, thus flood risk can be regarded as an additional characteristic of a property. The theoretical model described in this section is based on the characterisation of the HPF by Rosen (1974) and its extensions to the flood risk literature by MacDonald, Murdoch and White (1987), Carbone, Hallstrom and Smith (2006), Bin, Kruse and Landry (2008), Kousky (2010) and Bin and Landry (2013).

Let $\boldsymbol{S}$ represent a set of structural characteristics of a house such as age, number of bathrooms and lot size; $\boldsymbol{N}$ the neighborhood/locational characteristics such as crime rate, distance to central business centre or to a major motorway, and $\boldsymbol{E}$ environmental characteristics such as the level of pollution. Define $Z = \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{E}$. Furthermore, let the subjective probability of flooding, i.e. the homeowner's subjective assessment of flood risk, be a function $p(i, r)$ of the set of information, i, the individual holds about flood risk in the location of the property and r which represents the site attributes related to flood risk, which could be locational characteristics such as proximity to water bodies or elevation. The HPF describing the price of a property, P, might therefore be written as:

$$P = P\big(Z, r, p(i, r)\big) \tag{1}$$

Therefore, P is exogenous to individual buyers and sellers, but reflects subjective risk perception $p(i, r)$. Prices are assumed to be market clearing, given the inventory of housing choices and their characteristics. The housing market is assumed to be in equilibrium, which requires that individuals optimize their residential choice based on the prices in alternative locations. It is assumed that homebuyers are able to adjust the different levels of each characteristic by moving their residence; no transaction costs are considered.

It is important to distinguish the subjective assessment of the probability of flooding, p, from the objective measure of flood risk, π. This distinction implies three important things. First, the perceived risk is not necessarily equal to the objective risk. Second, changes in the objective risk are not necessarily perceived. Third, changes in the perceived risk do not necessarily arise from changes in the objective risk. In areas where flood risk disclosure is mandatory or public information about flood risk is available, the set of information, i, might include the objective probability of flooding, π.

The model uses an expected utility framework that incorporates risk factors associated with a property. The household's decision is modelled using the following state dependent utility function:

$$EU = p(i, r) \cdot U^F[Z, r, Q] + \big(1 - p(i, r)\big) \cdot U^{NF}[Z, r, Q] \tag{2}$$

where $U^F(\cdot)$ is the utility of the homeowner in a state where a flood occurs and $U^{NF}(\cdot)$ is the utility of the homeowner when there is no-flood. The budget constraint for the individual in state F (with perceived probability $p(i, r)$) and NF (with perceived probability $\left(1-p(i,r)\right)$) is given by equations (3) and (4), respectively, where M is total income.

$$F: \quad M = P\big(Z, r, p(i,r)\big) + Q + L(r) \tag{3}$$

$$NF: \; M = P\big(Z, r, p(i,r)\big) + Q \tag{4}$$

Note from equations (3) and (4) that the level of consumption of Q is different across states, in particular $Q^F < Q^{NF}$. Both, the level of utility and the marginal utility of income may change with the state. The conditional loss $L(r) \in (0, \bar{S})$, is a function of the locational risk characteristics of the house, r, and reflects the magnitude of the loss should state F occurs; $\bar{S}$ represents the structure replacement cost of the property. Thus, the occurrence of a flood is associated with a potential monetary loss $L(r)$ in equation (3).

The rational consumer will choose to live in a location that maximises his expected utility subject to the budget constraint. Maximising expected utility (2), with respect to the subjective probability of flooding, p, subject to the homeowner's budget constraint, and dividing by the expected marginal utility of income yields:

$$\frac{\partial P}{\partial p} = \frac{U^F - U^{NF}}{p(i,r)\dfrac{\partial U^F}{\partial Q} + \big(1 - p(i,r)\big)\dfrac{\partial U^{NF}}{\partial Q}} \tag{5}$$

Equation (5) is the coefficient on the risk variables estimated in hedonic regressions. It indicates that the marginal implicit hedonic price for flood risk reflects the incremental utility difference across states; dividing by the expected marginal utility of income produces a measure of marginal WTP.

2.3.1 The Role of Flood Defences

When a property is frequently subjected to flooding the owner may incur substantial repair costs and other additional losses. These future costs might easily exceed the cost of buying an equivalent property outside the flood risk area (Bin and Kruse 2006, Lamond 2012, MacDonald, Murdoch, and White 1987, Zimmerman 1979). Consumers will locate within a floodplain if they are compensated for accepting the potential loss (MacDonald, Murdoch, and White 1987). Intuitively this means that flood risk is capitalised into property prices. Alternative alleviation strategies include the construction of flood defences.

The main objective of structural flood defences is to contain floodwaters and to reduce the objective probability of flooding (π) in the defended area (Ackers, Rickard, and Gill 2009). Since consumers choose to live in a location which maximises expected utility subject to the budget constraint, a sales price differential will arise in locations protected by flood defences as consumers bid for locations with lower flood risk, i.e. the benefits from enhanced flood protection will capitalise and benefit homeowners in the form of higher property prices.

Formally, the standard of protection of a property resulting from the presence of a flood defence can be considered an additional characteristic, d, of a property, and therefore can be included in the HPF. Notice that although the main objective of a flood defence is to reduce the objective probability of flooding (π), this change might, or might not, be fully perceived by the individuals. Therefore the level of flood protection, d, provided by the presence of the defence also enters as an argument in the individuals' subjective assessment of the probability of flooding, $p(i,r,d)$. Thus, equation (6) represents the HPF considering the presence of flood defences.

$$P = P\big(Z, r, d, p(i,r,d)\big) \tag{6}$$

Considering the theoretical development in the previous section there are three ways in which the construction of flood defences can influence expected utility. First, it represents an exogenous change of the level of attribute d for those properties within the defended area. Second, since the properties are now protected to a certain extent, it is plausible to suggest that the amount of the monetary losses ($L(r,d)$) in the event of a flood (state F) will now be lower than they would otherwise be. Finally, a third source for a change in expected utility depends on the extent to which homeowners update their subjective assessment of the probability of flooding, $p(i,r,d)$, based on the presence of the flood defences.

Consider the HPF given in equation (6) and the expected utility to the homeowner in equation (2), the marginal bid for the construction of flood defences is then given by the following equation:

$$\begin{aligned}\frac{\partial P}{\partial d} = {} & \frac{p\frac{\partial U^F}{\partial d} + (1-p)\frac{\partial U^{NF}}{\partial d}}{p(i,r,d)\frac{\partial U^F}{\partial Q} + \big(1-p(i,r,d)\big)\frac{\partial U^{NF}}{\partial Q}} - \frac{p\frac{\partial U^F}{\partial Q}\cdot\frac{\partial L}{\partial d}}{p(i,r,d)\frac{\partial U^F}{\partial Q} + \big(1-p(i,r,d)\big)\frac{\partial U^{NF}}{\partial Q}} \\ & + \frac{\frac{\partial p}{\partial d}\left(U^F - U^{NF}\right)}{p(i,r,d)\frac{\partial U^F}{\partial Q} + \big(1-p(i,r,d)\big)\frac{\partial U^{NF}}{\partial Q}}\end{aligned} \tag{7}$$

Equation (7) is composed of three terms. The first term on the right represents the direct effect of the construction of flood defences on utility, net of any disamenity that could arise due to its construction such as losing direct access to a water body or river / costal front view. The second term considers how monetary losses in event of a flood change with the construction of flood defences. Finally, the third element is formed of two parts: the incremental option price for a unit risk reduction in flood risk, which is the same term as in equation (5), ($(U^F - U^{NF})/\big(p(i,r,d)\,\partial U^F/\partial Q + \big(1 - p(i,r,d)\big)\,\partial U^{NF}/\partial Q\big)$), multiplied by the change in the subjective assessment of the probability of flooding due to the construction of the defence ($\partial p/\partial d$).

2.3.2 The assumptions of the hedonic model

The theoretical representation of the hedonic price model derived by Rosen (1974) describe a situation of market equilibrium, where buyers and sellers are assumed to satisfy the following smoothness conditions: (i) differentiability of utility functions and cost functions; (ii) free mobility; (iii) the ability to consume and produce continuous quantities of Z, r, and d (see equation 1 and 6); (iv) perfect information about prices (P) and relevant characteristics (Z, r, i); and (v) no market power on part of any buyer and seller (Kuminoff and Pope, 2014; Pope 2008). Bajari and Benkard (2005) prove that under equilibrium conditions the price of a differentiated product can in fact be described as a function of its characteristics. However, Pope (2008), Kuminoff, Smith and Timmins (2013) and Bishop and Timmins (2015) suggest that relaxing any of these assumptions will violate the equilibrium conditions under which the estimates from hedonic models can be interpreted as welfare measure (WTP).

Kuminoff, Smith and Timmins (2013) describe the impact of relaxing the continuity assumption (iii). If at least one of the characteristics is discrete, the first order conditions for optimization of the hedonic price function will not adequately characterise equilibrium behaviour. This is important in practice because many amenities vary discretely. For the case of hedonic applications to the economics of flood risk, buyers are able to select properties over a continuous spectrum of flood risk. However, the use of a dummy variable denoting floodplain location as a proxy for level of risk represents a clear violation to this assumption. Pope (2008) suggests that this violation can result in attenuated estimates of the implicit price of the amenity/disamenity of interest.

Harding, Rosenthal and Sirmans (2003) and Pope (2008) suggest that relaxing assumption (iv and v) that both buyers and sellers are fully informed results in a similar attenuation bias. Pope (2008) illustrates the case of information asymmetries in a housing market with flood risk. The author suggests that sellers have lower search costs and are more informed about some housing characteristics, such as flood risk, than buyers. Under these circumstances, bargaining and search costs allow for transactions to take place anywhere between the maximum reservation bid of the buyers and the minimum reservation offer of the sellers. The size of the bias depends on the fraction of uninformed buyer in the market. The higher the fraction of uninformed buyers, the more attractive it is for sellesrs to wait for an uninformed buyer to make a bid on the house. A similar bias is imposed when relaxing the free mobility assumption (ii).

Finally, Kuminoff and Pope (2014) and Bishop and Timmins (2015) emphasise that the hedonic price model describes a situation of static equilibrium where consumers are assumed to be myopic with respect to the future evolution of prices and public goods. That is, the model considers market equilibrium and not the process that would follow an exogenous change in product attributes. Repeat-sales applications of the hedonic model address this issue by assuming that the gradient of the price function is constant over the duration of the study period. This assumption allows translating the identified parameters of the econometric model into welfare measures. Nonetheless, most recent developments in housing market models by Kuminoff, Smith and Timmins (2013), Kuminoff and Pope (2014) and Bishop and Timmins (2015) criticise this approach as it restricts preferences, income and technology to be constant over the duration of the study. The authors argue that the market clearing process can present endogeneity problems as the sorting of heterogenous individuals in the housing market will induce changes in the provision of local public goods affecting the quantity of amenity and the hedonic price paid for it. Each author has suggested a different alternative to try to avoid the endogeneity bias. Kuminoff, Smith and Timmins (2013) suggest the use of equilibrium sorting models; Kuminoff and Pope (2014) suggest the use of regression discontinuity designs; and Bishop and Timmins (2015) suggest the use of a likelihood-based estimation approach for recovering the MWTP function avoiding the endogeneity problem.

Although I recognise that the repeat-sales models might suffer from this endogeneity bias on the supply side due to endogenous variation in the level of public goods, it is important to note that alternatives to try to avoid this issue were under development at the time of writing this thesis. Future research should aim to incorporate these techniques into the analysis to mitigate this bias.

2.4 The Empirical Hedonic Model

Usual applications of the hedonic price model within the flood risk literature address the issue of floodplain location and its capitalisation in property prices using an additive representation of the HPF in equation (1), as follows:

$$lnP_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \phi p_i + \varepsilon_i \tag{8}$$

Where i denotes a specific house; j represents specific structural, neighborhood/locational and environmental characteristics of house i. P represents the sale price of the property; Z is the set of structural, locational and environmental characteristics of the house; r is usually given by the Euclidean distance to the nearest water body; and p is a proxy variable for flood risk, where a common alternative has been the use of a dummy variable indicating location in a floodplain at different levels of risk. β_0, β_j, γ and ϕ are estimated coefficients; note ϕ is the coefficient on the risk variable as denoted in equation (5). ε_i is the house-specific error term to which the usual assumptions apply i.e. $\varepsilon_i \sim \mathrm{N}(0, \sigma^2 \mathrm{I})$. Previous applications of the HPM to analyse the effect of flood alleviation schemes on property prices use a specification similar to (8), but where the variable p is a dummy variable taking the value of unity for those properties located in a floodplain impacted by the construction of a flood defence.

More recent hedonic models that deal with the economics of flood risk examine the effect of new information about flood risk and how this is capitalised into property prices of floodplain designated properties using a quasi-experimental design with a difference-in-differences (DID) approach. The strategy for identification relies on the occurrence of floods as a source of exogenous variation in the explanatory variable, i.e. the sale price of a house, by introducing a temporal element to the analysis with the use of a before-after approach. Thus, there are two dimensions distinguishing the structure of a quasi-experiment: the group assignment for each unit (house) in the study, whether it is inside or outside a floodplain, and the timing (t) of the potential outcome that is observed for each unit. The empirical model is represented as follows:

$$lnP_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \phi p_i + \alpha Flood_i + \psi(Flood_i \times p_i) + \gamma r_i + \varepsilon_{it} \tag{9}$$

The treatment group is distinguished by a dummy variable indicating floodplain location (p_i) and the treatment refers to the occurrence of a flood. The timing is the date of the sale in relation to the flood event and it is represented by the variable $Flood$, which is a dummy variable equal to one for sales occurring after the flood event of interest. The parameter ϕ represents the group effect, i.e. the pre-flood relative price differential between the control group (no floodplain location) and the treatment group (floodplain location); α captures the time effect, i.e. the relative price difference for all properties that were sold after the flood; and ψ represents the treatment response, i.e. the incremental effect due to information conveyed by the flood (treatment) in known risky locations (floodplains). That is,

$$\hat{\psi} = \left(\overline{lnP_1^{p=1}} - \overline{lnP_0^{p=1}}\right) - \left(\overline{lnP_1^{p=0}} - \overline{lnP_0^{p=0}}\right) \tag{10}$$

The key assumption for identification is that $E[\varepsilon_{it}|Flood_i] = 0$, for $t = 0, 1$ (before and after the flood).

Note that this approach uses a pooled cross-section of property prices over time, i.e. the cross-time comparison does not correspond to sales of the same property, and therefore it is conditioned on values of the other covariates Z_{ij} and r_i. Housing sales of the same region are observed over time and unobserved heterogeneity is controlled for using region or neighbourhood level fixed effects (Parmeter and Pope 2012). A shortcoming of this approach is, therefore, the amount of information it requires, since information on all the major structural and locational characteristics (Z_i and r_{i}) influencing the value of a house must be included in the regression to ensure unbiased estimates (Palmquist 1982, 2005). An alternative to address this issue is the use of a repeat-sales model, which is described below.

2.4.1 A Repeat-sales Model to Identify the Impacts of Flood Defences

The objective of this section is to describe the basic empirical repeat-sales model for the identification of the economic impacts of constructing flood defences. This model is derived from the standard HPM described above, but using actual panel data. We consider the sale prices of houses that have been sold multiple times over a given period of time. In between the times when a house is sold there are changes in some characteristics such as age, environmental quality and the general real state price level; however other characteristics of the house (structural and locational) remain the same. Therefore, by considering two sales of the same property it is possible to control for time-invariant characteristics and recover estimates for the effect of those aspects of homes' location that change over time. In this way, a repeat-sales specification allow us to evaluate the price effect of an environmental change which is not uniform across properties (Kousky 2010, Palmquist 1982, 2005).

Formally, consider the additive representation of the HPF in equation (11). This is similar to the DID representation in equation (9), with three important changes. First, it has now been indexed by t to identify the timing for the sale of each house i. Second, since now we are interested in the effect of the construction of a flood defence, the group assignment for each house is now given by the variable d which in its simplest form represents a dummy variable identifying properties located in areas that were impacted by the construction of a flood defence during the period of analysis. Finally, for the same reason, the timing of the potential outcome that is observed for each unit is now given by the variable $Defence$, which is a dummy variable equal to unity for those sales occurring after the construction of the flood defence.

$$lnP_{it} = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \theta d_i + \alpha Defence_{it} + \psi(Defence_{it} \times d_i) + \varepsilon_{it} \tag{11}$$

As the repeat-sales model requires at least two sales for each property, there are two sales periods, t and s. P_{it} denotes the outcome observed after the construction of the defence and P_{is} identifies the outcome prior to construction. Thus, for house i there is an earlier sale in year s for which the price is explained by an equation similar to (11) but where the variable $Defence$ takes the value of zero. Considering the difference in sales prices for the same home ($lnP_{it} - lnP_{is}$) yields equation (12).

$$\begin{gathered}(lnP_{it} - lnP_{is}) = (\beta_0 - \beta_0) + \sum_{j=1} \beta_j \left(Z_{ij} - Z_{ij}\right) + \gamma(r_i - r_i) + \theta(d_i - d_i) \\ +\alpha(Defence_{it} - Defence_{is}) + \psi[(Defence_{it} \times d_i) - (Defence_{is} \times d_i)] + (\varepsilon_{it} - \varepsilon_{is})\end{gathered} \tag{12}$$

One critical assumption for identification using the repeat-sales model is that all structural, locational, and neighbourhood characteristics (Z_i, r_i) of the property remain constant between the period of the two sales, t and s, as well as the parameters of the hedonic price function. Therefore these terms drop out of the equation (12) and time-invariant characteristics of the house are no longer a concern.[4] The resulting expression appears in equation (13).

[4] Notice that floodplains are defined as spatially delineated areas that would naturally be affected by flooding should a river or lake rises above its banks, or high tides and stormy seas cause flooding in coastal areas; therefore the construction of a flood defence does not change the floodplain designation status of a property, but the standard of protection for the benefited area.

$$\Delta ln(P_{its}) = \alpha Bracket_{its} + \psi(Bracket_{its} \times d_i) + \lambda_0 Year_t + \lambda_1 Year_s + \Delta\varepsilon_{its} \quad (13)$$

Notice that the term identifying properties that were sold after the construction of the flood defence, $Defence_i$, now translates into a dummy variable, $Bracket_{its}$, that identifies properties with sales transactions before and after the implementation of the project, i.e. sales that bracket the timing of the construction of the defence. If the construction occurred before the time of the first sale (s), it also takes place before the second sale (t) and $Defence_{it} - Defence_{is} = 0$, implying $Bracket_{its} = 0$. When both sales occur before the construction this variable is also zero, and it is impossible for the construction to be before the first sale and not before the second. The only way for $Defence_{it} - Defence_{is}$ to equal 1, $Bracket_{its} = 1$, is when the two sales bracket the date of construction of the defence. Following Kousky (2010) and Phaneuf and Requate (2011), the variables $Year_t$ and $Year_s$ are included to control for appreciation and age effects. Assuming there are no other changes in observable variables that contribute to price differences and that unobservables, represented by $(\varepsilon_{it} - \varepsilon_{is})$, are not correlated with the effect being measured; then $\hat{\psi}$ can be expressed as,

$$\hat{\psi} = \left(\overline{lnP_t^{d=1}} - \overline{lnP_s^{d=1}}\right) - \left(\overline{lnP_t^{d=0}} - \overline{lnP_s^{d=0}}\right) \quad (14)$$

where $\hat{\psi}$ is the estimate of the incremental price paid to acquire the condition represented by the group and time designations. That is, the incremental price paid to acquire the protection of the flood defence. So the repeat-sales model essentially becomes a first-differences specification of the DID model (Kousky, 2010).

Although the repeat-sales model allows us to exclude data on the characteristics of the properties that are assumed time-invariant and deals with possible omitted variable bias, it has additional complications. Previous studies suggest that the use of repeat-sales models might itself induce bias due to the subset of repeat sales being unrepresentative of the market as a whole, for instance an over-representation of low standard, frequently-traded properties (Lamond, Proverbs and Antwi, 2007; Steele and Goy, 1997). We do everything possible to minimise any potential bias by using a large dataset which includes all information on repeat sales at a national level in a sample that spans over almost 20 years. For longer time periods, the probability of re-sale increases and therefore more information is included in the repeat-sales model. Clapp, Giacotto and Tritiroglu (1991) argue that in the long run there are no systematic differences between the repeat sales sample and the full sample, and Nagaraja, Brown and Wachter (2014) highlight that as the sample period increases, the efficiency of the repeat sales method increases faster than that of standard hedonic models.

As mentioned before, a critical assumption for identification using the repeat-sales model is that the only element that the change in the price of the property between sales, t and s, is only due to a change in the level of the characteristic of interest (flood risk), and all other structural, locational and neighbourhood characteristics (Z_i, r_i) of the property remain constant. This assumption implies that any potential variations in housing prices due to changes in the quality of the properties between sales (e.g. refurbishments or the construction of an extra room) would be incorrectly associated to the change in the environmental amenity of interest, unless the quality changes are properly identified and included in the regression equation. The omission of relevant changes in property characteristics will result in omitted variable bias. Assuming that changes in this quality characteristics result in a positive variation of prices, the potential bias will act in different direction depending on the expected sign of the price variation due to the change in the level of the environmental amenity. If the amenity change is expected to result in a positive variation of prices (e.g. the construction of a flood defence) the parameters of the model will tend to overestimate the real effect for the amenity change. If, on the other hand, the amenity change is expected to result in a negative variation of prices (e.g. the occurrence of a flood) the parameters of the model will underestimate the negative effect of the amenity change.

It is important to consider, however, that the repeat-sales model compares the variation in the price of properties that were affected by a change in the level of an environmental amenity, against the variation in the price of properties which were unaffected by the environmental change. If the probability of quality changes in the structural characteristics of the properties (e.g. refurbishments or the construction of an extra room) is the same across the two groups of properties, the parameters of the repeat-sales model will still identify the mean price variation due to the change in the level of the environmental amenity. However, if the change in the environmental amenity increases (or decreases) the probability of changes in the quality characteristics of the properties, then the parameters of the repeat-sales model will be affected by the described omitted variable bias.

Authors such as Case and Quigley (1991) and Shiller (1993) suggest the use of ‘hybrid models’ to address the issue of the potential sample selection bias and a possible change in quality of properties between sales. These models combine the repeat sales sample and the standard hedonic sample to exploit all sales data (OECD, et al., 2013). However, they involve including housing characteristics in the traditional repeat-sales estimation. This information is not available in our data. Other authors such as Geltner (1996) and Edelstein and Quan (2006) suggest augmenting the repeat-sales sample by using assessment data to approximate the value of properties which have not been resold during the period of analysis. However, due to the data requirements of this approach it is impractical to apply it at a broad scale. Hill (2011) concludes that the standard repeat-sales approach should be preferred to an approach that imputes a second sale price to properties sold only once (OECD, et al., 2013).

More recent applications of the repeat-sales model such as Gibbons (2015), Bosker et al. (2014) and Nagaraja, Brown and Zhao (2011) suggest combining information from the repeat sales sample and the standard hedonic sample at the postcode level. However, this postcode fixed-effects design implies that the analysis is based on repeat-sales of the same, or similar housing units within postcode groups, and is itself likely to induce bias due to within-postcode heterogeneity of the housing units. The econometric model presented in this chapter avoids this issue by using repeat-sales of the same property matched at full address. This allows controlling for location at the finest level of detail. Furthermore, the use of a big dataset including all property transactions in England during the period of analysis results in a large sample of properties to identify the capitalisation of flood defences in property prices.

2.5 Data and Econometric Methodology

Data on property prices are taken from the England and Wales Land Registry ‘Price Paid’ housing transactions data. This dataset is publicly available and includes essential details on all residential property sales in England and Wales, going back to 1995, that were sold for full market value and were lodged for registration with the Land Registry. The data includes information on transaction sale price, date of transaction (DD/MM/YYY), address details, basic property characteristics – detached, semi-detached, terraced or flat/maisonette

–, it also indicates whether the property is new or second-hand, and whether it is sold on a freehold or leasehold basis.

The complete data from the Land Registry consists of over 19 million observations for properties sold in England and Wales between January 1995 and the end of July 2014. This is the period of information available at the time that the dataset was created. Since details on structural flood defences are available only for England, all observation corresponding to Wales were dropped. The remaining dataset includes over 18 million transactions.

The use of the repeat-sales model requires a panel data structure for properties that have been sold multiple times over the period of analysis. Housing units with repeat-sales were identified by matching the exact address of the properties considering four variables: full postcode (six-digit)[5], street, primary house number and secondary house number (for properties with a sub-building e.g. buildings divided into flats). Whenever there was a match for these four variables, the transaction was considered a repeat-sale. Over 6 million observations for properties with a single sale were dropped, as well as over 12,000 observations with matching street name, primary number and secondary number, but with a missing postcode (this was to avoid the possibility of matching houses with the same street name but different postcode and it only represents about 0.1% of our total sample of repeat sale transactions).

The final dataset includes over 12 million individual transactions that correspond to 4.8 million properties in England. All sale prices were time-adjusted to July 2014 GBP (£) using the county-specific House Price Index available through the Land Registry; this is to reflect real variation in property prices net out of general price trends in the housing market. On average, a house in the sample was sold 2.5 times between January 1995 and

[5] In practice the full postcode (postcode unit level) of a property in the UK can range between six and eight alphanumeric characters. Throughout this chapter we use the term '*six-digit postcode*' to refer to the full postcode of the property. Likewise, we use the term '*five-digit postcode*' meaning one character less than a full postcode, i.e. five to seven characters. Postcode units in the UK consist of an average of 17 houses grouped together.

July 2014, with a minimum of 2 and a maximum of 29 sales (an unbalanced panel structure). The average transaction price for a property was £234,129, with a minimum of £4,742 and a maximum of £44.2 million.

Finally, the between-sales growth rate for the price of each property was calculated as the first difference of the logged price, as shown in equation (12). Thus, the final dataset that is used for the estimation of the repeat sales model consists of over 7 million observations which represent the between-sales growth rate for approximately 4.8 million properties.

Licensed GIS data from the National Flood and Coastal Defence Database (NFCDD) was acquired from the UK Environment Agency. This dataset specifies the spatial location and main characteristics of structural flood defences in England. More specifically these data show flood defences that protect against river floods in 100-year floodplains, or sea floods in 200-year floodplains. The data also includes important characteristics of the defences such as the standard of protection[6], the length, the crest level[7], and year of construction. It also indicates the type of asset (wall, embankment, bridge, etc.), the type of protection it provides (fluvial or coastal flooding), a description of the structure, and a measure identifying the condition of the asset.

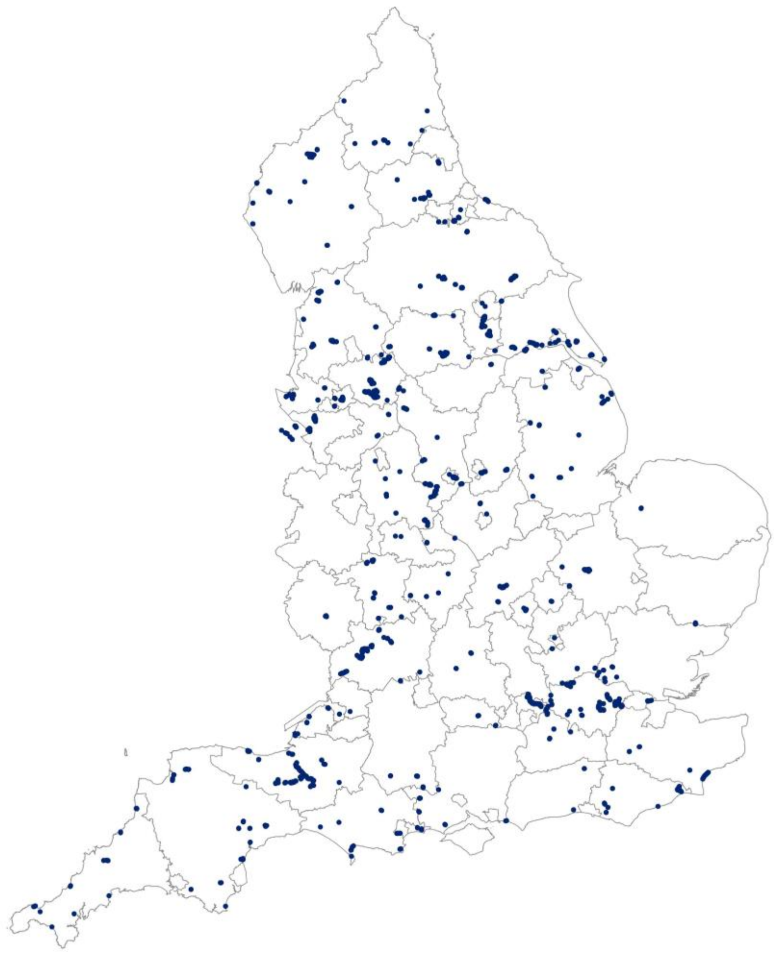
The NFCDD identifies a total of 24,257 structural flood defences in England constructed between 1739 and 2014. Due to the design of the analysis and the fact that the information on property prices is only available since 1995, the final dataset includes only information for flood defences that were built after this year. The final dataset consists of a total of 1,666 flood defences built between 1996 and 2014, representing 553 km of defences. It includes different types of structures built for flood protection such as floodwalls, embankments, bridge abutments and floodgates. Table A2.1 of the appendix shows a

[6] The standard of protection of a flood defences is the flood level (expressed as a return period) which a flood defence will withstand with a high degree of certainty (Kirby and Ash, 2000).

[7] The crest level of a flood defence is the height of the defence measured in meters above sea level (mAOD). The crest level of defence includes the height required to achieve the desired standard of protection, plus a suitable safety margin, a.k.a. freeboard, that allows for uncertainties (Ackers, Rickard and Gill, 2009).

description of the general features of the different types of flood defences included in the dataset. Map 2.1 below shows the spatial representation of the flood defences included in the analysis. A summary of the data on flood defences is presented in table 2.2.

Map 2.1. Structural flood defences constructed in England, 1996-2014



Source: Own elaboration based on data from the NFCDD.

Table 2.2. Summary of flood defence structures constructed in England after 1995

Type of flood risk	Number of defences	Length (km)
Coastal	224	102
Fluvial	1,442	451
Total	**1,666**	**553**

Source: Based on data from the NFCDD.

The GIS spatial representation of the flood defences was then merged with GIS full postcode data (six-digit) from the Ordnance Survey (available through the Digimap Resource Centre of the University of Edinburgh), to identify at the six-digit level the postcode in which the defences are located. A similar process was applied for the dataset containing the details of property prices to identify the spatial location of the properties at the full-postcode level. In this way, it was possible to identify the repeat-sales of properties that occur within postcodes where flood defences were constructed after 1995. The data on the year of construction of the defence and the date of transaction of the property allow us to identify those properties with transactions that bracket the construction of a defence.

Although there is a GIS dataset accessible from the Environment Agency delineating areas "benefited" by the construction of flood defences, this information is only available for a limited number of defences. Furthermore, in most cases the year of construction is not available or the polygon delineating the protected area results from the interaction of flood defences constructed in different years, which prevents the identification of the areas that benefited from each segment of the defence. Instead, we decided to approximate the area impacted by flood defences using the 5-digit postcode where the defence is located. By using this definition of the area 'impacted' by flood defences, rather than 'benefited', we wish to account for the possibility that disamenity impacts from the construction of flood defences extend over an area greater than that benefited from a reduction in flood risk. Therefore, to determine the benefits of flood defence projects it is important not to confine any analysis only to those areas enjoying benefits from a reduced risk of flooding. Our identification strategy consists of focusing on repeat-sales of the same property within 5-

digit postcode areas where defences were constructed.[8] We will later investigate impacts within much small 6-digit postcode areas which are highly unlikely to include any properties not directly benefiting from a reduction in the risk of flooding.

Other GIS datasets used in this chapter include Flood Map Layers (flood zone 3) and Recorded Flood Outlines, both available through the UK Environment Agency. The former shows the spatial delineation of the 100-year floodplain for fluvial flooding and 200-year floodplain for coastal flooding in England and Wales. The latter consists of spatial polygons indicating the extent of known individual flood events from rivers and the sea, including details such as the start and end date of the event, and the source of flooding.[9] Finally, GIS files containing the Rural-Urban Classification for England were accessible via Defra. By merging these files with the GIS full-postcode data and the spatial location of the house sales it was possible to identify the properties located inside a floodplain, those which are located in a postcode which has been previously flooded (including the date and duration of the flood event) and the rural-urban classification of the properties.

Due to the large computational requirements necessary to manipulate the huge number of observations involved in the analysis, all the computations described in this chapter were performed using the University of Birmingham's BlueBEAR HPC service, which provides a High Performance Computing service to the University's research community.[10]

[8] Merging the GIS data on flood defences with the GIS representation of the postcode units allow us to identify all the cases where flood defences are constructed across different postcodes to include them in the analysis.

[9] In locations which have been flooded more than once, the file overlaps individual polygons for each flood event.

[10] For further information on the BlueBEAR project of the University of Birmingham see: http://www.birmingham.ac.uk/bear.

2.5.1 The Econometric Model

The development of the empirical repeat-sales model to test for the price effect of constructing flood defences in the English housing market follows closely the identification strategy described in section 2.4.1. Using the final panel dataset containing over 12 million individual transactions corresponding to properties with at least one repeat-sale during the period of analysis, we begin by describing an empirical DID HPM for the price of each property, as in equation (15),

$$lnP_{it} = \beta_0 + \theta d_{it} + \alpha Defence_{ikt} + \psi(Defence_{ikt} \times d_{it}) + \varepsilon_{ikt} \qquad (15)$$

Where i denotes a specific house; k identifies the county in which property i is located, and t denotes the time of the transaction. The dependent variable, lnP, is the natural logarithm of the property sale price adjusted to July 2014 GBP. The variable d represents the group assignment for each house unit and is given by a dummy variable taking the value of 1 for properties located within a 5-digit postcode where flood defences were constructed during the period 1996-2014. All other structural, locational, and neighbourhood characteristics (Z_i, r_i) of properties are excluded. As mentioned before, the repeat-sales specification assumes these characteristics remain constant between two sales of the same property, and therefore these are not relevant for the estimation of the repeat-sales model. ε_{ikt} is the house-specific error term to which the usual assumptions apply i.e. $\varepsilon_{ikt} \sim \mathrm{N}(0, \sigma^2\mathrm{I})$.

The construction of the variable $Defence$ in equation (15) is more involved. Similar to the specification in equation (11), it represents the timing of the sale with respect to the construction of a flood defence. However, since counties in the UK constitute different political and administrative units, it makes sense to keep the comparison of price differential for properties before-and-after the construction of a defence within the geographical borders of the county in which the defence has been constructed. Thus, the variable $Defence$ in equation (15) is a county-house-time specific dummy that takes the value of 1 for sales within county k that occur after the construction of a flood defence in that county. Therefore $(Defence_{ikt} \times d_{it})$ is a dummy variable signalling those sales that occur after the construction of a flood defence, within 5-digit postcode areas where flood defences were constructed.

Following section 2.4.1, taking the first-difference of equation (15) yields the following specification of the basic repeat-sales model:

$$\Delta ln(P_{its}) = \alpha Bracket_{ikts} + \psi(Bracket_{ikts} \times d_i) + \lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts} \qquad (16)$$

Where the subscript s represents the time of a previous sale of property i. The dependent variable is now the price differential for property i between the period of the two sales, t and s. The variable $Bracket_{ikts}$ is a dummy variable which takes the value unity for properties whose sales bracket the timing of the construction of the defence within county k, where the flood defence was constructed, and $(Bracket_{ikts} \times d_i)$ is a dummy variable which takes the value unity for those properties whose sales bracket the timing of the construction of the defence within county k and that are located within the 5-digit postcode areas where flood defences were constructed. Following Kousky (2010) and Phaneuf and Requate (2011), the variables $Year_{is}$ and $Year_{it}$ are introduced to control for appreciation and age effects. The coefficient α represents the time effect, i.e. the relative price differential for all properties whose repeat-sales bracket the construction of a flood defence, and ψ represents the treatment response, i.e. the incremental effect due to the reduction of flood risk in 5-digit postcode areas where flood defences were constructed. That is,

$$\hat{\psi} = \left(\overline{lnP_t^{d=1}} - \overline{lnP_s^{d=1}}\right) - \left(\overline{lnP_t^{d=0}} - \overline{lnP_s^{d=0}}\right) \tag{17}$$

This coefficient can be interpreted as the incremental price paid to acquire the condition represented by the group and time designations, i.e. to acquire the protection of the flood defence. The key assumption for identification is that $E[\varepsilon_{ikts}|Defence_i] = 0$, for $t = 0, 1$ (before and after the flood).

Notice that the repeat-sales specification in equation (16) does not take account of other potential factors that can differentially affect the housing market prospects of protected properties, such as the characteristics of the property, the design characteristics of the flood defence structure and differences in flood risk perception. However, there are important reasons to believe that these three factors might play an important role in determining the extent to which the benefits of flood defence structures are capitalised into property prices.

It is a general practice in hedonic applications in the flood risk literature to control for different characteristics and types of ground floor properties, however the case of flats has been largely overlooked. A notable exception is the recent study by Meldrum (2015) who tests for the effect of floodplain designation on property prices in Boulder County, Colorado, US, with special attention paid to different type of structures: standalone homes and condominiums. We hypothesise that the heterogeneity in the types of residential property sold might play an important role in determining its vulnerability to flooding. For instance ground floor house designs such as detached, semi-detached and terraced houses might be more exposed to flooding than flats located above ground level. Therefore the demand for flood protection and the perception of the impacts of constructing flood defences might also be different. Even when comparing among different types of ground floor properties, general characteristics such as the average floor area associated with each type of construction might result in differences in the capitalisation of flood defence schemes.

Likewise, differences in the location of the property such as its rural/urban classification and its proximity to the coast might influence the extent to which the consequences of constructing flood defence schemes are capitalised into property prices. This might be due to differences in the characteristics of urban and rural properties, exposure to different types of flood risk (fluvial vs coastal flood risk), different levels of flood risk perception, or differences in the assessment of the negative visual and other amenity impacts associated with the construction of defences. We also allow for possible differences related to the price of properties, as these reflect differences in the level of income, which might influence preferences for ex-ante (e.g. construction of flood defence) vs. ex-post (e.g. emergency relief) flood alleviation measures, or preferences for hard (e.g. flood defences) vs. soft (e.g. flood insurance) flood risk management alternatives.

As mentioned earlier, the results by Lee and Li (2009) comparing the price effect of the construction of two different designs of detention basins for flood control reveal that even when analysing the same type of flood defence structure, differences in the design might influence the extent to which flood protection benefits are capitalised into property prices. The height (crest level) of the defence determines its standard of protection, i.e. the severity of the flood against which the defence provides protection. Flood defence structures with higher standards of protection represent reductions in objective flood risk which might also be associated with a higher perception of flood safety. Differences in length can result in bigger/smaller areas benefited by the defence and might also be associated with different levels of perception of flood safety. However, increasing the dimensions of the flood defence structure can also result in negative utility impacts due to visual intrusion and loss of other amenities.

The sample includes different types of flood defence structures that have been constructed in England during the period of analysis, namely: floodwalls, embankments, bridge abutments, high grounds, floodgates and demountable flood defences. Although all of them share the same objective to contain floodwaters, they possess different design and visual characteristics which might influence the way in which the benefits of flood defences are perceived. For instance, in most cases floodwalls are made of concrete with some form of cladding or decorative finish, whereas embankments are earthfill structures that are commonly covered by grass (Ackers, Rickard, and Gill, 2009). An important distinction is that of permanent versus demountable defences. Structures such as floodwalls, embankments, bridge abutments and high grounds are permanent defences, meaning they are fully in place and do not require operation during a flood event, whereas demountable defences and floodgates are pre-installed and require automatic or manual operation during a flood event. Flood defences can also be part of a more inclusive structure serving multiple purposes; this is the case of bridge abutments. We hypothesise that all these distinct characteristics attached to different types of flood defences can influence the extent to which the benefits of different types of defences are capitalised into property prices, for instance because of different levels of perceived protection.

Finally, based on an early proposition by Tobin and Newton (1986) and Montz and Tobin (1988), and recent studies by Pryce, Chen and Galster (2011), Atreya, Ferreira and Kriesel (2013) and Bin and Landry (2013) who analyse the effect of flood events on property prices and the associated dynamics of changes in flood risk perception through time, we hypothesise that the extent to which comparable flood defence structures capitalise into property prices across different locations might differ due to differences in their flooding history. The authors suggest that recent flood experiences raise perception of flood risk as people estimate the frequency or probability of an event by the ease with which instances of associations can be brought to mind. The effect then diminishes as people tend to forget about the risk of flooding as time passes (Pryce, Chen and Galster, 20011, Atreya, Ferreira and Kriesel, 2013). Therefore, we expect to find a greater capitalisation of flood defences in locations with recent and more severe flood experiences, i.e. those with a greater flood risk perception.

To control for these differences, we add four sets of variables to the original repeat-sales specification in equation (16). The first set, *house type*, includes one categorical variable identifying the price quartile of the property; four dummy variables to control for different types of properties (detached, semi-detached, terraced, flat); and dummy variables to control for differences in the duration of the contract (freehold or leasehold), rural/urban classification of the property, and the type of flood risk (fluvial or coastal). The second set of variables, *defence design*, includes two continuous variables controlling for the standard of protection (return period) and length of the defence. The third set of variables, *defence type,* includes six dummy variables to control for the different types of flood defences included in the analysis (floodwalls, embankments, bridge abutments, high grounds, floodgates and demountable flood defences). Finally, the fourth set of variables, *flood perception*, includes two variables that are used as a proxy measure of flood risk perception in locations that have been impacted by the construction of a defence. The first variable represents the number of months since the previous flood with respect to the second sale of the property, i.e. after the construction of the defence, and the second represents the duration, in number of days, of that flood as a measure of intensity. Equation

(18) below shows the final specification of the repeat-sales model to identify the capitalisation of flood defences into property prices.

$$\begin{aligned}\Delta ln(P_{its}) = {} & \alpha_1 Bracket_{ikts} + \alpha_2(Bracket_{ikts} \times house\_type_i) + \psi_1(Bracket_{ikts} \times d_i) \\ & + \psi_2(Bracket_{ikts} \times d_i \times house\_type_i) + \psi_3(Bracket_{ikts} \times d_i \times defence\_design_i) \\ & + \psi_4(Bracket_{ikts} \times d_i \times defence\_type_i) + \psi_5(Bracket_{ikts} \times d_i \times flood\_perception_i) \\ & + \lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts}\end{aligned} \tag{18}$$

The resulting expression is estimated using ordinary least squares (OLS). Notice that equation (18) includes the set of variables controlling for the *house_type* with and without the interaction with the group assignment variable, d, identifying the treated observations (properties located within the 5-digit postcode where flood defences were constructed). The objective is to identify the effect of the construction of flood defences on different types of houses. The variable *house_type* without the interaction with the group variable, d, allows for differences in time trends across different types of properties. That is, it isolates the treatment effect from a general time trend and a *house_type* specific trend. In this way the coefficient ψ_1 represents the treatment effect of the omitted *defence_type* category (floodwalls) in equation (18) on the price of the omitted *house_type* category (detached). That is,

$$\hat{\psi}_1 = \left(\overline{lnP_{t,x=h}^{d=1}} - \overline{lnP_{s,x=h}^{d=1}}\right) - \left(\overline{lnP_{t,x=h}^{d=0}} - \overline{lnP_{s,x=h}^{d=0}}\right) - \left(\overline{lnP_{t,x\neq h}^{d=1}} - \overline{lnP_{s,x\neq h}^{d=1}}\right) \tag{19}$$

This coefficient is called the difference-in-difference-in-differences (DDD) estimator, or triple difference estimator. The first subscript in the terms in brackets in equation (19) refers to the time of the sale, s for the first sale and t for the second sale. The second subscript, x, identifies the type of house. The superscript represents the group designation, $d = 1$ for treated and *d=0* for untreated observations. Thus, the DDD estimator represents the average price change between sales of houses type $x = h$ ($h = detached$) that were benefited by the construction of a defence, net out the average price change between sales of houses type $x = h$ that were not benefited by a defence, and the average price change between sales of all other house types $x \neq h$ that were benefited by the construction of a defence. Thus, the term in equation (19) can be interpreted as the incremental price paid by buyers of house type h to acquire the protection of the flood defence (floodwall). The differential effect for other types of properties, $x \neq h$, is given by the coefficient $\hat{\psi}_2$ in equation (18), and is measured over and above $\hat{\psi}_1$. Finally, the sets of variables *defence_design*, *defence_type* and *flood_perception*, represent characteristics that modulate the intensity of the treatment and therefore are only included in equation (18) with an interaction with the group assignment variable, d. The differentiated price impacts of these characteristics are given by the coefficients $\hat{\psi}_3,\ \hat{\psi}_4,\ \hat{\psi}_5$ in equation (18), and are measured over and above $\hat{\psi}_1$ which captures the omitted categories.

Table 2.3 shows a short description of the variables included in the model together with the usual summary statistics. The average transaction price of a property in the sample is £234,130 (July 2014 prices), with a price increase of 7.8% during an average period between sales of five years. The sample includes over 7 million properties with at least one repeat-sale, out of which 1.4 million (19%) have sales that bracket the construction of a flood defence in the county where they are located. Out of this, approximately 1%, 14,716 properties, represent treated observations, i.e. properties whose sales bracket the construction of a flood defence and are located within the 5-digit postcode area where the defence is constructed. Regarding the composition of the housing stock, in terms of the type of properties, the proportion of detached, semi-detached and terraced properties is around 20 – 30% each, with a smaller proportion of flats which represent 13% of the sample. Roughly 20% of these properties are located in rural areas, and 23% are located in coastal floodplains. If we focus on the sample of treated observations, it has a similar composition in terms of the type of properties. However, a greater proportion of the properties benefited by the construction of a flood defence are located in rural areas (30%), while a lower proportion of them correspond to properties in a coastal floodplain (9%).

Table 2.3. Summary statistics

	Variable	Description	No. Obs.	Mean	S.D.	Min.	Max.
	Price	Property sale price adjusted to July 2014 GBP	12,012,455	234,130	259,475	4,742	44,200,000
	Δln(Price)	House-specific firs-difference of the logged real price	7,222,401	0.078	0.252	-6.28	4.17
	Bracket (B)	Dummy variable = 1 if the two sales bracket the construction of a defence in a county where a defence was constructed		0.192	0.394	0	1
	Lyear (s)	Year of the first sale		2001	3.90	1995	2014
	Year (t)	Year of the second sale		2006	4.46	1995	2014
Bracket sample [1]							
House_type [2]	B*sdetached	Dummy variable = 1 if the sale corresponds to a semi-detached property	1,390,457	0.295	0.456	0	1
	B*terraced	Dummy variable = 1 if the sale corresponds to a terraced property		0.320	0.466	0	1
	B*flat	Dummy variable = 1 if the sale corresponds to a flat		0.135	0.343	0	1
	B*free	Dummy variable = 1 if the sale corresponds to a house acquired on a freehold contract		0.823	0.381	0	1
	B*rural	Dummy variable = 1 if the sale corresponds to a property located in a rural area		0.209	0.406	0	1
	B*coastal	Dummy variable = 1 if the sale corresponds to a property exposed to coastal flood risk		0.234	0.423	0	1
	B*quartile	Categorical variable which takes the value 1 to 4 to identify the quartile price of the property (lowest to highest price)		2.527	1.116	1	4
Bracket-defence sample [3]							
	B*Defence (D)	Dummy variable =1 if the sales bracket the construction of a defence and the property is located within the 5-digit postcode area where a flood defence was constructed	1,390,457	0.011	0.102	0	1
House_type [2]	B*D*sdetached		14,716	0.286	0.452	0	1
	B*D*terraced			0.331	0.470	0	1
	B*D*flat			0.136	0.343	0	1
	B*D*free			0.803	0.397	0	1
	B*D*rural			0.302	0.459	0	1
	B*D*coastal			0.091	0.288	0	1
	B*D*quartile			2.339	1.092	1	4
Defence_ design	B*D*sop	Standard of protection (sop) of the defence. Return period in number of years	14,716	108	159	0	1,000
	B*D*length	Length of the defence in meters		296	407	0.54	4,013
Defence_type [4]	B*D*embankment	Dummy variable = 1 if the property is benefited by the construction of an embankment	14,716	0.478	0.499	0	1
	B*D*bridgeabt	Dummy variable = 1 if the property is benefited by the construction of a bridge abutment		0.001	0.032	0	1
	B*D*highground	Dummy variable = 1 if the property is benefited by the construction of a high ground		0.069	0.254	0	1
	B*D*demount	Dummy variable = 1 if the property is benefited by the construction of a demountable defence		0.011	0.103	0	1
	B*D*floodgate	Dummy variable = 1 if the property is benefited by the construction of a floodgate		0.027	0.163	0	1
Flood_ perception	B*D*months	Number of months since the last flood, to the time of the second sale (t), in the benefited area	14,716	188	218	0	1,633
	B*D*duration	Duration of the last flood in number of days		52	119	0	364

Notes:
[1] The summary statistics under this title correspond to the 19% of the sample with repeat sales that bracket the construction of a flood defence in a county where a defence was constructed.
[2] Omitted categories are dummy variables for detached property, urban location and fluvial flood risk.
[3] The summary statistics under this title correspond to the 1% of the sample with repeat sales that bracket the construction of flood defence and are located within the 5-digit postcode area where the defence is constructed.
[4] The omitted category is a dummy variable for floodwall.

The average standard of protection for the impacted properties is a 108-year return period, that is, on average, they are protected against floods that can occur with a 1% annual probability. The average length of the structure is 296 meters. These properties are protected by different types of flood defences, the proportions of properties protected by each different type of structure are as follows: 41% floodwall, 48% embankment, 7% high ground, 3% floodgate, 1% demountable defence and 0.1% bridge abutment. Note that these figures do not describe the stock of defences considered for the analysis, but rather the proportion of treated properties protected by different types of defences. A summary of the characteristics of the stock of defences is presented in table A2.1 of the appendix.

Finally, the properties that are within the area impacted by a flood defence are located in postcodes (5-digit level) that, on average, experienced flooding 16 years before the second sale of the property (after the construction of the defence), with an average duration of the event of 7 weeks.

2.6 Results

In this section we present the regression results of the repeat-sales model specified in equation (18). The exposition of results is divided in three sections. Tables 2.4 and 2.5, in sections 2.6.1 and 2.6.2, respectively, show our main results using two different definitions of the area impacted by flood defences. For the results in table 2.4, section 2.6.1, we define the treatment group as described above, i.e. the 5-digit postcode where the defence is located. However, the consequences of flood defences, in terms of the reduced risk of flooding and the disamenity impacts, are likely to find expression at different geographical distances. Flood relief benefits might be experienced only in the immediate vicinity of the flood defence construction whereas disamenity impacts might occur over a somewhat wider area. For the results in table 2.5, section 2.6.2, we narrow down the definition of our treatment group to consider only properties within the 6-digit postcode area where the defence is located. In this way, we also look at the capitalisation of flood defences into the price of properties located closest to the source of risk which are the ones exposed to the highest risk. Map A2.1 in the appendix exemplifies the spatial difference between 5-digit and 6-digit postcode areas. We discuss the results for fluvial and coastal flood defences separately. The results in tables 2.4 and 2.5 prove to be robust across six different specifications where we change the sample and control group. In section A2.1 of the appendix we discuss the results of two additional robustness tests. The first one is a standard robustness test where we remove outlier observations, and the second one consists of a placebo test.

2.6.1 Treatment group: 5-digit postcode area

Table 2.4 shows the regression results of the repeat-sales model specified in equation (18) with the treatment group defined as the 5-digit postcode area where the defence is constructed. It includes six different specifications with different sample and control groups. The results in column (1) use the full sample as described above. Columns (3) and (5) divide the sample according to different types of flood risk, fluvial or coastal (tidal), to which the protected properties were exposed. Thus the treatment group in column (3) corresponds to those properties that were impacted by the construction of a flood defence against fluvial flooding, while the control group consists of those properties whose sales bracket the construction of a fluvial flood defence in the county were they are located. This distinction is especially relevant in counties were both type of flood defences, fluvial and coastal, were built during the period of analysis. A similar definition follows for the sample of the results in column (5) but with a focus on the construction of coastal flood defences. This allows for the possibility that the capitalisation process of the impacts of flood protection against different types of flood risk might be driven by different underlying factors. For instance, both types of floods possess different characteristics and their potential impacts are also different: fluvial floods are likely to be a result of heavy rain events whereas coastal floods are usually a result of storm surges created by storms like hurricanes and tropical cyclones.

One possible criticism as to the validity of the identification strategy is that it relies on a quasi-experimental design where the random assignment of the treatment is not guaranteed. That is, flood defences are only constructed in locations that are exposed to flood risk. It can be argued that the housing market in these regions possess some special characteristics and therefore comparing the price increase of properties impacted by the construction of defences against the price increase in all other properties anywhere in the county might lead to misleading conclusions. To address this issue and to test the robustness of the results, columns (2), (4) and (6) show the results of regressions with the relevant sample defined as described above, i.e. full sample, fluvial defences and coastal defences, respectively, but where the control group is now restricted to properties located inside the floodplain (FP). In this way, they compare the price increase of properties impacted by the construction of a flood defence, against that of properties which are exposed to a similar risk but where the level of flood risk remained unchanged.

Bin and Kruse (2006) and Bin et al. (2008) highlight that different types of flood risk possess distinctive characteristics that can have different implications in the housing market. For instance, different types of flood risk imply proximity to different sources of risk with different potential damages and amenity values. The authors conclude that different types of flood risk should be analysed individually. For these reasons, our preferred specifications correspond to the results in columns (4) and (6), where we analyse protection against different types of flooding separately, and where the control group corresponds to properties exposed to a similar risk. The exposition of the results focus on our preferred specifications, however the main results are robust across different specifications. All specifications include county level fixed-effects to control for between county heterogeneity. Heteroscedasticity robust standard errors (Huber 1967, White 1980) appear in parentheses.

The first group of variables in table 2.4, (A) *house_type*, correspond to the variables included in the model to allow for differences in the price trend across different types of properties (house type, urban/rural, inland/coastal and price) as part of our DDD strategy. In general, these variables are highly significant. This indicates that, regardless of the construction of a flood defence, different type of properties have enjoyed significantly different price trends during the period of analysis. This result highlights the importance of our DDD strategy of identifying the distinctive price effect of the construction of flood defences on properties with different characteristics.

The second section in table 2.4, *Bracket-defence sample*, includes our main results. The main coefficient of interest corresponds to the variable *B*Defence*. This represents our benchmark result for the capitalisation of flood defences on property prices, and it is highlighted in bold in table 2.4. The remaining four sets of variables identify differences in the capitalisation of flood defences across different types of properties ((B) *house_type*), different design characteristics of the defence (*Defence-design*), different types of flood defences (*defence_type*), and differences in flood risk perception (*Flood-perception*). The coefficients on these variables are interpreted over and above our benchmark coefficient (*B*Defence*). The omitted categories that result from the use of different sets of dummy variables are: detached, urban, and floodwall. The effect of these categories is captured by our benchmark coefficient. Therefore the coefficient on the variable *B*Defence* should be interpreted as the capitalisation of floodwalls into detached urban properties.

Table 2.4. Repeat-sales model: The effect of flood defences on property prices
(*Area impacted: 5-digit postcode*) [1]

	Variables	(1) All estimates	(2) All estimates FP	(3) Fluvial risk	(4) Fluvial risk FP	(5) Coastal risk	(6) Coastal risk FP
	Bracket sample						
	Bracket (B)	0.147***	0.186***	0.164***	0.202***	0.195***	0.267***
		(0.00154)	(0.00431)	(0.00168)	(0.00481)	(0.00500)	(0.0115)
(A) *House_type* [2]	B*sdetached	-0.0107***	-0.0280***	-0.0160***	-0.0314***	-0.0259***	-0.0454***
		(0.000641)	(0.00169)	(0.000737)	(0.00199)	(0.00141)	(0.00338)
	B*terraced	-0.0295***	-0.0483***	-0.0406***	-0.0586***	-0.0389***	-0.0625***
		(0.000676)	(0.00175)	(0.000795)	(0.00212)	(0.00146)	(0.00349)
	B*flat	-0.0307***	-0.0642***	-0.0527***	-0.0868***	-0.00468	-0.0583***
		(0.00143)	(0.00399)	(0.00156)	(0.00444)	(0.00437)	(0.00981)
	B*free	0.0511***	0.0409***	0.0492***	0.0410***	0.0859***	0.0607***
		(0.00127)	(0.00362)	(0.00133)	(0.00393)	(0.00419)	(0.00921)
	B*rural	0.0242***	0.0455***	0.0262***	0.0473***	0.0303***	0.0520***
		(0.000568)	(0.00135)	(0.000634)	(0.00157)	(0.00133)	(0.00281)
	B*coastal	0.0172***	0.0189***				
		(0.000443)	(0.00104)				
	B*quartile	-0.0632***	-0.0702***	-0.0706***	-0.0780***	-0.0678***	-0.0782***
		(0.000277)	(0.000712)	(0.000334)	(0.000894)	(0.000697)	(0.00161)
	Bracket-defence sample						
	B*Defence (D)	**0.0613*** **	**0.0490* **	**0.0548** **	**0.0568* **	**0.0147**	**-0.0175**
		(0.0201)	**(0.0260)**	**(0.0223)**	**(0.0295)**	**(0.0589)**	**(0.0748)**
(B) *House_type* [2]	B*D*sdetached	-0.0327***	-0.0233**	-0.0263***	-0.0194	-0.0212	-0.0129
		(0.00808)	(0.0118)	(0.00931)	(0.0139)	(0.0169)	(0.0232)
	B*D*terraced	-0.0407***	-0.0281**	-0.0302***	-0.0204	-0.0506***	-0.0445*
		(0.00860)	(0.0121)	(0.0102)	(0.0145)	(0.0180)	(0.0245)
	B*D*flat	-0.0711***	-0.0613***	-0.0576***	-0.0590**	-0.0502	0.00306
		(0.0168)	(0.0224)	(0.0182)	(0.0247)	(0.0516)	(0.0654)
	B*D*free	0.0257*	0.0362*	0.0106	0.0147	0.0750	0.111*
		(0.0154)	(0.0203)	(0.0159)	(0.0213)	(0.0516)	(0.0645)
	B*D*rural	-0.00636	-0.0332***	-0.00437	-0.0221**	-0.0506***	-0.115***
		(0.00606)	(0.00894)	(0.00674)	(0.0101)	(0.0139)	(0.0177)
	B*D*coastal	0.0688***	0.0767***				
		(0.00982)	(0.0123)				
	B*D*quartile	-0.0114***	-0.00856	-0.00411	-0.00160	-0.0178**	-0.0171*
		(0.00376)	(0.00523)	(0.00459)	(0.00648)	(0.00783)	(0.0101)
Defence_ design	B*D*sop	-6.28e-05***	-7.36e-05***	-4.26e-05**	-6.73e-05***	-6.61e-05**	-0.000114**
		(1.54e-05)	(2.12e-05)	(1.85e-05)	(2.43e-05)	(2.91e-05)	(5.04e-05)
	B*D*length	-1.77e-05**	-3.00e-05***	-3.64e-05***	-5.84e-05***	3.03e-05	5.09e-05*
		(7.99e-06)	(1.09e-05)	(1.01e-05)	(1.44e-05)	(1.97e-05)	(2.63e-05)
	B*D*(sop*length)	-1.50e-07***	-1.38e-07***	9.12e-08	1.88e-07*	-2.01e-07***	-2.19e-07***
		(2.74e-08)	(3.31e-08)	(7.52e-08)	(1.13e-07)	(3.77e-08)	(5.50e-08)
Defence_type [3]	B*D*embankment	-0.0130**	-0.00368	-0.0146**	-0.0139	-0.0162	0.0184
		(0.00587)	(0.00822)	(0.00689)	(0.00973)	(0.0119)	(0.0162)
	B*D*bridgeabt	-0.0497	-0.0522	-0.0709	-0.0493	-0.0347	-0.0481
		(0.0483)	(0.0505)	(0.0725)	(0.0712)	(0.0644)	(0.0689)
	B*D*highground	-0.00832	-0.00296	-0.00644	-0.00557	0.0854**	0.0721**
		(0.0121)	(0.0164)	(0.0132)	(0.0180)	(0.0387)	(0.0349)
	B*D*demount	-0.0694***	-0.0528*	-0.0712***	-0.0619**	-0.0688**	-0.0648
		(0.0180)	(0.0271)	(0.0220)	(0.0313)	(0.0301)	(0.0539)
	B*D*floodgate	-0.0125	0.0200	-0.0207	0.0153	0.0682***	0.0321
		(0.0137)	(0.0219)	(0.0164)	(0.0281)	(0.0252)	(0.0388)
Flood_ perception	B*D*months(sqrt) [4]	-0.00124***	-0.00232***	-0.00150***	-0.00276***	0.00200*	0.00190
		(0.000425)	(0.000631)	(0.000477)	(0.000749)	(0.00107)	(0.00134)
	B*D*duration	9.93e-05***	0.000127**	0.000116***	0.000159**	0.000242	0.000420*
		(3.45e-05)	(5.37e-05)	(3.91e-05)	(6.31e-05)	(0.000153)	(0.000239)
	B*D*months(sqrt)[4]*duration	7.45e-06***	9.63e-06**	3.93e-06	4.97e-06	-4.43e-06	-1.27e-05
		(2.85e-06)	(4.34e-06)	(3.66e-06)	(5.77e-06)	(8.15e-06)	(1.23e-05)

(Continued)

Table 2.4.Continue

Lyear (s)	-0.000421***	-8.34e-05	-0.000389***	0.000154*	-0.00174***	-0.00243***
	(2.98e-05)	(7.69e-05)	(3.16e-05)	(8.25e-05)	(9.44e-05)	(0.000218)
Year (t)	0.000473***	0.000116	0.000442***	-0.000121	0.00178***	0.00247***
	(2.98e-05)	(7.67e-05)	(3.15e-05)	(8.23e-05)	(9.41e-05)	(0.000217)
Observations	7,217,966	1,135,690	6,666,999	1,028,887	550,967	106,803
Treated Obs.	14,716	7,417	10,886	5,180	3,830	2,237
County FE	YES	YES	YES	YES	YES	YES
R-squared	0.111	0.110	0.111	0.108	0.127	0.155

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] The area impacted by the construction of a flood defence has been approximated as the 5-digit postcode area where the defence was constructed.

[2] Omitted categories are dummy variables for detached property, urban location and fluvial flood risk.

[3] The omitted category is a dummy variable for floodwall.

[4] Square root of the number of months since the previous flood with respect to the second sale.

For the case of fluvial flood defences in column (4) the coefficient on the variable *B*Defence* indicates that properties in urban areas exposed to fluvial flood risk and that were impacted by the construction of a floodwall were resold, on average, at a price 5.7% higher than those properties where the level of exposure to flood risk remained unchanged. The coefficient is only significant at the 10% significance level. This result might be interpreted as the WTP of homeowners to acquire the treatment state, i.e. a reduced level of flood risk (an average change in the standard of protection of 100 year return period). This effect does not consider the design characteristics of the structure or differences of flood risk perception that might result in different capitalisation rates, as detailed below.

The capitalisation of fluvial flood defences (column (4)) is not significantly different across different type of houses (semi-detached and terraced). For the case of flats, however, there is a significant effect in an opposite direction which outweighs the benefits associated with flood protection to houses with an overall effect close to zero (*B*Defence – B*D*Flat*). There are two potential reasons that can explain these contrasting results. First, it seems reasonable to expect a higher capitalisation of benefits for ground level properties as they are more exposed to flood damages. A house that is affected by flooding is likely to experience a whole range of direct and indirect, tangible and intangible, damages, whereas a flat located above ground level is usually only expected to experience indirect damages. This difference in future averted damages for different type of properties is likely to be reflected in different capitalisation rates in the housing market

The second reason is related to a change in the sorting process of individuals in the housing market. In locations which are known to be exposed to flood risk, individuals might have a preference to buy properties located above ground level to minimise expected damages in the event of a flood, pushing the price of these properties up. The construction of a flood defence changes the pre-existing conditions of flood risk in which individuals take decisions. After the construction of the defence ground floor properties are only exposed to the associated residual and failure risk. This change can lead to a resorting of individuals in the housing market pushing the demand of ground level properties up and that of flats down, accompanied by a corresponding change in prices. The interaction of these two effects implies that the construction of flood defences can potentially result in a decrease in the price of flats if the effect of the shift in demand towards ground level property is greater than the perceived benefits of the construction of flood defences for above ground level properties (which are likely to be small).

The coefficient on the variable *B*D*rural* in column (4), also indicates a lower capitalisation of flood defences constructed in rural areas compared to those constructed in urban regions. This result can be explained by differences in the negative amenity and environmental impacts associated with the disruption of the local environment. As mentioned before, authors such as Penning-Rowsell and Fordham (1994), Lee and Li (2009), Phillips (2011) and Penning-Rowsell et al. (2014) emphasise that the construction of flood defences can result on negative impacts on visual amenity, biodiversity and recreational values. Although these negative impacts are expected in both, rural and urban areas, they are likely to be higher in rural locations that offer greater natural environmental amenities and where the individuals can have a higher preference to keep the environment undisrupted. Other characteristics such as the length of the contract (*B*D*free*) (freehold/leasehold) and the price quartile of the property (*B*D*quartile*) do not appear to have a significant effect.

The design characteristics of the defence also play a significant role in determining the extent to which defences capitalise into property prices. The results in column (4) indicate that increasing the dimensions – height (*B*D*sop*) or length (*B*D*length*) – of the structure providing flood protection results in lower benefits to households. Although this might appear counterintuitive, we believe that it reflects the negative environmental and amenity impacts associated with structural flood protection. The results imply that the flood alleviation scheme which maximises the benefits is not the one which provides the maximum protection at the lowest cost, as the AFI methodology for benefit estimation suggests. Instead, as Penning-Rowsell et al. (2014) emphasises, there appears to be a trade-off for households between flood protection and amenity loss. The variables in table 2.4 also include an interaction term of the standard of protection and length (*B*D*(sop*length)*) to capture any composite effect associated with increasing the area of the structure. The coefficient on this variable is positive, which might capture the positive benefits associated with increased flood protection, although it is small and barely significant. Overall, the average design characteristics of a fluvial flood defence (105-year standard of protection and 313 meters long) result in a capitalisation rate 2% lower than it would otherwise be if there were not negative impacts associated with the construction of defences.

The coefficients on the group of variables controlling for differences in the type of defence (*Defence_type*) suggest that the type of flood defence does not appear to play a significant role (table 2.4, column (4)). This implies that the benefits of structural flood protection do not depend on the type of structure but on its design characteristics. The only one exception is the case of demountable flood defences (*B*D*demount*). According to the coefficient in column (4) of table 2.4, the construction of this type of defences result in a negative capitalisation rate around 6%. This outweighs the benefits associated with the construction of other type of defences (*B*Defence* = 5.7%). Although, in most cases, the use of demountable defences avoids the visual intrusion and loss of amenity that a permanent defence would entail, the results suggest that they possess characteristics that might result undesirable. A distinctive characteristic of these defences is that they require the construction of built-in foundations on top of which the defences are installed in the event of a flood warning. We suggest that these two factors drive the negative capitalisation rate. First, the foundations are permanent and visible, making evident a risk that would otherwise remain hidden, and also making evident that there is no permanent protection against this risk. Second, the deployment of demountable flood defences requires sufficient advance flood warning, and therefore there is always a risk that the defence elements are not deployed in time to avert flooding.[11] The interaction of these characteristics is likely to result in a decreased feeling of flood safety and enhanced flood risk perception.

Finally, the set of variables controlling for differences in flood risk perception (*Flood_perception*) are highly significant and have the expected sign. A recent discussion

[11] In fact, this was the case in Upton-on-Severn, England, during July 2007, when a delay of the delivery of the components of a demountable defence due to the disruption to transport infrastructure resulted in considerable flood damage (Ackers, Rickard, and Gill 2009).

by Atreya, Ferreira and Kriesel (2013) and Bin and Landry (2013) suggests that the effect of flooding on property prices decreases after a flood following a non-linear functional form. As the authors suggest, our model in table 2.4 includes the square root of the number of months with respect to the previous flood for properties benefited by the construction of a defence (*B*D*months(sqrt)*).[12] As expected, the coefficient on this variable indicates that the capitalisation of flood defences is larger in locations which have experienced flooding more recently. This implies that individuals in locations with greater flood risk perception are willing to pay more for flood risk protection. This price premium decreases in time as flood risk perception decreases and individuals tend to forget the risk of flooding. This result is in line with the idea of availability heuristic in risk perception suggested by Tversky and Kahneman (1973).

The results in column (4) also show that the capitalisation of defences is greater in locations which were more severely affected by flooding. This is measured by the number of days that the location remained flooded (*B*D*duration*). In general, the results suggest that the capitalisation of flood defences is greater for properties exposed to more recent and more severe flooding. We believe that these results reflect a price premium that people are WTP for flood protection in locations with increased flood risk perception. A variable interacting time since the previous flood and the duration of the event (*B*D*months(sqrt)*duration*) is not significant. These results are robust to other linear and non-linear functional forms of the time variable.

[12] The results are robust to other linear and non-linear functional forms of the time variable. The results for these specifications are available from the authors upon request.

2.6.1.1 Coastal flood defences

Column (6) in table 2.4 shows our preferred results regarding the capitalisation of coastal flood defences. The interpretation of coefficients is similar to that of fluvial defences. However, there are important differences in the results that are worth mentioning. The results suggest that the capitalisation of defences in coastal areas is mainly driven by those properties bought on a freehold contract. The coefficient on the variable *B*D*free* indicates that freehold properties that benefit from the construction of flood defences are sold at a price 11% higher than properties sold on leasehold. In principle, this result suggests that significant differences in the capitalisation of flood defences arise in the housing market due to differences in the duration of the contract. However, we suggest that it rather reflects differences in the capitalisation rate for different types of properties. This is because 98% of houses (detached, semi-detached and terraced) are sold on freehold, while 90% of the flats have a leasehold contract. Therefore, in practice the variable identifying freehold properties seems to capture differences in the capitalisation of the benefits of flood protection for houses and flats. After controlling for freehold/leasehold properties, there are no significant differences for semi-detached and detached houses. However, the capitalisation is significantly lower for terraced properties (*B*D*terraced*). As with fluvial defences, there appears to be no significant capitalisation of coastal defences on the price of flats (*B*Defence* + *B*D*flat*).

Similar to what we observed for fluvial defences, the capitalisation of coastal defences in rural areas (*B*D*rural*) is lower than in urban coastal areas. Again, we associate this negative impact with environmental disruption and loss of amenities. However, in coastal areas the negative effect is greater and outweighs the positive effect of the defence (*B*D*free* – *B*D*rural*). This can be explained because proximity to coastal water is usually associated with substantial amenity values. For instance, direct access to the beach or a seafront view tend to be highly valued in the housing market. These amenities can be significantly diminished or lost with the construction of coastal defences. Therefore, in rural coastal areas the value that individuals place on the loss of amenities and environmental impacts associated with defences might exceed the perceived, or real, benefits of flood risk reduction.

The coefficient for the variable *B*D*quartile* in column (6) suggests that the capitalisation of defences in coastal areas is significantly lower for more expensive houses. The sign of this coefficient is similar to the one observed for fluvial defences; however, it is only significant for coastal properties. We suggest that this negative effect is associated with increasing marginal negative effects of flood defences for more valued properties. That is, buyers of more expensive properties might place a higher value on the negative effects associated with defences. For instance, owners of highly valued properties might have a higher preference for soft and non-intrusive flood protection measures such as flood insurance and property level protection.

The effect of the design characteristics (*Defence_design*) of coastal defences on property prices (table 2.4, column (6)) is similar to that of fluvial defences. The net effect associated with the average design characteristics of a coastal defence (338-year standard of protection and 456 meters long) result in a capitalisation rate 5% lower than it would otherwise be if there were no negative effects associated with its dimensions. Notice that the marginal negative effect of increasing the standard of protection (*B*D*sop*) is greater for coastal defences, while the effect of the length (*B*D*length*) and the interaction effect (*B*D*(sop*length)* have opposite signs.

In general, the capitalisation of coastal defences on property prices does not vary across different types of defences (*Defence_type*). There is, however, one exception. The results suggest that the construction of one type of defences defined as 'high ground' results in significantly higher capitalisation rates (*B*D*highground*).[13] However, it is important to be cautious when interpreting this result. Our dataset includes only one of such defences constructed in coastal regions. The defence is located in the Isle of Portland, in Dorset County, and the coefficient refers to only 252 properties located within the area impacted by the defence. Therefore it is likely that this result is driven by specific characteristics of the region, rather than the type of the defence. Interestingly, differences in flood risk perception (*Flood_perception*) are not significant in determining the capitalisation of coastal defences.

It is important to note that in both cases, fluvial and coastal defences, the coefficient driving the capitalisation of defences on property prices is only significant at the 10% significance level. We hypothesised that the low significance of our main results might be related with the use of a broad definition of the area impacted by flood defences, i.e. our definition of the treatment group. As explained before, for our results in table 2.4 we define the area impacted by defences as the 5-digit postcode area where the defence is constructed. In the following section we present the results of the same set of regressions as in table 2.4, but we now define the area impacted by flood defences as the 6-digit postcode area where the defence is located. That is, we now focus on a much smaller area which is unlikely to include any properties not directly benefiting from a reduction in the risk of flooding. The Map A2.1 in the appendix shows an example comparing the spatial extent of a 5-digit and 6-digit postcode area for an embankment constructed in Oxfordshire.

[13] High ground defences include flood relief channels, raised roads and bank protections.

2.6.2 Treatment group: 6-digit postcode area

In this section, we estimate again the six models presented in table 2.4, but the area impacted by defences is now defined as the 6-digit postcode (full postcode) area where the defence is located. The idea is to identify the capitalisation of flood defences only for those properties which are in the immediately surrounding area of the defence.[14] These properties are the ones located closest to the source of flooding, and therefore the ones likely to receive the greatest benefits from flood protection per se. Thus, with this new definition for the treatment group we expect to find different capitalisation rates. An inevitable consequence of this approach, however, is the reduction in the number of treated observations. The results for this new set of regressions appear in table 2.5 below.

2.6.2.1 Fluvial flood defences

For the case of fluvial defences (column (4), table 2.5) the capitalisation of flood defences, measured by the variable *B*Defence,* is around 15% with a highly significant coefficient. This is almost three times higher than the one we observed in table 2.4 (6%) with our previous definition of the treatment group. Again, the capitalisation of defences does not appear to be significantly different across different type of houses (detached, semi-detached, terraced) in areas exposed to high levels of risk. Nevertheless, for the case of flats we observe a much lower capitalisation rate (*B*Defence* + *B*D*flat* = 1%). This is similar to the results that we observed in table 2.4. In this case, however, the negative coefficient on the variable *B*D*flat* does not completely outweigh the capitalisation for houses (*B*Defence*). Therefore, we observe a positive capitalisation of defences in the price of flats close to 1% in areas exposed to significant flood risk.

[14] Postcode units in the UK consist of an average of 17 houses grouped together.

Table 2.5. Repeat-sales model: The effect of flood defences on property prices
(*Area impacted: 6-digit postcode*) [1]

	Variables	(1) All estimates	(2) All estimates FP	(3) Fluvial risk	(4) Fluvial risk FP	(5) Coastal risk	(6) Coastal risk FP
	Bracket sample						
	Bracket (B)	0.147***	0.185***	0.165***	0.201***	0.195***	0.267***
		(0.00153)	(0.00424)	(0.00167)	(0.00472)	(0.00498)	(0.0114)
(A) *House_type* [2]	B*sdetached	-0.0109***	-0.0286***	-0.0161***	-0.0319***	-0.0263***	-0.0461***
		(0.000639)	(0.00167)	(0.000734)	(0.00197)	(0.00140)	(0.00334)
	B*terraced	-0.0299***	-0.0488***	-0.0408***	-0.0589***	-0.0395***	-0.0636***
		(0.000673)	(0.00173)	(0.000792)	(0.00209)	(0.00145)	(0.00344)
	B*flat	-0.0313***	-0.0647***	-0.0531***	-0.0872***	-0.00504	-0.0579***
		(0.00142)	(0.00392)	(0.00155)	(0.00436)	(0.00435)	(0.00973)
	B*free	0.0510***	0.0419***	0.0490***	0.0413***	0.0866***	0.0637***
		(0.00126)	(0.00355)	(0.00132)	(0.00385)	(0.00418)	(0.00917)
	B*rural	0.0241***	0.0444***	0.0261***	0.0464***	0.0300***	0.0500***
		(0.000564)	(0.00133)	(0.000630)	(0.00155)	(0.00132)	(0.00276)
	B*coastal	0.0172***	0.0189***				
		(0.000442)	(0.00104)				
	B*quartile	-0.0633***	-0.0702***	-0.0706***	-0.0778***	-0.0679***	-0.0787***
		(0.000276)	(0.000704)	(0.000332)	(0.000884)	(0.000693)	(0.00159)
	Bracket-defence sample						
	B*Defence (D)	**0.195*** **	**0.172*** **	**0.172*** **	**0.155*** **	**0.130**	**0.0709**
		(0.0409)	**(0.0419)**	**(0.0482)**	**(0.0490)**	**(0.0788)**	**(0.0802)**
(B) *House_type* [2]	B*D*sdetached	-0.0293	-0.0100	0.00392	0.0204	-0.0584	-0.0374
		(0.0211)	(0.0217)	(0.0258)	(0.0266)	(0.0363)	(0.0367)
	B*D*terraced	-0.0662***	-0.0472**	-0.0374	-0.0218	-0.110***	-0.0948**
		(0.0231)	(0.0237)	(0.0288)	(0.0294)	(0.0394)	(0.0403)
	B*D*flat	-0.198***	-0.170***	-0.172***	-0.146***	-0.113*	-0.0662
		(0.0337)	(0.0340)	(0.0384)	(0.0387)	(0.0607)	(0.0624)
	B*D*free	-0.0226	-0.0205	-0.0375	-0.0380	0.104**	0.128**
		(0.0273)	(0.0279)	(0.0299)	(0.0306)	(0.0491)	(0.0503)
	B*D*rural	-0.0141	-0.0423***	0.0149	-0.0152	-0.0460*	-0.0608**
		(0.0152)	(0.0155)	(0.0193)	(0.0195)	(0.0237)	(0.0240)
	B*D*coastal	0.0144	0.0119				
		(0.0163)	(0.0166)				
	B*D*quartile	-0.0356***	-0.0303***	-0.0251**	-0.0205	-0.0527***	-0.0455**
		(0.0101)	(0.0103)	(0.0127)	(0.0128)	(0.0179)	(0.0182)
Defence_ design	B*D*sop	8.39e-05	7.93e-05	-6.29e-05	-6.73e-05	0.000388***	0.000380***
		(6.91e-05)	(6.92e-05)	(4.90e-05)	(4.89e-05)	(0.000144)	(0.000145)
	B*D*length	-2.03e-05	-1.76e-05	-3.80e-05	-3.40e-05	3.08e-05	3.34e-05
		(2.45e-05)	(2.46e-05)	(2.42e-05)	(2.43e-05)	(6.81e-05)	(7.00e-05)
	B*D*(sop*length)	7.00e-09	1.99e-08	3.26e-07	3.44e-07	-1.09e-06**	-1.09e-06**
		(2.28e-07)	(2.29e-07)	(2.12e-07)	(2.12e-07)	(5.14e-07)	(5.14e-07)
Defence_type [3]	B*D*embankment	-0.00786	-0.00370	-0.00295	0.00132	-0.0382	-0.0305
		(0.0156)	(0.0159)	(0.0186)	(0.0189)	(0.0299)	(0.0299)
	B*D*bridgeabt	-	-	-	-	-	-
	B*D*highground	-0.0288	-0.0274	-0.0411	-0.0401	-0.00467	0.0357
		(0.0258)	(0.0269)	(0.0286)	(0.0286)	(0.0478)	(0.0757)
	B*D*demount	0.0246	0.0299	0.0139	0.0236	-0.0419	-0.0592
		(0.0487)	(0.0485)	(0.0568)	(0.0565)	(0.0858)	(0.0866)
	B*D*floodgate	0.0366	0.0382	-0.0840	-0.0810	0.208	0.192
		(0.0742)	(0.0743)	(0.0533)	(0.0537)	(0.155)	(0.154)
Flood_ perception	B*D*months(sqrt) [4]	-0.00282***	-0.00310***	-0.00297***	-0.00317***	-0.000448	-0.000486
		(0.000947)	(0.000962)	(0.00114)	(0.00115)	(0.00182)	(0.00182)
	B*D*duration	0.000234**	0.000215*	0.000302**	0.000292**	-0.000751*	-0.000825**
		(0.000111)	(0.000112)	(0.000132)	(0.000132)	(0.000388)	(0.000399)
	B*D*months(sqrt)[4]*duration	3.79e-06	5.49e-06	-5.00e-06	-4.57e-06	5.22e-05**	5.54e-05**
		(8.37e-06)	(8.44e-06)	(1.11e-05)	(1.11e-05)	(2.18e-05)	(2.26e-05)

(Continued)

Table 2.5.Continue

Lyear (s)	-0.000426***	-9.99e-05	-0.000395***	0.000139*	-0.00175***	-0.00244***
	(2.98e-05)	(7.68e-05)	(3.16e-05)	(8.25e-05)	(9.43e-05)	(0.000217)
Year (t)	0.000478***	0.000132*	0.000447***	-0.000106	0.00179***	0.00248***
	(2.97e-05)	(7.66e-05)	(3.15e-05)	(8.23e-05)	(9.40e-05)	(0.000217)
Observations	7,217,966	1,135,690	6,666,999	1,028,887	550,967	106,803
Treated Obs.	1,824	1,794	1,331	1,309	493	485
County FE	YES	YES	YES	YES	YES	YES
R-squared	0.112	0.111	0.112	0.108	0.127	0.156

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] The area impacted by the construction of a flood defence has been approximated as the 6-digit postcode area where the defence was constructed.

[2] Omitted categories are dummy variables for detached property, urban location and fluvial flood risk.

[3] The omitted category is a dummy variable for floodwall.

[4] Square root of the number of months since the previous flood with respect to the second sale.

Comparing the results for fluvial defences (column (4)) in tables 2.4 and 2.5, it is also important to highlight the loss in significance of the variables that were previously associated with the negative environmental and amenity impacts. These variables are: the capitalisation of coastal defences in rural areas (*B*D*rural*) and the effect of the design characteristics of defences (*B*D*sop, B*D*length, B*D*(sop*length)*). In table 2.5, the coefficients keep the same sign as in table 2.4, but when we look at properties located closest to the defence (table 2.5) these are no longer significant. We associate this difference in the significance of results with spatial differences in the relative preferences for flood risk reduction and environmental damage as households locate closer to the source of flooding. This implies that individuals exposed to more severe flooding (those located closest to the source of flooding) place a higher value in the benefits of flood risk reduction associated with defences rather than in their negative environmental impacts. That is, the trade-off between flood protection and amenity loss is different for individuals exposed to different levels of risk.

2.6.2.2 Coastal flood defences

The results for the capitalisation of coastal defences in the price of properties located closest to the sea (column (6), table 2.5) tell a similar story. There are, however, important differences to highlight. As before, the main capitalisation of defences in coastal areas is driven by properties sold on a freehold contract (*B*D*free*). As we explained before, due to the composition of the sample regarding the type of contract this variable is likely to reflect differences in the capitalisation of defences for houses and flats. In this sense, the results in table 2.5 suggest that houses exposed to significant flood risk in coastal areas and that benefit from the construction of flood defences are sold at a price 13% higher than properties where the level of flood risk remained unchanged. This result is 1% higher than what we found with our previous definition of the treatment group (column (6), table 2.4), and is close to the capitalisation rate of 15% that we observed for properties located closest to the construction of fluvial defences (column (4), table 2.5). As before, there appears to be no significant capitalisation of defences on the price of flats in coastal areas, and there is a lower capitalisation rate for terraced properties (*B*D*terraced*) and highly valued houses (*B*D*quartile*).

There are also differences to highlight related to the environmental and amenity impact of defences for properties exposed to significant coastal flood risk (table 2.5). Results of column (6) in tables 2.4 and 2.5 suggest that the capitalisation of coastal defences in rural areas is significantly lower compared to urban regions (*B*D*rural*). In both cases, we associate this result to the environmental disruption of defences in coastal rural areas, where individuals are likely to place a higher value in conserving environmental amenities. For the results in table 2.4 where we use a broad definition of the area impacted by defences, the negative effect for rural areas outweighs the positive capitalisation of defences found for urban properties (*B*D*free – B*D*rural = -0.5%*). However, in table 2.5 where we focus only on the group of properties closest to the defence, this negative effect is smaller but does not outweigh the capitalisation in urban areas (*B*D*free - B*D*rural= 7%*).

These results show something similar to what we observed for the capitalisation of fluvial defences. Individuals located closer to the source of flooding appear to place a higher value on the benefits of flood risk reduction than in the environmental disruption of defences. However, in contrast to the results for fluvial defences, the capitalisation of coastal defences in rural areas is still significantly lower even when looking only at those properties located closest to the source of flooding. We believe that this difference in the capitalisation of fluvial and coastal defences in high risk rural areas occurs due to the substantial amenities associated with proximity to coastal waters such as direct access to the beach or seafront view, which tend to be highly valued in the housing market. Therefore, although households located closer to the sea might place a higher value on the benefits of risk reduction, the capitalisation of defences in rural areas is still significantly lower due to the loss of highly valued amenities.

We reach a similar conclusion when comparing the results in tables 2.4 and 2.5 for the effect of the design characteristics of defences in coastal areas (column (6), variables *B*D*sop*, *B*D*length*, *B*D*(sop*length)*). For properties located closest to the defence (column (6), table 2.5) there is still a significant negative effect associated to the average dimensions of a defence which result in a 4% lower capitalisation. Again, we interpret this reduction in the negative effect of increasing the dimensions of the structure with spatial differences in the relative preferences for flood protection and amenity loss as individuals locate closer to the source of risk. However, this result contrasts with what we observe for the case of fluvial defences (column (4), table 2.5) where the negative effects associated with the dimensions of the defence are no longer significant when looking at highly exposed properties. We believe that this difference in the capitalisation of the design characteristics for fluvial and coastal defences is also associated with the significant amenity loss in coastal areas, causing a lower capitalisation rate even for highly exposed properties.

Overall, we suggest that our results indicate differentiated trade-off rates between flood protection and amenity loss in two dimensions: first, a different trade-off for fluvial and coastal defences, where amenity loss appears to have a higher weight in coastal areas; and second, a spatial difference in the trade-off rate for properties in ‘high risk’ (6-digit postcode) and ‘low risk’ (5-digit postcode) areas, where flood protection appears to have a higher weight in highly exposed areas. Notice that this is only an *ad-hoc* classification based on the proximity of the properties to the defence to facilitate the interpretation and comparison of our results, and it might not correspond to an accurate description of the level of risk. These differences remain an area of further research. Section A2.1 of the appendix shows additional robustness tests.

2.7 Interpretation of Results

From the results in tables 2.4 and 2.5 (columns (4) and (6)) it is possible to estimate the net effect of the construction of flood defences for different types of risk, different types of properties (house/flat – urban/rural) and different levels of risk, by substituting the average design characteristics of fluvial and coastal, as well as the average values for the variables controlling for differences in flood risk perception (see table A2.1 of the appendix)[15]. The results appear in table 2.6 below. For the case of flats we only report estimates for urban areas as most of the flats are located in these regions. The proportion of flats in rural areas only represents about 5% of the total rural housing stock included in the sample. The monetary values were calculated considering the average price of each relevant property type and they represent the net present value discounted in perpetuity of all future benefits/disbenefits (direct/indirect – tangible/intangible) derived from the construction of flood defences. All Values appear in July 2014 GBP (£).

The results suggest that the overall effect of the construction of flood defences on property prices can be either positive or negative, ranging from a price increase around 13% for houses in high risk (6-digit) urban areas protected against fluvial flooding, to a decrease of -5% for flats in low risk (5-digit) urban areas. In general, the extent to which flood defences capitalise into the price of properties depends on characteristics such as the level of risk, the type of property and the type of risk. Houses in urban areas are benefited by a price increase that ranges from 1% to 13%, for a median-priced house in 2014 this represents £2,000 to £30,000. As expected, the benefits are greater for houses exposed to a high level of risk, for which the capitalisation rate is 13% and 9% for houses exposed to fluvial and coastal flood risk, respectively. Notice, however, that in low-risk urban areas the capitalisation of fluvial defences is lower than that of coastal defences. These results suggest that the benefits of flood protection decrease as houses are located further away from the source of risk, and that this effect is more pronounced for properties exposed to fluvial flooding.

[15] For areas exposed to fluvial flood risk, there is an average of 188 months with respect to the previous flood, with and average duration of 58 days. For areas exposed to coastal flood risk, the average months with respect to the previous flood is 177 months, with an average duration of 32 days.

Table 2.6. Capitalisation of flood defences on house prices in England, 1996-2014
(*Capitalisation rates in parentheses*)

	Type of property		Fluvial risk	Coastal risk
Low risk (5-digit)	**House**	**Urban**	£2,059 (0.9%)	£20,521 (7.5%)
		Rural	-£2,974 (-1.3%)	-£10,945 (-4.0%)
	Flat	**Urban**	-£9,505 (-5.0%)	-£6,845 (-3.6%)
High risk (6-digit)	**House**	**Urban**	£29,287 (12.8%)	£23,531 (8.6%)
		Rural	£25,855 (11.3%)	£6,840 (2.5%)
	Flat	**Urban**	-£3,333 (-1.8%)	-£7,986 (-4.2%)

Note: The monetary values are calculated using the sample average price of a house located in a fluvial or coastal flood risk area: £228,804 and £273,617, respectively. For the case of flats we use the average price of £190,142 for a flat located in a fluvial floor risk area. All prices are in July 2014 GBP.

For houses located in rural areas the sign of the capitalisation rate differs for low-risk and high-risk areas. In low-risk rural areas the construction of flood defences results in a price decrease of -1% and -4% for houses exposed to fluvial and coastal flooding, respectively, which for a median-priced house in 2014 is equivalent to a decrease of -£3,000 and -£11,000 in the price of the property. As mentioned before, we suggest that this negative effect is the result of the negative amenity and environmental impacts associated with the construction of flood defences in rural areas where the individuals might have a higher preference to keep the environment undisrupted. The discount is higher in coastal areas where the construction of flood defences might result in loss of highly valued amenities. In general, the results suggest that in low-risk rural areas the negative impacts of flood defences might outweigh the benefits of flood protection. However, in high-risk rural areas the benefits of flood protection appear to be higher than the negative effects associated with amenity loss, which results in higher house prices. For fluvial flood risk the capitalisation rate is around 11% (£26,000) and is comparable to the benefits of flood protection in urban areas, whereas for coastal flood risk it is around 3% (£7,000), which is 5% lower than that in urban areas.

Finally, the construction of flood defences result in a decrease in the price of flats that ranges from -2% to -5%, which for a median-priced flat in 2014 represents a real price decrease between -£3,000 and -£10,000. In areas exposed to fluvial flood risk the discount is greater in low-risk areas than in high-risk areas, whereas in coastal areas it is close to -4% regardless of the level of risk. In both cases, we suggest that the negative capitalisation rate for flats is the result of two effects that have been mentioned before: lower benefits from flood protection for properties located above ground coupled with a loss of environmental amenities, and a resorting of individuals in the housing market after the construction of a defence increasing the demand for ground level properties.

To summarise, the results suggest that the benefits of the construction of flood defences are capitalised into the price of the properties at a rate that ranges between 1% and 13%, depending on the level of risk, the type of risk and the type of property; for a median-priced house in 2014 these represent £2,000 to £30,000. However, there is evidence which suggest significant negative impacts of flood defences that ranges from a price discount of -1% to -9% (-£3,000 to -£10,000) for properties which are not directly affected by floods (flats), and in locations were defences may result in loss of significant amenity values (rural areas).

The results presented in this section are interpreted as individual’s WTP for the construction of structural flood defences. Shogren (1990) and Shogren and Crocker (1991) emphasise that the mechanism used to reduce risk is important to determine the welfare impact of flood protection. The construction of a flood defences represents a collective mechanism flood protection. However, individuals confronted with flood risk have a portfolio of ex-ante reduction mechanisms to decrease the probability and severity of an ex-post monetary or non-monetary loss, including both self-protection and self-insurance (Shogren, 1990). Shogren and Crocker (1991) emphasise that the existence of alternative mechanisms for self-protection (or self-insurance) influence individuals' WTP for collective protection mechanisms (such as the construction of flood defences). The authors suggest that individuals place a significantly greater value on private mechanisms than collective mechanisms for risk reduction. This implies that our results should only be interpreted as the individuals' WTP for structural flood protection, and not the value that individuals place on flood risk reduction. Different alternative for flood protection might be valued in a different way. The comparison of individual's WTP for alternative measures of flood protection remains an area of future research.

Our results represent the net present value discounted in perpetuity of all future benefits/disbenefits (direct/indirect – tangible/intangible) derived from the construction of flood defences. With our current specification it is not possible to disentangle the value of changes in the level of flood risk from the value of changes in the amenity value of proximity to water bodies induced by the construction of flood protection. Identifying these two effects separately would require to include in our model variables that measure the extent to which the construction of flood protection affects the environmental amenities in the area where the defence was constructed. These might include variables measuring changes in visibility or biodiversity impacts due to the construction of structural flood defences. Such strategy would allow us to disentangle the value of the amenity impacts of flood defences from the benefits of flood protection.

The results suggest that under specific circumstances individuals are willing to pay for the construction of structural flood protection. However, as it has been noted, individuals confronted with flood risk have a portfolio of ex-ante reduction mechanisms to decrease the probability and severity of an ex-post monetary or non-monetary loss. One of these alternatives is that individuals can decide to buy an insurance policy to avoid the risk of potential financial loss. In the UK, a highly competitive insurance market allows individuals to buy flood insurance at a competitive rate. Furthermore, flood insurance is often one important requisite to get a mortgage to buy a property in the floodplain (Lamond, Proverbs and Hammond, 2009). Despite the fact that the majority of homeowners inside the floodplain can be expected to have a flood insurance policy, the evidence still reveals significant positive WTP for structural flood protection. This indicates that structural flood protection is perceived to provide additional benefits to the ones provided by flood insurance. In other words, the market of flood insurance fails to completely eliminate the negative externalities associated with flooding such that government intervention is justified in the form of the construction of structural flood protection. Flood insurance leads to only a mitigation of financial losses associated to flood risk rather than an elimination of the risk (Harrison, Smersh and Schwartz, 2001). If the payment from the insurer is perceived to be less than the loss from flooding the individual will be WTP for additional flood additional mechanisms of flood protection. This difference might arise due to the existence of non-insurable costs associated with flooding, including disruption of normal life and loss of items with sentimental value, psychological stress to residents and hassle and deprivation of being displaced.

The following section compares our results with the residential benefit assessment of flood alleviation schemes suggested by the *Multi-Coloured Manual* (Penning-Rowsell et al., 2014), and with the benefit estimates of FCERM capital projects suggested by Defra for the purpose of funding allocation (Defra, 2011).

2.8 Discussion: The MCM and the FCRPF

In the UK, the Government – via Defra and the EA – requires the use of the AFI method to assess the economic benefits of all publicly funded strategies to reduce potential economic flood and erosion damages within England and Wales (EA, 2010; Penning-Rowsell et al., 2014). The guidance and data for the implementation of this method is detailed in the *Flood and Coastal Erosion Risk Management Appraisal Guidance* (FCERM-AG) (EA, 2010) and the 2013 edition of the *Flood and Coastal Erosion Risk Management: A Manual for Economic Appraisal*, also referred as the *Multi-Coloured Manual* (MCM) (Penning-Rowsell et al., 2014). Regarding the appraisal of flood damages to residential properties, chapters 3 and 4 of the MCM details the methodology and assumptions that are used to compile the data on direct and indirect flood damages and to construct the depth/damage and loss/probability relationships; it also provides advice on how to incorporate intangible damages into the analysis. In what follows, we cite extensively the methodology described in the MCM, therefore appendix A4 of this chapter presents a summary of this methodology to facilitate the reader's understanding of the discussion.[16]

The MCM estimates the weighted annual average damage (WAAD) to the average house with no flood warning and no flood protection to be on the order of £4,728 (2013 GBP) (see table A2.4 of the appendix).[17] This value considers only direct damages to properties that result from the occurrence of a flood event.[18] Using the information from the MCM that appears in table A2.4 of the appendix, we calculate the present value lifetime benefits

[16] The depth/damage data is accessible in an on-line platform known as the MCM-Online (http://www.mcm-online.co.uk/), upon the payment of the corresponding license.
[17] This figure is based on estimates of total weighted damage per return period that considers flood events with a different range of depths. For more details see section A2.2 of the appendix.
[18] The MCM (Penning-Rowsell et al., 2014) also provides guidelines for the quantification of indirect and intangible damages. For more details see section A2.2 of the appendix.

to homeowners that result from reducing the level of exposure to flooding. This calculation involves four steps that are illustrated in equations (21), (22) and (23), below. First, equation (21) estimates the per property expected annual damage (*EAD*) at time *s*, before the construction of the flood relief project, by multiplying the value of the expected direct damage (*EDD*) from flood events with different return periods (*rtn*) from table A2.4 in the appendix, by its respective annual probability of occurrence (1/*rtn*). In a similar way, it is possible to estimate the *EAD* at time *t*, after the construction of the project, for properties at different levels of risk. In equation (22) we estimate the stream of expected annual benefits (*EAB*) as the reduction in annual expected damage per property protected based on moving a single house to lower levels of risk. Finally, in equation (23) we estimate the present value benefits (PVB) of risk reduction by discounting the *EAB* in perpetuity using the standard discount rate of 3.5% suggested by the Treasury 'Green Book' (HM Treasury, 2003) for the appraisal of public capital projects, and time-adjusted to July 2014 GBP values using the general House Price Index from the Land Registry.

$$EDD_{rtn} \times \left(\frac{1}{rtn}\right) = AED_s \tag{21}$$

$$EAB = AED_s - AED_t \tag{22}$$

$$PVB_{2014} = \left(\frac{EAB}{0.035}\right) \times \left(\frac{HPI_{July\ 2014}}{HPI_{2013}}\right) \tag{23}$$

The results appear in table 2.7 below. The classification of the levels of risk from "*Very significant*" to "*Low*" correspond to that made by Defra in the FCRPF for the purpose of funding allocation.

Table 2.7. MCM: Direct benefits from flood risk reduction to residential property

Reduce level of risk [1] **From / to**	**Significant** (2.5%)	**Moderate** (1.0%)	**Low** (0.5%)	**Average**
Very significant (5.0%)	£32,593	£45,704	£52,909	£43,735
Significant		£13,111	£20,316	£16,714
Moderate			£7,205	£7,205
Low			-	-
Average				£22,551

Note: Values in parentheses correspond to the annual probability of flooding.
[1] The categories of risk are taken from Defra's FCRPF and have been adjusted from table A2.4 of the appendix as follows. *Very significant*: average damage for the regions with a 20% and 10% annual probability of flooding. *Significant*: average damage for the regions with a 4% and 2% annual probability of flooding. *Moderate*: damage for the region with a 1% annual probability of flooding. *Low*: damage for the region with a 0.5% annual probability of flooding.

Briefly, the results from the MCM in table 2.7 suggest that the average benefits of constructing a flood defence for a house exposed to the highest levels of risk (*very significant* risk) are close to £44,000, and can be lower or higher depending on the extent of the reduction in the level of risk, i.e. the standard of protection of the project. The magnitude of the benefits decreases for properties benefited by the construction of the defence but exposed to lower levels of risk. The results suggest that the average benefits for a property exposed to *significant* risk are close to £17,000 and for those exposed to moderate risk they decrease to £7,000. On average, the benefits of reducing the level of risk for a property are of the order of £23,000.

On the other hand, central government funding for FCERM capital projects is allocated via Defra on a project-by-project basis through the FCRPF following the guidelines described in the corresponding policy statement (see Defra, 2011). The amount of grant available for each project is determined according to a formula that combines the economic, social and environmental benefits delivered by the project, with a principle of 'payment for outcomes' (Defra, 2011; Penning-Rowsell and Pardoe, 2012a; Penning-Rowsell et al., 2014). One of the three major components to determine the total amount of funding available for a specific project is the value of the benefits for householders as a result of

FCERM project. These benefits are multiplied by the corresponding ‘payment rate’ per unit of outcome benefit achieved, determined by Defra in the FCRPF policy statement (Defra, 2011).

The benefits to householders from flood risk protection are defined in the FCRPF as the value of household damages being avoided as a result of the change in the annual chance of flooding resulting from the project. To estimate the benefits per property protected they follow a similar procedure as described in the MCM. However, for simplicity, they assume that whenever a flood occurs it causes £30,000 of damages per property, regardless of the return period of the flood. That is, they assume that the expected direct damage (*EDD*) in equation (21) is £30,000 and does not vary for floods with different return periods (*rtn*). Following this assumption, the expected annual damage (*EAD*) at time *s* and *t*, before and after the construction of the project, are calculated as in equation (21) based on the annual probability of flooding for houses at different levels of risk. The expected annual benefits (*EAB*) are then calculated following equation (22) as the reduction in *EAD* based on moving a single house to lower levels of risk. The resulting annual stream of benefits is then discounted according to the HM Treasury discounting rules (3.5% discount rate) and added to yield the present value benefits (*PVB*) to householders from flood risk protection.

Following these steps, table 2.8 below shows the benefits of flood risk reduction to householders determined by Defra for the purpose of funding allocation. These benefits correspond only to the outcome measure 2 (OM2) which is associated with the reduction in direct damages to residential properties and their contents.[19] Defra (2011) suggests to evaluate the annual benefits of FCERM projects over a 50-year lifetime period, however, for comparability of the results we discount the annual stream of benefits in perpetuity.

[19] Other outcome measures include the benefits to businesses, agricultural productivity and protection for natural and local infrastructure, as well as the environmental benefits of the project.

Following Defra (2011), we use the standard discount rate of 3.5% suggested by the Treasury 'Green Book' (HM Treasury 2003). The monetary values correspond to the current values applicable for the FCRPF for the period 2012-2015. The classification of the levels of risk from "*Very significant*" to "*Low*" is also in line with the FCRPF guidelines.

Table 2.8. FCRPF: Direct benefits from flood risk reduction to residential property

Reduce level of risk From / to	**Significant** (2.5%)	**Moderate** (1.0%)	**Low** (0.5%)	**Average**
Very significant (5.0%)	£21,429	£34,286	£38,571	£31,429
Significant		£12,857	£17,143	£15,000
Moderate			£4,286	£4,286
Low			-	
Average				£16,905

Note: Assume £30,000 damage per flood event, irrespective of the return period of the flood.

According to the methodology suggested by Defra in the FCRPF for the purpose of funding allocation, the average benefits form reducing the level of risk for a house exposed to the highest level of risk (*very significant* risk) are close to £31,000. The magnitude of the benefits decreases for properties benefited by the implementation of the project but exposed to lower levels of risk. The average benefits of reducing the level of risk exposure for a property are close to £17,000. Using the figures in table 2.8, it is possible to determine the total present value benefits (TPVB) to households of each project considering two things: the total number of houses benefited by the project, and the reduction in the level of risk for each property. Finally, the total amount of funding available for each project through Defra's FCRPF under OM2 is determined by multiplying the TPVB by the corresponding payment rates for protecting households. The payment rates vary for areas with different levels of deprivation as follows: 20% most deprived areas, 45p per £1 benefit; 21-40% most deprived areas 30p per £1 benefit; and for the 60% least deprived areas, 20p per £1 benefit.

Table 2.9 compares the average results from tables 2.7 and 2.8 with the results that we obtained from the econometric model for fluvial and coastal defences (table 2.6). In this comparison, we focus only on the positive benefit estimates from table 2.6. Columns (1) and (2) of table 2.9 show the results from the econometric model for fluvial and coastal defences, respectively, and columns (3) and (4) show the corresponding benefits of flood defences using the methodology described in the MCM and FCRPF, respectively. In order to make comparable our results from the econometric model (columns (1) and (2)) with the categories of risk of the MCM and the FCRPF (columns (3) and (4)) we assume the following classification of risk: *very significant* risk for properties located within the 6-digit postcode area where a defence was constructed, and a *moderate* risk for properties within the 5-digit postcode area; the simple average of these two areas corresponds to the monetary value under the category of *significant* risk. Notice this is only an *ad-hoc* classification for the purpose of this comparison and might not correspond to an accurate description of the level of risk. All monetary values correspond to July 2014, GBP.

Table 2.9. Economic benefits of structural flood protection to residential properties

Level of risk	Repeat-sales model		MCM	Defra FCRPF
	Fluvial risk	Coastal risk		
	(1)	(2)	(3)	(4)
Very significant	£27,571 [1]	£23,531	£43,735	£31,429
Significant	£14,815 [2]	£22,026 [2]	£16,714	£15,000
Moderate	£2,059	£20,521	£7,205	£4,286
Average	**£14,815**	**£22,026**	**£22,551**	**£16,905**

Notes:
[1] Corresponds to the average benefits of fluvial flood defences for urban (£29,287) and rural (£25,855) houses in the 6-digit postcode where the defence is located ('high risk') (see table 2.6).
[2] Corresponds to the average benefits for properties exposed to very significant and moderate risk.

The results in table 2.9 indicate that, for the case of fluvial flood risk, the benefit estimates from the MCM, overestimate the price premium that people are WTP in the housing market for urban houses that have been protected against flooding. This implies that the current official methodology to estimate the benefits of FCERM capital projects to householders overestimates the economic benefits of flood protection as measured by the WTP. However, this does not appear to have implications for the purpose of government funding allocation to protect households from fluvial flood risk, as the results from the econometric model in column (1) are in line with the benefit estimates used by Defra for the purpose of funding allocation (column (4)). It is only at the lowest level of risk that the FCRPF overestimates the capitalisation of flood defences on property prices. However, on average the results of the FCRPF are only 14% higher than the results from the econometric model. These results imply that the benefit estimates for funding allocation for flood alleviation projects to urban properties are according to the WTP for flood protection in the housing market, which implies an economically efficient allocation of resources as authors such as Braden and Johnston (2004) and Kind (2014) suggest.

For the case of coastal flood risk, the price premium that people are WTP for an urban house protected against flooding (column (2)) is greater, on average, than the benefit estimates from the FCRPF (column (4)). This is especially true for properties at the lowest level of risk, where the results from the econometric model are 380% greater than estimates from the FCRPF. This indicates that the level of funding allocated by Defra for flood risk protection to urban coastal properties is lower than the WTP of coastal householders for flood protection, which might result in a socially inefficient level of risk protection for coastal houses. In this case the results from the econometric model are more in line with the benefit estimates suggested by the MCM. It is important to highlight that currently Defra do not provide different assumptions for funding allocation to FCERM projects for fluvial and coastal flood risk. Although as a part of outcome measure 3 (OM3)

Defra provides additional funding for projects to protect properties against coastal erosion, this only considers properties next to the coastline that are benefited by delaying the process of coastal erosion, and does not consider flood risk reduction for properties at different level of risk. These results suggests that it is important to consider different criteria for the allocation of funding to fluvial and coastal flood relief projects in urban areas, as individuals appear to place a higher value on flood risk protection in coastal areas.

It is important to emphasize that the monetary values in columns (1) and (2) represent the net present value discounted in perpetuity of all future benefits/disbenefits (direct/indirect – tangible/intangible) to urban households derived from the construction of flood defences, whereas the values in column (3) and (4) only represent the discounted present value of direct benefits. Thus, the results from the MCM and the FCRPF represent only a lower bound estimate of the benefits to households from flood risk protection, and the conclusions in the last two paragraphs might change depending on the size of the indirect benefits. For assessing indirect damages in the generalised project appraisal the MCM suggests to use average rental costs of the house vacated in evacuation circumstances, and a value of £225 per property per year for intangible health benefits (see section A2.2 of the appendix).

Finally, it is important to remember that columns (1) and (2) of table 2.9 only consider the positive capitalisation rates of flood risk protection that result from the econometric model. However, the results also suggest that there are significant negative impacts of flood defences that range from a price discount of -1% to -9% (-£3,000 to -£10,000) for properties which are not directly affected by floods (flats), and in locations were defences may result in loss of significant amenity values. These potential negative impacts that can result from the construction of flood defences are not currently considered by methodologies which define the benefits of flood risk reduction as the sum of AFI of flooding, such as the MCM and Defra's FCRPF. This is especially relevant for the case of estimates using the FCRPF methodology, as these are used to determine the amount of public funding allocated to each project. Omitting these potential negative impacts for the purpose of funding allocation can result in a socially inefficient level of flood risk protection by funding projects in locations where they might not be desirable. It is important to mention that about 40% of the flood relief projects constructed during the period of analysis are in rural areas; this represents 664 defences that account for 209 km.

2.9 Conclusions

In flood prone countries, including the UK, the construction of flood defences has been the traditional method of protecting low-lying communities against flooding. Despite the increasingly large amounts of money invested every year for the maintenance and construction of structural flood protection, there is a surprising lack of research on the ex-post evaluation of the economic benefits delivered by these projects. The objective of this chapter is to fill this gap in the literature by analysing the economic impacts to residential properties of the construction of all structural flood protection projects undertaken in England during the period 1995-2014.

To the best of our knowledge this is the first study to use a difference-in-differences (DID) hedonic price framework to measure the ex-post economic benefits to households from the construction of flood defences. The identification strategy consists of the use of a repeat-sales specification to estimate the capitalisation of flood relief projects constructed between two sales of the same property. Data on property prices are taken from the England and Wales Land Registry 'Price Paid' housing transactions data. The final sample includes information on over 12 million individual property transactions, which represent about 4.8 million houses that experienced at least one repeat-sale during the period of analysis. The spatial location of the properties is identified at the 6-digit postcode level. This information is then merged with GIS data from the UK Environment Agency containing the spatial location and main characteristics of structural flood defences in England. Other GIS datasets used for the analysis include: spatial delineation of flood zone areas, recorded individual flood outlines and rural-urban classification of land.

Evidence from the econometric model suggests that the construction of flood defences is capitalised into property prices; however, the extent and direction of the capitalisation depends on multiple factors such as the type and the level of risk, the type of the property, the design characteristics of the defence and the flooding history in the location where the defence is constructed. As expected, the benefits are higher for properties exposed to higher potential damages from flooding; that is, ground level properties (houses), properties exposed to higher levels of risk, and those located in coastal areas.

Differences in the flooding history also play a significant role; the benefits are higher for those properties with more recent and more severe experience with flooding, this result is associated with increased flood risk perception. This raises the interesting question of whether flood defence projects should be evaluated on the basis of the objective or subjective probability of flooding. Two sites might possess the same objectively determined risk of future flooding but a flood defence project will generate greater benefits if implemented in a location with the more recent flood history.

On the other hand, there are also negative amenity and environmental impacts associated with the construction of defences. These appear to be especially relevant in rural and coastal areas, where individuals can have a higher preference to keep the environment undisrupted; and for properties exposed to low levels of risk, where individuals might place a higher weight on preserving the environmental characteristics of the site than on flood protection. Differences on the structure constructed for flood protection do not seem to play a significant role, except for the use of demountable flood defences which have a significant negative effect associated with enhanced flood risk perception.

The results indicate that the benefits from flood protection are capitalised into the price of urban houses at a rate that ranges between 1% and 13%, depending on the type and level of risk; for a median-priced house in 2014 these represent £2,000 to £30,000. For the case of rural properties and flats, the construction of defences result in significant negative impacts that range from a price discount of -1% to -9% (-£3,000 to -£10,000). For rural properties the negative impacts are associated with amenity and environmental impacts of defences, and for the case of flats it is likely also to be the result of a change in the sorting process of individuals in the housing market towards buying ground level properties which becomes more desirable after the construction of a flood defence, therefore pushing the price of flats down.

Important policy implications result from this analysis. First, it is important to highlight that the results of the benefits from fluvial flood protection for urban properties are in line with the benefit estimates suggested by Defra for the purpose of funding allocation, which indicates a socially efficient allocation of resources. However, for coastal properties in urban areas the benefits by Defra underestimate the amount of money that people are WTP in the housing market for flood protection. Currently, Defra follows the same criteria for funding allocation to fluvial and coastal flooding; the results suggest that this is likely to result in a socially inefficient level of protection for coastal properties. It is important to establish different criteria for the allocation of funding to fluvial and coastal flood relief projects to ensure a socially efficient level of protection. The benefits suggested by the Multi-coloured Manual (MCM) overestimates the economic benefits of flood protection against fluvial flooding by at least 40%; however this is likely to be reflected only in the official estimates of the benefits from risk reduction, without implications for funding allocation.

There are significant negative impacts associated with the construction of defences, however these are not currently considered on the estimation of benefits by Defra or the MCM. Omitting these potential negative impacts for the purpose of funding allocation is likely to result in a socially inefficient level of protection by funding too much projects in locations where they might not be desirable. It is important that Defra considers individual preferences and utility impacts when estimating the benefits of flood relief projects. This implies, moving away from a definition of benefits based on averted future impacts of flooding to the use of WTP as a more comprehensive measure of economic value to guide the allocation of resources. Furthermore, the use of demountable flood defences should be discouraged, as there is evidence which suggest that they result in significant negative impacts, especially for properties at low levels of risk. Instead other alternatives should be explored to reduce the visual disamenity of defences such as the glass flood defences recently installed in some areas of Cumbria and Somerset in England.

Several areas of further research emerge from this analysis. Although the results provide evidence on the existence and the magnitude of negative impacts associated with the construction of defences, more research is needed to determine the magnitude and causes of these impacts, and how do they change for different types of risk and different levels of risk. Further studies in this area should consider the use of equilibrium sorting models, as the evidence suggests that the construction of defences lead to changes in the sorting process of individuals in the housing markets. These changes should be identified and considered for the purpose of funding allocation. More research is needed to measure the benefits of flood protection in different geographical regions and with a different policy background. It is also important to analyse individual's preferences towards the use of structural flood protection, compared to alternative flood alleviation measures such as property-level protection, flood warnings, flood insurance and post-disaster relief. Finally, special attention should be devoted to the benefits of multi-functional flood defences and its potential to mitigate the adverse effects associated with standard flood defences.

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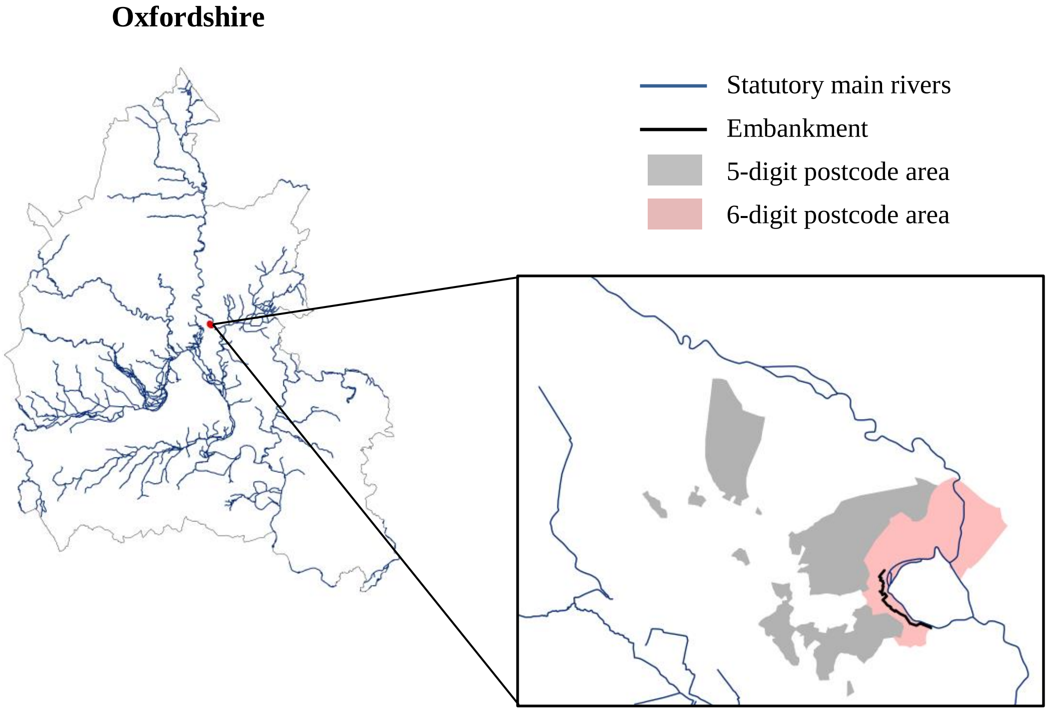
Appendix

Table A2.1. Summary characteristics of stock of flood defences
(*by type of defence and type of flood risk*)

	Number of defences	SOP (return period)	Length (meters)
By type of defence			
Embankment	764	115	412
Wall	713	177	194
High ground	132	65	682
Flood gate	38	35	3
Bridge abutment	8	106	18
Demountable defence	6	100	118
Beach	5	200	1,121
By type of flood risk			
Fluvial	1442	105	312
Coastal	224	338	456

Source: Based on data from the NFCDD.

Map A2.1. Example: Area impacted by the construction of an embankment in Oxfordshire
(*5-digit and 6-digit postcode*)



Source: Own elaboration based on spatial data from the NFCDD.

Appendix. Section A2.1

Robustness Tests

We undertake two additional sets of regressions to test the robustness of the results of our preferred specifications for fluvial and coastal flood defences in columns (4) and (6) of tables 2.4 and 2.5. The results of these additional regressions are included in tables A2.2 and A2.3 of this appendix. The first test consist of a standard robustness test where we remove outlier observations. The objective is to test for the possibility that the results might be driven by specific set of properties with extreme prices, either too high or too low. The results appear in table A2.2 below. Columns (1) through (4) of table A2.2 show the results for the regressions in columns (4) and (6) of tables 2.4 and 2.5, but with a sample that excludes the 1% of observations with the highest and lowest prices. All the results are robust to this change and in some cases the significance of the coefficients improved.

The second robustness test consists in a *placebo test*. The objective is to test for the possibility that the significant capitalisation of defences that we observed in tables 2.4 and 2.5 might be driven by different local characteristics not associated with the construction of flood defences. This test consists of a ‘false experiment’ where the ‘treatment group’ is formed by repeat-sales of those properties located in areas impacted by the construction of a flood defence (5-digit and 6-digit postcode), but whose sales do not bracket its construction. That is, we look at exactly the same locations as we did in tables 2.4 and 2.5, but analysing the change in the price of properties for which the two sales occur either after or before the construction of the defence. We can illustrate the repeat-sales specification of the econometric model for the *placebo test* with the following equation*:*

$$\Delta ln(P_{its}) = \alpha_1 \overline{Bracket}_{ikts} + \alpha_2\left(\overline{Bracket}_{ikts} \times house\_type_i\right) + \psi_1\left(\overline{Bracket}_{ikts} \times d_i\right) \tag{A1}$$
$$+\psi_2\left(\overline{Bracket}_{ikts} \times d_i \times house\_type_i\right) + \psi_3\left(\overline{Bracket}_{ikts} \times d_i \times defence\_design_i\right)$$
$$+\psi_4\left(\overline{Bracket}_{ikts} \times d_i \times defence\_type_i\right) + \psi_5\left(\overline{Bracket}_{ikts} \times d_i \times flood\_perception_i\right)$$
$$+\lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts}$$

Equation (A1) is similar to the econometric specification of our main repeat-sales model in equation (18) but in this case we use a variation of the variable $Bracket_{ikts}$, that we represent as $\overline{Bracket}_{ikts}$ to identify properties which two sales are during the 'false treatment' period. That is, the variable $\overline{Bracket}_{ikts}$ is a dummy variable which takes the value of unity if the two sales of the property, at time *t* and *s*, occur either before or after the construction of a flood defence in county *k* where they are located. The variable d_i is defined as in equation (18), that is, it represents the group assignment for each house unit and it is given by a dummy variable which takes the value of 1 for properties located within an area impacted by a flood defence, either 5-digit or 6-digit postcode area, accordingly. Therefore the variable $\left(\overline{Bracket}_{ikts} \times d_i\right)$ is a dummy variable which identifies our false treatment group; it takes the value of unity if the property is located in an area impacted by a flood defence, but for which the two sales occur either after or before the construction of the defence. All other variables are defined as in equation (18). Since these properties did not experience a change in the level of risk in the period between sales, we do not expect to find any significant effect associated to the construction of the defence or its structural characteristics.

The results of the *placebo test* appear in table A2.3 of the appendix. Columns (1) and (2) show the results for fluvial and coastal defences, respectively, with the area impacted by the defence defined as the 5-digit postcode where the defence is located. Columns (3) and

(4) show the corresponding results with our narrower definition of the treatment group as the 6-digit postcode area where the defence is located. The results show that our benchmark coefficient capturing the capitalisation of floodwalls on detached urban properties ($\bar{B}$**Defence*) is either not significant or has the opposite sign. Furthermore, all variables associated with the characteristics of defences (*defence_design* and *defence_type*) are not significant. These results are as expected. As mentioned earlier, the *placebo test* consists in a false experiment where no flood defence was constructed between the two sales of the properties considered in the false treatment group. Therefore, any significant variable associated to the construction of the defence would have put into serious question the validity of our identification strategy. Based on this test, we argue that our main results in tables 2.4 and 2.5 are indeed associated to the construction of a flood defence and its design characteristics.

Table A2.2. Repeat-sales model. Robustness test: Excluding extreme values
(*Fluvial and coastal risk. Excludes top 1% and bottom 1% of observations*) [1]

		5-Digit		6-Digit	
	Variables	(1) **Fluvial risk FP**	(2) **Coastal risk FP**	(3) **Fluvial risk FP**	(4) **Coastal risk FP**
	Bracket sample				
	Bracket (B)	0.211***	0.289***	0.211***	0.288***
		(0.00460)	(0.0110)	(0.00452)	(0.0110)
House_type [2]	B*sdetached	-0.0298***	-0.0444***	-0.0305***	-0.0450***
		(0.00193)	(0.00330)	(0.00191)	(0.00326)
	B*terraced	-0.0546***	-0.0616***	-0.0549***	-0.0626***
		(0.00206)	(0.00341)	(0.00204)	(0.00337)
	B*flat	-0.0870***	-0.0658***	-0.0874***	-0.0649***
		(0.00422)	(0.00948)	(0.00415)	(0.00943)
	B*free	0.0366***	0.0439***	0.0371***	0.0476***
		(0.00370)	(0.00888)	(0.00362)	(0.00887)
	B*rural	0.0482***	0.0513***	0.0473***	0.0493***
		(0.00152)	(0.00275)	(0.00150)	(0.00270)
	B*coastal				
	B*quartile	-0.0808***	-0.0820***	-0.0805***	-0.0824***
		(0.000875)	(0.00157)	(0.000864)	(0.00155)
	Bracket-defence sample				
	B*Defence (D)	0.0577**	-0.0414	0.186***	0.0472
		(0.0290)	(0.0749)	(0.0462)	(0.0809)
House_type [2]	B*D*sdetached	-0.0238*	-0.0128	0.0172	-0.0395
		(0.0132)	(0.0233)	(0.0250)	(0.0370)
	B*D*terraced	-0.0231*	-0.0440*	-0.0243	-0.0986**
		(0.0137)	(0.0245)	(0.0272)	(0.0406)
	B*D*flat	-0.0508**	0.0181	-0.156***	-0.0562
		(0.0241)	(0.0655)	(0.0363)	(0.0629)
	B*D*free	0.0294	0.129**	-0.0468	0.151***
		(0.0210)	(0.0646)	(0.0288)	(0.0507)
	B*D*rural	-0.0243**	-0.118***	-0.0189	-0.0634***
		(0.00973)	(0.0177)	(0.0186)	(0.0241)
	B*D*coastal				
	B*D*quartile	-0.00552	-0.0123	-0.0245**	-0.0425**
		(0.00627)	(0.0102)	(0.0124)	(0.0182)
Defence_design	B*D*sop	-7.14e-05***	-0.000132***	-8.17e-05*	0.000384***
		(2.39e-05)	(4.81e-05)	(4.86e-05)	(0.000145)
	B*D*length	-6.64e-05***	4.92e-05*	-5.94e-05***	3.32e-05
		(1.33e-05)	(2.64e-05)	(2.24e-05)	(7.01e-05)
	B*D*(sop*length)	1.99e-07*	-1.99e-07***	4.21e-07**	-1.08e-06**
		(1.06e-07)	(5.29e-08)	(1.97e-07)	(5.14e-07)
Defence_type [3]	B*D*embankment	-0.00991	0.0169	-0.00160	-0.0400
		(0.00925)	(0.0162)	(0.0169)	(0.0300)
	B*D*bridgeabt	-0.0568	-0.0495	-	-
		(0.0706)	(0.0678)		
	B*D*highground	0.00682	0.0701**	-0.0277	0.0344
		(0.0164)	(0.0349)	(0.0266)	(0.0750)
	B*D*demount	-0.0583*	-0.0669	0.0242	-0.0615
		(0.0311)	(0.0541)	(0.0561)	(0.0873)
	B*D*floodgate	0.0112	0.0289	-0.0844	0.192
		(0.0280)	(0.0389)	(0.0538)	(0.154)
Flood_perception	B*D*months(sqrt) [4]	-0.00298***	0.00195	-0.00340***	-0.000276
		(0.000712)	(0.00134)	(0.00108)	(0.00183)
	B*D*duration	0.000129**	0.000393*	0.000191*	-0.000592
		(5.99e-05)	(0.000233)	(0.000105)	(0.000389)
	B*D*months(sqrt)[4]*duration	7.86e-06	-1.08e-05	4.62e-06	4.52e-05**
		(5.46e-06)	(1.21e-05)	(8.65e-06)	(2.22e-05)

(Continued)

Table A2.2.Continue

Lyear (s)	0.000388***	-0.00220***	0.000376***	-0.00221***
	(8.08e-05)	(0.000216)	(8.07e-05)	(0.000215)
Year (t)	-0.000354***	0.00223***	-0.000341***	0.00225***
	(8.06e-05)	(0.000215)	(8.05e-05)	(0.000214)
Observations	1,010,031	103,561	1,010,031	103,561
Treated Obs.	5,130	2,227	1,291	483
County FE	YES	YES	YES	YES
R-squared	0.122	0.172	0.122	0.172

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.
[1] Refers to the real price of the properties.
[2] Omitted categories are dummy variables for detached property, urban location and fluvial flood risk.
[3] The omitted category is a dummy variable for floodwall.
[4] Square root of the number of months since the previous flood with respect to the second sale.

Table A2.3. Repeat-sales model. Robustness test: Placebo regression
(*Fluvial and coastal risk*) [1]

		5-Digit		6-Digit	
	Variables	(1) **Fluvial risk FP**	(2) **Coastal risk FP**	(3) **Fluvial risk FP**	(4) **Coastal risk FP**
	Bracket sample				
	$\overline{Bracket}$ ($\bar{B}$)	0.211***	0.112***	0.210***	0.112***
		(0.00191)	(0.00845)	(0.00190)	(0.00843)
(A) *House_type* [2]	$\bar{B}$*sdetached	-0.0610***	-0.00707*	-0.0611***	-0.00723*
		(0.000846)	(0.00421)	(0.000843)	(0.00420)
	$\bar{B}$*terraced	-0.0739***	0.00800**	-0.0741***	0.00746*
		(0.000859)	(0.00407)	(0.000856)	(0.00406)
	$\bar{B}$*flat	-0.111***	0.00915	-0.111***	0.00842
		(0.00159)	(0.00674)	(0.00158)	(0.00672)
	$\bar{B}$*free	0.0444***	0.0407***	0.0444***	0.0405***
		(0.00134)	(0.00538)	(0.00133)	(0.00536)
	$\bar{B}$*rural	0.0455***	0.0123***	0.0454***	0.0123***
		(0.000712)	(0.00326)	(0.000709)	(0.00325)
	$\bar{B}$*coastal				
	$\bar{B}$*quartile	-0.0920***	-0.0560***	-0.0919***	-0.0560***
		(0.000354)	(0.00149)	(0.000353)	(0.00149)
	Bracket-defence sample				
	$\bar{B}$*Defence ($\bar{B}$*D)	**-0.0751*****	**0.100**	**-0.0489***	**0.0808**
		(0.0138)	**(0.0805)**	**(0.0268)**	**(0.151)**
(B) *House_type* [2]	$\bar{B}$*D*sdetached	0.00116	-0.0565	0.0199	-0.0200
		(0.00826)	(0.0527)	(0.0172)	(0.100)
	$\bar{B}$*D*terraced	0.00432	-0.0788	0.0159	-0.0266
		(0.00785)	(0.0515)	(0.0157)	(0.0977)
	$\bar{B}$*D*flat	0.00822	-0.134*	-0.00151	-0.0937
		(0.0120)	(0.0688)	(0.0224)	(0.116)
	$\bar{B}$*D*free	-0.00790	0.00391	-0.0256	0.0204
		(0.00940)	(0.0448)	(0.0170)	(0.0697)
	$\bar{B}$*D*rural	-0.0182***	-0.0246	-0.0191	-0.0543
		(0.00613)	(0.0335)	(0.0127)	(0.0703)
	$\bar{B}$*D*coastal				
	$\bar{B}$*D*quartile	0.0175***	-0.0293*	0.0129**	-0.0484
		(0.00281)	(0.0163)	(0.00600)	(0.0347)
Defence_ design	$\bar{B}$*D*sop	-1.42e-05	-0.000187	-3.13e-05	-0.000529*
		(1.46e-05)	(0.000123)	(3.92e-05)	(0.000311)
	$\bar{B}$*D*length	-3.75e-06	-4.74e-05	-8.87e-06	6.69e-05
		(7.28e-06)	(5.91e-05)	(1.80e-05)	(0.000260)
	$\bar{B}$*D*(sop*length)	4.08e-08	5.53e-07	1.82e-07	1.09e-06
		(3.96e-08)	(4.08e-07)	(1.60e-07)	(1.02e-06)
Defence_type [3]	$\bar{B}$*D*embankment	-0.00201	-0.0295	-0.0166	-0.0747
		(0.00551)	(0.0279)	(0.0118)	(0.0462)
	$\bar{B}$*D*bridgeabt	-0.00937		-	-
		(0.0402)			
	$\bar{B}$*D*highground	-0.0219**	-0.0318	-0.0216	0.113
		(0.0104)	(0.174)	(0.0215)	(0.277)
	$\bar{B}$*D*demount	-0.00174	0.130	0.0148	0.0517
		(0.0364)	(0.116)	(0.0722)	(0.173)
	$\bar{B}$*D*floodgate	0.0227	-0.0150	-0.0335	
		(0.0164)	(0.0705)	(0.0487)	
Flood_ perception	$\bar{B}$*D*months(sqrt) [4]	0.000308	-0.000217	0.000299	0.00173
		(0.000343)	(0.00241)	(0.000769)	(0.00527)
	$\bar{B}$*D*duration	0.000148***	0.000394	0.000295***	0.00673
		(4.44e-05)	(0.000806)	(9.15e-05)	(0.00549)
	$\bar{B}$*D*months(sqrt)[4]*duration	-8.32e-06***	1.64e-05	-1.57e-05***	-0.000268
		(3.02e-06)	(4.70e-05)	(6.02e-06)	(0.000279)

(Continued)

Table A2.3.Continue

Lyear (s)	-0.00120***	-0.00409***	-0.00120***	-0.00410***
	(7.56e-05)	(0.000209)	(7.56e-05)	(0.000209)
Year (t)	0.00124***	0.00411***	0.00125***	0.00412***
	(7.53e-05)	(0.000208)	(7.53e-05)	(0.000208)
Observations	1,030,068	107,537	1,030,068	107,537
Treated Obs.	18,963	8,472	5,196	1,752
County FE	YES	YES	YES	YES
R-squared	0.158	0.131	0.158	0.131

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] Refers to the real price of the properties.

[2] Omitted categories are dummy variables for detached property, urban location and fluvial flood risk.

[3] The omitted category is a dummy variable for floodwall.

[4] Square root of the number of months since the previous flood with respect to the second sale.

Appendix. Section A2.2

A2.2. The Multi-Coloured Manual (Penning-Rowsell et al., 2014):

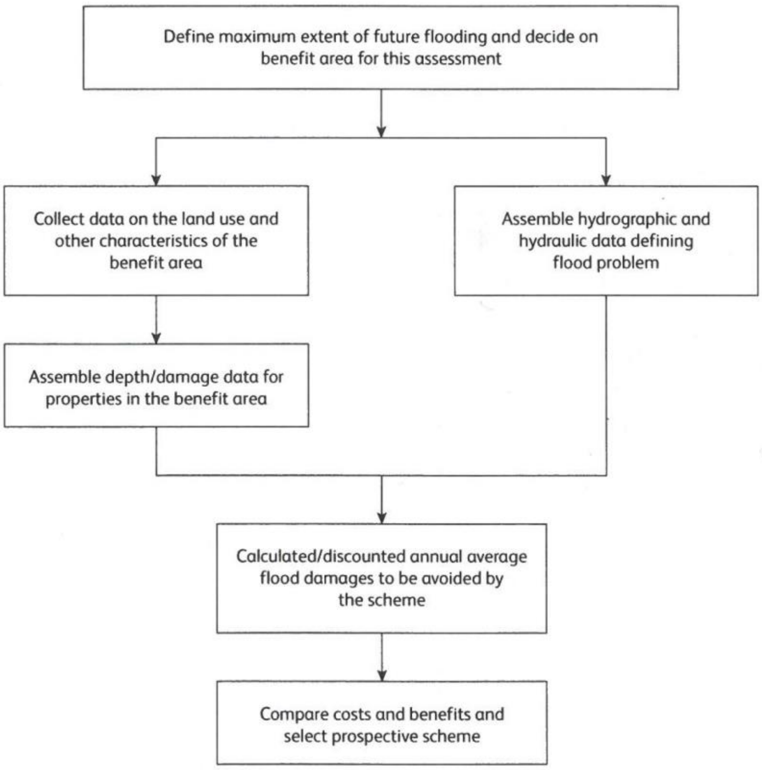
The 2013 *Flood and Coastal Erosion Risk Management: A Manual for Economic Appraisal*, is also referred as the *Multi-Coloured Manual*. This manual is produced by the Flood Hazard Research Centre at the Middlesex University, UK, with support from the Department for Environment, Food and Rural Affairs (DEFRA) and the Environment Agency (EA) and its use is recommended by the Government for the benefit assessment of schemes and policies to reduce potential economic flood and erosion damages within England and Wales (Johnson, Penning-Rowsell and Tapsell, 2007; Penning-Rowsell et al., 2014). The Manual is an update of the 2005 Multi-Coloured Manual (Penning-Rowsell et al. 2005), which is in itself a synthesis of three previous manuals dealing with different aspects of the economic assessment of flood alleviation schemes: the ‘Blue Manual’ focusing on the benefits of flood risk management (Penning-Rowsell and Chatterton 1977); the ‘Red Manual’ with an emphasis on the economic assessment of indirect benefits (Parker, Green, and Thompson 1987) and the ‘Yellow Manual’ looking at coastal erosion risk management and sea defence benefits (Penning-Rowsell et al. 1992).

The 2013 Mulit-Coloured Manual (MCM) consists of 10 chapters: chapters 1-3 describe the UK’s current strategies and policies for Flood and Coastal Erosion Risk Management (FCERM), and basic concepts and methodologies related to the economic appraisal of flood and erosion risk management schemes; chapters 4-10 are devoted to provide data defining the depth/damage relationship in the UK for the different land uses, to explain how this information has been gathered and to provide advice on how to use them. In section 1 of this appendix we summarise the methodology proposed in the MCM to assess the benefits of flood alleviation schemes (chapter 3 of the MCM). Sections 2 summarise the MCM approach to residential benefit assessment of flood alleviation schemes (chapter 4 of the MCM).

1. MCM Approach to Residential Benefit Assessment of Flood Alleviation Schemes

The benefits of flood risk reduction are defined as the sum of future flood damage averted as a result of flood alleviation schemes that reduce the frequency of flooding. The methodology described in the Manual for assessing these benefits consists of two things: (1) a hazard assessment detailing the probability of future flood events to be averted and (2) a vulnerability assessment with information on the damage that would have been caused by those floods. Overall, a total of six steps have to be followed to quantify the economic benefits of flood alleviation schemes. These steps are represented in figure A2.1 below, and are briefly described in this section.

Figure A2.1 Stages for the economic assessment of flood alleviation schemes



Source: Penning-Rowsell et al., 2014

1.1. Define maximum extent of future flooding and decide on benefit area for this assessment

The first step to estimate the benefits of a flood alleviation scheme is to identify the area affected by the flood problem, both directly and indirectly, and that will be benefited by the implementation of the flood alleviation scheme. The Manual suggests that this area is defined by the maximum historical extent of flooding in the area or catchment involved, and that in the UK this area can be approximated using the indicative floodplain maps.

1.2.Assemble hydrographic and hydraulic data defining flood problem

The Manual highlights that one of the most important inputs to benefit assessment is the data describing the topographic characteristics of the floodplain, and the hydraulic profiles that intersects this surface. In general, the use of high definition light detection and ranging (LIDAR) data is advised to define the topographic characteristics of the floodplain. Regarding the data defining the flood surface area, it is necessary to use hydraulic models to convert the topographic data and flood discharge into flood surfaces. There is a wide range of hydraulic models that can be used to this purpose, the Manual makes special mention of three models: (1) the ISIS model developed by Halcrow Group Limited, (2) the MIKE 11 model by Danish Hydraulic Institute (DHI) and (3) the JFlow by JBA Consulting. Then damage models can be used to generate three-dimensional flood surfaces to identify the flooded area and depth that would result from the occurrence of flood events with different return periods (probabilities of occurring). It is also important to have data on the future expected number of flood events of different severities in the benefited area; it is advised to concentrate on high-frequency events.

1.3. Collect data on the land use and other characteristics of the benefit area

The methodology described in the Manual to quantify potential flood damages varies depending on the current land use of the area affected by flooding (although future land use changes might occur these are not considered in the Manual). Different methodologies are presented for: (1) residential property, (2) non-residential property, (3) coastal areas, (4) recreational areas and (5) agricultural land. The land use is also important to define the characteristics of the damages, as well as the threshold level of flooding at which damage is expected. Therefore, it is important to have information on the land use of the affected area for the proper economic assessment of potential flood events.

1.4. Assemble depth/damage data for properties in the benefit area

The depth/damage data defines the expected economic damages in the occurrence of flood events with different depths. The majority of the MCM Manual is devoted to provide data defining the depth/damage relationship in the UK for the different land uses, to explain how this information has been gathered and to provide advice on how to use them. Depth/damage data are provided in an on-line platform known as MCM-Online (http://www.mcm-online.co.uk/) which is accessible upon the payment of the corresponding license.

1.5. Calculated/discounted annual average flood damages to be avoided by the scheme

Once all the previous steps have been followed, we will have the following information:

- Hazard assessment: the probability of future flood events to be averted.
- Vulnerability assessment: the damage that would have been caused by these floods.

This information is then used to construct loss-probability curves that describe the relationship between estimated flood damages and flood probability. Combining this information we get the annual expected average flood damages for the location of interest.

1.6. Compare costs and benefits and select prospective schemes

Finally, with information on the standard of protection that alternative flood alleviation schemes would provide it is possible to quantify the annual expected flood damages averted by each alternative, i.e. the benefits of the flood protection scheme. Considering all the costs associated with each alternative (including future maintenance costs) and the expected life of the project, it is possible to compare the present value costs and benefits of the alternatives and to identify those with a higher benefit-cost ratio.

2. MCM Approach to Residential Benefit Assessment of Flood Alleviation Schemes

Chapter 4 of the MCM describe the data and methodology to estimate expected flood damages to residential properties and related social impacts, a summary of this chapter is presented in this section of the appendix. The structure of the chapter follows the general classification of flood damages as direct or indirect, and by whether they are tangible or intangible. The structure of this section is as follows. Section 2.1 summarises the economic assessment of direct tangible damages, and section 2.2 does the same for indirect tangible damages. Chapter 4 of the MCM also discusses the difficulties to assess intangible flood damages, and provides information and guidance for the assessment of intangible health impacts; this information is summarised in section 2.3. Other social impacts such as vehicle damage, damage to ‘park homes’, and damage reduction effect of property level protection and flood warnings are summarised in section 2.4. Finally, section 2.5 summarises the data detailed in the MCM for a generalised project appraisal.

2.1. Direct Flood Damages

Direct residential flood damages result from the physical contact of flood water with damageable property (building fabric and inventory). To assess direct residential averted flood damages from FCERM schemes, the Manual relies on the use of 'synthetic' damage data, i.e. damage data that has been collected based on the market prices of housing contents susceptible to flooding. Flood damage potential is estimated using details of the effects that flood waters of varying depths and durations would have on the different components of a property, including dwelling's inventory and building fabric. These data are available via MCM-online.

The detail of the data provided corresponds to:

- Five house types: detached, semi-detached, terrace, bungalow and flat.
- Six building periods: Pre-1919, 1919-1944, 1945-1964, 1965-1974, 1975-1985 and Post-1985.
- Four different approximated social grades of the dwellings' occupants: as identified in the UK National Readership Survey.

This results in a total of 140 datasets. In this way, every dwelling in Great Britain can be classified using three variables: house type, age and the occupants' social grade. This classification will then be used to predict the characteristics, extent and value of the expected damage due to flood events with different depths and durations (long and short duration).

The Manual makes a distinction between financial and economic losses. Financial losses are represented by the cost of replacement of damaged items at current market prices, whereas the assessment of economic losses is based on pre-flood value, i.e. depreciated value. The data available in the MCM-Online correspond to economic values. The Average Remaining Value (ARV) of inventory is used to ensure that damage figures reflect pre-flood values of inventory stock and not the cost of replacing damaged goods at current market prices. The value of all items listed in the MCM-Online dataset are assumed to be halfway through their lives. In addition, taxes are also discounted, as these represent transfer payments within the economy and not real resource costs.

2.1.1. Standard Depth/Damage data

The expected flood damage on building fabric and the components of house inventory is evaluated two characteristics of flood events:

- Flood duration: long duration (>12 hours) and short duration (<12 hours) floods, and
- Flood depth: fifteen flood depths ranging from -0.3m (to include damage to sub-floor areas) up to 3.0m (see table 4.6 in Penning-Rowsell et al., 2014).

Therefore the dataset does not consider characteristics such as flood velocities, sediment loads or pressure differentials.

2.1.2. Building fabric data

The potential damage to building fabric items is calculated using ground floor plans of twenty-eight typical dwelling types (available online). These plans are classified according to the different house types and building periods detailed above. The likely decorations and building fabric of each dwelling type is determined following expert judgement with specialists, and critical depths are identified at which flood waters are expected to cause damage. The final dataset can be used to calculate building fabric damage costs for each flood duration, flood depth and house type.

The assumptions to identify susceptibility of residential property building fabric to flooding are listed in table 4.4 of Penning-Rowsell et al. (2014). These include assumptions regarding susceptibility of (1) paths and paved areas, boundary fences, etc., (2) external main building, (3) internal plasterwork, (4) floors, (5) joinery, (6) internal decorations and (7) plumbing, central heating and electrical installations. These assumptions characterise the expected damage to the different components of the building fabric depending on the materials of construction and the characteristics of the flood (depth and duration).

2.1.3. Inventory data

The potential of flood damage also depends on the number, quality, value and susceptibility of the housing inventory. Households' possessions are identified according to house type, age and the following classification of four social grades from the UK National Readership Survey (see table 4.8 in Penning-Rowsell et al., 2014):

- Social Grade AB: Upper middle class.
- Social Grade C1: Lower middle class.
- Social Grade C2: Skilled working class.
- Social Grade DE: Working class and those at the lowest level of subsistence.

The inventory list, inventory prices and ownership figures by social grade are determined using data from the Office of National Statistics, and store catalogues and website. All inventory items are assumed to be halfway through their lives, i.e. 50% depreciation following a linear depreciation trend, and taxes are discounted. Ownership figures for collective household items, such as food, clothes and toys, etc., are not available by social grade. The value of this items is based on monthly, yearly or five-yearly expenditure, depending on the nature of the item, and the social grade.

The assumptions for the susceptibility of housing inventory items to floodwaters are listed in table 4.5 of Penning-Rowsell et al. (2014). These include assumption for different categories of inventory items: (1) domestic appliances, (2) electrical goods, (3) furniture, (4) floor coverings, curtains and personal effects, and (5) health equipment. These assumptions detail the susceptibility to damage at different levels of flood-depth and the two basic flood durations. 'Good quality' housing contents are ascribed to social grade AB, 'medium quality' to social grades C1 and C2 and 'poor quality' to social grade DE.

2.1.4. Drying-out and clean-up costs

The clean-up data are provided by the National Flood School measured as drying and clean-up costs per square metre (£/m^2). Separate datasets for short-duration and long-duration floods are presented. A refrigerant dehumidification method is assumed for all properties, and the drying period and clean-up costs depend on the duration and depth of the flood event. The dataset for drying and clean-up costs is accessible through the MCM-Online dataset; the figures do not include VAT. This dataset can be used to estimate clean-up costs for the five different house types considered in the Manual, and for the following five categories of flood waters: (1) major clean/grey, (2) minor black, (3) major flood/storm, (4) major flood including sewage and (5) major flood 'contaminated'.

2.2. Indirect Flood Damages

The indirect flood losses refer to the additional costs induced by direct impacts and can occur outside the time and space of the flood event. Indirect flood losses include disruption to household due to flood damage, evacuation costs, loss of utility services, loss of income/earnings, additional communication costs, etc. The Manual considers potential evacuation costs to be a significant component of the costs of flooding, and identify the components contributing most to evacuation costs: (1) temporary accommodation, (2) food, (3) increased travel and time costs and (4) loss of earnings.

2.2.1. Temporary and alternative accommodation

When properties are affected by flooding, temporary evacuation from the property might be necessary during the period of emergency for reasons of public health and to allow flood damages to be repaired until the property is safe to return to. The Manual proposes to use flood depth as a variable to indicate the evacuation duration, and the basis to estimate potential evacuation costs from flooding. Based on figures from the RPA/FHRC (2004) (see Defra and EA, 2005) the Manual shows the probability of evacuation and duration in relation to flood depth (see table 4.18 in Penning-Rowsell et al., 2014). In general, as flood depth increases both, the likely number of properties evacuated and the mean duration of evacuation, increase.

Data from Doncaster Council (2008) is used to determine the proportion of evacuees that would opt for different options of accommodation (see table 4.19 in Penning-Rowsell et al., 2014): (1) rest centres (42%), (2) friends and family (38%), (3) hotels/B&Bs (9%), and (4) other (11%). It is recognized that, in general, people deciding to use rest centres and friends and family accommodation will not incur in additional accommodation costs. The Manual presents estimates of the accommodation costs for the proportion of people using hotel/B&B accommodation, and for people choosing 'other' type of accommodation the renting costs of alternative accommodation are suggested.

Table 4.20 in Penning-Rowsell et al. (2014) shows the average costs of temporary hotel or B&B accommodation for up to 8 weeks. The table also provides information on the percentage of evacuees that would remain in such a type of accommodation as the time from evacuation elapses. The value for the costs for accommodation are classified as low, medium or high costs, in this way they can be matched according to the social grade of the evacuated properties. Likewise, table 4.21 shows the estimated average costs of renting different types of alternative accommodation (detached, semi-detached or terraced) for a period of up to 52 weeks; the costs are also classified as low, medium or high cost accommodation.

2.2.2. Food costs

The Manual suggests that during the period of evacuation expenditure on food could be significantly higher, as meals cannot be prepared at home and have to be bought at restaurants or cafes. Table 4.22 in Penning-Rowsell et al. (2014) shows the estimated average extra food costs per household evacuated to hotel/B&B accommodation. These additional costs are presented for a time span of up to 8 weeks, and are also classified as low, medium, or high food costs.

2.2.3. Travel and time costs

Another concept of indirect costs associated with the evacuation during the emergency period are the additional travel and time costs to evacuees through the process of evacuation and during the stay in temporary/alternative accommodation. Additional travel and time costs are classified in the Manual as costs due to additional distance travelled for four main reasons: (1) schools, (2) work, (3) shopping, and (4) trips to visit the flooded property. Time costs are calculated as 50% of the national average hourly wage rate. Table 4.24 in Penning-Rowsell et al. (2014) shows the average extra travel and time costs associated with alternative accommodation, due to the aforementioned reasons, per household evacuated. Additional travel and time costs are presented for a time span of up to 52 weeks, and are also classified as low, medium, or high travel costs.

2.2.4. Loss of earnings

The Manual also considers the fact that it is common for evacuees to take time off work to organise the repair and recovery of their property. Based on figures from RPA/FHRC (2004) (see Defra and EA, 2005) and Tunstall (2009), it is suggested that 61% of employees affected by flooding take time off work as a result of their evacuation. The average length of time taken off is estimated to be 13 days per household. Using this information, the average lost earnings per household are estimated to range from £140 (low), £270 (medium) and £395 (high) per flood event.

2.3. Intangible effects of flooding

The importance and difficulties to quantify the intangible effects of flooding are mentioned throughout the Manual. Although the flood risk literature recognises a broad range of potential intangible impacts of flooding, the Manual only provides guidance to quantify the value of human health consequences of flooding and incorporate them into the appraisal process; a discussion regarding the assessment of risk to life from flooding is also presented.

The effects of flooding on human health might be far reaching and range from injuries that can occur during, or immediately after, a flood, to more long-term physical and psychological consequences that can extend for weeks or months following an event. The Manual suggests using an estimate of £225 (2013 prices) per household per year as the WTP to avoid stress and health effects caused by flooding. This value is based on an updated figure of £200 suggested by Defra (2004) in the Flood and Coastal Defence Project Appraisal Guidance, to estimate the value of the intangible impacts of flooding. To incorporate this value into economic appraisal of flood relief projects Defra (2004) suggests the use of a risk reduction matrix of intangible benefits associated with flood defence improvements, which relates the change in the probability of flooding resulting from the flood defence scheme (standard of protection) to the monetary reduction in potential health expenses associated to flooding. The updated matrix to 2013 prices is presented in table 4.34 of the Manual.

The Manual points out that the value suggested by Defra (2004) might be too low, and that a figure of £2,513 per household per event developed by JBA (2012) is now used more commonly. This figure is made up of an estimated value of £1,065 per person and the assumption that there are 2.36 persons per house. The value considers the £225 per household per year suggested by Defra as the WTP to avoid stress and health effects caused by flooding, plus an estimate of medical and productivity costs for an average of four months that include general practitioner care, cognitive behavior therapy and non-direct counselling. The Manual concludes that more research is needed in this area.

In many situations the occurrence of flood events might also represent a threat to life. The Manual indicates that, if necessary, the risk to life from flooding might be valued using a figure of £1,145 million per fatal casualty prevented (at 2000 values) presented in HM

Treasury's 'Green Book' (HM Treasury, 2003) and which was originally developed by the Department of Transport to value deaths in road accidents. Thus, this figure might be multiplied by the estimated number of fatalities. However, the Manual suggests being cautious when using this figure to assess the benefits of reducing the risk to life as a result of flood relief schemes. The authors analyse the circumstances that have resulted in fatalities from flooding in past flood events in England and Wales, and conclude that, in recent years, the majority of deaths during flood events have not been related to the characteristics of the flood itself, but with behavioural responses or actions of the victims. The advice of the Manual is to use this value only for cases where specific characteristics of the flood (such as speed of on-set, velocity of flow, or expected depth) lead to a higher potential for risk to life.

2.4. Other things to consider

In addition to the information provided on the appraisal of direct and indirect, tangible and intangible, impacts of flood waters on household inventory and building fabric items, the Manual also provides information and guidance to account for the possible presence of 'Park Homes' and vehicle damage, and to quantify the damage reducing effect of flood warning and property-level protection measures. This information is briefly summarised below.

- Flood damage to 'Park Homes': A distinction is made between 'park home' and caravan. The former are technically mobile although it is unusual for them to be moved once installed on a site, whereas the latter are deemed to be movable if threatened by flooding provided that there is a substantial warning period. Therefore, damages from flooding are only expected to park homes, and in cases where flood depth is expected to be 60 cm or higher, as they are located above ground levels. Due to the high susceptibility of these homes total loss figures (half the replacement cost to account for depreciation) should be considered for flood depths beyond the 60 cm threshold level.
- Vehicle damages: Based on previous research and analysis of previous flood experiences the Manual suggests to consider the following figures. An average vehicle ownership rate of 1.15 cars per household should be considered, 1.61 and 0.99 in rural and urban areas, respectively. It should be assumed that 25% of occupants will move their vehicles to safer locations following a flood warning. It is further assumed that the number of damaged vehicles is 28% of the number of residential and commercial properties at risk in the benefited area; this is because not all the people living in the area is expected to be present at the moment when the flood hits. An average value per vehicle of £3,100 is suggested (an average value of £3,600 per residential property). Due to the physical characteristics and high susceptibility of vehicles to flood waters a total loss should be assumed for flood depths greater than 0.35m above ground level.
- Damage reducing effect of property-level protection (PLP): An important distinction is made between resistance and resilience measures. The former are measures designed to prevent the entry and build-up of flood water within a property, examples are demountable doors and airbrick covers. The latter refers to internal components of dwellings that will make them less susceptible to damage in the event of a flood. Based on previous research and analysis of previous flood experiences the Manual suggests to consider the following figures:

  - Resistance measures: an uptake rate of 8.1% has to be assumed for areas with a 1.3%, or greater, annual probability of flooding (where annual flooding probability is lower a cero uptake rate is assumed). This uptake rate is further subdivided into warning-dependent (WDRM, 4.8%) and warning-independent (WIRM, 3.2%), depending on whether their installation depend on the previous issue of a flood warning or not. Averted damages due to the installation of WIRM depend on an estimated 75% effectiveness rate (e.g. they are only effective for relatively shallow floods), whereas those related to WDRM depend on three things: 30% ‘reliability and availability’ coefficient which defines the proportion of homeowners/tenants receiving the flood warning, a 63% coefficient which defines the proportion of homeowners operating the measures (some of them might not be at home to install the WDRM) and the 75% effectiveness coefficient for those of them who installed the WDRM. The interaction of all these uncertainties results in a frequency of adoption of WIRM of 2.4% and 6.8% for WDRM (see equations 4.1 and 4.2 of the Manual for further details). Potential savings of £65.7 per m^2 are suggested for WIRM, and £33.87 per m^2 for WDRM.
  - Resilience measures: an uptake rate of 8% has to be assumed for areas with a 1.3%, or greater, annual probability of flooding (where annual flooding probability is lower a cero uptake rate is assumed), with a 50% effectiveness coefficient. Potential savings of £64.74 per m2 are suggested for properties equipped with resilience measures.
- Damage reducing effect of flood warnings: Effective and timely warning can result in lower levels of flood damage. Once a flood warning has been issued, property occupants might be able to remove damageable contents to flood free locations (e.g. an upper floor) and reduce the potential damage. Based on previous research and analysis of previous flood experiences the Manual suggests to consider the following figures. Only 21% of the total potential damages can be influenced by the provision of a flood warning (potentially movable items during the warning period). It should be assumed that 30% of householders will receive a warning and respond with varying degrees of effectiveness that depend on the warning lead-time. For those receiving a flood warning less than eight hours prior to a flood it is assumed that 55% of the potentially movable items could be saved; this figure increases to 71% for those with more than an eight hour warning lead-time.

2.5. Generalised project appraisal

As an initial stage to estimate the benefits of flood alleviation schemes to residential properties, the Manual suggests to undertake a generalised project appraisal to have an indication of the likely magnitude of the benefits and to determine whether more time and economic resources should be spent on additional studies. This process relies on assumptions of the expected frequency and depth of future flood events, to calculate the weighted annual average damages (WAADs) to an average property. Then, using information on the size of the benefited area (which depends on the characteristics of the scheme being appraised), and the number of residential properties within this area, it is possible to use the WAAD to provide an approximate estimate of the order of potential benefits of a hypothetical flood alleviation scheme. It is important to note that the values reported in this section only consider direct damages (guidance is provided to account for indirect and intangible damages).

Table A2.4 below shows the calculation of the WAAD reported in the MCM for an average property with no flood protection and no flood warning (for detailed information regarding the assumptions on flood frequency and the potential distribution of flood depths see table 4.32 of the MCM). In this case, the MCM estimates a WAAD of £4,728 (2013 prices) per property.

Table A2.4. WAAD calculations: residential property with no protection

Return period (years)	Exceedence probability	Damage (£)	Probability of flood in interval	Mean damage (£)	Annual interval damage (£)
2	0.5	0			
			0.3	4,750	1,425
5	0.2	9,500			
			0.1	13,673	1,367
10	0.1	17,847			
			0.06	18,781	1,127
25	0.04	19,716			
			0.02	21,538	431
50	0.02	23,360			
			0.01	24,739	247
100	0.01	26,119			
			0.005	26,118	131
200	0.005	26,119			
				Weighted annual average damage	**4,728**

Note: Figures are expressed in sterling 2013 prices.
Source: Penning-Rowsell et al., 2014.

Combining this information it is possible to obtain a rough estimate of the potential direct damages to residential properties averted due to hypothetical flood alleviation schemes that provide different standards of protection. As mentioned before, these values only represent a benefit estimate due to adverted direct damages. For assessing indirect damages in the generalised project appraisal the Manual suggests to use average rental costs of the house vacated in evacuation circumstances, and a value of £225 per property per year for intangible health benefits (see sections 2.2 and 2.3 of this appendix).

Chapter 3

The economics of flooding in the UK: A flood profile of property prices in England

N.B. During the preparation of this Thesis, previous versions of this chapter were submitted for presentation at the following conferences. In some cases these had been made public as part of the conference proceedings. When this is the case I include the link to the corresponding webpage.

- June, 2016. Workshop on Analysing the Impact of Extreme Weather Events from a Microeconomic Perspective. German Institute for Economic Research (DWI). Berlin, Germany.

- May, 2016. PhD Colloquium on Environmental and Energy Economics and Management, University of Birmingham, United Kingdom.

Abstract

We use a repeat-sales model to analyse the evolution of the price of properties affected by flooding in England between 1995 and 2014. The final dataset includes information on over 12 million individual property transactions, which represents about 4.8 million houses with at least one repeat-sale. This database is merged with high-definition GIS data containing the spatial delineation of over 140 thousand flood incidents in England that account for a total flooded area of 2,654 km^2 during the period of analysis. The results suggest that the average post-flood price of properties affected by inland and coastal flooding, respectively, is 12.6% and 13.6% lower than comparable not-flooded properties; for a median-priced house in 2014 these represent £29,317 and £21,832. The discount, however, is short-lived. On average, properties affected by inland flooding recover half-life value of the post-flood discount after 4 years and only 2 years for coastal properties. The magnitude of the impact depends on different characteristics of the properties (type of property, price level, and rural/urban classification), characteristics of the flood (source and duration) and the existence of structural flood protection. There is no evidence of increasing negative impacts associated with repeated flooding. The results suggest that current estimates of flood damages used to allocate funding for flood protection can be improved by considering characteristics of affected properties such as the type of properties, price level, or rural/urban classification.

Keywords: Flood risk, housing prices, repeat-sales, hedonic valuation

JEL Code: Q51, R21, Q54

3.1 Introduction

During recent years the United Kingdom (UK) has experienced an increasing number of floods which have been accompanied by an increase in related damage costs over time. Recent floods in England highlight the major implications of these events. The Easter river floods in 1998 caused damages of over £350m (Bye and Horner, 1998). During autumn 2000 widespread flooding across much of England had an estimated cost of the order of £1.0bn (EA, 2001). In 2007, over 55,000 properties were flooded causing total damages of around £3.2bn (EA, 2010). In 2012, widespread floods across the country resulted in an estimated cost to the UK economy close to £600m (Met Office and JBA, 2012; EA, 2013). During the winter 2013/2014 extreme weather conditions also caused widespread flooding in the south of England leading to total economic damages of £1.3bn; the greatest proportion of these damages corresponding to residential properties (Met Office, 2014; EA, 2016). More recently, storms Desmond and Eva caused severe flooding during December 2015-January 2016 in the north of England (Met Office, 2016). At the time of writing this chapter, no official damage and loss assessment was published for the last event, however the Association of British Insurers (ABI) estimates total payments on the order of £1.3bn to customers that were affected (ABI, 2016). All these major floods have been caused by record-breaking weather conditions (Bye and Horner, 1998; Met Office and JBA, 2012; Mett Office, 2014; Met Office, 2016).

Nowadays flood risk represents a significant UK policy issue. It is estimated that there is a total of 2.8 million properties in England exposed to some level of risk in 2014, out of which 690 thousand are properties at *very significant* risk (75-year return period or greater). The expected annual damages to residential properties amounts to £270m; although this figure considers only direct damages[1] (Sayers et al., 2015). The projections of future flood risk by Sayers et al. (2015) for the UK Climate Change Risk Assessment 2017 suggest that for a scenario assuming no population growth the number of properties in England exposed to *very significant* risk could increase between 43 and 130% in 2080. This increase is only due to changing weather conditions considering different climate change scenarios. Under these circumstances, the expected direct annual damages to residential properties are expected to increase between 47 and 470%, which represents expected annual damages in the range of £397m to £1.5bn (Sayers et al., 2015). If we consider the effect of population growth, new developments will add to future costs of flooding. The UK Committee on Climate Change (2015) points out that each year 4,600 new homes are built in areas exposed to significant flood risk, almost 50% of these are constructed in areas at *very significant* risk.

The prevalence of flooding together with the continuous development on floodplains and the expected increase in flood risk due to climate change highlight the importance of understanding the implications of flooding to households. Samwinga, Proverbs and Homan (2004) and Lamond, Proverbs and Hammond (2010) emphasise that one of the major concerns of British homeowners affected by flooding is the long-term economic or financial impact in terms of the insurability and saleability of their property. Brignall and Jones (2016, *The Guardian*) also document the fear of homeowners that their properties lose value and in some cases they “*have become virtually unsellable*” after the recent floods in the north of England in December 2015. Despite the relevance of this topic for

[1] See Chapter 2 for a definition of direct damages.

UK, to the best of our knowledge there is only one significant study analysing the effect of flooding on property prices in England: Lamond, Proverbs and Hammond (2010).

There is a relatively large body of literature that looks at the effect of a flood on the price on properties located in the floodplain, most of these studies are applications to the United States' (US) housing market (see Chapter 1). However, there is a lack of research on the effect of flooding on the price of *inundated* properties, this is usually due to missing information regarding the properties that are affected at each particular flood event. The objective of this chapter is to analyse the evolution of the price of properties affected by flooding in England using a repeat-sales representation of a hedonic model. To the best of our knowledge previous applications of the hedonic model to analyse the price of inundated properties include only Daniel, Florax and Rietveld (2007, 2009) and Atreya and Ferreira (2011, 2012a, 2012b, 2015). In both cases the authors use a difference-in-differences (DID) specification of a hedonic model. The former consider properties affected by flooding from the Meuse River in the Netherlands in 1993 and 1995. The latter look at the price of properties inundated after storm Alberto in 1994 in Albany, Georgia, US.

This chapter contributes in several aspects to the existing literature on the economics of flood risk. Unlike most of the previous hedonic applications that focus on the effect of a flood on the price of properties in the floodplain, we analyse the evolution of the price of properties affected by flooding. We avoid using the cross-sectional approach prevalent in the existing literature, which for identification requires controlling for a large number of factors (some of them non-observable) potentially determining house prices. Instead, we follow a repeat-sales specification to analyse the evolution of the price of properties affected by flooding. Our analysis goes beyond the scale of usual empirical studies which focus on a single or multiple sites, conducting a comprehensive analysis considering all individual flood events on records in England between 1995 and 2014. The sample includes information on over 12 million individual property transactions, which represent about 4.8 million houses with at least one repeat-sale during the period of analysis. We use high-resolution GIS data with over 140 thousand GIS polygons delineating the area affected by each individual flood event on records in England; these represent a total flooded area of 2,654 km^2 during the period 1995-2014. To the best of our knowledge this is the first study to analyse the effect of flooding from different sources including inland and coastal flooding. We also consider the case of repeated flooding and the effect of flooding on the price of flats, things which have been largely overlooked in the literature.

Briefly, the results suggest that the average post-flood price of properties affected by inland and coastal flooding, respectively, is 12.6% and 13.6% lower than comparable not-flooded properties; for a median-priced house in 2014 these represent £29,317 and £21,832. The discount, however, is short-lived. On average, properties affected by inland flooding recover half the value of the post-flood discount after 4 years and only 2 years for coastal properties. The magnitude of the impact depends on different characteristics of the properties (type of property, price level, and rural/urban classification), characteristics of the flood (source and duration) and the existence of structural flood protection. There is no evidence of increasing negative impacts associated with repeated flooding. The results suggest that current estimates of flood damages used by the UK Department for Environment, Food and Rural Affairs (Defra) to allocate funding for flood protection can be improved by considering characteristics of affected properties such as the type of properties, price level, or rural/urban classification.

The reminder of this chapter is organized as follows. Section 3.2 presents a review of the literature on the use of hedonic models to estimate the effect of flooding on property prices. Section 3.3 shows the theoretical representation for the application of the hedonic model. Section 3.4 describes previous empirical applications of the hedonic model to the literature on the economics of flooding and presents our identification strategy using the repeat-sales model. Section 3.5 describes the database and the econometric model. Section 3.6 shows our main results. Section 3.7 discuss the implications of our results and section 3.8 concludes. Robustness tests are presented in section A3.1 of the appendix.

3.2 Literature Review

The hedonic price model (HPM) has been the usual theoretical framework to analyse the effect of hazards on property values, including flood risk. In this section we discuss the empirical applications of the HPM to the literature on the economics of flood risk. The literature review is organised as follows. First, we describe current application of the HPM to the flood risk literature by classifying the evidence into three groups according to the area of study, namely: (1) implicit price of risk, (2) effect of a flood on the implicit price of risk, (3) the effect of a flood on inundated properties. Second, once we have characterised this distinction, we discuss the evidence available from studies considered in the third branch of literature, to which this chapter contributes. Finally, we discuss other hedonic applications relevant to this chapter such as the evidence available for the UK and studies investigating the effect of repeated flooding on the price of properties.

We can classify the empirical applications of the HPM to the literature on the economics of flood risk in three groups according to the focus of the studies. The first group consists of studies which try to identify the implicit price of flood risk in the housing market by looking at the effect of floodplain designation on property prices. Within this group, MacDonald, Murdoch and White (1987) are probably the first authors to provide a theoretical framework for the interpretation of hedonic estimates to the analysis of the effect of flood risk on the price of properties. In general, these studies use a standard representation of a HPM to compare the price of properties located inside and outside the floodplain considering different levels of risk. The resulting price differential is interpreted as the implicit price of risk in the housing market. Empirical applications of the hedonic model in this group include MacDonald, Murdoch and White (1987), Donnelly (1989), Speyrer and Ragas (1991), Bin (2004), Bin and Kruse (2006), Rambaldi et al. (2012) and Meldrum (2015), among others.

The second group of studies analyse the effect of flooding on the price of properties located inside the floodplain. Bin and Polasky (2004) observe that previous studies which associate the implicit price of flood risk with a significant discount on the price of properties analyse locations which had experienced recent flooding, whereas results from locations with no recent flood experience do not show a significant discount. The authors suggest that the occurrence of a flood provides new information to individuals regarding the level of risk in their location, increasing individuals' perception of flood risk and the associated discount for living in a floodplain (expected increase in future flood losses). In general, these studies use a DID specification of a hedonic model to analyse the price differential for floodplain location before and after a flood. The coefficient on the post-flood variable is interpreted as the information update on the price of properties in the floodplain due to the occurrence of a flood. Empirical application in this group of studies include Bin and Polasky (2004), Hallstrom and Smith (2005), Kousky (2010), Atreya, Ferreira and Kriesel (2013), Bin and Landry (2013) and Rajapaksa et al. (2016), among others. Other authors, for instance Harrison, Smersh and Schwartz (2001), Troy and Romm (2004), Pope (2008), Samarasinghe and Sharp (2010), and Rajapaksa et al. (2016), use DID hedonic price models to analyse the effect of changes in regulations, such as floodplain zoning, on the price of properties in the floodplain. More recent applications in this group focus not only on the price update of properties in the floodplain after a flood, but also investigate the evolution of prices following the event. In this way, evidence from authors such as Atreya and Ferreira (2011, 2012a, 2012b, 2015), Atreya Ferreira and Kriesel (2012, 2013) and Bin and Landry (2013), suggest that the post-flood discount for properties inside the floodplain diminishes as time passes by and people tends to forget about the risk that flooding represents.

The third group of studies use DID hedonic price models to analyse the effect of flooding on the price of inundated properties (realisation of a flooded state). Unlike studies in group two which analyse the effect of flooding on the price of floodplain designated properties (flooded or not), studies in group three focus only on the effect of the flood on *inundated* properties. In these studies, the information on the actual inundated area is used to tease out the information effect of a flood to identify the effect of flood damages (direct and indirect), and other potential costs associated with flooding (monetary and non-monetary), on the price of affected properties. Empirical applications in this group of studies are those by Daniel, Florax and Rietveld (2007, 2009) and Atreya and Ferreira (2011, 2012a, 2012b, 2015). This chapter contributes to this third branch of the flood risk literature. [2]

Daniel, Florax and Rietveld (2007, 2009) use a DID HPM to analyse the price of properties in seven municipalities in the Netherlands that were affected by flooding from the Meuse River in 1993 and 1995. Both papers represent different versions of the same study using transaction values of houses observed between 1990 and 2004. In both cases, the sample includes over 9,500 transactions, among which 313 concern houses that were flooded or surrounded by water in at least one of the events. The authors identify the properties affected by flooding using aerial photos of the River Meuse showing the area flooded during each event. They control for the presence of water-related amenities by including variables indicating the proximity to the river and the proportion of water in the total area of the neighbourhood. The results by Daniel, Florax and Rietveld (2009) indicate that after the first flood affected properties were sold at a price 4.6% lower than comparable properties not affected by flooding. The price differential increases to 9.1% after the second flood. Using a spatial specification of the DID hedonic model, Daniel, Florax and Rietveld (2007) conclude that houses were not discounted after the first flood, but found a discount of 7.8% after the second flood. The discount is in the range of 7.9% and 11.4% when considering spatial correlation. In both studies, the results suggest that the discount remains persistent during the years following the second flood. Although the authors reported to have the transactions price of flats in the sample, they dropped out these observations from the analysis.

[2] Chapter 1 of this Thesis presents a meta-analysis on the results of all the individual studies considered in groups (1) and (2) of the flood risk literature.

The studies by Atreya and Ferreira (2011, 2012a, 2012b, 2015) use a DID HPM to identify the effect of flooding on inundated properties after a large flood in 1994 due to tropical storm Alberto in Albany, Georgia, US. All the studies are slightly different applications of the same study which was finally published by Atreya and Ferreira (2015). The sample is restricted to the flood inundation study area at Flint River, Albany, which includes around 3,000 single-family residences. The authors use a map of the area that was inundated in 1994 to identify properties located within the affected area. They also use flood zone maps to identify all properties located inside the floodplain and to separate the information effect of the flood on properties in the floodplain from the effect of the flood on inundated properties. The econometric models include the distance from each property to the river to control for the amenity value of proximity to water. The results indicate that immediately after the flood properties in the inundated area were sold at a price 48% lower than comparable properties outside this area. The discount ranges between 33% to 52% depending on the econometric specification and whether the inundated property is inside or outside the floodplain. After controlling for location within the inundated area, there is no significant additional discount associated with being in the floodplain. The authors suggest that the post-flood discount is mainly driven from an inundation effect rather than an informational effect, and that previous studies that do not account for location in the inundation area might overestimate the information effect of a flood on properties in the floodplain. In all cases, the results indicate that the discount on inundated properties is short lived, decreasing at a rate of around 6% per year and lasting, therefore, about 8 years. A shortcoming of this study is that the identification of the inundated area is based on geospatial simulations of a flood with the characteristics of the 1994 flood in Albany and not on actual inundation maps. The resulting simulated inundation area is likely to differ from the actual inundated area.

There are only a handful of applications of the hedonic model to the flood risk literature in the UK. To the best of our knowledge, it is only the studies by Lamond and Proverbs (2006), Lamond, Proverbs and Antwi (2007) and Lamond, Proverbs and Hammond (2010) which analyse this issue. The studies correspond to the second branch of the literature which analyses the effect of a flood on the implicit price of risk in the housing market. In all three studies the authors evaluate the effect of the 2000 floods in England on the price of properties in the floodplain, but are unable to identify flooded properties. They identify properties inside the floodplain using flood zone maps accessible through the UK Environment Agency (EA). Lamond and Proverbs (2006) use a standard hedonic model with a sample of 159 properties in Barlby, North Yorkshire, that were sold over the period 2000-2006. The authors conclude that after the flood properties in the floodplain were sold at a price 17.5% lower than comparable properties outside the floodplain. This discount is only significant for the two years following the event. Lamond, Proverbs and Antwi (2007) use a repeat sales hedonic model to analyse the change in the price of 32 properties with sales before and after the flood in Bewdley, Worcestershire, during the period 2000-2005. Some of these properties were resold more than once, so the final sample includes 41 pairs of sales. The results show that the growth in the price of properties inside the floodplain was 6% lower than for properties outside the floodplain. There is evidence of depressed growth up to five years after the event (end of the sample). One shortcoming of the studies by Lamond and Proverbs (2006) and Lamond, Proverbs and Antwi (2007) is that they both rely on small samples for the identification of the effect of flooding on property prices. Furthermore, the standard hedonic model by Lamond and Proverbs (2006) do not control for property characteristics that can influence the price of houses other than the type of property (detached, semi-detached, terraced).

Lamond, Proverbs and Hammond (2010) address these issues to a significant extent. Similar to Lamond, Proverbs and Antwi (2007), the authors use a repeat sales model to analyse the effect of the 2000 flood on the growth rate of the price of properties in the floodplain. The study focus on 13 locations in England[3] with a sample that consists of 1,303 repeat sales with transactions before and after the flood during the period 2000-2006. The authors conclude that the price of significantly at risk properties grew at a rate 9% lower than the price of properties outside the floodplain, after the area suffered flooding in 2000. The discount is greater in areas flooded more frequently. For properties in floodplains which have been flooded more than once the growth rate is 15% lower, and 35% lower in locations with three or more floods. The impacts are seen to decline with time with evidence of depressed growth up to six years after the event (end of sample). To the best of our knowledge, hitherto this represents the most significant study available analysing the effect of flooding on the price of floodplain properties in England, however it also has important limitations. For instance, it only considers evidence from one flood event, it excludes from the analysis properties affected by coastal flooding, and it does not consider the possibility that different types of housing might have different price trends which might threaten identification.

Researchers have also been interested in the effect of repeated flooding on the price of properties. In particular, there are two studies using a DID specification of the HPM to analyse the change in property prices following two flood events within sample. One is the aforementioned study by Daniel, Florax and Rietveld (2007, 2009) which focuses on properties affected by flooding form the Meuse River, Netherlands, in 1993 and 1995. The

[3] Malton and Norton, Woking, Shrewsbury, Bewdley, Selby and Barlby, Lewes, Hatton, Ruthin, Mold, Newport, Southsea, West Bridgford and Wakefield.

second study is by Bin and Landry (2013) who examine the price of floodplain properties with different levels of risk in Pitt County, North Carolina, US, following flood events due to Hurricane Fran (1996) and Floyd (1999); they use a sample of 4,800 properties for the period 1992-2000. In both cases, the authors conclude that the update in the implicit price of risk is larger after the second flood. Daniel, Florax and Rietveld (2007, 2009) suggest that after the first flood affected properties were sold at a price 4.6% lower than comparable properties not affected by flooding. The price differential increases to 9.1% after the second flood. Bin and Landry (2013) conclude that after the first flood prices of properties in the 100-year floodplain decline about 9%, and 13% after the second flood. However, neither Daniel, Florax, and Rietveld (2007, 2009) nor Bin and Landry (2013) include variables to control for the decay in the implicit price of risk after the floods. Furthermore, the authors consider only one event of repeated flooding and the larger and significant discount after the second flood might well be due to specific characteristics of the second event, such as intensity, affected area, or media coverage, to name but a few, and not as a result of increased flood risk perception associated with repeated flooding. It is important to note that Lamond, Proverbs and Hammond (2010) also include information of properties in locations which have been flooded more than once. However, their analysis focuses only on the effect of one flood (the 2000 flood in England) on the price of properties with different flooding history and not on the effect of different flood events.

Finally, Meldrum (2015) is probably the only existing study analysing the effect of flood risk on the price of flats. The authors use a hedonic price model to identify the effect of floodplain designation across different type of properties – standalone homes and condominiums – sold in Boulder County, Colorado, US, between 1995 and 2010. The sample includes observations for 40,101 standalone homes and 8,604 condominiums. The author uses a dummy variable to distinguish those properties located inside the 100-year floodplain. The results suggest that for the case of standalone properties there is no significant effect associated with floodplain designation. However, condominiums inside the floodplain are sold at a price 15% lower than comparable properties outside the floodplain. The author concludes that these results within the specific context of Boulder, Colorado, are due to information asymmetries related to the cost of insurance across different type of properties, and not due to a higher valuation of risk for individuals living in condominiums.

The remainder of the chapter describes the theoretical development of the HPM, the identification strategy and the empirical results.

3.3 The Hedonic Model for Flood Risk Valuation

Economic theory suggests that the costs of current and expected future flooding is capitalised in the price of properties exposed to flooding. Early research by Ridker and Henning (1967) suggests that if the costs derived from housing rise (e.g. if additional maintenance and cleaning costs are required), the price of the property will be discounted in the market to reflect people's evaluation of these changes. The use of HPMs has been especially popular to estimate the effect of flood risk on property prices, evaluating three different cases: (1) the effect of floodplain designation on property prices; (2) the effect of a flood on floodplain designated properties; and (3) the effect of a flood on flooded properties. In the three cases the theoretical derivation of the effect of interest is based on the expected utility representation of the HPM by MacDonald, Murdoch and White (1987), however these three effects have a different theoretical representation. In this section we present the theoretical derivation of the HPM with special emphasis on identifying the third case (3), i.e. the effect of a flood on flooded properties. We also highlight the important differences that arise when comparing this to the other two cases. For the complete theoretical derivation of the theoretical effect of floodplain designation on property prices (case (1)) and the effect of a flood on floodplain designated properties (case (2)), please refer to section 1.2 of Chapter 1 of this Thesis.

The theoretical model described in this section is based on the characterisation of the hedonic price function (HPF) by Rosen (1974) and its extensions to the flood risk literature by MacDonald, Murdoch and White (1987), Carbone, Hallstrom and Smith (2006), Bin, Kruse and Landry (2008), Kousky (2010) and Bin and Landry (2013). The HPF describes the price of a quality-differentiated commodity as a function of its multiple attributes. When an individual decides where to live this decision also includes the level of flood risk they face, thus flood risk can be regarded as an additional characteristic of a property.

Let $\boldsymbol{S}$ represent a set of structural characteristics of a house such as age, number of bathrooms and lot size; $\boldsymbol{N}$ the neighborhood/locational characteristics such as crime rate, distance to central business centre or to a major motorway, and $\boldsymbol{E}$ environmental characteristics such as the level of pollution. Define $Z = \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{E}$. Furthermore, let the subjective probability of flooding, i.e. the homeowner's subjective assessment of flood risk, be a function $p(i, r)$ of the set of information, i, the individual holds about flood risk in the location of the property and r which represents the site attributes related to flood risk, which could be locational characteristics such as proximity to water bodies or elevation. The HPF describing the price of a property, P, might therefore be written as:

$$P = P\big(Z, r, p(i, r)\big) \qquad (1)$$

Therefore, P is exogenous to individual buyers and sellers, but reflects subjective risk perception $p(i,r)$. Prices are assumed to be market clearing, given the inventory of housing choices and their characteristics. The housing market is assumed to be in equilibrium, which requires that individuals optimize their residential choice based on the prices in alternative locations. It is assumed that homebuyers are able to adjust the different levels of each characteristic by moving their residence; no transaction costs are considered.

It is important to distinguish the subjective assessment of the probability of flooding, p, from the objective measure of flood risk, π. This distinction implies three important things. First, the perceived risk is not necessarily equal to the objective risk. Second, changes in the objective risk are not necessarily perceived. Third, changes in the perceived risk do not necessarily arise from changes in the objective risk. In areas where flood risk disclosure is mandatory or public information about flood risk is available, the set of information, i, might include the objective probability of flooding, π.

The model uses an expected utility framework that incorporates risk factors associated with a property. The household's decision is modelled using the following state dependent utility function:

$$EU = p(i,r) \cdot U^F[Z,r,Q] + \big(1 - p(i,r)\big) \cdot U^{NF}[Z,r,Q] \tag{2}$$

where $U^F(\cdot)$ is the utility of the homeowner in a state where a flood occurs and $U^{NF}(\cdot)$ is the utility of the homeowner when there is no-flood. The budget constraint (M) for the individual in state F (with perceived probability $p(i,r)$) and NF (with perceived probability $\big(1 - p(i,r)\big)$) is given by equations (3) and (4), respectively.

$$F: \quad M = P\big(Z, r, p(i, r)\big) + Q + L(r) \tag{3}$$

$$NF: M = P\big(Z, r, p(i, r)\big) + Q \tag{4}$$

Note from equations (3) and (4) that the level of consumption of Q is different across states, in particular $Q^F < Q^{NF}$. Both, the level of utility and the marginal utility of income may change with the state. The conditional loss $L(r) \in (0, \bar{S})$, is a function of the locational risk characteristics of the house, r, and reflects the magnitude of the loss should state F occur; $\bar{S}$ represents the structure replacement cost of the property. Thus, the occurrence of a flood is associated with a potential monetary loss $L(r)$ in equation (3).

At this point it is important to highlight the main differences between the theoretical representations of three different applications of the HPM to the flood risk literature. In all three cases the decision of the individual is modelled using the expected utility framework in equation (2). The first case (1) corresponds to the effect of floodplain designation on property prices. In this case, the expected utility of the individual, ceteris paribus, depends on the subjective perception of flood risk ($p(i, r)$) and the conditional loss ($L(r)$) should state F occur. The implicit price of flood risk in the housing market is then given by $\partial P / \partial p$.

The second case (2) corresponds to the effect of a flood on the price of floodplain designated properties. In this case, the occurrence of a flood is considered to provide new information (i) to homeowners in the floodplain to update their subjective assessment of the probability of flooding ($p(i, r)$). This increase in the perceived probability of a flood (state F) is reflected in property prices; the corresponding price update is given by $\partial P / \partial i$, that is, the change in subjective probability is converted to a monetary trade-off. Notice that this effect represents only the change in prices due to the information conveyed by the flood and excludes the value of flood damages on affected properties as well as potential changes in the cost of insurance. Therefore, results from previous studies that try to identify the information effect of a flood on floodplain designated properties might be biased as they fail to account for the potential discount on affected properties due to flood damages (Atreya and Ferreira, 2015). Notable exceptions are Atreya and Ferreira (2011, 2012a, 2012b, 2015) that use flood inundation maps to tease out the inundation effect from the information effect of the flood, and Hallstrom and Smith (2005) that focus on the effect of a flood on "near miss" properties – houses with pre-existing known risk but not hit by the flood – in Florida, US. In a similar way, other authors such as Harrison, Smersh and Schwartz (2001), Troy and Romm (2004), Pope (2008), Samarasinghe and Sharp (2010), and Rajapaksa et al. (2016) analyse the effect of new information that arise from changes in regulations on the price of properties, for instance floodplain zoning. A detailed derivation of these two effects appear in sections 1.2.2 and 1.2.5 of Chapter 1 of this Thesis.

The third set of applications of the HPM to the flood risk literature (3) refers to the effect of a flood on flooded properties, which is the focus of this chapter. The occurrence of a flood can be considered as a realisation of the flooded state (F) for affected properties. In this way, the post-flood price of a property is likely to reflect three things: (1) the price discount for being located in a flood prone area (for flooded properties within the floodplain), (2) the monetary investment required to restore the property to pre-flood conditions, and (3) the information conveyed by the flood on affected properties. These are explained below.

3.3.1 The price discount for floodplain location

The rational consumer will choose to live in a location which maximises his expected utility subject to the budget constraint. If a property is subject to frequently substantial flooding, the owner may incur in substantial repair costs and additional associated losses; alleviating strategies include constructing floodproofing structures, purchasing flood insurance, and engaging in environmental flood control practices. All these future costs might easily exceed the cost of buying an equivalent property outside the flood risk area (Bin and Kruse, 2006; Lamond, 2012; MacDonald, Murdoch, and White, 1987; Zimmerman, 1979). Consumers will locate within a floodplain if they are compensated for accepting the potential loss (MacDonald, Murdoch, and White, 1987). Intuitively this means that flood risk is capitalised into property prices.

Formally, maximising expected utility (2), with respect to the subjective probability of flooding, p, subject to the homeowner's budget constraint, and dividing by the expected marginal utility of income yields:

$$\frac{\partial P}{\partial p} = \frac{U^F - U^{NF}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \tag{5}$$

Equation (5) is the coefficient on the risk variable estimated in standard hedonic regressions. It indicates that the marginal implicit hedonic price for flood risk reflects the incremental utility difference across states; dividing by the expected marginal utility of income produces a measure of marginal WTP. This implies that properties in locations that improve the chances of state NF will get bid up, ceteris paribus. The marginal WTP for a reduction of p and yet remaining indifferent is captured by the sales price differential resulting in housing markets as consumers bid for locations with lower p. This justifies interpreting the coefficients from hedonic regressions as estimates of the amount of compensation a homeowner requires, through a lower property price, to move into a riskier area (Bin et al., 2008; Kousky, 2010; MacDonald, Murdoch, and White, 1987).

3.3.2 The effect of flood damages on property prices

The theoretical model considers the potential monetary losses associated with flood damages as part of the budget constraint of the individual in the flooded state (F) in equation (3). This conditional monetary loss $L(r) \in (0, \bar{S})$, is a function of the locational risk characteristics of the house, r, and reflects the magnitude of the loss should state F occur, where $\bar{S}$ represents the structure replacement cost of the property. However, the monetary investment, for any level of $L(r)$, required from the homeowner to restore the property to pre-flood conditions is different for individuals with and without a flood insurance policy.

For individuals without flood insurance they have to cover the full monetary investment to restore the property to pre-flood conditions. If the individual decides to sell his property without restoration, then we expect the value of flood damages $L(r)$ to be fully discounted from the price of the property. Post-flood investment in house restoration is expected to capitalise in the post-flood value of the property. Authors such as Montz (1992), Tobin and Montz (1994) and Lamond and Proverbs (2006) suggest the possibility of post-flood property values being higher than pre-flood values after full restoration of the property. This can be the case in properties were the post-flood reinstatement results in improved housing characteristics due to building standards exceeding the original specification, updated fixtures and decoration, or the installation of flood resilient measures (Lamond and Proverbs, 2006). Chapter 2 of this Thesis shows that post-flood investment in public infrastructure such as flood protection might also have some positive capitalisation on property prices, especially for properties exposed to the highest level of risk.

In locations where flood insurance is available individuals can decide to buy insurance policy to avoid the risk of potential financial loss. Those individuals who decide to buy flood insurance policy are assumed to change an unknown loss into a known payment. As mentioned in section 3.3.1, economic theory suggests that the cost of flood insurance (and non-insurable losses) capitalise in the price of floodplain designated properties. However in the event of a flood, even homeowners with a flood insurance policy are likely to incur in monetary expenses that can be of three different types: excess on insurance claims, monetary losses not covered by flood insurance, and a potential increase in insurance premiums. The following description of the role of flood insurance in property prices follows closely the modification of the expected utility HPM by Bin and Landry (2013).

The insurance cover on the property is given by $C \in (0, \bar{S})$, where $\bar{S}$ represents the structure replacement cost of the property. The known insurance payment (premium) is $I(\pi(r), C)$ which is assumed to be a function of the objective probability of flooding $\pi(r)$ rather than $p(i, r)$, i.e. flood insurances is assumed to be risk based, and a function of the level of cover on the property. The household's decision is modeled using the same state dependent utility function as in equation (2). The budget constraint for the individual in state FI (flooded with insurance policy) and NFI (not flooded and with insurance policy) is given by equations (6) and (7), respectively:

$$FI: \quad M = P\big(Z, r, p(i, r)\big) + Q + L(r) + I(\pi(r), C) - C \tag{6}$$

$$NFI\text{: } M = P\big(Z, r, p(i, r)\big) + Q + I(\pi(r), C) \tag{7}$$

That is, whenever the individual decides to buy an insurance policy we also need to subtract the cost of insurance from total income, and add the compensation from the insurer should state FI occurs. If the payment from the insurer in state FI is perceived to be equal to the loss, $L = C$ (full cover, no excess payment), then the level of consumption of Q will be the same across states and the house is restored to pre-flood conditions at no additional cost. In case the individual is required to pay excess on insurance claims or he does not hold a full insurance cover, then $L \neq C$ and the level of consumption Q will be lower in the flooded state (FI). The extent of this reduction in consumption will be equal to the out-of-pocket payments required to restore the property. Repairs, improvements and modifications undertaken after a flood are likely to capitalise in the post-flood value of the property.

It is important to consider that the reinstatement of a flooded property can be a lengthy process. Lamond and Proverbs (2006) estimates that the average reinstatement period for seriously flooded properties is about six months. However it is possible that immediately after the flood homeowners, especially those without flood insurance, decide only to undertake the most urgent and necessary repairs to return to the property, and postpone other minor repairs over long periods of time. Investment in public infrastructure such as flood defences might also take some years. This implies that full recovery of property values can take from some months to several years. The time and extent of recovery depends on several things such as the extent of flood damages, post-flood emergency management, quality of restoration, betterments to the property, among others.

If the occurrence of a flood results in an update of the objective probability of flooding, π, this will increase insurance premiums $I(\pi(r), C)$, and therefore the costs of being located inside the floodplain. Changes in information associated with risk factors will be reflected in the implicit price of risk in the housing market as outlined in equation (5) above. In this case, the individual maximises the expected utility in equation (2) with respect to p, subject to the state dependent budget constraint of the individual with flood insurance in equations (6) and (7). This yields:

$$\frac{\partial P}{\partial p} = \frac{U^{FI} - U^{NFI}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} - \frac{\frac{\partial I}{\partial \pi}}{p(i,r)\frac{\partial U^F}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \tag{8}$$

Therefore an increase in the price of insurance premiums following a flood would result in an increase of the implicit price of flood risk in the housing market as it increases the cost of being located inside the floodplain.

MacDonald, Murdoch, and White (1987) note that if the payment from the insurer in state FI is perceived to be equal to the loss from flooding ($C = L$) such that the utility function is state independent, then:

$$U^{FI} = U^{NFI} \text{ ; then } \frac{\partial P}{\partial p} = -\frac{\partial I}{\partial \pi}$$

That is, under these specific circumstances the sales price differential is determined by the change in insurance cost resulting from changes in the probability of flooding. This reasoning has led some to use the estimated present value cost of future insurance premiums as a proxy for the benefits of flood prevention schemes in countries such as the UK (Crichton, 2005). However, evidence suggests that the PV of insurance payments is likely to be less than the property price discount for living in an area prone to flooding (see for example MacDonald, Murdoch and White, 1987; Speyrer and Ragas, 1991; Bin, Kruse and Landry, 2008 and Atreya and Ferreira, 2011). If the payment from the insurer is perceived to be less than the loss from flooding ($L > C$), then:

$$U^{FI} < U^{NFI}\text{ ; then } \frac{\partial P}{\partial p} > -\frac{\partial I}{\partial \pi}$$

Under these circumstances the individual will be WTP to increase the probability of the desired state (NFI), regardless of the change in insurance cost. Therefore, if the individual purchases insurance the WTP for a reduction of π is dependent upon the perceived difference between the loss from flooding and the payment from the insurance company should state FI occurs (MacDonald, Murdoch, and White, 1987). This difference arises due to the existence of non-insurable costs associated with flooding, including disruption of normal life and loss of items with sentimental value, psychological stress to residents and hassle and deprivation of being displaced. Insurance leads to only a mitigation of financial losses associated to flood risk rather than an elimination of the risk (Harrison, Smersh, and Schwartz, 2001). The HPF capitalises insurance cost and residual risk of non-insurable losses (Bin and Landry, 2013).

3.3.3 The effect of new information on flooded properties

Authors such as Bin and Polasky (2004), Hallstrom and Smith (2005), Kousky (2010), and Rajapaksa et al. (2016), argue that the occurrence of a flood provides new information to homeowners regarding the level of risk in their location. They suggest that individuals use this information to reassess their subjective assessment of the probability of flooding, p, which results in an update of the price differential for floodplain location. As previous studies suggest, this information effect will be capitalised in the price of properties in the floodplain as the perception of risk increases. This includes flooded and not-flooded properties. However, the extent of the capitalisation across properties might be different depending on which properties are perceived as more risky. For instance, the increase on flood risk perception might be higher for properties in the inundated area.

The marginal effect of information is to change the perceived probability of a flood. The decision of the individual is again modelled using the expected utility framework in equation (2), where the level of utility depends on the state of the individual F (loss) or NF (no-loss). The conditional budget constraint is given by equations (3) and (4).[4] Maximising expected utility subject to the individual's budget constraint and solving for the partial derivative of the HPF with respect to the new information, i, yields:

$$\frac{\partial P}{\partial i} = \frac{\frac{\partial p}{\partial i}\left(U^{F} - U^{NF}\right)}{p(i,r)\frac{\partial U^{F}}{\partial Q} + \left(1 - p(i,r)\right)\frac{\partial U^{NF}}{\partial Q}} \tag{9}$$

Equation (9) multiplies the *ex-ante* discount for floodplain properties in equation (5), by the change in the subjective probability of flooding due to an information update. This expression represents the effect of new information on property values, where the change in subjective probability is converted to a monetary trade-off. However, it is important to note that, as Atreya and Ferreira (2011, 2012a, 2012b, 2015) and Hallstrom and Smith (2005) point out, in order to identify the pure information effect of a flood it is necessary to isolate the effect of flood damages, otherwise results might be biased.

[4] This can be extended, without any loss of generality, to consider the case of homeowners with a flood insurance policy using the state dependent budget constraint in equations (6) and (7). An expression considering this is provided by Carbone, Hallstrom, and Smith (2006) in equation (4).

3.4 The Empirical Hedonic Model

Usual applications of the hedonic price model within the flood risk literature address the issue of floodplain location and its capitalisation in property prices using an additive representation of the HPF in equation (1), as follows:

$$lnP_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \gamma r_i + \phi p_i + \varepsilon_i \qquad (10)$$

Where i denotes a specific house; j represents specific structural, neighborhood/locational and environmental characteristics of house i. P represents the sale price of the property; Z is the set of structural, locational and environmental characteristics of the house; r is usually given by the Euclidean distance to the nearest water body; and p is a proxy variable for flood risk, where a common alternative has been the use of a dummy variable indicating location in a floodplain at different levels of risk. β_0, β_j, γ and ϕ are estimated coefficients; note ϕ is the coefficient on the risk variable as denoted in equation (5). ε_i is the house-specific error term to which the usual assumptions apply i.e. $\varepsilon_i \sim N(0, \sigma^2 I)$.

More recent hedonic applications on the economics of flood risk examine the information effect of a flood on the price of floodplain designated properties using a quasi-experimental design with a difference-in-differences (DID) approach. The strategy for identification relies on the occurrence of floods as a source of exogenous variation in the explanatory variable, i.e. the sale price of a house, by introducing a temporal element to the analysis with the use of a before-after approach. Thus, there are two dimensions distinguishing the structure of a quasi-experiment: the group assignment for each unit (house) in the study, whether it is inside or outside a floodplain, and the timing (t) of the potential outcome that is observed for each unit. The empirical model is represented as follows:

$$lnP_i = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \phi p_i + \alpha Flood_i + \psi(Flood_i \times p_i) + \gamma r_i + \varepsilon_{it} \tag{11}$$

The treatment group is distinguished by a dummy variable indicating floodplain location (p_i) and the treatment refers to the occurrence of a flood. The timing is the date of the sale in relation to the flood event and it is represented by the variable $Flood$, which is a dummy variable equal to one for sales occurring after the flood event of interest. The parameter ϕ represents the group effect, i.e. the pre-flood relative price differential between the control group (no floodplain location) and the treatment group (floodplain location); α captures the time effect, i.e. the relative price difference for all properties that were sold after the flood; and ψ represents the treatment response, i.e. the incremental effect due to information conveyed by the flood (treatment) in known risky locations (floodplains). That is,

$$\hat{\psi} = \left(\overline{lnP_1^{p=1}} - \overline{lnP_0^{p=1}}\right) - \left(\overline{lnP_1^{p=0}} - \overline{lnP_0^{p=0}}\right) \tag{12}$$

The key assumption for identification is that $E[\varepsilon_{it}|Flood_i] = 0$, for $t = 0, 1$ (before and after the flood). Previous studies by Bin and Polasky (2004), Kousky (2010), Atreya, Ferreira and Kriesel (2013), Bin and Landry (2013), and Rajapaksa et al. (2016) among others, use this identification strategy to identify the information effect of a flood on floodplain designated properties. However, the authors do not control for potential negative impacts on property prices due to flood damages on affected properties. Atreya and Ferreira (2011, 2012a, 2012b, 2015) and Hallstrom and Smith (2005) argue that results from these studies represent biased estimates of the information effect of the flood as the authors fail to disentangle the effect of flood damages on flooded properties. Atreya and

Ferreira (2011, 2012a, 2012b, 2015) suggest to address this issue using flood inundation maps to separate the information effect of the flood on properties in the floodplain from the effect of the flood on inundated properties. Hallstrom and Smith (2005) suggest to analyse the information effect of the flood by focusing only on “near miss” properties, that is, properties in the floodplain but that were not hit by the flood.

Note that the econometric approach described in this section uses a pooled cross-section of property prices over time, i.e. the cross-time comparison does not correspond to sales of the same property, and therefore it is conditioned on values of the other covariates Z_{ij} and r_i. Housing sales of the same region are observed over time and unobserved heterogeneity is controlled for using region or neighbourhood level fixed effects (Parmeter and Pope 2012). A shortcoming of this approach is, therefore, the amount of information it requires, since information on all the major structural and locational characteristics (Z_i and r_{i}) influencing the value of a house must be included in the regression to ensure unbiased estimates (Palmquist 1982, 2005). An alternative to address this issue is the use of a repeat-sales model, which is described below.

3.4.1 A Repeat-sales Model to Identify the Effect of a Flood on Inundated Properties

The objective of this section is to describe the basic empirical repeat-sales model for the identification of the effect of the flood on the price of inundated properties. This model is derived from the standard HPM described above, but using actual panel data. We consider the sale price of houses sold multiple times over a given period of time. During the period between sales, there are changes in some characteristics of the properties such as age, environmental quality and the general real state price level; however other characteristics of the house (structural and locational) remain the same. Therefore, by considering two sales of the same property it is possible to control for time-invariant characteristics and recover estimates for the effect of those aspects of homes' location that change over time. In this way, a repeat-sales specification allow us to evaluate the price effect of an environmental change which is not uniform across properties (Kousky 2010, Palmquist 1982, 2005).

Formally, consider the additive representation of the HPF in equation (13). This is similar to the DID representation in equation (11), with two important changes. First, it has now been indexed by t to identify the timing for the sale of each house i. Second, since now we are interested in the effect of the flood on inundated properties, the group assignment for each house is now given by the variable IND which in its simplest form represents a dummy variable identifying properties located in areas that were directly affected by flooding (inundated) during the period of analysis. Similar to equation (11), we define the timing of the potential outcome that is observed for each unit using the variable $Flood$, which is a dummy variable equal to unity for sales occurring after the time of the flood.

$$lnP_{it} = \beta_0 + \sum_{j=1} \beta_j Z_{ij} + \phi p_i + \gamma r_i + \theta IND_i + \alpha Flood_{it} + \psi(Flood_{it} \times IND_i) + \varepsilon_{it} \quad (13)$$

As the repeat-sales model requires at least two sales of each property, there are two sales periods, t and s. P_{it} denotes the outcome observed after the flood and P_{is} identifies the outcome prior to the flood. Thus, for house i there is an earlier sale in year s for which the price is explained by an equation similar to (13) but where the variable $Flood$ takes the value of zero. Considering the difference in sales prices for the same home ($lnP_{it} - lnP_{is}$) yields equation (14).

$$(lnP_{it} - lnP_{is}) = (\beta_0 - \beta_0) + \sum_{j=1} \beta_j \left(Z_{ij} - Z_{ij}\right) + \phi(p_i - p_i)$$
$$+\gamma(r_i - r_i) + \theta(IND_i - IND_i) + \alpha(Flood_{it} - Flood_{is}) \tag{14}$$
$$+\psi[(Flood_{it} \times IND_i) - (Flood_{is} \times IND_i)] + (\varepsilon_{it} - \varepsilon_{is})$$

One relevant assumption for identification using the repeat-sales model is that all structural, locational, and neighbourhood characteristics (Z_i, p_i, r_i) of the property remain constant between the period of the two sales, t and s, as well as the parameters of the hedonic price function. Therefore these terms drop out of the equation (14) and time-invariant characteristics of the house are no longer a concern. The resulting expression appears in equation (15).

$$\Delta ln(P_{its}) = \alpha Bracket_{its} + \psi(Bracket_{its} \times IND_i) + \lambda_0 Year_t + \lambda_1 Year_s + \Delta\varepsilon_{its} \tag{15}$$

Notice that the term identifying properties that were sold after the flood, $Flood_i$, now translates into a dummy variable that we call $Bracket_{its}$, which identifies properties with sale transaction before and after the flood, i.e. sales that *bracket* the timing of the flood. If the flood occurred before the time of the first sale (s), it also takes place before the second sale (t) and $Flood_{it} - Flood_{is} = 0$, implying $Bracket_{its} = 0$. When both sales occur before the flood this variable is also zero, and it is impossible for the flood to be before the first sale and not before the second. The only way for $Flood_{it} - Flood_{is}$ to equal 1, $Bracket_{its} = 1$, is when the two sales bracket the date of the flood. Following Kousky (2010) and Phaneuf and Requate (2011), the variables $Year_t$ and $Year_s$ are included to control for appreciation and age effects. Assuming there are no other changes in observable variables that contribute to price differences and that unobservables, represented by $(\varepsilon_{it} - \varepsilon_{is})$, are not correlated with the effect being measured; then $\hat{\psi}$ can be expressed as,

$$\hat{\psi} = \left(\overline{lnP_t^{IND=1}} - \overline{lnP_s^{IND=1}}\right) - \left(\overline{lnP_t^{IND=0}} - \overline{lnP_s^{IND=0}}\right) \quad (16)$$

where $\hat{\psi}$ is the estimate of the price reduction for properties with the condition represented by the group and time designations. That is, the price reduction for properties sold in the inundated area after the flood. So the repeat-sales model essentially becomes a first-differences specification of the DID model (Kousky, 2010).

Although the repeat-sales model allows us to exclude data on the characteristics of the properties that are assumed time-invariant and deals with the possible omitted variable bias, it has additional complications. Previous studies suggest that the use of repeat-sales models might induce bias due to the subset of repeat sales being unrepresentative of the market as a whole, for instance an over-representation of low standard, frequently-traded properties (Lamond, Proverbs and Antwi, 2007; Steele and Goy, 1997). We undertake all possible steps to minimise any potential bias by using a large dataset which includes all information on repeat sales at a national level in a sample that spans over almost 20 years. For longer time periods, the probability of re-sale increases and therefore more information is included in the repeat-sales model. Clapp, Giacotto and Tritiroglu (1991) argue that on the long run there are no systematic differences between the repeat sales sample and the full sample, and Nagaraja, Brown and Wachter (2014) highlight that as the sample period increases, the efficiency of the repeat sales method increases faster than that of standard hedonic models.

Authors such as Case and Quigley (1991) and Shiller (1993) suggest the use of 'hybrid models' to address the issue of the potential sample selection bias and a possible change in quality of properties between sales. These models combine the repeat sales sample and the standard hedonic sample to exploit all sales data (OECD, et al., 2013). However, they involve including housing characteristics in the traditional repeat-sales estimation. This information is not available in our data. Other authors such as Geltner (1996) and Edelstein and Quan (2006) suggest augmenting the repeat-sales sample by using assessment data to approximate the value of properties which have not been resold during the period of analysis. However, due to the data requirements of this approach it is impractical to apply it at a broad scale. Hill (2011) concludes that the standard repeat-sales approach should be preferred to imputing the price of properties that were sold only once (OECD, et al., 2013).

More recent applications of the repeat-sales model such as Gibbons (2015), Bosker et al. (2014) and Nagaraja, Brown and Zhao (2011) suggest combining information from the repeat sales sample and the standard hedonic sample at the postcode level. However, this postcode fixed-effects design implies that the analysis is based on repeat-sales of the same, or similar housing units within postcode groups, and is likely to induce bias due to within postcode heterogeneity of the housing units. The econometric model presented in this chapter avoids this issue by using repeat-sales of the same property matched at full address. This allows controlling for location at the finest level of detail. Furthermore, the use of a big dataset including all property transactions in England during the period of analysis results in a large sample of properties to identify the capitalisation of flood defences in property prices.

3.5 Data and Econometric Methodology

Data on property prices are taken from the England and Wales Land Registry ‘Price Paid’ housing transactions data. This dataset is publicly available and includes essential details on all residential property sales in England and Wales, going back to 1995, that were sold for full market value and were lodged for registration with the Land Registry. The data includes information on transaction sale price, date of transaction (DD/MM/YYY), address details, basic property characteristics – detached, semi-detached, terraced or flat/maisonette –; it also indicates whether the property is new or second-hand, and whether it is sold on a freehold or leasehold basis.

The complete data from the Land Registry consists of over 19 million observations for properties sold in England and Wales between January 1995 and the end of July 2014. This is the period of information available at the time our dataset was created. We focus on the analysis of the price of properties affected by flooding in England, therefore all observation corresponding to Wales were dropped. The remaining dataset includes over 18 million transactions.

The use of the repeat-sales model requires a panel data structure for properties that have been sold multiple times over the period of analysis. Housing units with repeat-sales were identified by matching the exact address of the properties considering four variables: full postcode (six-digit)[5], street, primary house number and secondary house number (for properties with a sub-building e.g. buildings divided into flats). Whenever there was a match for these four variables, the transaction was considered a repeat-sale. Over 6 million observations for properties with a single sale were dropped, as well as over 12,000 observations with matching street name, primary number and secondary number, but with a missing postcode (this was to avoid the possibility of matching houses with the same street name but different postcode and it only represents about 0.1% of our total sample of repeat sale transactions).

[5] In practice the full postcode (postcode unit level) of a property in the UK can range between six and eight alphanumeric characters. Throughout this chapter we use the term '*six-digit postcode*' to refer to the full postcode of the property. Postcode units in the UK consist of an average of 17 houses grouped together.

The final dataset includes over 12 million individual transactions that correspond to 4.8 million properties in England. All sale prices were time-adjusted to July 2014 GBP (£) using the county-specific House Price Index available through the Land Registry; this is to reflect real variation in property prices net out of general price trends in the housing market. On average, a house in the sample was sold 2.5 times between January 1995 and July 2014, with a minimum of 2 and a maximum of 29 sales (an unbalanced panel structure). The average transaction price for a property was £234,129, with a minimum of £4,742 and a maximum of £44.2 million.

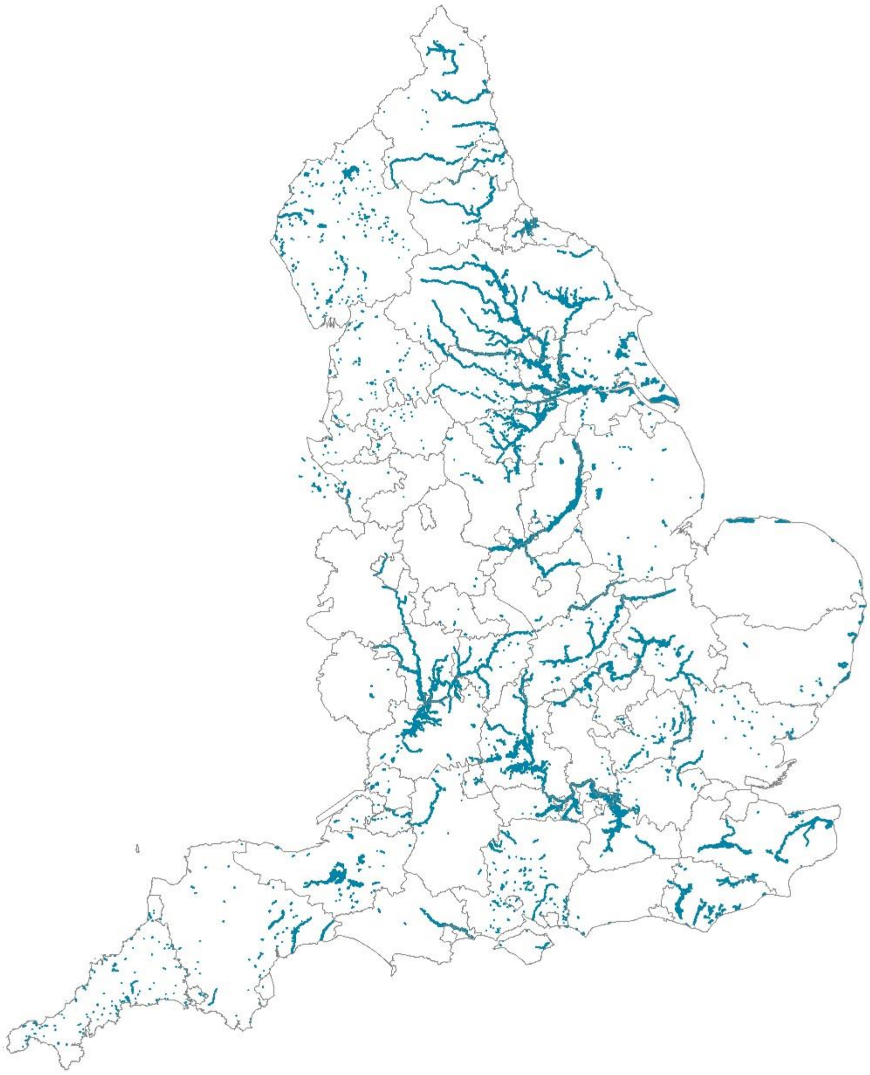
Finally, the between-sales growth rate for the price of each property was calculated as the first difference of the logged price, as shown in equation (14). Thus, the final dataset that is used for the estimation of the repeat sales model consists of over 7 million observations which represent the between-sales growth rate for approximately 4.8 million properties.

We use publicly available GIS data from the UK Environment Agency (EA) to identify the area affected by each individual flood. The dataset contains spatial polygons showing the Recorded Outlines of Individual Flood Events (henceforth ROIFE) in England. The data also includes important characteristics of the floods such as the start and end date of the flood (DD/MM/YYY), the source of the flood (inland or coastal) and the cause of the flood (for instance, overtopping of defences, channel capacity exceeded – no raised defences, etc.). This information is collected by the EA from different sources including, but not limited to, aerial photographs, visual examination, local authorities and surveyed data from the EA and private consultants.

At the time that this dataset was constructed the dates of the floods recorded in the ROIFE data span November 1703 to February 2014. Due to the design of the analysis and the fact that the information on property prices is only available since 1995, our final dataset includes only spatial information on flood events after 1995. The ROIFE identifies a total of 141,841 polygons delineating the area affected at individual flood events in England, which represents a total flooded area of 2,654 km^2 during the period of analysis. The polygons overlap in locations which were flooded more than once.

The total flooded area includes two types of flooding: inland (95%) and coastal (5%). For the case of inland flooding we differentiate flood events from two sources: fluvial and sewer flooding. In these two cases, flooding is likely to result from the same underlying phenomenon, namely a prolonged period of heavy rainfall. However, fluvial flooding occurs when an overflow of rivers, or other secondary watercourses, cause them to exceed their capacity, and sewer flooding occurs when surface water run-off exceeds the capacity of the drainage system. Sewer flooding represents only a small fraction (0.6%) of the total inland flooded area. Coastal flooding refers always to the intrusion of seawater which results storm surges created by storms like hurricanes and tropical cyclones. The potential implications of different types of flooding for households are discussed later in this chapter. Map 3.1 below shows the spatial representation of the total flooded area considered in the analysis. A summary of the data on flood polygons from different sources is presented in table 3.1.

Map 3.1. Recorded outlines of individual flood events in England, 1995-2014



Source: Own elaboration based on data from the ROIFE dataset, UK Environment Agency.

Table 3.1. Summary of flood incidents from different sources in England, 1995-2014

Source of flooding	Number of polygons	Area (km^2)
Inland	134,807	2,558
Fluvial	133,119	2,543
Sewer	1,688	15
Coastal	7,034	96
Total	**141,841**	**2,654**

Source: Based on data from the ROIFE dataset, UK Environment Agency.

The GIS spatial representation of the flooded area was then merged with GIS full postcode data (six-digit) from the Ordnance Survey (available through the Digimap Resource Centre of the University of Edinburgh), to identify at the six-digit level the postcodes that were affected by flooding during the period of analysis. We also identify properties affected by repeated flooding in postcodes where flood polygons overlap. Likewise, we merged the GIS postcode data with the dataset containing the details on property prices to determine the spatial location of the properties at the full-postcode level. By merging these datasets, it was possible to identify the repeat-sales of properties that occur within postcodes that were hit by flooding after 1995. The date of the flood, together with the date of transaction of the property allow us to identify the properties with transactions that *bracket* the occurrence of a flood.

One limitation of our data is that we do not have specific information on those properties that suffered water intrusion during the floods. However, the spatial flood outlines allow us to identify with high accuracy the properties that are located in postcodes that were hit by flooding. Full-postcodes in the UK consist of an average of 17 houses grouped together, so that properties that we label as being within the inundated area were either flooded or surrounded by water during the event. Thus, our identification strategy consists of focusing on repeat-sales of the same property within postcodes that were affected by flooding.[6] Map A3.1 in the appendix shows an example of the spatial representation of the flood outlines and affected postcodes for an area in Oxford flooded multiple times during the period of analysis.

[6] Merging the GIS data containing the flood outlines with the GIS representation of the postcode units allow us to identify all the cases where flooding occurs across different postcodes to include them in the analysis.

Although we take all possible steps to minimise potential bias, we note that the possibility of measurement error arises from our identification strategy by including properties that fall within the inundation area but that were not inundated. It is also possible that the inundation maps do not represent accurately the area flooded and we omit properties that fall outside the inundated area but that were actually inundated. In both cases, this will tend to bias our estimates upwards, i.e. to reduce the estimated discount for inundated properties. Therefore our results should be considered conservative estimates of the effect of the flood on the price of inundated properties. We also do not have information on the intensity of the flood (flood depth or speed of flood water), however we use the duration of the flood, measured as the number of days that the area remained flooded, as a proxy measure for intensity.

Other GIS datasets used in this chapter are: Flood Map Layers for England (flood zone 3) from the UK Environment Agency that show the spatial delineation of the 100-year floodplain for inland flooding and 200-year floodplain for tidal flooding; and Rural-Urban Classification of land accessible via Defra (Department for Environment, Food and Rural Affairs). By merging these files with the GIS full-postcode data and the spatial location of the house sales it was possible to identify the properties located inside a floodplain, those which are located in a postcode affected by flooding (including the date and duration of the flood event) and the rural-urban classification of the properties.

Due to the large computational requirements necessary to manipulate the huge number of observations involved in the analysis, all the computations described in this chapter were performed using the University of Birmingham's BlueBEAR HPC service, which provides a High Performance Computing service to the University's research community.[7]

3.5.1 The Econometric Model

The development of the empirical repeat-sales model to test for the price effect of flooding in the English housing market follows closely the identification strategy described in section 3.4.1. Using the final panel dataset containing over 12 million individual transactions corresponding to properties with at least one repeat-sale during the period of analysis, we begin by describing an empirical DID HPM for the price of each property, as in equation (17),

$$lnP_{it} = \beta_0 + \theta IND_{it} + \alpha Flood_{ikt} + \psi(Flood_{ikt} \times IND_{it}) + \varepsilon_{ikt} \tag{17}$$

Where i denotes a specific house; k identifies the county in which property i is located, and t denotes the time of the transaction. The dependent variable, lnP, is the natural logarithm of the property sale price adjusted to July 2014 GBP. The variable IND represents the group assignment for each house unit and is given by a dummy variable taking the value of 1 for properties located in a postcode (six-digit level) that was directly affected (fully or partially) by a flood (inundated) during the period 1995-2014. All other structural, locational, and neighbourhood characteristics (Z_i, p_i, r_i) of properties are excluded. As mentioned before, the repeat-sales specification assumes these characteristics remain constant between two sales of the same property, and therefore these are not relevant for the estimation of the repeat-sales model. ε_{ikt} is the house-specific error term to which the usual assumptions apply i.e. $\varepsilon_{ikt} \sim \mathrm{N}(0, \sigma^2\mathrm{I})$.

[7] For further information on the BlueBEAR project of the University of Birmingham see: http://www.birmingham.ac.uk/bear.

The construction of the variable $Flood$ in equation (17) is more involved. Similar to the specification in equation (13), it represents the timing of the sale with respect to a flood. However, since counties in the UK constitute different political and administrative units, it makes sense to keep the comparison of price differential for properties before-and-after the flood within the geographical borders of the county in which the event occurs. Thus, the variable $Flood$ in equation (17) is a county-house-time specific dummy that takes the value of 1 for sales within county k that occur after a flood event. Notice that in locations that experienced repeated flooding during the period of analysis the time of the sale after a flood is restricted by the time of the occurrence of the second flood. Therefore $(Flood_{ikt} \times IND_{it})$ is a dummy variable signalling those sales that occur after a flood event (or between floods in locations with repeated flooding) within a six-digit postcode that was affected by the flood (inundated).

Following section 3.4.1, taking the first-difference of equation (17) yields the following specification of the basic repeat-sales model:

$$\Delta ln(P_{its}) = \alpha Bracket_{ikts} + \psi(Bracket_{ikts} \times IND_i) + \lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts} \quad (18)$$

Where the subscript s represents the time of a previous sale of property i. The dependent variable is now the price differential for property i between the period of the two sales, t and s. The variable $Bracket_{ikts}$ is a dummy variable which takes the value of one for properties whose sales *bracket* the date of a flood within county k, where the flood occurred, and $(Bracket_{ikts} \times IND_i)$ is a dummy variable which takes the value of unity for those properties whose sales *bracket* the timing of a flood within county k and that are located within a six-digit postcode areas that was affected (fully or partially) by the flood (inundated). Following Kousky (2010) and Phaneuf and Requate (2011), the variables $Year_{is}$ and $Year_{it}$ are introduced to control for appreciation and age effects. The coefficient α represents the time effect, i.e. the relative price differential for all properties whose repeat-sales *bracket* the occurrence of a flood, and ψ represents the treatment response, i.e. the price discount for properties located within six-digit postcode areas that were directly affected by flooding. That is,

$$\hat{\psi} = \left(\overline{lnP_t^{IND=1}} - \overline{lnP_s^{IND=1}}\right) - \left(\overline{lnP_t^{IND=0}} - \overline{lnP_s^{IND=0}}\right) \quad (19)$$

This coefficient is the estimate of the price reduction for properties with the condition represented by the group and time designations. That is, the price reduction for properties sold in the inundated area after the flood. The key assumption for identification is that $E[\varepsilon_{ikts}|Flood_i] = 0$, for $t = 0, 1$ (before and after the flood). The size of this coefficient is expected to reflect three different effects as specified in equations (5), (8) and (9) above, namely: (1) the price discount for properties located in a flood prone area (for flooded properties within the floodplain), (2) the effect of flood damages on property prices, and (3) the effect of new information on flooded properties.

Notice that the repeat-sales specification in equation (18) does not take account of other potential factors that can differentially affect the housing market prospects of affected properties, such as the characteristics of the property, the characteristics of the flood and differences in flood risk perception. To address this issue we include three additional sets of variables to the original repeat-sales specification in equation (18). Below, we explain the rationale and justification for each of the variables that were included. The resulting expression appears in equation (20).

The first set of variables control for differences in property characteristics (*house_type*) using a total of eight variables. First, we hypothesise that the heterogeneity in the types of residential property sold might play an important role on its vulnerability to flooding. For instance ground floor house designs such as detached, semi-detached and terraced houses might be more exposed to flood damages than flats located above ground level. Therefore the extent of the price discount after a flood might also be different for different types of properties. Even when comparing among different types of ground floor properties, general characteristics such as the average floor area associated to each type of construction might result in differences in the extent to which the occurrence of a flood capitalises into the price of properties.

Likewise, differences in the location of the property such as its rural/urban classification or whether it is in the seaside or riverside might influence the extent of the discount after a flood. This might be due to differences in characteristics of urban and rural properties, exposure to different types of flood risk (inland vs coastal flood risk), different levels of flood risk perception, or differences in the amenity value associated with proximity to sea or river waters. We also allow for possible differences related to the price of properties, as these might be associated with differences in the quality of the construction materials and therefore with the value or extent of flood damages. Differences in property prices might also reflect differences in the level of income, which might indicate different preferences for ex-ante (e.g. construction of flood defence) vs. ex-post (e.g. emergency relief) flood alleviation measures, or preferences for hard (e.g. flood defences) vs. soft (e.g. flood insurance) flood risk management alternatives.

The last difference concerning property characteristics is related to the valid regulation on flood insurance at the time of the transaction. One limitation of this study is that there is no information available on the specific conditions or status of flood insurance for the properties considered in the sample. Therefore, it is not possible to disentangle the effect of flood damages on inundated properties from a potential increase in the price of insurance premium, increase in excess charges in the event of a flood, or the house becoming uninsurable after the flood. However, we include a dummy variable to control for potential price effects arising due to changes in the regulations of the insurance industry to provide flood insurance to homeowners. Historically, since the late 1960s flood insurance cover in the UK is included within the standard general household insurance cover at a subsidised rate as a result of an agreement (gentlemen's agreement) between the ABI and the UK Government (Lamond, Proverbs and Hammond, 2009). After widespread floods in the country during 1998 and 2000 the conditions of this agreement were called into question and renewed into what is known as the 'statement of principles' first agreed in 2002 (ABI, 2002, 2005, 2008). This changed dramatically the conditions of flood insurance for properties exposed to high levels of risk. Under the 'statement of principles' insurers were allowed to price flood insurance policies based on risk and to refuse to issue a policy to homeowners with an annual flooding probability greater than 1.3% (1 in 75 years) if there are no plans to improve flood defences in the area within the next 5 years (Lamond, Proverbs and Hammond, 2009; ABI, 2008). Lamond, Proverbs, and Hammond (2009) and Lamond and Proverbs (2008) suggest that this led to different kinds of difficulties for homeowners in the floodplain, especially for those recently flooded, including: premium increase, excess increase, flooding excluded from policy, refusal to quote and refusal to renew. These changes might result in different capitalisation rates of a flood event for properties affected by flooding after the change in the policy took place.

Therefore, the set of variables *house_type* in equation (20) includes the following variables to control for differences in property characteristics. One categorical variable identifying the price quartile of the property; four dummy variables to control for different type of properties (detached, semi-detached, terraced, flat); and dummy variables to control for differences in the duration of the contract (freehold or leasehold), the rural/urban classification of the property, and to identify properties sold after the change in the flood insurance regulation in 2002.

The second set of variables in equation (20) controls for differences in the characteristics of the flood (*Flood_type*). Our sample includes properties affected by flooding from different sources, namely: inland and coastal flooding. Although, in general, households affected by flooding will suffer from the intrusion of water into their properties, different types of flooding might possess different characteristics which can influence the extent to which the flood affects the post-flood price of the property. For instance, sewer flooding might contain faeces or other debris, brown water, and can cause odour which might require additional cleaning costs, disinfection, and can cause health issues; seawater flooding might also imply additional cleaning costs due to flooding with salty water, or can cause additional damages due to wave action. Thus, we hypothesise that flooding from different sources might capitalise to a different extent on the price of properties due to differences in the potential monetary loss associated with different types of flooding. We also identify those properties affected by flooding in locations where flood defences are in place, this is because existing flood defences can help to reduce current and expected future flood damages. Therefore, the set of variables *Flood_type* includes three dummy variables to identify the source of flooding (fluvial, sewer, sea) and one dummy variable to identify flooding in locations where flood defences are in place, i.e. locations where the cause of the flood is an overtopping of flood defences.

Finally, the third set of variables concerns differences in the flooding history of the properties (*Flood_history*). As mentioned above, previous studies suggest that the information effect of a flood diminishes as time elapses and people tend to forget about the risk of flooding (see for example Atreya Ferreira and Kriesel, 2012, 2013 and Bin and Landry, 2013). Based on these results, we expect to find a similar profile of property prices after a flood, i.e. a large discount for properties sold immediately after a flood which then recedes as time passes. However, since we focus on properties located within the inundated area our results will also capture the effect of flood damages on the price of properties (Atreya and Ferreira 2011, 2012a, 2012b, 2015). Therefore, we expect the post-flood discount to be larger than was found in previous studies looking at the information effect of a flood. In this case, the post-flood discount is not only expected to diminish with time as people forget about the risk of flooding, but also as homeowners (or insurance companies) invest in repairs to bring the property to pre-flood conditions (or even above). The recovery of property prices can also be explain by pressures from the supply side (housing developers) in the housing markets. This is because governments bear a large proportion of the costs of flooding by providing funding for flood protection and clean-up efforts after a flood. This creates incentives to build on floodplains as developers do not bear the full cost of development in flood prone areas. Under these circumstances developers might find it profitable to buy land for development at discounted prices in the aftermath of a flood to sell it in the future at higher prices as individuals forget about the risk of flooding and prices recover.

Differences in the intensity of the flood might also influence individual's perception of flood risk as well as the extent of flood damages. Previous studies by Daniel, Florax and Rietveld (2007, 2009), Bin and Landry (2013), Lamond, Proverbs and Hammond (2010) and Pryce, Chen and Galster (2011) suggest that differences in flooding history in terms of the frequency of flooding are also important to determine the size of the post-flood discount.

Thus, the set of variables *Flood_history* includes five variables to control for potential differences in flood risk perception across regions with different flood history. The first variable represents the number of months since the previous flood with respect to the second sale of the property, i.e. after the flood. The second variable represents the duration, in number of days, of the flood as a measure of intensity. The third variable is an interaction between the number of months since the previous flood and the duration of the flood; this variable is included to consider the possibility that the effect of flooding on the price of properties might be more persistent in locations that experience more intense flooding. The last two, are dummy variables identifying properties in postcodes that were affected by flooding multiple times during the period of analysis. One of these variables takes the value of unity if the sale occurs after the second flood; the second variable takes the value of unity if the sale is after three or more floods in the postcode where the property is located.

Equation (20) below shows the final specification of the repeat-sales model that we use to identify the effect of flooding on property prices.

$$\begin{aligned}\Delta ln(P_{its}) &= \alpha_1 Bracket_{ikts} + \alpha_2(Bracket_{ikts} \times house\_type_i) \\ &+\psi_1(Bracket_{ikts} \times IND_i) + \psi_2(Bracket_{ikts} \times IND_i \times house\_type_i) \\ &+\psi_3(Bracket_{ikts} \times IND_i \times F\_type_i) + \psi_4(Bracket_{ikts} \times IND_i \times F\_history_i) \\ &+\lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts}\end{aligned} \tag{20}$$

The resulting expression is estimated using ordinary least squares (OLS). Notice that equation (20) includes the set of variables controlling for the *house_type* with and without the interaction with the group assignment variable, IND, identifying the treated observations (properties located in postcodes affected by flooding during the period of analysis). The objective is to identify the effect of the flood on different type of houses. The variable *house_type* without the interaction with the group variable, IND, allows for differences in time trends across different types of properties. That is, it isolates the treatment effect from a general time trend and a *house_type* specific trend. In this way the coefficient ψ_1 represents the treatment effect of the omitted *flood_type* category (fluvial) in equation (20) on the price of the omitted *house_type* category (detached). That is,

$$\hat{\psi}_1 = \left(\overline{lnP^{IND=1}_{t,x=h}} - \overline{lnP^{IND=1}_{s,x=h}}\right) - \left(\overline{lnP^{IND=0}_{t,x=h}} - \overline{lnP^{IND=0}_{s,x=h}}\right) - \left(\overline{lnP^{IND=1}_{t,x\neq h}} - \overline{lnP^{IND=1}_{s,x\neq h}}\right) \tag{21}$$

This coefficient is called the difference-in-difference-in-differences (DDD) estimator, or triple difference estimator. The first subscript in the terms in brackets in equation (21) refers to the time of the sale, s for the first sale and t for the second sale. The second subscript, x, identifies the type of house. The superscript represents the group designation, $IND = 1$ for treated and *IND=0* for untreated observations. Thus, the DDD estimator represents the average price change between sales of houses type $x = h$ ($h = detached$) that were affected by flooding, net out the average price change between sales of houses type $x = h$ that were not affected by the flood, and the average price change between sales of all other house types $x \neq h$ that were affected by flooding. Thus, the term in equation

(21) can be interpreted as the reduction in the price paid by buyers of house type h to acquire a property affected by flooding (fluvial). The differential effect for other types of properties, $x \neq h$, is given by the coefficient $\hat{\psi}_2$ in equation (20), and is measured over and above $\hat{\psi}_1$. Finally, the sets of variables *F_type* and *F_history*, represent characteristics that modulate the intensity of the treatment and therefore are only included in equation (20) with an interaction with the group assignment variable, IND. The differentiated price impacts of these characteristics are given by the coefficients $\hat{\psi}_3,\ \hat{\psi}_4$ in equation (20), and are measured over and above $\hat{\psi}_1$ which captures the omitted categories.

Table 3.2 shows a short description of the variables included in the model together with the usual summary statistics. On average, transaction price of a property in the sample is £234,130 (July 2014 prices), with a price increase of 7.8% during an average period between sales of five years. The sample includes over 7 million properties with at least one repeat-sale, out of which 1.8 million (25%) have sales that *bracket* the occurrence of a flood in the county where they are located. Out of this, 14,206 properties, approximately 1%, represent treated observations, i.e. properties whose sales bracket the occurrence of a flood and are located within a postcode affected by flooding (inundated).

Regarding the composition of the housing stock, in terms of the type of properties, the proportion of detached, semi-detached and terraced properties is around 20 – 30% each, with a smaller proportion of flats which represent 18% of the sample and a slightly higher proportion of terraced properties accounting for 33% of the sample. Roughly 18% of these properties are located in rural areas, and around 80% are sold on a freehold contract. Around 69% of the properties had their second sale after 2002, that is, after the introduction of the ‘statement of principles’ which changed the conditions of flood insurance for properties exposed to significant levels of risk. If we focus on the sample of treated observations, it has a similar composition in terms of the type of properties. However, a greater proportion of the properties affected by flooding are located in rural areas (31%), while a lower proportion of them correspond to properties in a coastal floodplain (9%).

Table 3.2. Summary statistics

	Variable	Description	No. Obs.	Mean	S.D.	Min.	Max.
	Price	July 2014 GBP	12,012,455	234,130	259,475	4,742	44,200,000
	Δln(Price)	House-specific firs-difference of the logged real price	7,222,401	0.078	0.252	-6.28	4.17
	Bracket (B)	Dummy=1, sale before and after a flood		0.247	0.431	0	1
	Lyear (s)	Year of first sale		2001	3.901	1995	2014
	Year (t)	Year of second sale		2006	4.465	1995	2014
Bracket Sample [1]							
House_type [2]	B*detached	Dummy =1, detached	1,787,079	0.209	0.407	0	1
	B*sdetached	Dummy=1, semi-detached		0.277	0.447	0	1
	B*terraced	Dummy=1, terraced		0.329	0.469	0	1
	B*flat	Dummy=1, flat		0.184	0.388	0	1
	B*free	Dummy=1, freehold		0.769	0.421	0	1
	B*rural	Dummy=1, rural		0.176	0.380	0	1
	B*quartile	Categorical 1 to 4. 1 represents the lowest quartile.		2.484	1.097	1	4
	B*after2002	Dummy=1, sale after 2002		0.695	0.460	0	1
Bracket-Flooded Sample [3]							
	B*Inundated (IND)	Dummy=1, bracket and flooded	1,787,079	0.008	0.0889	0	1
House_type	B*IND*detached		14,206	0.270	0.444	0	1
	B*IND*sdetached			0.255	0.436	0	1
	B*IND*terraced			0.312	0.463	0	1
	B*IND*flat			0.163	0.369	0	1
	B*IND*free			0.801	0.399	0	1
	BF*IND*rural			0.311	0.463	0	1
	BF*IND*quartile			2.729	1.092	1	4
	BF*IND*after2002			0.689	0.462	0	1
F_type [4]	B*IND*sea	Dummy=1 if Coastal flood	14,206	0.186	0.389	0	1
	BF*IND*sewer	Dummy=1 if Sewer flood		0.023	0.149	0	1
	BF*IND*defence	Dummy=1 if existing flood defence		0.076	0.264	0	1
F_history	BF*IND*mnths	Number of months since last flood (2nd sale)	14,206	32	24.8	0	183
	BF*IND*dur	Duration of last flood (days)		5.6	42.9	0	364
	BF*IND*2F	Dummy=1 if 2dn time flooded		0.135	0.341	0	1
	BF*IND*3F+	Dummy=1 if 3rd time flooded or more		0.064	0.245	0	1

Notes:

[1] The summary statistics under this title correspond to the 25% of the sample with repeat sales that *bracket* the occurrence of a flood in the affected county.

[2] Omitted categories are dummy variables for detached property, urban location and properties sold on leasehold.

[3] The summary statistics under this title correspond to the 1% of the sample with repeat sales that *bracket* the occurrence of a flood and are located within a postcode affected by flooding.

[4] The omitted category is a dummy variable for fluvial.

Our sample includes properties affected by flooding from different sources. The properties affected by inland flooding represent 81% of the treated sample, where 79% are properties affected by fluvial flooding and 2% correspond to properties affected by flooding from the sewer or drainage. The remaining 19% of properties correspond to those affected by coastal flooding. In 8% of the cases the inundation occurred in areas were flood defences are in place. On average, the second sale of an affected property in our sample occurred 32 months (2 - 3 years) after a flood, with an average duration of a flood is 5 to 6 days. In 13% of the cases the property is located in a postcode which was previously inundated during the period of analysis (since 1995), and in 6% of the cases the postcode was affected by flooding two or more times before.

3.6 Results

Table 3.3 shows the results of the regression of the repeat-sales model in equation (20). It includes six different specifications with different samples and control groups. Column (1) considers the full sample, including all properties affected by different sources of flooding, namely: fluvial, sewer and coastal flooding. These properties are identified using dummy variables for each different type of flooding, where the omitted category is fluvial flooding. The underlying assumption in this specification is that the effect of flooding from different sources on the price of properties differs only in its mean, while the effect of all other parameters is constant across different types of flooding.

Columns (3) and (5) divide the sample according to different types of flooding to which the properties were exposed, inland or coastal flooding. By running separate regressions we allow the parameters in the equation to differ across different types of flooding. The distinction is important as both types of floods possess different characteristics and their potential impacts are also different. Thus, in column (3) the treatment group corresponds to all properties affected by inland flooding between sales, while the control group are those properties with repeat sales that *bracket* the occurrence of inland flooding in the county where they are located. A similar definition follows for the sample in column (5), but where the treatment group are the properties affected by coastal flooding, and the control group are those properties that *bracket* the occurrence of a coastal flood in the county where they are located. The distinction in the control group is especially relevant in counties that were affected by both types of flooding during the period of analysis.

One possible criticism to the validity of our identification strategy is that it relies on a quasi-experimental design where the random assignment of the treatment is not guaranteed. That is, flooding occurs mostly in locations which are exposed to flood risk. It can be argued that the housing market in these regions possess some special characteristics and attracts buyers with distinctive preferences. Therefore comparing the price change of properties affected by flooding against the price change of all other properties anywhere in the county might lead to misleading conclusions. To address this issue, columns (2), (4) and (6) show the results of regressions with the relevant sample defined as above, full sample, inland flooding and coastal flooding, respectively, but where the control group is restricted to properties located inside the floodplain (FP). In this way, we compare the price change of properties affected by flooding, against that of properties exposed to a similar risk but which were not affected by a flood during the period of analysis. There are two additional implications of restricting the sample to include only properties in the floodplain. First, we exclude flooded properties located out of the floodplain which represent 12% of the total sample of treated observations (1,718 properties); 85% of these (1,465) correspond to inland flooding, the rest (253) are properties affected by coastal flooding. Second, since we restrict the control group to consider only properties in the floodplain we tease out the information effect of the flood on flooded properties from the information effect on all other floodplain designated properties.

Bin and Kruse (2006) and Bin et al. (2008) highlight that different types of flood risk possess distinctive characteristics that can have different implications in the housing market. For instance, different types of flood risk imply proximity to different sources of risk with different potential damages and amenity values. The authors conclude that different types of flood risk should be analysed individually.[8] Furthermore, the issue of the non-random assignment of the treatment in the housing market suggest that the appropriate control group to identify the effect of a flood on the price of inundated properties should be restricted to the set of properties exposed to a similar risk (properties in the floodplain) but which were not affected by flooding. Therefore our discussion of results presented in table 3.3 focuses on columns (4) and (6) as the preferred specifications. Column (4) looks at the effect of inland flooding on the price of affected properties, where the control group includes all other properties in the floodplain that *bracket* the occurrence of an inland flood in the county where they are located. The results in column (6) are defined in a similar way but with reference to coastal flooding. The main results, however, are robust across different specifications. All specifications include county level fixed-effects to control for between county heterogeneity. Heteroscedasticty robust standard errors (Huber, 1967; White, 1980) appear in parentheses.

The first section in table 3.3 (*Bracket sample*) includes the coefficients of the variables that control for difference in the time trend across different types of properties (DDD

[8] This conclusion is also supported by the results of the meta-analysis presented in Chapter 1 of this Thesis.

specification). These variables include the type of property (*B*sdetached*, *B*terraced*, *B*flat*), the type of contract (*B*free*), the rural/urban classification of land (*B*rural*), the price quartile of the property (*B*quartile*) and a dummy variable to identify the properties that were sold after the change in the flood insurance regulation in 2002 (*B*after2002*). The omitted categories are detached properties, leasehold contract, urban locations and properties sold before the change in the flood insurance regulation. The average price growth rate for a property with the characteristics of the omitted categories and with repeat sales before and after a flood (not inundated) is captured by the coefficient on the variable *Bracket(B)*. In general, all the variables included in the model to control for differences in the time trend across different types of properties are highly significant. This indicate that, regardless the occurrence of a flood, properties with different characteristics have different price trends during the period of analysis. This result highlights the importance of our DDD strategy to the identification of the effect of flooding on houses with different characteristics.

3.6.1 Results for Inland Flooding

The second section in table 3.3 (*Bracket-Flooded Sample*) shows the main results. As mentioned before, the discussion of results focuses on columns (4) and (6), as these are the preferred specifications; however, the results are robust across different specifications. We deal first with the results for inland flooding in column (4). The effect of a flood on the price growth rate of inundated properties with the characteristics of the omitted categories (detached properties, leasehold contract, urban locations and properties sold before the change in the flood insurance regulation) is captured by the coefficient on the variable *B*Inundated* (IND). This coefficient in column (4) suggests that inland flooding capitalises into the price of detached properties with a discount of 34%. Notice that this figure represents the price discount for a property sold *immediately* after a flood. As we discuss later, the results suggest that the size of the discount decreases as houses are sold further away in time from the date of the flood. The effect of inland flooding on properties with different characteristics, different types of flooding and different flood history is measured over and above this benchmark figure.

The results in column (4) indicate different capitalisation rates across different types of properties, among which detached properties experience the greatest discount. The coefficient on the variables *B*IND*sdetached*, *B*IND*terraced* and *B*IND*flat* indicate the differential effect of a flood on the price of different types of properties with respect to that of detached properties (omitted category). Thus, the effect of a flood for different types of properties is measured over and above the coefficient on the variable *B*inundated*. Inland flooding capitalises on the price of semi-detached properties with a discount of 28% (-0.34+0.06), the discount for terraced properties is around 25% (-0.34+0.09), and 24% for flats (-0.34+0.10). As expected, flats are the properties which experience the smallest discount, however it surprising to find such a high discount for properties where the majority are not likely to be directly affected by flooding. Due to data limitations we are not able to distinguish the effect on flats located on the ground floor from those located in upper floors. The different capitalisation rate for different types of ground level properties might be associated with different characteristics of the properties such as floor area or number of rooms.

Differences in the type of contract under which the property is sold (freehold/leasehold) do not appear to influence the extent to which flooding capitalises in the price of properties. Although the sign of the coefficient on the variable *B*IND*free* indicates that flooding has a greater impact on the price of freehold properties, this coefficient is not significant. The coefficient on the variable *B*IND*rural* indicates that flooding has a greater impact on the price of properties in rural areas. For the case of inland flooding in column (4) this coefficient suggests that the price discount for affected properties in rural areas is 3.6% higher than comparable affected properties in urban areas. This result might be associated with different characteristics of housing in rural areas that makes them especially susceptible to flooding or with differences in the way and amount in which post-flood relief assistance is delivered in rural and urban areas.

Table 3.3. Repeat-sales model: The effect of flooding on property prices

	Variables	(1) All estimates	(2) All estimates FP	(3) Inland	(4) Inland FP	(5) Coastal risk	(6) Coastal risk FP
	Bracket Sample						
	Bracket (B)	0.104***	0.115***	0.102***	0.109***	0.118***	0.203***
		(0.00127)	(0.00361)	(0.00139)	(0.00404)	(0.00418)	(0.00961)
House_type [1]	B*sdetached	-0.0144***	-0.0224***	-0.0116***	-0.0177***	-0.0644***	-0.0789***
		(0.000568)	(0.00151)	(0.000618)	(0.00167)	(0.00149)	(0.00359)
	B*terraced	-0.0148***	-0.0218***	-0.0110***	-0.0173***	-0.0861***	-0.0962***
		(0.000586)	(0.00152)	(0.000635)	(0.00167)	(0.00166)	(0.00404)
	B*flat	-0.0207***	-0.0229***	-0.0128***	-0.00747**	-0.148***	-0.178***
		(0.00111)	(0.00315)	(0.00122)	(0.00350)	(0.00296)	(0.00793)
	B*free	0.0316***	0.0339***	0.0326***	0.0399***	0.0342***	0.0194***
		(0.000969)	(0.00282)	(0.00107)	(0.00318)	(0.00229)	(0.00636)
	B*rural	0.00885***	0.0199***	0.00747***	0.0196***	0.0314***	0.0445***
		(0.000500)	(0.00118)	(0.000549)	(0.00132)	(0.00125)	(0.00273)
	B*quartile	-0.0443***	-0.0457***	-0.0433***	-0.0448***	-0.0939***	-0.0955***
		(0.000225)	(0.000604)	(0.000242)	(0.000662)	(0.000778)	(0.00193)
	B*after2002	-0.0195***	-0.0277***	-0.0184***	-0.0278***	-0.0275***	-0.0226***
		(0.000396)	(0.00105)	(0.000435)	(0.00118)	(0.00168)	(0.00417)
	Bracket-Flooded Sample						
	B*Inundated (IND)	-0.346***	-0.358***	-0.323***	-0.335***	-0.479***	-0.472***
		(0.0150)	(0.0163)	(0.0159)	(0.0173)	(0.0420)	(0.0438)
House_type [1]	B*IND*sdetached	0.0620***	0.0708***	0.0553***	0.0625***	0.108***	0.120***
		(0.00622)	(0.00679)	(0.00666)	(0.00729)	(0.0176)	(0.0186)
	B*IND*terraced	0.0830***	0.0954***	0.0769***	0.0883***	0.144***	0.158***
		(0.00629)	(0.00687)	(0.00661)	(0.00723)	(0.0196)	(0.0208)
	B*IND*flat	0.119***	0.122***	0.102***	0.104***	0.249***	0.251***
		(0.0130)	(0.0139)	(0.0141)	(0.0152)	(0.0350)	(0.0368)
	B*IND*free	-0.00732	-0.0146	-0.00546	-0.0103	-0.0177	-0.0389
		(0.0114)	(0.0122)	(0.0124)	(0.0133)	(0.0305)	(0.0320)
	B*IND*rural	-0.0365***	-0.0458***	-0.0278***	-0.0358***	-0.0827***	-0.0869***
		(0.00465)	(0.00505)	(0.00510)	(0.00554)	(0.0120)	(0.0129)
	B*IND*quartile	0.0523***	0.0566***	0.0487***	0.0524***	0.0893***	0.0929***
		(0.00255)	(0.00282)	(0.00275)	(0.00305)	(0.00725)	(0.00782)
	B*IND*after2002	0.0542***	0.0598***	0.0475***	0.0548***	0.083***	0.093***
		(0.00575)	(0.00616)	(0.00633)	(0.00676)	(0.0152)	(0.0162)
F_type [2]	B*IND*sea	-0.0362***	-0.0342***				
		(0.00620)	(0.00664)				
	B*IND*sewer	-0.0591***	-0.0537***	-0.0535***	-0.0486***		
		(0.0123)	(0.0151)	(0.0123)	(0.0150)		
	B*IND*defence	0.0701***	0.0624***	0.0764***	0.0537***	0.0426***	0.0454***
		(0.00916)	(0.00955)	(0.0139)	(0.0142)	(0.0141)	(0.0152)
F_history [3]	B*IND*mnths(sqrt) [4]	0.0126***	0.0122***	0.0101***	0.00945***	0.0198***	0.0192***
		(0.000946)	(0.00103)	(0.00105)	(0.00114)	(0.00221)	(0.00237)
	B*IND*dur	-0.000158***	-0.000161***	-0.000172***	-0.000179***	0.000973	0.00119
		(2.49e-05)	(3.19e-05)	(2.62e-05)	(3.45e-05)	(0.000720)	(0.000793)
	B*IND*mnths(sqrt)*dur	-1.03e-05	-1.14e-05	-7.62e-06	-7.96e-06	-0.000334	-0.000414
		(6.28e-06)	(7.15e-06)	(6.43e-06)	(7.43e-06)	(0.000186)	(0.000207)
	B*IND*2F	-0.00237	-0.00326	-0.00783	-0.00886	0.0238	0.0260*
		(0.00620)	(0.00644)	(0.00675)	(0.00705)	(0.0152)	(0.0156)
	B*IND*3F+	-0.00857	-0.00659	-0.00526	-0.00373	-0.0365	-0.0313
		(0.00830)	(0.00841)	(0.00872)	(0.00883)	(0.0260)	(0.0263)

(Continued)

Table 3.3.Continue

Lyear (s)	-0.000990***	-0.000980***	-0.00103***	-0.00106***	-0.00227***	-0.00182***
	(2.90e-05)	(7.54e-05)	(2.95e-05)	(7.67e-05)	(0.000207)	(0.000525)
Year (t)	0.00104***	0.00101***	0.00108***	0.00109***	0.00498***	0.00364***
	(2.89e-05)	(7.52e-05)	(2.94e-05)	(7.66e-05)	(0.000227)	(0.000584)
Observations	7,222,401	1,137,605	6,910,817	1,086,267	311,584	51,338
Treated Obs.	14,206	12,488	11,561	10,096	2,645	2,392
County FE	YES	YES	YES	YES	YES	YES
R-squared	0.108	0.103	0.107	0.103	0.170	0.173

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] Omitted categories are dummy variables for detached property, urban location and properties with repeat sales before change in the flood insurance regulation in 2002.

[2] The omitted categories are dummy variables for fluvial flooding and for those properties affected by flooding in locations without flood defences.

[3] The omitted category represents properties with repeat sales before and after the first flood, during the period of analysis, in the postcode where they are located.

[4] Square root of the number of months since the previous flood with respect to the second sale.

The coefficient on the variable *B*IND*quartile* (5.2%) indicates that the price discount on affected properties is higher for low-price properties (quartile=1) and decreases for more expensive properties. Notice that this figures refer to the discount in proportion to the price of the property and does not mean that the monetary amount of the discount is greater for the lowest-priced properties, as will be discussed later.

The coefficient on the variable *B*IND*after2002* indicates that the discount on affected properties is smaller for those sold after the change in the flood insurance regulation in 2002. Column (4) of table 3.3 suggests that for properties affected by inland flooding after 2002 the discount was 5.5% lower. This is somewhat unexpected. As mentioned before, authors such as Lamond, Proverbs, and Hammond (2009) and Lamond and Proverbs (2008) suggest that the change in the flood insurance regulation in 2002 led to different kind of difficulties for owners of properties in the floodplain, especially for those recently flooded, such as premium increase, excess increase or even refused flood insurance. We expected to see these difficulties reflected in higher discounts for affected properties, however the results show an opposite sign.

One possibility is that the change in the regulation could be anticipated by homeowners and capitalised before the change took place, and which at the end turned out not to have consequences as negative as had been feared. This view accords with what Lamond, Proverbs and Hammond (2008) and Lamond and Proverbs (2009) suggest. The authors refer to the fact that the discussion on the need to change flood insurance regulation and to adopt a new scheme that prices flood insurance more according to risk started soon after the widespread floods in 1998 and intensified further after the floods in 2000. This was a highly mediatic discussion which culminated with the change in the flood insurance regulation in 2002. Furthermore, Lamond, Proverbs and Hammond (2009) conclude that the change in regulation did not have the expected negative consequences to homeowners. This is because individuals were unexpectedly still able to engage in market search strategies in a highly competitive insurance market which allowed the majority of individuals in high risk properties to obtain flood insurance at standard rates. The effect of changes in the flood insurance regulation on the price of properties remains an area of further research.

Regarding differences in the type of flooding, the coefficient on the variable *B*IND*sewer* in column (4) indicates that the discount on the price of properties affected by sewer flooding is around 5% greater compared to properties affected by other types of inland flooding. This is likely to be due to additional cleaning and disinfection costs, and potential health issues associated with sewer flooding. Floods can also occur in locations with standing flood defences due to an overtopping or failure of defences. The coefficient on the variable *B*IND*defence* indicates that the price discount on affected properties is 5% smaller in locations where flood defences are in place. We believe that this coefficient reflects a reduction of flood damages due to flood protection compared with affected properties in locations without flood defences. The expected future flood damages after a flood might also be lower where there are flood defences.

The last set of variables in our model controls for differences in the flooding history of the properties (*F_history*), the objective is to capture differences in flood risk perception which can arise in locations with a different flood history. The variable *B*IND*mnths(sqrt)* controls for the number of months elapsed since the flood to the time of the second sale of the property. A recent discussion by Atreya, Ferreira and Kriesel (2013) and Bin and Landry (2013) suggests that the effect of flooding on property prices decreases after a flood following a non-linear path. Following these authors our model in table 3.3 includes the time variable as the square root of the number of months with respect to the previous flood (*mnths(sqrt)*).[9] The positive coefficient on this variable in column (4) suggests that the price discount on properties affected by inland flooding decreases as the number of months elapsed since the flood to the date of the second sale increase. As mentioned before, this is likely to be the result of two things. First, individuals (or insurance companies) investing in repairs to bring the property to pre-flood conditions (or above); and second, a decrease in flood risk perception as time passes by and people tend to forget about the risk of flooding. The extent to which each of these effects contributes to the recovery of property price remains an area of further research.

The variable *B*IND*dur* controls for differences in flood history in terms of the duration (number of days) of the previous flood. As expected, the negative coefficient in column (4) indicates a greater price discount for affected properties in areas where the inundation

[9] The results are robust to other linear and non-linear functional forms of the time variable. The results for these specifications are available from the authors upon request.

lasted longer. This might be due to greater flood damages and enhanced risk perception associated with long lasting inundations. However, although the coefficient on this variable is highly significant, the size of the coefficient is close to zero (-0.000172). Even if we consider the average number of days that a property remained flooded in our sample (between 5 to 6 days), the effect of the duration of the flood on the price discount of the property is almost negligible, only 0.1%. We believe that this result suggests that the extent of flood damages does not depend on the number of days a property remains flooded. Instead, once there has been water intrusion into a property, the damage is already done and the additional number of days that it remains flooded will only cause a marginal increase in the overall price discount. Authors such as Bartosova et al. (1999) and Penning-Rowsell et al. (2014) suggest that flood depth and the speed of flood water are the most important characteristics determining the extent of flood damages. This information, however, was not available to us for the sample of floods considered in the analysis. The effect of these flood characteristics on the price discount of properties remains an area of further research.

The last three coefficients that control for differences in flood history (*F_history*) for inland flooding (column (4)) are not significant. The insignificant and close to zero coefficient on the variable *B*IND*mnths(sqrt)*dur* suggests that the persistence of the post-flood discount does not differ among floods with different duration. This result supports our previous hypothesis which suggests that once a property has been flooded, the duration of the flood does not have a meaningful impact in determining the post-flood discount. The coefficients on the variables *B*IND*2F* and *B*IND*3F+* identifying sales of properties with a history of repeated flooding during the period of analysis are also not significant. Notice that these insignificant coefficients do not mean that there is no discount for properties suffering repeated flooding, it rather indicates that the extent of the post-flood discount on properties which are flooded repeatedly is not significantly different from the discount on properties which only suffer one flood during the period of analysis. Previous authors looking at the effect of repeated flooding on the price of properties (Daniel, Florax and Rietveld, 2007, 2009; Bin and Landry, 2013 and Lamond, Proverbs and Hammond, 2010) suggest that the post-flood discount of a property is greater for properties flooded more than once. Our results suggest that this will be the case only if the second flood occurs before full recovery of property prices.

The last two variables in the model, *Lyear (s)* and *Year (t)*, control for appreciation and age effects following Kousky (2010) and Phaneuf and Requate (2011). The coefficients in column (4) indicate that these variables are highly significant and their sing is as expected. The negative coefficient on the variable *Lyear (s)* suggests that if the year of the first sale is closer in time to the year of the second sale, then the price growth rate of the property will be smaller. On the other hand, the positive coefficient on the variable *Year (t)* suggests that if the year of the second sale is further away in time from the year of the first sale, then the price growth rate of the property will be greater. The robust and significant effect of this variables across all specifications highlight the importance of controlling for appreciation effects for the identification of the effect of a flood on property prices.

3.6.2 Results for Coastal Flooding

Column (6) of table 3.3 shows the results of the capitalisation of coastal flooding on the price of affected properties. The interpretation of the coefficients is similar to the one discussed above for the case of inland flooding. Most of the variables have the same sign and significance; however, there are important differences related to the magnitude of the coefficients that are worth mentioning. As before, the effect of coastal flooding on the price growth rate of inundated properties with the characteristics of the omitted categories (detached properties, leasehold contract, urban locations and properties sold before the change in the flood insurance regulation) is captured by the coefficient on the variable *B*Inundated* (IND). This coefficient in column (6) suggests that coastal flooding capitalises into the price of detached properties with a discount of 47%. Notice that the size of the discount associated with coastal flooding is greater than the 34% discount associated with inland flooding in column (4). We suggest that this difference is related to greater potential damages and cleaning costs that can arise due to the intrusion of sea water into the property and the effect of wave action. Also notice that, similar to the case of inland flooding, this figure represents the price discount for a property sold immediately after a flood. The effect of inland flooding on properties with different characteristics, different type of flooding and different flood history is measured over and above this benchmark figure.

The results for coastal flooding in column (6) also suggest different capitalisation rates across different types of properties, among which detached properties experience the greatest discount. The coefficient on the variables *B*IND*sdetached*, *B*IND*terraced* and *B*IND*flat* indicate the differential effect of a flood on the price of different types of properties. In this way, coastal flooding capitalises into the price of semi-detached properties with a discount of 35% (-0.47+0.12), the discount for terraced properties is around 31% (-0.47+0.16), and 22% (-0.47+0.25) for flats located in areas affected by coastal flooding. For the case of ground level properties, semi-detached and terraced, the discount is greater for properties affected by coastal flooding than the 28% and 25%, respectively, associated with inland flooding. We associate this difference with greater potential damages related to the intrusion of sea water. However, for the case of flats for which the majority of properties are not likely to suffer water intrusion, the price discount is very similar across different types of flooding with 22% and 24% for coastal and inland flooding, respectively. This result is somehow expected, as we would not expect to see different capitalisation rates for different types of flooding for flats where the majority of properties are not likely to suffer from water intrusion. The discount on flats might be driven by the inclusion of repeat-sales of ground level apartments in the sample which might had been directly affected by flooding, and other factors such as increased flood risk perception and indirect flood losses suffered by flats in upper levels. Due to data limitations we are not able to distinguish the effect on flats located on the ground floor from those located in upper floors.

Similar to the case of inland flooding, differences in the type of contract (freehold/leasehold), given by the coefficient on the variable *B*IND*free* in column (6), are not significant to determine the price discount associated with coastal flooding. The capitalisation of coastal flooding in rural areas is also greater than in urban areas. The coefficient on the variable *B*IND*rural* indicates that the discount on rural properties affected by coastal flooding is about 8% greater than comparable properties affected in urban areas. This coefficient is greater than the differential effect of inland flooding in rural areas. This might be associated with differences in the potential damages of coastal flooding in rural areas where the lack of urban infrastructure might not help to mitigate additional potential damages of, for instance, wave action. This might also be associated with differences in the way and extent to which post-flood relief assistance is delivered in rural areas affected by inland and coastal flooding.

The coefficient on the variable *B*IND*quartile* (9.3%) in column (6) indicates that the price discount on properties affected by coastal flooding is higher for low-price properties (quartile=1) and decreases for more expensive properties. This result is similar to the one observed for inland flooding, however the coefficient on properties affected by coastal flooding is greater than the 5.2% we observed for inland flooding in column (4). This difference might be driven by a high demand of highly valued properties along the coast. The coefficient on the variable *B*IND*after2002* that identifies affected properties sold after the change in the flood insurance regulations in 2002 is positive, as it is for inland flooding. In this case, the coefficient in column (6) suggests that for properties affected by coastal flooding after 2002 the discount was 9% lower. Again, we believe that the positive coefficient is associated with the anticipation of the change in the flood insurance regulation, which in the end did not have the expected negative consequences as Lamond, Proverbs, and Hammond (2009) and Lamond and Proverbs (2008) suggest.

The coefficient on the variable *B*IND*defence* for properties affected by coastal flooding (column (6)) suggests that the price discount of an affected property is 4.5% smaller in locations with a flood defence. This is similar to the case of inland flooding. We believe it reflects some of the benefits of flood defences in the event of a flood which materialise in less flood damages than comparable locations with no flood protection.

The last set of variables in column (6) controls for differences in flood history (*F_history*) for properties affected by coastal flooding. For most of these variables the results are similar to the ones we observe for inland flooding. It is however important to highlight two things. The coefficient on the variable *B*IND*mnths(sqrt)* is significant and has the same sign that we observe for inland flooding, however, the magnitude of the coefficient is considerably higher for coastal properties. As suggested before, the positive coefficient on this variable indicates that the price discount on properties affected by flooding decreases as the number of months elapsed since the flood to the date of the second sale increase. Therefore, a greater coefficient for properties affected by coastal flooding implies that post-flood property prices in coastal areas recover faster than prices of properties affected by inland flooding. One possible explanation for this is that individuals might see the flood event as an opportunity to buy a sea front property at a discounted price, driving the demand for this properties up and therefore the recovery of prices. In this case, the benefits of buying a property close to sea water might be perceived as higher than the expected negative impacts associated with flood risk. A recent research by Knight Frank (2016) confirms that over the last two decades high demand for coastal properties in the south of England has driven the price of properties up in the region. The authors use the same publicly available data from the Land Registry going back to 1995. Their results suggest that, the average annual growth rate of the price of coastal properties, in 35 cities included in the analysis, was 2.7% higher than comparable non-coastal properties during the period of analysis. The authors conclude that by 2016, this annual premium has resulted in prices of waterfront properties being as much as 71% higher than comparable properties located just a mile inland.

The coefficient on the variables *B*IND*dur* and *B*IND*mnths(sqrt)*dur* in column (6) suggest that the duration of coastal flooding does not have a significant effect on the post-flood discount. This result is similar to the one that we observe for the duration of inland flooding in column (4) where the marginal effect of increasing the duration of the flood is almost negligible. The interpretation of the coefficients on the variables *B*IND*2F* and *B*IND*3F+* in column (6) suggest that the extent of the post-flood discount on properties which are flooded repeatedly is not significantly different from the discount on properties which only suffer one flood during the period of analysis. This result is similar to the one that we observe for inland flooding. The variables *Lyear (s)* and *Year (t)* are significant and have the expected sign. Section A3.1 of the appendix shows additional robustness tests. The following section presents the discussion and interpretation of our main results in table 3.3.

3.7 Discussion

In this section we discuss the interpretation of our main results in table 3.3. We focus on two main issues. First, we explain what the coefficients in table 3.3 suggest about the size of the post-flood discount for affected properties and its interpretation in monetary units (£). Second, we discuss what the coefficient on the time variable (number of months) suggest about the recovery path of property prices, and what this implies about the time it takes for the prices of affected properties to recover. We organise this discussion by different types of flooding. First, we focus on the interpretation of the results for properties affected by inland flooding using the coefficients in column (4) of table 3.3; then we focus on the interpretation for coastal flooding using the results in column (6) of table 3.3.

Table 3.4 shows the discount for properties affected by inland flooding. Notice that the coefficient on the variable *B*Inundated* in column (4) of table 3.3 suggests a discount of 33.5% for detached properties (omitted category) affected by inland flooding. However, the coefficient on the variable *B*IND*quartile* is also positive and significant, indicating that the discount is greater (in proportion to the price) for the group of properties with the lowest price, and then it decreases as the price of the house increase. Therefore, the post-flood discount on detached properties ($Discount_{Detached}$) is given by:

$$Discount_{Detached}: \beta_{B*Inundated} + (\beta_{B*IND*quartile} * quartile) \quad (23)$$

For other types of properties we need to add the differential effect given by the coefficient on the variables *B*IND*sdetached*, *B*IND*terraced* and *B*IND*flat*, for semi-detached, terraced and flats, respectively. Table 3.4 shows the post-flood discount for different types of properties affected by inland flooding across different quartiles. Table 3.4 also includes a column indicating what the results suggest about the number of years (Yrs.) it would take for the property to recover half the value of the post-flood discount. Notice that this represents an indicative measure as our model does not specify the extent of the post-flood price recovery. This is estimated using the coefficient on the variable *B*IND*mnths(sqrt)* in table 3.3. This coefficient indicates the marginal decrease in the discount when the square root of the number of months increases from the date of the flood to the date of the second sale. The values for the column (Yrs.) in table 3.4 are reported in numbers of years. All figures in table 3.4 are estimated using the coefficients in column (4) of table 3.3, as this is our preferred specification for inland flooding. All monetary values are reported in July 2014 GBP.

The results in table 3.4 suggest that the overall average discount for properties affected by inland flooding is around 12.6%, which represents £29,317 for an average valued inland property in 2014. Regarding the persistence of the post-flood discount, the results suggest that, on average, it takes around 4 years for the properties to recover half the value of the post-flood discount. However, the size of the discount and time to recovery is different across different types of properties and different price quartiles.

The post-flood discount for properties affected by inland flooding ranges between 15% and 10% for detached, semi-detached, terraced properties and flats, which represents £57,517 to £14,966 (July 2014 GBP). The discount is higher for less expensive properties (quartile one) and then it decreases as the price of the property increase. Notice, however, that in most of the cases a decrease in the percentage discount of the property across quartiles does not mean a smaller discount in monetary units. For instance, the results in table 3.4 suggest a discount of 28% for detached properties in the first quartile, which represents £44,027, whereas for the quartile of most expensive properties the discount is around 12.5% which represents £63,648. Regarding the persistence of the discount, the results in table 3.4 suggest that it takes between 3 to 6 years for prices of affected properties to recover by half, depending on whether it is a detached, semi-detached, terraced property or a flat.

Table 3.4. Effect of inland flooding on property prices:
Per type of property and quartile
(*Inland flooding; column (4) of table 3.3*)

Quartile	Detached		Semi-detached		Terraced		Flat	
	Disc. (%)	**Yrs.**	**Disc.** (%)	**Yrs.**	**Disc.** (%)	**Yrs.**	**Disc.** (%)	**Yrs.**
1	-28.26 [-44,027]	19	-21.90 [-22,161]	11	-19.24 [-17,330]	9	-18.16 [-17,648]	8
2	-23.02 [-40,468]	12	-16.66 [-25,769]	6	-14.00 [-20,742]	5	-12.92 [-18,438]	4
3	-17.78 [-43,468]	7	-11.42 [-25,740]	3	-8.76 [-19,124]	2	-7.68 [-15,761]	1
4	-12.54 [-63,648]	4	-6.18 [-23,893]	1	-3.52 [-13,719]	0	-2.44 [-8,391]	0
Average	**-15.19 [-57,517]**	**6**	**-13.04 [-24,690]**	**5**	**-11.63 [-17,874]**	**4**	**-9.65 [-14,966]**	**3**

Overall average discount: -12.62 % [-£29,317]
Average half-life recover: 4 years

Note: All monetary values are reported in July 2014 GBP. Figures refer to the time taken to recover half of the price discount experienced immediately after flooding.
Source: Own elaboration based on results from table 3.3.

Table 3.5 shows the discount and time to recovery for properties affected by coastal flooding. For coastal properties, the overall average discount around 13.6%, which represents £21,832 for an average valued coastal property in 2014. Although the percentage discount for coastal properties is slightly greater than the discount of 12.6% for inland houses, the monetary discount is greater for properties in inland floodplains. This difference is driven by highly valued properties (quartiles 3 and 4) in inland floodplains.

Table 3.5. Effect of coastal flooding on property prices: Per type of property and quartile
(*Coastal flooding; column (6) of table 3.3*)

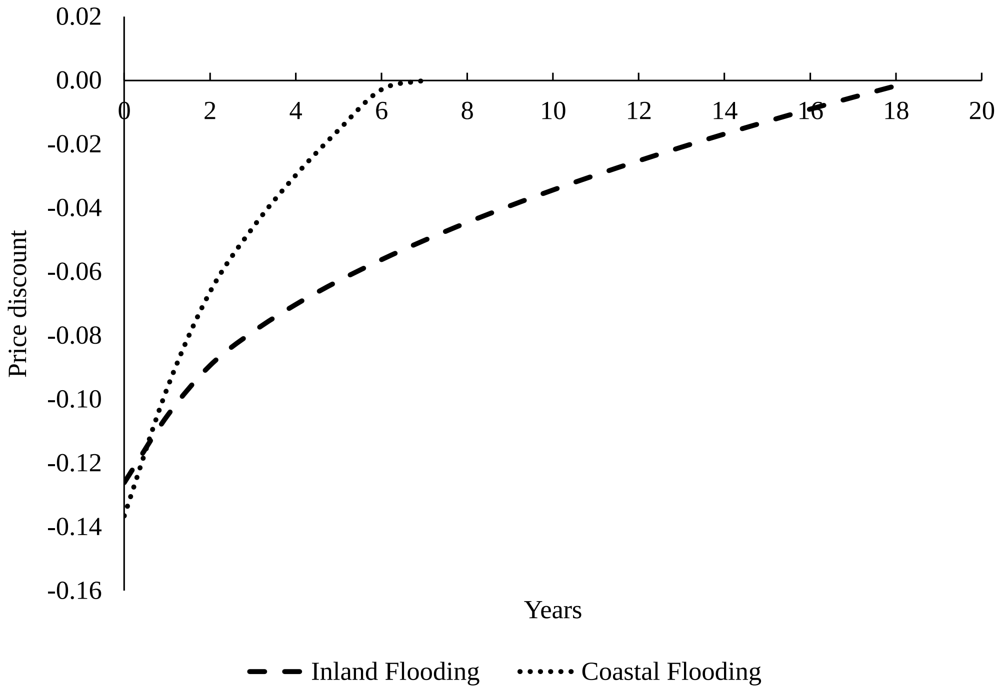
Quartile	Detached		Semi-detached		Terraced		Flat	
	Disc. (%)	**Yrs.**	**Disc.** (%)	**Yrs.**	**Disc.** (%)	**Yrs.**	**Disc.** (%)	**Yrs.**
1	-37.91 [-75,749]	8	-25.61 [-27,542]	4	-22.31 [-18,372]	3	-12.51 [-11,527]	1
2	-28.62 [-48,346]	5	-16.32 [-23,455]	2	-13.02 [-18,409]	1	-3.22 [-4,396]	0
3	-19.33 [-45,266]	2	-7.03 [-15,730]	0	-3.73 [-8,351]	0	6.07 [11,097]	0
4	-10.04 [-44,304]	1	2.26 [8,615]	0	5.56 [20,519]	0	15.36 [48,489]	0
Average	**-17.36 [-46,625]**	**2**	**-14.80 [-19,714]**	**2**	**-15.20 [-14,032]**	**2**	**-1.43 [3,979]**	**0**

Overall average discount: -13.66 % [-£21,832]
Average half-life recover: 2 years

Note: All monetary values are reported in July 2014 GBP. Figures refer to the time taken to recover half of the price discount experienced immediately after flooding.
Source: Own elaboration based on results from table 3.3.

The results in table 3.5 also suggest that the post-flood price recovery of properties in coastal areas is faster than in inland areas taking an average of 2 years for half-life price recovery of affected properties, compared to 4 years for inland properties. For the case of terraced properties in quartile 3 and flats in quartile 2 the discount lasts less than a year, and highly valued semi-detached, terraced properties and flats do not appear to be discounted. As we mentioned before, we believe the faster price recovery in coastal areas is due to a high demand for seafront properties. Figure 3.1 below illustrates the different price path to recovery for properties affected by inland and coastal flooding.

Figure 3.1. Post-Flood profile of property prices in England: Inland and coastal flooding



Source: Own elaboration based on results from table 3.3.

In general, the results indicate that low-income regions are the most affected by flooding, where the post-flood reduction of property prices is greater and prices remain depressed during longer period of times. Currently, Defra estimates the benefits of relief projects financed through the Flood and Coastal Resilience Partnership Funding (FCRPF) by quantifying the sum of averted future flood impacts that result from flood protection (Defra, 2011).[10] To this purpose, they use a flat figure of £30,000 as an estimate of the amount of damages per flood per property. Although this figure is surprisingly close to our average discount estimate of £29,317 and £21,832 for inland and coastal properties,

[10] For details refer to section 2.8 of chapter 2 in this Thesis.

respectively, the results in tables 3.4 and 3.5 suggest that it is important to consider the characteristics of the properties benefited by the project. For instance, a flat figure of £30,000 might underestimate the amount of damages in locations where the stock of benefited properties is composed by highly valued detached properties for which our results suggest a post-flood (inland) price discount of £63,648. Likewise, it would overestimate flood damages for highly valued terraced properties affected by inland flooding where our results suggest a post-flood discount around £13,719. Therefore, the use of a flat figure for all types of properties to estimate the benefits of flood defences might result in a socially inefficient level of flood protection in areas particularly vulnerable to flooding. Differences between rural and urban areas should also be considered.

3.8 Conclusions

During recent years the UK has experienced an increasing number of floods which have been accompanied by an increase in related damage costs over time. These major floods have been caused by record-breaking weather conditions. There is a relatively large body of literature that looks at the effect of a flood on the price on properties located in the floodplain. However, there is a lack of research on the effect of flooding on the price of inundated properties, this is usually due to missing information regarding the properties that are affected at each particular flood event.

The objective of this chapter is to analyse the effect of flooding on the price of properties in England and the post-flood evolution of property prices. To this purpose we follow a repeat-sales specification to analyse the effect of flooding on property prices and to track the evolution of prices after a flood. The analysis goes beyond the scale of usual empirical studies which focus on a single or multiple sites, conducting a comprehensive analysis considering all individual flood events on records in England between 1995 and 2014. To the best of our knowledge this is the first study to analyse the effect of flooding from different sources including fluvial, sewer and coastal flooding. We also consider the case of repeated flooding and the effect of flooding on the price of flats, which have been largely overlooked in the literature. Data on property prices are taken from the England and Wales Land Registry 'Price Paid' housing transactions data. The final sample includes information on over 12 million individual property transactions, which represent about 4.8 million houses that experienced at least one repeat-sale during the period of analysis. This information is merged with high-resolution GIS data from the UK Environment Agency that contains a total of 141,841 spatial polygons delineating historical recorded outlines of individual flood events in England, which account for a total flooded area of 2,654 km^2 during the period of analysis. Other GIS datasets used for the analysis include: spatial delineation of flood zone areas, recorded individual flood outlines and rural-urban classification of land.

Evidence from the econometric model suggests that the average post-flood price of properties affected by inland and coastal flooding, respectively, is 12.6% and 13.6% lower than comparable not-flooded properties; for a median-priced house in 2014 these represent £29,317 and £21,832. The discount, however, is short-lived. On average, properties affected by inland flooding recover half the value of the post-flood discount after 4 years and only 2 years for coastal properties. The discount is mainly associated with flood damages and the information effect of a flood on affected properties. The discount is around 5% greater for properties affected by sewer flooding and those located in rural areas. The former is associated with increased cleaning costs and health risks; the latter is likely to result from more intense flooding and a poorer flood risk management strategy in these regions.

The magnitude and persistence of the discount varies across different types of properties and different price levels. In general, the discount is greater for detached properties affected by flooding, and it decreases for semi-detached and terraced houses. This is associated with specific characteristics of the design of different type of ground level properties such as flooded area. The size of the discount is also relatively higher for less valued properties. As expected, flats experienced the lowest discount after a flood as they are less likely to be affected by flood damages. However, it is interesting to see a large post-flood discount of the order of 10% for flats located in inland floodplains. This is likely to be driven by sales of affected ground level flats in the aftermath of a flood. Unfortunately, our data do not allow us to differentiate sales of flats in ground level to those located in upper levels which are less likely to be directly affected by flooding. In coastal floodplain the average post-flood discount of a flat is only 1.4%.

Floods also occur in locations with standing flood defences due to an overtopping or failure of defences. The results suggest that the post-flood discount in inland and coastal floodplains with flood defences is around 5% lower than it would otherwise be without flood protection. This result suggests that flood protection not only reduces the probability of a flood for the benefited areas, but also reduces flood damages in the event of a flood. Contrary to what previous studies suggest (Daniel, Florax and Rietveld, 2007, 2009; Bin and Landry, 2013 and Lamond, Proverbs and Hammond, 2010) our results indicate that there is no evidence of increasing negative impacts associated with repeated experience with flooding. However, the price discount associated with a second flood will be larger if the flood occurs before full recovery of prices in the region. The price discount after a second flood can also be larger due to specific characteristics of the flood such as the source of flooding or its duration.

The results have important policy implications. They are useful to identify locations where flood risk management strategies should be prioritised. In general, the results indicate that low-income regions are the most enduringly affected by flooding, where the post-flood reduction of property prices is greater and prices remain depressed during longer period of times. The results are also useful to estimate the value of flood damages and to improve the estimation of benefits for the purpose of funding allocation. Currently, Defra uses a figure of £30,000 of damages per flood per property to estimate the benefits of flood relief projects financed through the FCRPF. This is surprisingly close to our average estimate for the post-flood discount of £29,317 and £21,832 for inland and coastal properties, respectively. However, our results suggest that the estimates can be improved by considering important characteristics of affected properties such as their type, price level, or rural/urban classification. For instance, Defra’s estimate of flood damages of £30,000 per flood per property, underestimates the amount of damages in locations where the stock of affected properties is composed by highly valued detached properties where our results suggest a post-flood (inland) price discount of £63,648. Likewise, it overestimates flood damages for highly valued terraced properties affected by inland flooding where our results suggest a post-flood discount around £13,719.

One important area of further research that emerges from this analysis is to identify the effect of changes in the price, excess or terms and conditions of flood insurance policies on the price of inundated properties. Due to lack of property level data, we are not able to disentangle the effect of flood damages from the potential effect associated with changes in the conditions of flood insurance. We tried to address this issue using a dummy variable to identify properties sold after the introduction of the Statement of Principles (SP) in 2002. The SP modified the conditions of flood insurance for properties at the highest level of risk, insurers were allowed to price flood insurance policies based on risk and to refuse to issue a policy to homeowners if there were no plans to improve flood defences in the area within the next 5 years. However our results suggest that these changes might have been anticipated and capitalised before the change in the policy took place, and eventually it might not have had the expected negative consequences. We believe that more research is needed in this area, especially in light of the introduction of FloodRe, the new strategy by the UK Government to manage flood risk in high risk areas.

FloodRe is introduced in April 2016 and works as a re insurance scheme for properties at high risk to which insurers can access at a subsidised rates based on council tax bands and with a fixed excess on flood claims. The objective is to provide flood insurance at an affordable price for properties at the highest level of risk. It is introduced for 25 years as a transition to risk based flood insurance pricing, and it excludes properties constructed since 2009. We believe this provides a great opportunity to test the effect of change in flood insurance regulations on the price of properties in the floodplain and the extent to which flood events are capitalised. This is an area which has not been analysed for the UK. Other areas of further research include the effect of alternative measures of flood intensity on the price of affected properties, such as flood depth or speed of flood water, and the extent to which post-flood restoration of affected properties and the decrease in flood risk perception as time passes contribute to the post-flood recovery of property prices.

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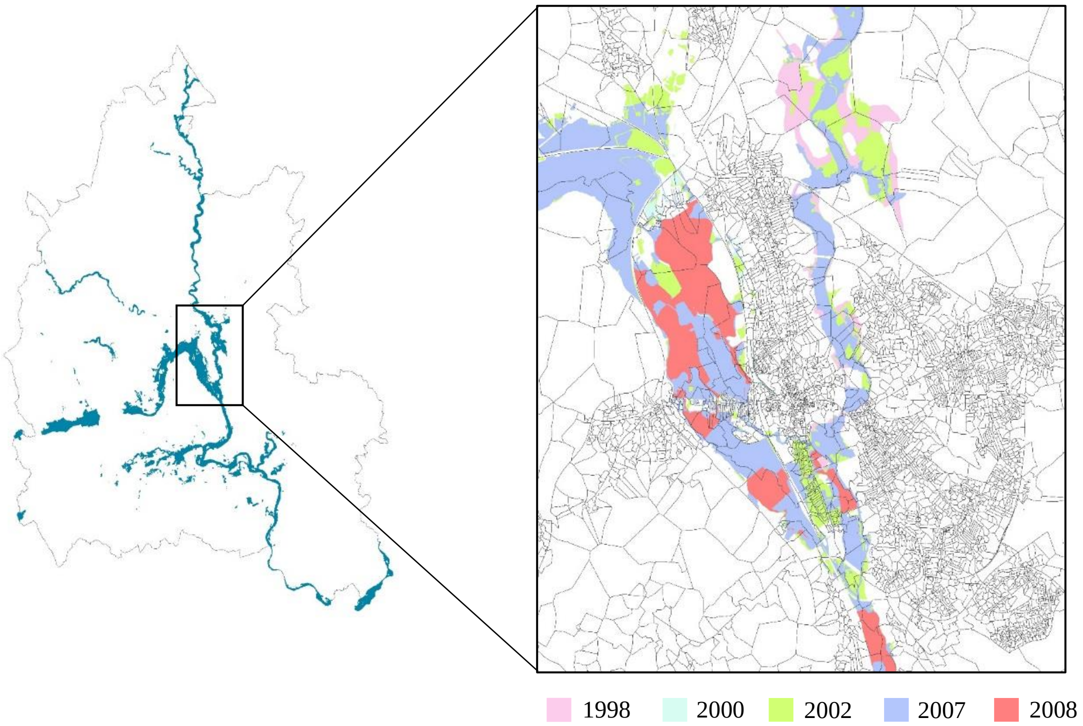
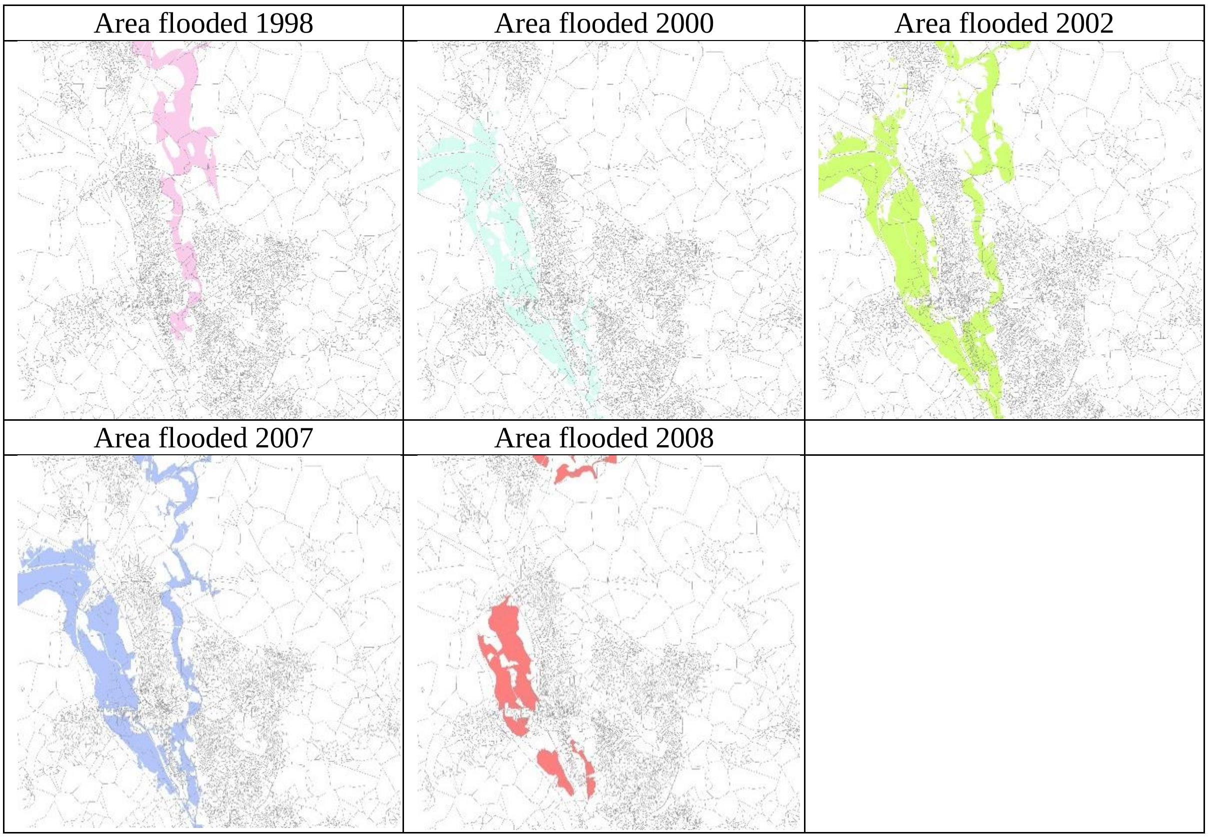
Appendix

Map A3.1. Example: Area affected by inland flooding in Oxfordshire

A. Area flooded 1995-2014 **B. Area flooded by year 1998-2008** (*6-digit postcode area*)





Source: Own elaboration based on data from the ROIFE dataset, UK Environment Agency.

Appendix. Section A3.1

Robustness Tests

As we show in table 3.3, our results are robust to changes in the control group and in the treatment group. In column (1) the treatment group includes all properties affected by different types of flooding, where the control group represents all other properties in the county with repeat sales before and after the flood. In columns (3) and (5) we divide the treatment group in properties affected by different types of flooding, inland and coastal flooding, respectively, while we keep the definition of the control group similar to that in column (1). In columns (2), (4) and (6), the treatment group is defined as in columns (1), (3) and (5), respectively, but we restrict the control group to include only properties located inside the floodplain (FP). In this way, we compare the price change of properties affected by flooding, against that of properties exposed to a similar risk but which were not affected by a flood during the period of analysis. The main results are robust across all specifications, and the interpretation of results in the previous sections use the results from column (4) and (6) as the preferred specifications. In this appendix we present the results of two additional robustness test: first, a standard robustness test that removes outlier observations from the sample; and second, a *placebo test* that consists in a false experiment.

The first test consists in removing the outlier observations from the sample. We run this test to ensure that our results are not driven by a specific set of properties with extreme prices, either too high or too low. More specifically, we exclude from our sample the 1% of properties with the highest prices, we do the same for the 1% of properties with the lowest prices. The results of this test appear in table A3.1 below. The control and treatment groups through columns (1) to (6) are specified as in table 3.3. In general, there is no any relevant difference to report between our main results in table 3.3 and the results of the robustness test in table A3.1. This suggest that all our results are robust to excluding properties from the sample with extreme prices (either too low or too high).

The second robustness test corresponds to a placebo test. The objective is to test for the possibility that the significant capitalisation of flood events that we observe in our results in table 3.3 might be driven by different local characteristics not associated with the occurrence of a flood. In other words, we want to test if our identification strategy is really capturing the effect of a flood on property prices and not other characteristics of the housing market not associated with the occurrence of a flood. In this way, our placebo test consists in a “false experiment” where the “treatment” group is now formed by properties located in areas that were affected by flooding but which repeat-sales do not happen before and after the flood. That is, we look at exactly the same locations as we did in table 3.3, but analysing the change in the price of properties for which the two sales occur either after or before the flood. The econometric model for the placebo test appears in equation (A1) below.

$$\begin{aligned}\Delta ln(P_{its}) = {} & \alpha_1 \overline{Bracket}_{ikts} + \alpha_2\left(\overline{Bracket}_{ikts} \times house\_type_i\right) \\ & +\psi_1\left(\overline{Bracket}_{ikts} \times IND_i\right) + \psi_2\left(\overline{Bracket}_{ikts} \times IND_i \times house\_type_i\right) \\ & +\psi_3\left(\overline{Bracket}_{ikts} \times IND_i \times F\_type_i\right) + \psi_4\left(\overline{Bracket}_{ikts} \times IND_i \times F\_history_i\right) \\ & +\lambda_0 Year_{is} + \lambda_1 Year_{it} + \Delta\varepsilon_{ikts}\end{aligned} \tag{A1}$$

Equation (A1) is similar to the econometric specification in equation (20), but in this case we use a variation of the variable $Bracket_{ikts}$, that we represent as $\overline{Bracket}_{ikts}$ to identify properties which two sales are during the “false treatment” period. That is, the variable $\overline{Bracket}_{ikts}$ is a dummy variable which takes the value of one if the two sales of the property, at time t and s, occur either before or after a flood event in county k where they are located. Our variable IND_i is defined as in equation (20), that is, it represents the group assignment for each house unit and is given by a dummy variable which takes the value of 1 if the property is located in a postcode (six-digit level) that was affected by a flood during the period of analysis, 1995-2014. In this way, the variable $(\overline{Bracket}_{ikts} \times IND_i)$ is a dummy variable which identifies our "false treatment" group; it takes the value of one if the property is located in a postcode that was affected by flooding during the period of analysis, but for which the two sales are either before or after the event.

As in equation (20), the set of variables $house\_type_i$ in equation (A1) controls for different characteristics of the properties. However, it is important to note a slightly change that we made to define the values for the variables controlling for differences in the type of flooding (F_type_i) and differences in flood history ($F\_history_i$). Although our "false treatment" group of properties is located in areas that were affected by a flood, their repeat sales do not *bracket* (occur before and after) the occurrence of the flood. Therefore the values for the set of variables F_type_i and $F\_history_i$ in our placebo regression correspond to the characteristics of the previous flood in the postcode where they are located. In practice, this restricts our sample of "false treated" observations to properties with the two sales after the occurrence a flood during the period of analysis, or between floods for properties in locations that were flooded more than once. That is, our "false treatment" group in equation (A1) looks at the change in the price of properties with two sales during the recovery period after a flood.

The results of our placebo regression appear in table A3.2 below. Similar to our results in table 3.3, the control group for the regressions in table A3.2 changes across specifications from columns (1) to (6). The first section in table A3.2 (*Bracket sample*) includes the coefficients of the variables that control for difference in the time trend across different types of properties (DDD specification). In general, all the variables included in the model to control for differences in the time trend across different types of properties are highly significant. This is similar to what we observe in table 3.3.

The second section in table A3.2 (*Bracket placebo flooded sample*) shows the main results of our placebo experiment. The variable $\bar{B}$**Inundated* shows the price growth rate differential for properties located in postcodes affected by flooding but for which the repeat sales are both after a flood, or between flood for postcodes affected more than once, with respect to the price growth rate of the properties in the control group. The coefficient is highly significant across specifications and has a positive sign, opposite to the sign of the coefficient that we found in table 3.3. This positive coefficient indicates that the prices of properties in areas affected by flooding, but for which repeat sales do not bracket the occurrence of a flood, grew at a faster rate than the price of properties in each corresponding control group. This result is as expected and consistent with the idea of post-flood price recovery for properties located in affected areas. The coefficient is consistent across different types of flooding.

There are other important aspects to highlight from the results of the placebo test in table A3.2. For the case of inland flooding in columns (3) and (4), the negative and significant coefficient on the variables $\bar{B}$**IND*sdetached* and $\bar{B}$**IND*terraced* suggest that the speed of recovery for semi-detached and terraced properties is slower than that of detached houses. The coefficient on the variable $\bar{B}$**IND*sewer* in table A3.2 suggests that the price of properties in locations affected sewer flooding recover faster than properties affected other type of inland flooding. For the case of coastal flooding (columns (5) and (6)) there appears not to be any significant difference across different types of properties. All other variables associated with characteristics of the properties or the flood are not significant.

Finally, the positive and significant coefficients on the variable $\bar{B}$*IND*mnths(sqrt) might indicate that there is still some ongoing recovery of property prices even after some time has elapsed since the previous flood. The average number of months since the previous flood to the date of the first sale for the placebo sample is around 38 months (3 years). Notice, however, that for both types of flooding (inland and coastal flooding in columns (3) to (6)) the coefficient of the variable $\bar{B}$*IND*mnths(sqrt) in table A3.2 is considerably smaller than the one we observe in table 3.3. This suggests a slow down on the recovery process of property prices as the time with respect to the previous flood increases.

Table A3.1. Repeat-sales model. Robustness test: Excluding extreme values
(Excludes top 1% and bottom 1% of observations)

	Variables	(1) All estimates	(2) All estimates FP	(3) Inland	(4) Inland FP	(5) Coastal risk	(6) Coastal risk FP
	Bracket Sample						
	Bracket (B)	0.106***	0.119***	0.103***	0.113***	0.377***	0.264***
		(0.00122)	(0.00346)	(0.00133)	(0.00387)	(0.00402)	(0.00932)
House_type [1]	B*sdetached	-0.0117***	-0.0202***	-0.00843***	-0.0153***	-0.0636***	-0.0762***
		(0.000552)	(0.00146)	(0.000599)	(0.00162)	(0.00145)	(0.00349)
	B*terraced	-0.0101***	-0.0197***	-0.00614***	-0.0155***	-0.0814***	-0.0915***
		(0.000569)	(0.00148)	(0.000615)	(0.00163)	(0.00162)	(0.00390)
	B*flat	-0.0148***	-0.0173***	-0.00508***	-0.00124	-0.149***	-0.171***
		(0.00105)	(0.00298)	(0.00116)	(0.00333)	(0.00282)	(0.00736)
	B*free	0.0319***	0.0327***	0.0343***	0.0392***	0.0300***	0.0185***
		(0.000913)	(0.00267)	(0.00101)	(0.00302)	(0.00214)	(0.00599)
	B*rural	0.00942***	0.0206***	0.00845***	0.0206***	0.0303***	0.0436***
		(0.000485)	(0.00114)	(0.000533)	(0.00128)	(0.00120)	(0.00262)
	B*quartile	-0.0460***	-0.0474***	-0.0451***	-0.0468***	-0.0952***	-0.0954***
		(0.000220)	(0.000595)	(0.000237)	(0.000653)	(0.000758)	(0.00187)
	B*after2002	-0.0226***	-0.0298***	-0.0212***	-0.0296***	-0.0270***	-0.0227***
		(0.000381)	(0.00102)	(0.000419)	(0.00114)	(0.00161)	(0.00402)
	Bracket-Flooded Sample						
	B*Inundated (IND)	-0.403***	-0.420***	-0.369***	-0.388***	-0.506***	-0.515***
		(0.0149)	(0.0160)	(0.0159)	(0.0172)	(0.0413)	(0.0430)
House_type [1]	B*IND*sdetached	0.0585***	0.0685***	0.0510***	0.0601***	0.109***	0.118***
		(0.00609)	(0.00665)	(0.00648)	(0.00710)	(0.0176)	(0.0186)
	B*IND*terraced	0.0759***	0.0909***	0.0702***	0.0844***	0.135***	0.150***
		(0.00622)	(0.00679)	(0.00651)	(0.00713)	(0.0196)	(0.0207)
	B*IND*flat	0.119***	0.125***	0.0957***	0.100***	0.289***	0.287***
		(0.0128)	(0.0136)	(0.0140)	(0.0151)	(0.0312)	(0.0323)
	B*IND*free	-0.00233	-0.00672	-0.00714	-0.00919	0.0265	0.00619
		(0.0112)	(0.0118)	(0.0123)	(0.0132)	(0.0261)	(0.0266)
	B*IND*rural	-0.0376***	-0.0472***	-0.0299***	-0.0380***	-0.0802***	-0.0854***
		(0.00454)	(0.00493)	(0.00494)	(0.00536)	(0.0119)	(0.0128)
	B*IND*quartile	0.0599***	0.0636***	0.0559***	0.0594***	0.105***	0.107***
		(0.00249)	(0.00275)	(0.00266)	(0.00294)	(0.00738)	(0.00788)
	B*IND*after2002	0.0596***	0.0661***	0.0515***	0.0592***	0.112***	0.125***
		(0.00545)	(0.00583)	(0.00590)	(0.00629)	(0.0149)	(0.0159)
F_type [2]	B*IND*sea	-0.0360***	-0.0327***				
		(0.00612)	(0.00657)				
	B*IND*sewer	-0.0541***	-0.0541***	-0.0482***	-0.0487***		
		(0.0119)	(0.0150)	(0.0119)	(0.0150)		
	B*IND*defence	0.0689***	0.0599***	0.0777***	0.0542***	0.0402***	0.0422***
		(0.00902)	(0.00939)	(0.0139)	(0.0142)	(0.0138)	(0.0149)
F_history [3]	B*IND*mnths(sqrt) [4]	0.0102***	0.00973***	0.00819***	0.00749***	0.0135***	0.0121***
		(0.00107)	(0.00118)	(0.00117)	(0.00129)	(0.00279)	(0.00300)
	B*IND*dur	-0.000141***	-0.000139***	-0.000155***	-0.000156***	0.000848	0.00103
		(2.40e-05)	(2.99e-05)	(2.43e-05)	(3.10e-05)	(0.000722)	(0.000794)
	B*IND*mnths(sqrt)*dur	-1.09e-05*	-1.22e-05*	-8.42e-06	-9.24e-06	-0.000303	-0.000375*
		(6.19e-06)	(6.97e-06)	(6.24e-06)	(7.09e-06)	(0.000187)	(0.000207)
	B*IND*2F	-0.000439	-0.00145	-0.00535	-0.00650	0.0246	0.0272*
		(0.00615)	(0.00640)	(0.00669)	(0.00699)	(0.0151)	(0.0155)
	B*IND*3F+	-0.0122	-0.0105	-0.00934	-0.00805	-0.0345	-0.0290
		(0.00781)	(0.00791)	(0.00809)	(0.00818)	(0.0259)	(0.0262)

(Continued)

Table A3.1.Continue

Lyear (s)	-0.000851***	-0.000793***	-0.000893***	-0.000878***	-0.00250***	-0.00197***
	(2.83e-05)	(7.39e-05)	(2.88e-05)	(7.53e-05)	(0.000201)	(0.000514)
Year (t)	0.000907***	0.000825***	0.000948***	0.000909***	0.00457***	0.00350***
	(2.82e-05)	(7.38e-05)	(2.87e-05)	(7.51e-05)	(0.000219)	(0.000570)
Observations	7,077,953	1,115,490	6,770,225	1,064,561	307,728	50,929
Treated Obs.	14,035	12,335	11,425	9,972	2,610	2,363
County FE	YES	YES	YES	YES	YES	YES
R-squared	0.125	0.116	0.124	0.116	0.196	0.190

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] Omitted categories are dummy variables for detached property, urban location and properties with repeat sales before change in the flood insurance regulation in 2002.

[2] The omitted categories are dummy variables for fluvial flooding and for those properties affected by flooding in locations without flood defences.

[3] The omitted category represents properties with repeat sales before and after the first flood, during the period of analysis, in the postcode where they are located.

[4] Square root of the number of months since the previous flood with respect to the second sale.

Table A3.2. Repeat-sales model. Robustness test: Placebo regression [1]

	Variables	(1) **All estimates**	(2) **All estimates FP**	(3) **Inland**	(4) **Inland FP**	(5) **Coastal risk**	(6) **Coastal risk FP**
	Bracket Sample						
	$\overline{Bracket}$ ($\bar{B}$)	0.0867***	0.0857***	0.0853***	0.0808***	0.0839***	0.0540***
		(0.00124)	(0.00349)	(0.00136)	(0.00389)	(0.00131)	(0.00817)
House_type [2]	$\bar{B}$*sdetached	-0.0131***	-0.0192***	-0.0103***	-0.0152***	-0.0112***	-0.00828**
		(0.000567)	(0.00149)	(0.000616)	(0.00165)	(0.000601)	(0.00330)
	$\bar{B}$*terraced	-0.0130***	-0.0178***	-0.00907***	-0.0137***	-0.0102***	0.0136***
		(0.000585)	(0.00150)	(0.000633)	(0.00164)	(0.000620)	(0.00321)
	$\bar{B}$*flat	-0.0192***	-0.0187***	-0.0113***	-0.00359	-0.0163***	0.00370
		(0.00111)	(0.00309)	(0.00122)	(0.00344)	(0.00117)	(0.00745)
	$\bar{B}$*free	0.0303***	0.0320***	0.0312***	0.0386***	0.0293***	0.0135**
		(0.000967)	(0.00276)	(0.00107)	(0.00311)	(0.00102)	(0.00685)
	$\bar{B}$*rural	0.00761***	0.0162***	0.00645***	0.0174***	0.00434***	-0.00766***
		(0.000498)	(0.00116)	(0.000547)	(0.00129)	(0.000542)	(0.00294)
	$\bar{B}$*quartile	-0.0435***	-0.0442***	-0.0424***	-0.0438***	-0.0423***	-0.0279***
		(0.000225)	(0.000600)	(0.000242)	(0.000657)	(0.000235)	(0.00105)
	$\bar{B}$*after2002	-0.0314***	-0.0375***	-0.0319***	-0.0386***	-0.0305***	-0.0357***
		(0.000229)	(0.000593)	(0.000236)	(0.000611)	(0.000242)	(0.00110)
	Bracket Placebo Flooded Sample						
	$\bar{B}$*Inundated (IND)	0.0933***	0.0939***	0.0895***	0.0874***	0.0653**	0.165**
		(0.0136)	(0.0151)	(0.0137)	(0.0152)	(0.0291)	(0.0709)
House_type [2]	$\bar{B}$*IND*sdetached	-0.0305***	-0.0321***	-0.0287***	-0.0295***	-0.0133	-0.0200
		(0.00591)	(0.00637)	(0.00593)	(0.00639)	(0.0131)	(0.0259)
	$\bar{B}$*IND*terraced	-0.0312***	-0.0343***	-0.0290***	-0.0316***	0.00659	-0.0134
		(0.00586)	(0.00633)	(0.00588)	(0.00636)	(0.0129)	(0.0262)
	$\bar{B}$*IND*flat	-0.0162*	-0.0170	-0.0159	-0.0160	-0.00787	-0.0384
		(0.00984)	(0.0110)	(0.00987)	(0.0110)	(0.0195)	(0.0515)
	$\bar{B}$*IND*free	0.00767	0.00717	0.00543	0.00499	-0.00697	-0.0511
		(0.00852)	(0.00963)	(0.00853)	(0.00966)	(0.0157)	(0.0472)
	$\bar{B}$*IND*rural	0.00435	0.00171	0.00105	-0.00263	0.00145	-0.0635***
		(0.00404)	(0.00427)	(0.00406)	(0.00430)	(0.00955)	(0.0170)
	$\bar{B}$*IND*quartile	-0.000648	-0.00511**	0.00137	-0.00273	0.0356***	0.0141
		(0.00211)	(0.00228)	(0.00211)	(0.00229)	(0.00462)	(0.00987)
	$\bar{B}$*IND*after2002	-0.00430	-6.43e-06	-0.00298	0.00188	0.000132	0.00385
		(0.00473)	(0.00515)	(0.00473)	(0.00516)	(0.0102)	(0.0212)
F_type [3]	$\bar{B}$*IND*sea	0.0569	0.0449				
		(0.0648)	(0.102)				
	$\bar{B}$*IND*sewer	0.109***	0.0967***	0.110***	0.0986***		
		(0.0187)	(0.0261)	(0.0187)	(0.0261)		
	$\bar{B}$*IND*defence	-0.00969	-0.00741	-0.0103	-0.0103	-0.0244	-0.0106
		(0.00734)	(0.00763)	(0.00727)	(0.00770)	(0.0239)	(0.0297)
F_history [4]	$\bar{B}$*IND*mnths(sqrt) [5]	0.00292***	0.00290***	0.00248***	0.00262***	0.00373*	0.00540*
		(0.000929)	(0.000972)	(0.000939)	(0.000980)	(0.00226)	(0.00324)
	$\bar{B}$*IND*dur	2.99e-05	5.45e-05**	4.29e-05**	6.89e-05***	-6.91e-06	-0.000733
		(2.09e-05)	(2.24e-05)	(2.09e-05)	(2.25e-05)	(6.04e-05)	(0.000937)
	$\bar{B}$*IND*2F	-0.0133*	-0.00702	-0.0121	-0.00523	0.0395	0.00877
		(0.00740)	(0.00758)	(0.00742)	(0.00760)	(0.0363)	(0.0837)
	$\bar{B}$*IND*3F+	0.00679	0.00865	0.00489	0.00745	-0.0137	-0.0112
		(0.00755)	(0.00789)	(0.00766)	(0.00799)	(0.0182)	(0.0293)

(Continued)

Table A3.2.Continue

Lyear (s)	-0.00219***	-0.00240***	-0.00228***	-0.00254***	-0.00216***	-0.00216***
	(3.02e-05)	(7.88e-05)	(3.07e-05)	(8.02e-05)	(3.19e-05)	(0.000149)
Year (t)	0.00225***	0.00244***	0.00234***	0.00258***	0.00222***	0.00220***
	(3.01e-05)	(7.87e-05)	(3.07e-05)	(8.01e-05)	(3.19e-05)	(0.000149)
Observations	7,222,401	1,137,605	6,910,817	1,086,267	6,421,037	336,241
Treated Obs.	66,602	58,077	61,112	52,677	5,490	5,400
County FE	YES	YES	YES	YES	YES	YES
R-squared	0.110	0.106	0.110	0.107	0.111	0.120

Notes: Robust standard errors in parentheses. *, ** and *** means rejection of the null hypothesis at the 10%, 5% and 1% significance level.

[1] Treatment group: properties in postcodes affected by flooding but with the two sales after the flood (recovery period).

[2] Omitted categories are dummy variables for detached property, urban location and properties with repeat sales before change in the flood insurance regulation in 2002.

[3] The omitted categories are dummy variables for fluvial flooding and for those properties affected by flooding in locations without flood defences.

[4] The omitted category represents properties with repeat sales before and after the first flood, during the period of analysis, in the postcode where they are located.

[5] Square root of the number of months since the previous flood with respect to the second sale.

Conclusions, Limitations and Future Research

The frequency and intensity of flooding has increased over the last few decades. Although the number of people affected by flooding is usually larger in developing countries, it is developed countries which display most of the economic losses due to asset accumulation in flood-prone areas. The UK is not an exception, despite large amounts of money invested every year in flood risk management, flooding is an increasingly prevalent occurrence in the country causing millions of pounds of losses every year. In England, current annual flood damages to residential properties are in the order of £270m, and this figure could increase up to £1.5bn by the end of the century due to population increase and climate change. There is, therefore, an urgent need to reconsider the current approach to flood risk management in the country. In this thesis we have presented three essays that contribute to the debate on the economic valuation of flood risk, with an emphasis on English households.

Economic theory provides a way to estimate the economic benefits of reducing flood risk by looking at individual's WTP in the housing market. If a property is subject to substantial flooding, repair costs and associated flood losses might easily exceed the cost of buying an equivalent property outside the floodplain. Therefore, in a housing market with flood risk, individuals bid up the price of properties that reduce the chances of being flooded. This results in a price differential for properties exposed to different levels of risk. Throughout the three chapters of this thesis we have investigated different aspects of the capitalisation of flood risk in the housing market, namely: floodplain location, flood relief projects, and the impact of flooding.

In the first chapter we analysed the price differential for properties in the floodplain by means of a meta-analysis. Our analysis makes several contributions to better understanding the welfare impact of effect of flood risk as revealed by floodplain location. It greatly extends and corrects the only existing meta-analysis in this area. The main contributions of our meta-analysis include the use of weighting schemes to avoid the overrepresentation of studies contributing more than one estimate, a separate analysis of fluvial and coastal studies, the use of a variable to account for the flood history in the location of primary studies and the analysis of the post-flood price dynamics. When we incorporate these elements into the analysis, the results suggest that the actual effect of floodplain location on house prices is utterly different to that reported in the previous meta-analysis.

We showed that there are important differences in the capitalisation of risk across different types of flood risk. For the case of coastal flood risk, the results point to the existence of a price premium rather than a discount. However, this is likely to be driven by serious endogeneity issues in primary studies which fail to control for amenity values associated with proximity to the coast. We suggest that it is currently impossible to draw sensible conclusions from studies undertaken in coastal regions. For the case of fluvial flood risk, floodplain location is associated with a significant price discount. The size of the discount varies depending on the level of risk and the time with respect to the previous flood. The results also highlight the main role of flood risk perception in determining the extent of the discount. The price discount increases after a flood and then prices recover as time elapses and individuals forget about the risk of flooding. The discount is more persistent for properties exposed to more frequent and more severe flooding. Overall, our results suggest that for properties in floodplains exposed to fluvial flood risk, the price discount for floodplain location is around five percent; almost an order of magnitude different to those obtained by the only other meta-analysis which suggests the discount is almost negligible.

In the second chapter we used a repeat-sales hedonic model to investigate the benefits of flood relief projects in England by looking at the capitalisation of structural flood protection on property prices. To the best of our knowledge this is the first study to provide an ex-post evaluation of the benefits of structural flood protection using a DID repeat-sales hedonic approach. We use big data containing information on the price of all properties in England which were sold at least twice during the period 1995-2014, and all flood defences constructed during the same period. This is a comprehensive analysis looking at different aspects of the benefits of structural flood protection, such as the type of the defence, the length and the standard of protection, as well as characteristics of the properties and flood history.

The results showed that flood defences capitalise into the price of properties; however, the extent and direction of the capitalisation depends on multiple factors such as the level of risk, the type of property, the design characteristics of the defence and the flooding history in the location where the defence is constructed. The benefits are higher for properties exposed to higher potential flood damages, that is, ground level properties and properties exposed to higher levels of risk (nearer to the flood defences). Differences in the flooding history also play a significant role; the benefits are higher for those properties with more recent and more severe experience with flooding, this result is associated with increased flood risk perception. On the other hand, there is evidence of potential negative amenity and environmental impacts associated to the construction of defences. The use of demountable flood defences can help to reduce the visual disamenity, however it is likely to result in negative impacts due to an increase in risk perception. Instead, we suggest that the use of glass floodwalls, such as the ones recently installed in areas of Cumbria and Somerset, can help to minimise this issue. The results suggest that individuals trade-off flood protection and amenity loss in at least two dimensions. Homeowners exposed to low levels of risk appear to have a higher preference to avoid the environmental disruption of tall and lengthy flood defences, as well as individuals living in areas with highly valued environmental amenities such as rural and coastal areas. Under these circumstances, the construction of flood defences can result in a *decrease* in the price of properties – a most remarkable finding.

In the third chapter we used a repeat-sales hedonic model to investigate the effect of flooding on affected properties. Our analysis distinguishes itself from previous studies in that we focus only on those properties located within an inundated area. For this purpose, we merged high resolution GIS data delineating the areas affected by flooding with our dataset containing information on repeat housing sales. In this way we identified the change in the price of properties that were affected by flooding between sales, and the post-flood dynamics of prices. This chapter also contributes to the literature in several ways. Again our analysis goes beyond the scale of usual empirical studies which focus on a single or multiple sites, conducting a comprehensive analysis considering all individual flood events on records in England during the period of analysis. To the best of our knowledge, this is the first study to analyse separately flooding from fluvial, sewer and coastal sources. We also contribute to the scarce literature that analyses the effect of repeated flooding and the effect of floods on the price of flats.

The results suggest that, after a flood, affected properties are sold at a significant discount, compared to similar non-affected properties. We associate this discount with the occurrence of flood damages and heightened risk perception. The extent of the discount depends on the type of property and the characteristics of the flood. The discount is greater for detached properties, and it decreases for semi-detached and terraced houses. Flats experienced the smallest discount after a flood, as they are less likely to be affected by flood damages. Regarding differences associated to the type of flooding, the discount is greater for properties affected by sewer and coastal flooding, as they can in incur in additional flood losses. The discount is also greater in areas that remain flooded for longer periods of time, however this effect is almost negligible because once floodwaters have entered a house most of the damage has already been done. In all cases, however, the post-flood discount is followed by a rapid recovery of prices as individuals invest in repairing their properties and they forget about the risk of flooding. The recovery of prices is considerably faster in areas affected by coastal flooding; this is likely to be due to a high demand for waterfront properties in coastal areas. In general, the post-flood discount is larger and more persistent in locations where housing prices are already lower.

Key policy implications are derived from these essays on the economic valuation of flood risk. Evidence on the existence of amenity impacts associated with the construction of flood defences suggest that the economic benefits of structural flood protection are less than anticipated. In fact, there are remarkable examples of areas where the construction of flood defences can results in negative welfare impacts. These are currently not considered for the allocation of funding to flood protection by the UK Government, which results in providing too much funding for locations where they are not desirable. We suggest that the negative impacts of flood protection have to be accounted for and incorporated into the estimation of benefits. The results also indicate that low-income regions are the most affected by flooding, where the post-flood reduction of property prices is greater and prices remain depressed during longer period of times. Overall, our results provide a sound economic basis to guide the allocation of resources for flood alleviation strategies in a socially efficient way.

LIMITATIONS Although we have made efforts to conduct an analysis as comprehensive as possible and our empirical evidence has been corroborated using different robustness checks, there are inevitably some limitations to highlight.

In the first chapter, the generalisability of our results is limited by the lack of research outside the US. Therefore, it is possible that the conclusions of the meta-analysis are only really applicable to the US, and that the observed price discount and time of recovery are mainly determined by US flood policies. One reason might be that the search of studies was limited to the use of English as the main language for dissemination of research. Even then, the meta-sample only includes a handful of studies from other English speaking countries. Therefore, we believe that this limitation is due to a general lack of hedonic applications outside the US, and not a result of restricting the sample to studies using the English language. Furthermore, although we made all efforts to control for the time with respect to the previous flood in each location, the date for each study was calculated using their average sample year. For some studies where the sample extends over several years, this might not be enough to fully capture complex post-flood dynamics. This represents a potential source of bias for our estimates on the persistence of the post-flood discount.

For the second and third chapters, the main limitations are related to the methodology and the dataset used for estimation. Although the dataset available from the UK Land Registry contains all sale property transactions in England since 1995, it does not include the property characteristics required to undertake a standard hedonic model. Therefore our estimation method was limited to the use of the repeat-sales methodology. Despite the fact that we made all efforts to minimise the weakness associated to the use of this methodology and the results have been corroborated by a large number of robustness checks, there are still some factors that might result in a bias or pose a threat to identifying the effects of interest. For instance, the dataset does not allow us to distinguish flats located in the ground floor from those located on upper floors. Therefore, our estimates for the benefits of flood protection and the effect of a flood on flats might be driven by apartments located in the ground floor. In this case, using our results to evaluate the benefit/damages considering all flats, regardless of their floor level, might lead to misleading conclusions.

We attempted to minimise the potential sample selection bias inherent to the repeat-sales methodology by including in our sample information from all properties in England with repeat-sales during the period of analysis. Although this increased the precision of our estimates, it resulted in a very large dataset which also entailed certain limitations. We required the use of a high performance computer cluster for estimations, and the level of detail in the analysis was limited by the availability of the data for the scope and time frame specified in the analysis and the practicability of assembling the data in cases where this was not available. For instance, it was not possible to control for all other different aspects, such as public infrastructure and services, which could have changed between repeat-sales of the properties and which might confound the identification of the benefits/damages associated with defences/floods. There was no data available to identify possible refurbishment or structural modifications of the properties. Information related to the flood insurance status or the level or indeed the availability of cover at the property level was also not available. The data available on the characteristics of defences/floods were also limited, and therefore we could not control for specific details of the defences, such as the materials for its construction or the use of glass floodwalls, or for specific characteristics of the floods, such as its depth or velocity.

FUTURE RESEARCH The results presented in this thesis contribute to the development of a research agenda that can be extended in a number of ways.

So far, most of the studies that evaluate the implications of flood risk on property prices use proxy variables to identify properties in the 100-year or 500-year floodplain. However floodplains are broad areas with various level of risk at the property level. It would be interesting to explore the use of different measures of risk that can identify more accurately the actual level of risk for each individual property. This would help researchers to measure more precisely the WTP for marginal increases in the level of risk, which might in turn assist with better planning of public policies. Our meta-analysis also highlights the need of future research to understand better the implications of flood risk on property prices in countries other than the US. More research is also needed to analyse the effect of coastal flood risk on property prices using better controls for amenities associated with proximity to the coast e.g. tools measuring the precise distance to the seafront and the extent to which particular properties enjoy a sea view.

It is well known that investment in flood defence infrastructure can generate some externalities. In chapter 2 we encountered negative impacts from more imposing flood defences likely associated with the visual intrusion and loss of access to waterbodies. However there are other externalities that remain an area of future research. For instance, the construction of flood defences can exacerbate flooding elsewhere along a river catchment, essentially shifting the externality to other households. We believe this is an important area of research where the use of river flow simulations could be exploited. The use of different kinds of flood defence schemes such as, using farmland to store water or multi-functional flood defences, can also yield a number of positive benefits to biodiversity and recreation that should be clearly considered and incorporated into benefit-cost analysis. Due to the national scope of our analysis it was not possible to incorporate more detailed data on the physical characteristics of the defences, however future studies can do this by comparing specific case studies or by using choice experiments to identify how individuals benefit from different attributes of flood defences. Are people WTP the additional costs associated with the use of glass in floodwalls?

There is a general agreement in the literature in that the occurrence of flooding has a negative impact on property prices. Previous studies suggest that this is the result of an increase in flood risk perception, however it has been suggested the negative impact is mainly driven by flood damages in affected areas. In chapter 3, we have taken a step forward in addressing this issue by looking only at the effect of a flood on inundated properties. Yet, it is important to make additional efforts to identify the ‘pure’ information effect of flooding. We believe that this might be achieved using our current dataset to focus on the change in prices of properties located in the vicinity of affected properties i.e. those properties experiencing a ‘near miss’.

Finally, our results suggest that the construction of flood defences or the occurrence of flooding can result in a re-sorting of individuals in the housing market. Therefore, we believe that it would be extremely interesting to complement this research with results obtained by using equilibrium sorting models to help understand, from a different perspective, the complex dynamics that follow these events and to identify the full welfare impact of significant investments in flood defences that might well differ substantially between e.g. property owners and tenants.