The relationship between Research & Development stock of knowledge and firm performance indicators: size, exports and productivity, in the UK economy

Does investing in R&D pay off, when and for whom?

by

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Abstract:

Although the 'endogenous growth' theory links macroeconomic growth to firms' Research & Development (R&D), (Romer 1986, 1990; Lucas 1988), still, there is no comprehensive and conclusive research showing how undertaking R&D affects individual firm performance. Using several market indicators such as size, exports and productivity, this study provides a valuable input in the UK context by analysing a panel of 956 R&D active firms during 2003/4 - 2013/14, employing an empirical approach.

We find no statistically significant relationship between a firm's R&D stock of knowledge and its size (measured in terms of both absolute size and size relative to its industry) across 'All-Firms' dataset as well as a subset of only highly innovative firms.

Employing an econometric approach, which is new in this area - Generalised Structural Equation Modelling (GSEM), we evidence two-way causality between a firm's R&D stock of knowledge and its exports, both positively affecting each other, depending on firm productivity.

In line with Bravo-Ortega *et al.* (2013), we find that at a firm-level, R&D stock of knowledge affects productivity by two channels: directly and indirectly through export levels. However, we find no evidence of 'selection' bias in both export (more productive firms are more likely to become exporters) and R&D activities (more productive firms are more likely to engage in R&D/innovation activities). Contrary to the *'learning by exporting'* hypothesis, (i.e. exporting increases firm productivity), we evidence a negative relationship between a firm's labour productivity and its export intensity (running in both directions).

Declaration

I hereby declare that this thesis is my own work and effort and that it has not been submitted anywhere for any award. Where other sources of information have been used, they have been acknowledged.

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Remaining errors are under my responsibility.

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Chapter 1: Introduction

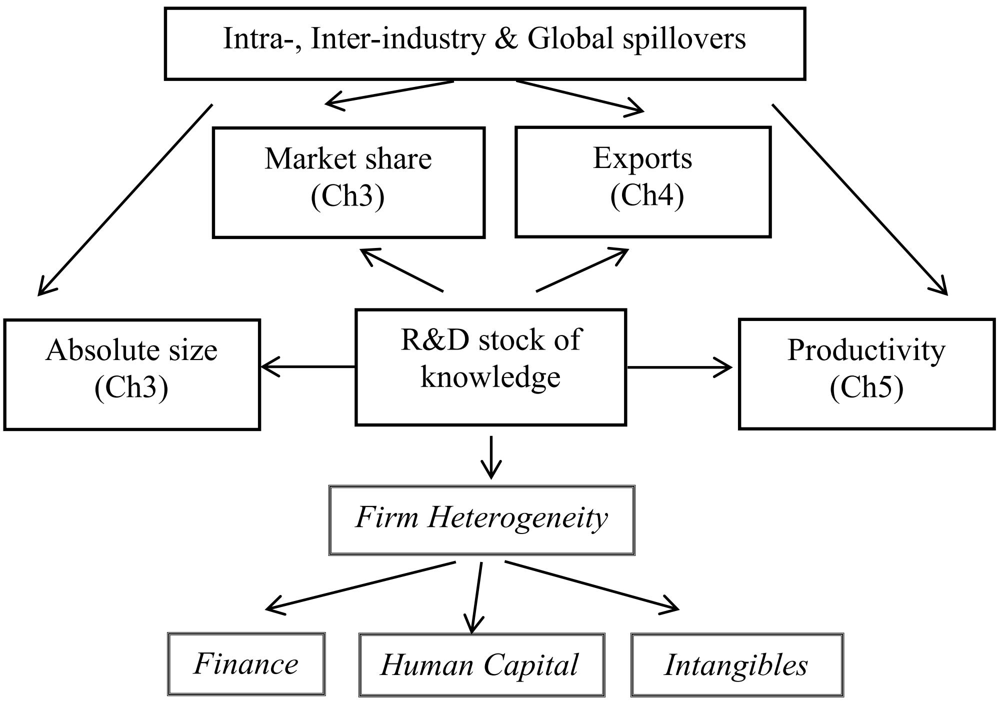
Although according to the ‘endogenous growth’ theory, which links macroeconomic growth to firms’ R&D, innovation leads to economic growth (Romer 1986, 1990; Lucas 1988), there is no comprehensive and conclusive research showing how undertaking R&D affects individual firm performance. Using several market indicators such as size, exports and productivity, this study provides a valuable input in the UK context by analysing a panel of 956 firms during 2003/4 - 2013/14 and employing an empirical approach.

1.1 Introduction and research structure

Although according to the 'endogenous growth' theory, which links macroeconomic growth to firms' R&D, innovation leads to economic growth (Romer 1986, 1990; Lucas 1988), at a firm-level, this is not so widely and conclusively investigated. Indeed, recent research policy debates cast doubt that firms' R&D expenditure translates into satisfactory macroeconomic growth rates (Andersson *et al*. 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011).

This research aims to empirically explore the relationship between R&D stock of knowledge and firm performance in the UK economy, measured by a number of market indicators such as size, exports and productivity, and accounting for a broad range of firms' heterogeneity. The scheme is presented in Figure 1.

Figure 1: Research structure



This study is relevant to a diverse range of stakeholders such as academics, practitioners, governments, professional bodies, analysts, consultants, shareholders and the general public. It asks the important question: 'Does an increase in a firm's R&D expenditure, proxied by its stock of knowledge, lead to an increased firm performance, measured by its market indicators such as size, exports and productivity, in the UK economy?'

As innovative products/services are usually an outcome of a firm's R&D activities (Mairesse & Mohnen 2005), this research uses the R&D stock of knowledge as a measure of 'innovation input', in line with Coe & Helpman (1994), Blundell *et al*. (1999) and Cameron *et al.* (2005). The estimation is based on Griliches (1979) perpetual inventory method, using data on both accumulated 'knowledge capital' and current R&D expenditure, accounting for the rate of stock depreciation. The study employs the Organisation for Economic Co-operation and Development *(OECD*) '*Frascati Manual'* definition of 'R&D' in line with the international accounting standards (IAS 38), official statistics and firms' accounting practices. According to the '*Frascati Manual'* (*OECD* 1993), R&D *'comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge and the use of this stock of knowledge to devise new applications'* (p. 29). Due to the unavailability of reliable data, this study does not account for process and product innovation as there is a significant overlap in the UK firms reporting of both types of innovation, and only a small number of innovations could be unambiguously defined as either product or process innovation (Simonetti *et al.* 1995). A similar situation is reported in recent times for Slovenia (Damijan *et al.* 2012).

This study is structured as follows. The introduction (Chapter 1), presents the research context and aims, addressing the research questions and providing justification for this study. It also discusses the choice of performance indicators. The study's contributions to theoretical knowledge, management practice and policy implications are also outlined. Chapter 2 describes the dataset, which is used in all chapters. Chapters 3 to 5 are structured similarly: a general introduction to the chapter is followed by a literature review on the topic and hypotheses to be tested. Next, each chapter's baseline specification and estimation methodology are explained, and justification of the conceptual framework methods provided, followed by a summary statistics section. Each chapter results are described and interpreted in the subsequent section, and a summary finalises the chapter. Chapter 3 investigates the relationship between firm size (measured in both absolute and relative to its industry's size terms) and R&D stock of knowledge. Chapter 4 analyses the link between firm exports and R&D stock of knowledge, while Chapter 5 - the correlation between firm productivity and R&D stock of knowledge. Finally, Chapter 6 completes the thesis, summarising the results and discussing policy implications. It also outlines opportunities for future research.

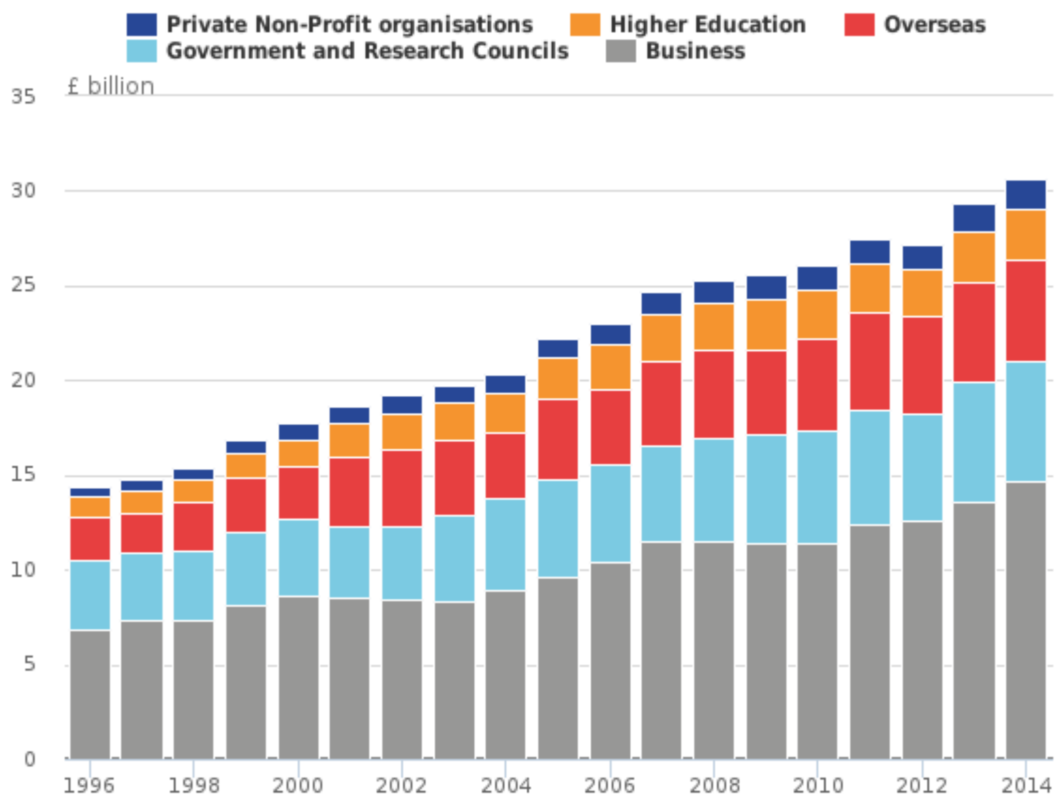
1.2 Background

There is a general consensus in the literature that technological progress stimulates macroeconomic growth and that a substantial part of technological advances comes from R&D activities of profit-seeking firms. The classical and early neoclassical economists regard technological progress as exogenous, while Schumpeter (1942) argues that technological progress is endogenous: corporate search for profits leads to the implementation of productivity and efficiency gains, arising from innovation. This

Schumpeterian approach is integrated into the neo-classical 'endogenous growth' theory (Romer 1986, 1990; Lucas 1988), which links macroeconomic growth to firms' R&D, and is the overarching theoretical framework of this thesis.

In terms of the UK firms, Figure 2 shows that during the years from 1996 to 2014, the largest funder of the R&D conducted in the UK is the business sector (in grey) accounting, on average, for almost half of the total UK R&D funding per year.

Figure 2: R&D by funding sector in the UK (1996-2014) (current prices)



Source: Office for National Statistics[1] Statistical bulletin: UK Gross domestic expenditure on research and development: 2014

1 http://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/bulletins/ukgrossdomesticexpenditureonresearchanddevelopment/2014

The creation of new knowledge is vital for firms' competitive advantage and superior long-run performance (Barney 1991, Drucker 1995, Brown & Eisenhardt 1997). However, firm R&D expenditure is linked to a number of interacting, simultaneous market failures, namely uncertainty, inappropriability (the inability of the firm to appropriate the full benefits of its innovation), and indivisibility (investment in R&D are fixed costs, not infinitely divisible), (Spence 1984). R&D is a risky, insecure activity, and its output (e.g. knowledge creation) has the quality of a 'public-good', prone to knowledge spillovers. Furthermore, there are increasing returns to scale involved in the use of new technology (Oliveira *et al.* 2006, List & Zhou 2007).

Firms generate profitable innovations not only through in-house R&D but also, through other channels, e.g. 'out-sourcing of specific activities', to benefit from the R&D performed by other firms (Chesbrough 2003) or mergers and acquisitions (M&A), to take advantage of joint R&D efforts in particular activities. Firms can obtain valuable knowledge also by 'reverse-engineering', examining patent applications, analysing scientific and trade publications, poaching talent from competitors, participating in trade shows and conferences, learning from customers, suppliers, and collaborators (Levin *et al*. 1987, Appleyard 1996). They can also engage in illegal practices, e.g. offering bribes to acquire trade secrets (Carlton 1992).

1.2.1 Performance indicators

Examining the contribution of firm in-house R&D stock of knowledge to its performance a variety of well-known indicators have been chosen, e.g. market performance indicators namely size, exports and productivity.

1.2.1.1 Firm size

As proxies for firm size, various studies employ sales, total assets, value-added or the number of employees (Zadeh & Eskandari 2012). Kaen & Baumann (2003) argue that firm value-added is a better measure of size in comparison to total sales or total assets as it covers the complicated framework of the firm, associated with the requirements of a highly talented workforce, coordination and cost controls (Zadeh & Eskandari 2012).

Most empirical researchers measure firm size in terms of its absolute size (Kamien & Schwartz 1982, Cohen & Levin 1989) or in rare cases, relative to its corresponding industry size. This research will measure firm size in both absolute (value-added) and relative to its industry's size terms (i.e. market share). Firm absolute size is an important measure in regard to firm innovative activities and related benefits such as economies of scale, productivity, efficiency and access to funds. The use of firm relative size enables measurement of a firm's performance against its peers and direct rivals and, in this sense, is also a measure of firm competitive pressure. Market share normalises for factors generally outside of the control of the firm, e.g. the effects of inflation or industry growth/decline, triggered by factors in other industries or the general economy. As total sales depend heavily on the intermediate inputs intensity, this disregards the differences in intermediate inputs-output ratios across industries and may result in a poor goodness of fit of the estimated model (Pagano & Schivardi 2003). Therefore, the study employs value-added: '*the total return generated by a firm through the utilisation of its productive capacity, i.e. labour and capital in the broad classical sense'* (Riahi-Belkaoui 1999, p. 117). Value-added is generally accepted as a measure of the firm's contribution to society. However, Mairesse & Hall (1996) in their study use both total sales and value-added, and report that sales, as a dependent variable, performs relatively well. Therefore, in order to conduct robustness tests, this study will use total sales as an alternative measure of firm output.

1.2.1.2 Firm exports

The other market indicator employed in this research is firm exports, generally regarded to increase firm performance by enabling a more efficient use of resources, better capacity utilisation and economies of scale, in terms of larger international markets (Bhagwati 1978, Krueger 1978, Obstfeld & Rogoff 1996). Most empirical researchers use export propensity (whether or not a firm is an exporter) as a measure of firm exports, reflecting the researchers' assumptions that export intensity is a firm decision which is made simultaneously with export propensity (Hiep & Nishijima 2009, Iyer 2010). In addition, this study employs export intensity (exports as a proportion of total sales) reflecting the modern research findings that both decisions are different, independent and subject to heterogeneous influences (e.g. Helpman *et al.* 2008, Lawless & Whelan 2008). In Chapter 5 we also use export growth, estimated as the growth rate in a firm's exports over the 11-year period being studied. Export growth is used widely by research scholars as a complementary measure to export propensity and export intensity (Zou & Simona 1998, Katsikeas *et al.* 2000).

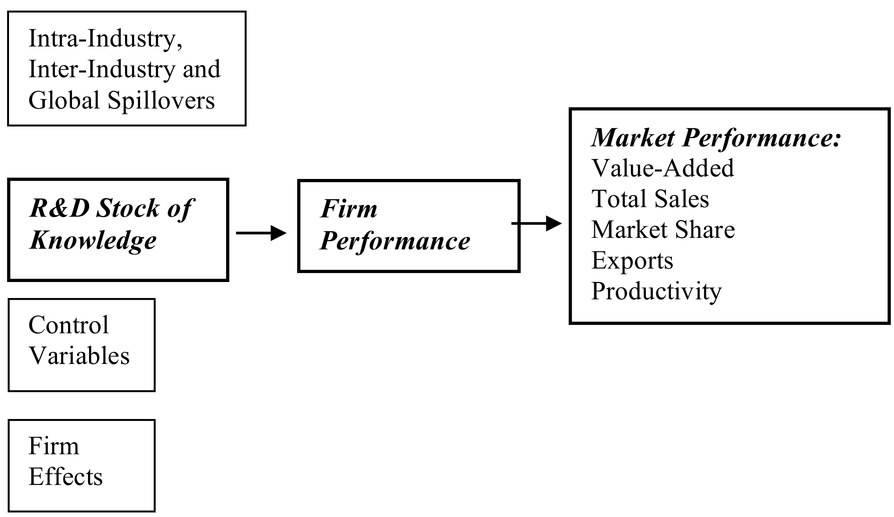
1.2.1.3 Firm productivity

According to the 'endogenous growth' theory, R&D positively and significantly influences firms' productivity growth (Romer 1986, 1990; Lucas 1988; Krugman 1991; Grossman & Helpman 1991b). Firm productivity is the quantity of output that a firm can produce utilising a given level of inputs; this definition is free from any assumption of optimality or efficiency in the firm production process (Hall 2011). Firm-level productivity is proxied by labour productivity and by Total Factor Productivity (TFP). Firm labour productivity is measured by value-added per employee. Firm TFP is calculated by the method of Levinsonh & Petrin (2003).

1.3 Research aims and research questions

Against the above background the research aims, summarised in Figure 3, are to investigate the relationship between R&D stock of knowledge and firm performance measured by a variety of market indicators, using the same dataset, and to provide a credible addition to the current literature on the topics, in the UK context.

Figure 3: Conceptual framework of the research



The research tests various hypotheses that an increase in R&D stock of knowledge feeds through, after a time-lag, to improved firm performance, measured by its market indicators.

The research questions and associated hypotheses are:

- Chapter 3: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market performance indicator: size, in both absolute (value-added) and relative to its industry's size terms (market share)?'

H1: A firm's R&D stock of knowledge is positively associated with its absolute size.

H2: A firm's R&D stock of knowledge is positively associated with its market share.

- Chapter 4: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market performance indicator: exports?'

H3: A firm's R&D stock of knowledge positively affects its export activities or, in other words, *'exporting by innovating'* hypothesis.

H4: A firm's export activities positively affect its R&D stock of knowledge or, in other words, *'innovating by exporting'* hypothesis.

H5: A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics.

- Chapter 5: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market performance indicator: productivity?'

H6: A firm's R&D stock of knowledge positively affects its productivity.

H7: At a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels.

The second hypothesis in Chapter 5 (*H7*) is motivated by the work of Bravo-Ortega *et al.* (2013).

1.4 Contribution to knowledge and management practice

The study's contribution to the current literature and practice is as follows:

1.4.1 Dataset

The study examines the impact of R&D stock of knowledge on various firm performance indicators, employing the same firm-level datasets for each indicator researched. This aims to provide a comprehensive understanding of the subject as well as reliable and credible empirical evidence. To date, research on R&D and firm performance is fragmented. Different studies use different datasets, analysing a single indicator of firm performance without taking into account the effect of the other performance indicators at the same time and their interdependencies, complementarities and dynamics. Contrary to most of the studies in this area, which report a great number of firms in their datasets, but only a small number of which are R&D active, in this study, our datasets include only R&D active firms. For example, Criscuolo & Haskell (2003) report a sample of 1596 firms in their Community Innovation Survey (*CIS*) 2 and 4567 in their *CIS* 3, but only 509 R&D active firms are included in both surveys. Examining the impact of R&D cooperation on firms' productivity on a sample of Belgian manufacturing firms during 1995-1999, Cincera *et al.* (2003) report 599 firms of which only 222 are R&D active. Hall *et al.* (2008) report 9462 firms in their dataset drawn from three surveys of which only 608 R&D active firms appear in all three of them.

1.4.2 Internal and external R&D effects

The research employs a comprehensive set of variables, accounting for both firm-level R&D/innovation as well as for different external technological effects. At a firm-level, the R&D stock of knowledge is employed as a measure of innovation input. The benefit of this is that it takes into account both 'knowledge capital' accumulated over the years and current R&D expenditure, accounting for the rate of stock depreciation. This is in contrast to most of the other studies in this area which use R&D intensity, a dummy for whether the firm undertakes R&D or other measures of innovation instead of R&D stock of knowledge. Using R&D intensity and dummy variables as proxies for innovation makes the research results not fully applicable for policy-makers as these proxies only provide an indication of the impact of different types of innovation on productivity (Hall 2011, Mohnen & Hall 2013). Furthermore, these proxies reflect various projects without measuring their level of success - the most successful projects are mixed with barely successful ones. Also, they do not control for size - larger firms with a greater number of projects have a better opportunity to deliver a successful innovative product or service with at least one of them (Hall 2011, Mohnen & Hall 2013).

According to Mohnen & Hall's (2013) survey, there is complementarity between R&D/innovation and intangibles, acknowledged earlier by Griliches (1990) who advocates that other 'innovation spending', not reported as R&D, is also important for firm performance. Accounting for such spending, we include firm intangible assets which incorporate patents, brand names, copyrights, customer lists, franchises, customer and supplier relationships and marketing rights, licenses, operating rights record masters, secret processes, trademarks, and trade names (IAS 38). The study also includes intra-, inter-industry and global spillovers to account for different external technological effects. To the extent of our knowledge, to date, there is no other research which explores the effect of firm R&D stock of knowledge, intangible assets, intra-, inter-industry and global spillovers on firm performance, measured by a comprehensive set of market indicators and employing the same dataset.

1.4.3 Performance measurement framework

Although the 'endogenous growth' theory advocates that innovation leads to economic growth at a macro-level, at the level of an individual firm, this is not so conclusively explored. Indeed, recent policy debates challenge the view that firms' R&D expenditure results in satisfactory macroeconomic growth rates (Andersson *et al*. 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011). Gaining competitive advantage through R&D activities in the hope of developing winning innovative products and services is a costly, risky business for individual firms (Thatcher & Pingry 2009). Empirical research provides inconsistent and in many cases conflicting results, unable to confidently back up the firm's R&D expenditure (Shy 1995, Huang & Liu 2005). According to some studies (Geroski *et al.* 1993, Long & Ravenscraft 1993, Jones 1995, Van Reenen 1997, Vivero 2002), R&D activities are vital for increasing firm performance in terms of sales, productivity, efficiency, growth, profits and long-term performance. R&D expenditure may reduce production costs and lead to growth in firm value-added (Mansfield 1996). According to other studies (Gou *et al.* 2004, Lin & Chen 2005), R&D intensity is negatively and significantly related to firm productivity and profitability. Some researchers show that there is a time-lag between investment in R&D, decreasing production cost and generating profits, which if not taken into account may lead to negative results (Jefferson *et al.* 2006, Ding *et al*. 2007, Coad & Rao 2008).

This research uses a single performance measurement framework which includes a number of firm performance indicators. This aims to provide clarification of the current inconclusiveness in the literature by offering a richer, more comprehensive and subtle interpretation on how R&D stock of knowledge influences firm performance. The idea is extensively articulated, structured and linked in a way that suggests new theoretical bearings and strategies for practical applications.

1.4.4 Advanced econometric technique

In order to allow for comparability of the results and to maintain consistency throughout the entire thesis, our econometric strategy involves a comprehensive system of empirical approaches, within which there are different options.

In Chapter 4 and 5, this study employs an econometric technique, new in this field - the GSEM, a unified estimation approach with which the effects of R&D stock of knowledge on different firm performance indicators are modelled simultaneously. It is based on the work of Rabe-Heskesh & Pickles (2004) and elaborately discussed by Roodman (2011) in his ‘cmp' STATA approach, which is the initial realisation of GSEM. Both ‘cmp' and GSEM are built on the generalised linear model framework. However, STATA GSEM manages also multiple equation systems and latent variables (Baum *et al*. 2015). It allows for accounting of several potential issues, e.g. simultaneity, interdependencies and different dynamics between the variables researched, which are unaccounted for by the single-equation modelling (Baum *et al*. 2015). The GSEM can deal with the endogeneity, expressed in a simultaneous system of equations - the full-information maximum likelihood (FIML) estimates, computed by GSEM can manage this type of simultaneity (Roodman 2011). The idea of using

GSEM in this research is inspired by the work of Baum *et al*. (2015), who employ this approach in estimating the link between R&D, innovation and productivity.

1.4.5 Relevance

The study is relevant to a diverse range of audiences such as academics, practitioners, investors, governments, professional bodies, analysts, consultants, shareholders and the general public. The research offers insights to firms investigating their R&D investment needs and assistance to business analysts and investors. Offering evidence of, and insights into the firm-level R&D investment, the study will facilitate policy-makers to fine-tune their policy mechanisms for encouraging firm R&D activities to promote sustainable economic growth.

The study has a logico-scientific design: important arguments, empirical truth, and boundary conditions. It tests theories that explain the causes and consequences of the relationship between R&D and firm performance in its context. The research is structured and linked in a way that suggests new bearings and strategies for practical applications (Rindova 2008).

Chapter 2: The Dataset

The study examines the impact of R&D stock of knowledge on various firm performance indicators, employing the same firm-level datasets for each indicator researched. Our panel dataset is unbalanced (allowing for both entry and exit) with data missing for some firms. The total number of firms included in our ‘All-Firms’ dataset is 956; of these, 772 firms belong to the high and medium-high R&D intensity sectors (the ‘Innovators’ subset) and 184 firms belong to the medium-low and low R&D intensity sectors.

2.1 Dataset sources

The dataset is a unique compilation of R&D data as well as other firm financial and operational statistics, based on various sources. Throughout the entire research, we use the same dataset.

2.1.1 Firm-level data

The main body of the dataset is constructed by merging data from the database *Financial Analysis Made Easy* (*FAME*), the UK *R&D Scoreboard*[2] and the UK *Value Added Scoreboard*[3], published by the Department for Innovation, Universities & Skills[4] (*DIUS*), (previously known as UK Department of Trade & Industry (*DTI*)) in cooperation with the Department for Business, Innovation & Skills (*BIS*). Wherever applicable, the *EU Industrial R&D Scoreboard*[5] was also used for additional matching and confirming of the data. The measurement of the UK R&D investment is in line with the accounting definition provided in the Statement of Standard Accounting Practice (*SSAP*) 13 'Accounting for research and development', based on the *OECD* '*Frascati Manual'* (*OECD* 1993) definition of corporate R&D.

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[2]Accessed via the UK government website: http://webarchive.nationalarchives.gov.uk/20101208170217/http://www.innovation.gov.uk/rd_scoreboard/?p=31

[3] Accessed via the UK government website: http://webarchive.nationalarchives.gov.uk/20100908131539/http://innovation.gov.uk/value_added/default.asp?page=60

[4] The Department for Innovation, Universities & Skills (*DIUS*) now functions within the Department for Business, Innovation & Skills (*BIS*)

[5] Accessed via the EU website: http://iri.jrc.ec.europa.eu/scoreboard.html

2.1.1.1 The FAME database

FAME is a firm-level database providing comprehensive financial and operational data, assembled by the electronic publishing and consultancy firm 'Bureau van Dijk'. The database includes information on firms' profiles, profit and loss accounts, ownership, balance sheet, industry association and other performance indicators, as well as other business records. It provides data on firms registered at the UK *Companies House*[6], therefore, it depends on firms' reports of annual accounts. This means that the *FAME* data is usually up to two years old as new firms entering the market have about two years to report their first annual accounts (*BERR* 2009)[7]. Also, as only large firms are legally obliged to report employment, turnover and assets, the smaller firms are unlikely to share their data. Consequently, the *FAME* dataset is biased towards larger corporations. However, the bias is reduced as in the last few years the dataset incorporates more small and medium firms, which declare their balance sheet statistics (Ribeiro *et al.* 2010). For a comprehensive analysis of the *FAME* dataset, see *BERR* (2009), Geishecker *et al.* (2009) and Ribeiro *et al.* (2010).

2.1.1.2 The R&D and the Value Added Scoreboards

The *R&D Scoreboard* comprises data of firm-level R&D expenditure, financial and other performance indicators of UK innovative firms (including foreign-owned firms whose R&D is performed and reported in the UK850, and in the later years, UK1000). It includes the overall level of R&D funded by UK firms, not all of which is conducted in the UK. The R&D expenditure contained in the scoreboard is the cash

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[6] *Companies House* is a UK government agency, funded by the Department for Business, Energy & Industrial Strategy, which incorporates and dissolves limited companies, registers the data firms are legally obliged to supply, and makes the records available to the public.

[7] Department for Business, Enterprise and Regulatory Reform (*BERR*) was a UK government department created in 2007 on the disbanding of the *DTI*. However, it was itself disbanded in 2009 on the creation of the Department for *BIS.*

investment funded by the firms themselves. It does not include the R&D performed under contract for customers (such as governments or other organisations) and R&D expenditure made by any associated organisation or joint venture (though joint venture firms that publish accounts and disclose R&D are included).

The *Value Added Scoreboard* includes the firms with the highest contributions to value-added in the UK and Europe, examining how efficiently they employ their workers and assets to generate wealth, and exploring the sustainability of this performance.

This research merges the *R&D Scoreboard* data with the *Value Added Scoreboard* statistics in a way, similar to that in the Kumbhakar's *et al.* (2010) study. However, while Kumbhakar *et al.* (2010) use the data to examine the top EU R&D investors, this study focuses on the UK firms only. The benefit of using the *Value Added Scoreboard* is that the value-added variable is directly obtainable. The *R&D Scoreboard* and *Value Added Scoreboard* are published independently each year up to 2009/10. Both scoreboards rank the top UK firms in each field on either R&D investment or value-added, respectively, based on statistics from the companies' annual reports. The merging process was possible, as the non-anonymous data permits identifications of the companies that are included in both scoreboards. Also, precise reporting of M&A permits controlling for the corresponding volume effects. In addition, the scoreboards incorporate some common variables, e.g. firm-level number of employees, total sales and other firm-level data, which facilitates double checking the matching of the corresponding firms.

2.1.1.3 Matching the datasets

The matching of the companies in the UK *R&D Scoreboard* and the *Value Added Scoreboard* was conducted manually due to reporting inconsistencies. This is mainly due to the fact that different consultancy companies have collected the data and conducted the data analysis in regard to different scoreboards. Also, since the last *R&D Scoreboard 2010*, further scoreboards have not been produced (equivalently, the last *Value Added Scoreboard* was produced in 2009).

The matching between each company in *FAME* and the *R&D Scoreboard,* as well as the *Value Added Scoreboard,* was complex. It involved a manual matching technique, based on precise criteria (e.g. firm current and previous name(s), incorporation date, location, turnover, and the number of employees) to prevent mistakes (different corporation names, firm location, company status). Those companies, that were not found in *FAME,* were searched in other related databases (e.g. *Amadeus*[8], *OECD ORBIS*[9]). Missing data for a particular firm in one of the two scoreboards has been added if present in the other. All data is verified by cross-referencing with *FAME*. Where matches were established the companies were included. Regarding R&D expenditure, to avoid mismatches between the *R&D Scoreboard* and *FAME* database due to some reporting differences, only firms where reporting on both databases matches on average for the previous years, are included in regard to the recent years. The data is also cross-referenced with information from the *EU R&D*

[8] A database of comparable firm statistics across Europe providing comprehensive financial and operational data, assembled by the electronic publishing and consultancy firm *'Bureau van Dijk'*

[9] *OECD ORBIS* micro-database incorporates more than 200 variables providing financial and other operational data for over 44 million firms at a global level.

Scoreboards, wherever data was available. Only companies whose statistics matched consistently were included.

2.1.2 Intra- and inter-industry R&D spillovers data

Estimating intra- and inter-industry spillovers, data was merged from the *R&D Scoreboard*, *FAME*, the UK Office for National Statistics (*ONS)*, *Eurostat*[10] and *OECD*[11] R&D data, based on specific criteria in regard to the *Industry Classification Benchmark*[12] (*ICB*) industry classification, used in this research.

The *ONS* publishes statistics covering public and private investment in R&D in the UK in their yearly statistical issues of *Gross Domestic Expenditure on R&D*, *GERD - Business Enterprise R&D* and UK *Government Expenditure on Science, Engineering and Technology* series (*SET* statistics, previously published by *BIS*).

Eurostat covers data on R&D expenditures within the members of the EU in regard to the industry of performance and the source of funds. The data is collected through statistical surveys which are frequently conducted at each state-level in regard to the R&D performing organisations in the private and public sectors.

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[10] *Eurostat* is the statistical office of the EU providing statistics that facilitate comparisons between EU nations and regions. http://ec.europa.eu/eurostat/statistics-explained/index.php/R_%26_D_expenditure

[11] *OECD.Stat* incorporates data and metadata for *OECD* nations and other non-member countries. http://stats.oecd.org/

[12] The *ICB* is a system grouping over 70,000 firms and 75,000 securities globally, facilitating the comparison of firms across four levels of classification and national boundaries. The *ICB* system is supported by the *ICB* Database, which is maintained by FTSE International Limited. http://www.icbenchmark.com/

The *OECD Analytical Business Enterprise Research and Development* (*ANBERD*) database covers annual data on investment in R&D by industry and mitigates the issues of international comparability and interruptions in the time-series of the formal business enterprise R&D data. The *ANBERD* database contains various estimations and is published under the responsibility of the Secretary General of the *OECD*. *ANBERD* is not a part of the official reporting of business enterprise R&D data of the member states. However, it provides a means of cross-referencing with the officially reported data on *Eurostat*.

The *OECD Structural Analysis (STAN)* database for industrial analysis includes industrial performance indicators at a comprehensive level of activity across nations, allowing for comparison, as the data is compatible with other related *OECD* databases. As the data is based on the member nations' yearbook national accounts, it utilises data from other sources, e.g. national industrial surveys and censuses to approximate any omitted observations. Hence, it is not an official representation of each member state submission of formal data.

2.1.3 Global R&D spillovers data

Global R&D expenditure is taken from two main sources: the *OECD* database and *The United Nations Educational, Scientific and Cultural Organization* (*UNESCO*) databank. The R&D data provided by the *OECD* includes the organisation's 34 member states and 7 non-members states (*OECD* 2013). The *UNESCO*'s Institute for Statistics dataset is larger, including data on additional countries (*UNESCO* 2013). The data does not account for the entire global R&D expenditure as many countries do not report such statistics at all, while others have started to report it more recently. In some cases, both datasets use predicted values of the total R&D expenditure for some nations which are consequently updated on a regular basis with the actual values.

Therefore, for each year in our dataset, the number of the countries reporting their total R&D expenditure is different.

Cross-national comparisons of investment in R&D and funding requires currency conversions. Therefore, the international convention of converting foreign currencies into UK pounds via purchasing power parity (*PPP*) indicators of price level differences across countries was used, based on *Eurostat* and *OECD* statistics.

2.2 Dataset characteristics

2.2.1 Data organisation

The dataset refers to a 12-month accounting timeframe during the eleven-year period from 2003/04 to 2013/14. Initially, our dataset consisted of over 3000 firms. Controlling for outliers, the observations in the 1% tails for each of the variables of interest are excluded. This way, observations, which may capture large mergers, firm shocks, or coding errors are removed. Additional data trimming was performed to remove observations where turnover, the number of employees, constructed capital stock, intermediate inputs, or constructed R&D stock and intangible assets intensity are non-positive and where intermediate inputs are greater than output. We also removed observations where total assets minus total fixed assets are negative, exports are larger than total sales and intangible assets are greater than the total assets. In line with the general practice for dynamic model analysis, we also dropped all firms with less than three consecutive years of observations (Chen & Guariglia 2013). As per Wakelin (2001), firms which increased their turnover by over 80% in any year are excluded as it is likely to have been subject to a merger. Hence, productivity fluctuations are likely to be due to the merger alone, therefore, it may bias the dataset.

Contrary to many other studies in this area (Criscuolo & Haskell 2003; Cincera *et al.* 2003; Hall *et al.* 2008), which report a large number of firms in their datasets, but only a small number of which are R&D active, in this study, we include only R&D active firms.

The dataset includes only firms with unconsolidated accounts to prevent double counting of firms, members of a particular group, which would be added to the dataset if firms with consolidated accounts were also members of it. The unbalanced panel dataset allows for both entry and exit and thus, to some extent accounts for possible 'selection' and 'survivor' bias. Dataset controls for M&A were put into place to ensure the comparability of the panel data, e.g. M&A are regarded as a new 'entry' and the merged firms are treated as 'exit' from the dataset.

2.2.2 Classification of the firms

Similarly to Kumbhakar *et al.* (2010), the study employs the method of industrial classification used by *BERR*, constructed upon *ICB* sector classification. The *ICB* clusters together firms with similar primary revenue sources. It includes 10 industries, disaggregated into 18 super-sectors, 39 sectors, and 104 sub-sectors in an increasing direction of disaggregation. Each stock is uniquely categorised, based on the firm's primary revenue source, in one of the 104 sub-sectors. Subsequently, it is automatically and uniquely catalogued into one of the 39 sectors, one of the 18 super-sectors and one of the ten industries. Our firms are analysed at sector level *ICB* classification (Table 1).

Table 1: 'All-Firms' analysis: sectors by R&D intensity

N of Ind.	*Ind. Group*	*Sector Description*	*N of Firms*	*N of Obs.*	*Sectors by R&D Intensity*
		Industry groups according to R&D intensity (R&D as % of net sales)			
1.	2710	Aerospace & Defence	49	539	***High R&D intensity Sectors (above 5%)***
2.	4570	Pharmaceuticals & Biotechnology	186	2046	
3.	9530	Software & Computer Services	264	2904	
4.	9570	Technology Hardware & Equipment	186	2046	
		Totals:	***685***	***7535***	
1.	3350	Automobiles & Parts	69	759	***Medium-high R&D intensity Sectors (between 2% and 5%***
2.	3760	Personal Goods	18	198	
		Totals:	***87***	***957***	
1.	3530	Beverages	8	88	***Medium-low R&D intensity Sectors (between 1% and 2%***
2.	3570	Food Producers	74	814	
		Totals:	***82***	***902***	
1.	0530	Oil & Gas Producers	12	132	***Low R&D intensity Sectors (less than 1%)***
2.	1730	Forestry & Paper	26	286	
3.	1770	Mining	10	110	
4.	3780	Tobacco	3	33	
5.	7530	Electricity	23	253	
6.	7570	Gas, Water & Multi-utilities	28	308	
		Totals:	***102***	***1122***	

Source: IRI Scoreboard sector groups by R&D intensity: Reference 'The 2013 EU Industrial R&D Investment Scoreboard' EU Commission, JRC/DG RTD

The firms are grouped according to the EU Industrial R&D Investment (*IRI*) scoreboard sector groups, classified by R&D intensity with reference to: *'The 2013 EU Industrial R&D Investment Scoreboard'* of the EU Commission[13]. Table 1 shows that there are four high R&D intensity sectors in this research: Aerospace & Defence, Pharmaceuticals & Biotechnology, Software & Computer Services and Technology Hardware & Equipment. The R&D intensity in these sectors is above 5%.

There are two medium-high R&D intensity sectors: Automobiles & Parts and Personal Goods. The R&D intensity in this group is between 2% and 5%. The medium-low R&D intensity sectors in our sample of 'All-Firms' are: Beverages and Food Producers. The R&D intensity in these sectors is between 1% and 2%. The low R&D intensity sectors in our study are: Oil & Gas Producers, Forestry & Paper, Mining, Tobacco, Electricity and Gas and Water & Multi-utilities. The R&D intensity in these sectors is less than 1%.

The total number of firms included in our 'All-Firms' dataset is 956; of these, 772 firms belong to the high and medium-high R&D intensity sectors (the 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity sectors.

Initially, the idea was to group the firms into 'High-Tech Firms' including the firms from both high and medium-high R&D intensity sectors and 'Low-Tech Firms', including the firms from medium-low and low R&D intensity sectors. However, the number of firms with sufficient R&D data in regard to medium-low and low R&D intensity sectors is very low in order for our preferred econometric method - the Generalised Method of Moments (GMM) - to provide results which satisfy the requirements of the model. All our experiments provided invalid estimators due to the

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[13] *: IRI* scoreboard sector groups by R&D intensity. Reference*: 'The 2013 EU Industrial R&D Investment Scoreboard'* EU Commission, JRC/DG RTD. http://iri.jrc.ec.europa.eu/scoreboard13.html

'weak instruments' problem[14]. Therefore, we analyse the firms at the 'All-Firms' level (the entire dataset, Table 2) and at the 'Innovators' sub-sample level, which includes only the firms from high and medium-high R&D intensity sectors. Both our panel datasets are unbalanced with data missing for some firms.

Table 2: Summary statistics: 'All-Firms' analysis

Summary statistics: 'All-Firms' dataset						
N of Ind.	*Ind. Group*	*Sector Description*	*N of Firms*	*N of Obs.*	*% of Total Obs.*	*Cumulative*
1.	*0530*	*Oil & Gas Producers*	*12*	*132*	*1.26*	*1.26*
2.	*1730*	*Forestry & Paper*	*26*	*286*	*2.72*	*3.97*
3.	*1770*	*Mining*	*10*	*110*	*1.05*	*5.02*
4.	*2710*	*Aerospace & Defence*	*49*	*539*	*5.13*	*10.15*
5.	*3350*	*Automobiles & Parts*	*69*	*759*	*7.22*	*17.36*
6.	*3530*	*Beverages*	*8*	*88*	*0.84*	*18.20*
7.	*3570*	*Food Producers*	*74*	*814*	*7.74*	*25.94*
8.	*3760*	*Personal Goods*	*18*	*198*	*1.88*	*27.82*
9.	*3780*	*Tobacco*	*3*	*33*	*0.31*	*28.14*
10.	*4570*	*Pharmaceuticals & Biotechnology*	*186*	*2046*	*19.46*	*47.59*
11.	*7530*	*Electricity*	*23*	*253*	*2.41*	*50.00*
12.	*7570*	*Gas, Water & Multi-utilities*	*28*	*308*	*2.93*	*52.93*
13.	*9530*	*Software & Computer Services*	*264*	*2904*	*27.62*	*80.54*
14.	*9570*	*Technology Hardware & Equipment*	*186*	*2046*	*19.46*	*100.00*

[14]. The instruments are 'weak' (poor predictors) when they do not explain the endogenous variables in the first stage equation (Roodman 2009). Although the System GMM is more robust to weak instruments than the difference GMM, it still can suffer weak instrument issues. The dynamic panel GMM can generate too many instruments, which could overfit the endogenous variables and lead to a 'weak-instruments' bias (Roodman 2009). Some of the solutions are: restricting the number of lagged levels employed in the instrument matrix; collapsing the instrument matrix; or combining the two methods (experimented with in this research). A standard test of weak instruments in dynamic panel GMM regressions does not exist (Bazzi & Clemens 2009).

The number of firms and observations of each sector as well as their percentage of the total observations is provided in Table 2. In our 'Innovators' sub-sample, the firms from the high R&D intensity sector Aerospace & Defence represent 6.35% of the data, the firms from Pharmaceuticals & Biotechnology - 24.09%, the firms from Software & Computer Services - 34.2% and the firms from Technology Hardware & Equipment - 24.09%. The firms from the medium-high R&D intensity sector Automobiles & Parts represent 8.94% while the firms from the Personal Goods sector - 2.33%.

2.3 Deflators

All relevant UK variables are deflated employing the aggregate GDP deflator while all R&D variables are deflated using the UK R&D deflator, both published by the *ONS*. GDP and R&D deflators are applied to convert the data series into constant prices.

This study utilises the R&D deflators, newly developed by the *ONS*, to deflate R&D expenditure, instead of the GDP deflators, which allows capturing the R&D-cost idiosyncrasies that differ across industries (Appendix 1).

2.4 Limitations and considerations

There are some limitations and considerations in regard to the dataset. The principal limitation is that it relies on the disclosure of R&D expenditure in published annual reports and accounts. In addition, the dataset reflects the more benign economic environment of the 11-year period researched, although the 2007-09 period captures to some extent the effect of the global economic downturn. Some researchers on corporate behaviour, regarding investment decisions during a financial crisis, evidence that in recessions most firms reduce their investments in innovation and marketing activities to save resources (e.g. Srinivasan *et al.* 2010).

Furthermore, the 'Innovators' sub-sample of firms are not randomly selected from the population (only the highest R&D investors for each year of publication are researched in the R&D Scoreboards). The consequences are that the analysis of the 'Innovators' sub-sample is not generally applicable to all firms, but only to firms with high R&D activities. However, the inclusion of the firms from eight medium-low and low-tech firms in the 'All-Firms' sample, to a great extent, mitigates the issue of generalisability of the research findings.

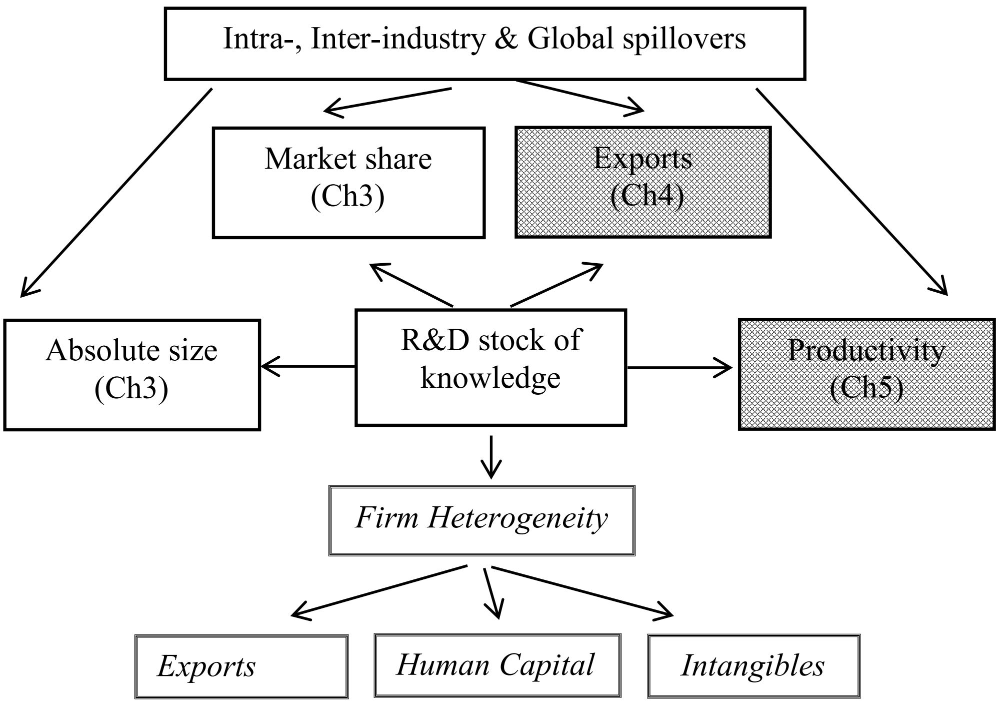
Chapter 3: The Relationship between R&D Stock of Knowledge/Innovation and Firm Size

We find no statistically significant relationship between a firm's R&D stock of knowledge and its size (measured in terms of both absolute size and size, relative to its industry) across 'All-Firms' dataset as well as a subset of only highly innovative firms.

3.1 Introduction

Schumpeter (1942) advocates that the corporate search for profits drives the implementation of efficiency improvements coming from innovation. This Schumpeterian view is integrated into the neo-classical framework of 'endogenous growth' theory, which links macroeconomic growth to firms' R&D. Although according to the 'endogenous growth' theory, innovative activities by firms lead to economic growth (Romer 1986, 1990; Lucas 1988), at a firm-level, this is not so widely and conclusively investigated so as, to confidently back up firms' increasing R&D expenditure. In Chapter 3 we investigate the relationship between R&D stock of knowledge and firm size (in both absolute and relative to its industry size terms), accounting for firm heterogeneity (Figure 4).

Figure 4: Research structure: Chapter 3



We test the Schumpeterian (1942) hypothesis that innovation increases with firm size, hence larger firms are more innovative than smaller ones, however, modified from the perspective of an individual firm. That is, we test whether R&D stock of knowledge is positively associated with firm size.

The study findings are important from both micro- and macroeconomic perspectives. At a microeconomic level, it aims to provide justification for the firms' investment in R&D. At a macroeconomic level, it contributes to the current literature debate which casts doubt that firms' R&D expenditure translates into satisfactory macroeconomic growth rates (Andersson *et al*. 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011). The initial models of the 'endogenous growth' theory were too hopeful and optimistic and raised idealistic expectations that macroeconomic growth is proportional to firms' R&D expenditure (Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011).

The literature on the above Schumpeterian (1942) hypothesis remains empirically inconclusive, providing conflicting results (Kamien & Schwartz 1982, Cohen & Levin 1989, Symeonidis 1996, Van Dijk *et al*. 1997, Klette & Griliches 2000, Mazzucato 2000). This research aims to provide a credible and comprehensive evidence in regard to the relationship between R&D stock of knowledge and firm size as the inconclusiveness of the studies on this topic has significant policy implications.

The study provides an important addition to the current literature in the UK context. Historically, the studies on this topic investigate the effect of firm R&D/innovation on either its absolute size or on its size relative to its industry. Contrary to these studies, this chapter explores the effect of the R&D stock of knowledge on both absolute firm size and on firm size, relative to its industry, using the same dataset.

Another contribution is that this study employs a comprehensive set of variables, accounting for both firm-level R&D/innovation as well as for different external technological effects. At a firm-level, the R&D stock of knowledge is employed as a measure of innovation input. According to Griliches (1990), other 'innovation spending', not regarded as R&D, is also important for firm performance. Accounting for such spending we include firm intangible assets. According to Mohnen & Hall's (2013) survey, there is complementarity between R&D/innovation and intangibles. The study also includes intra-industry, inter-industry and global spillovers to account for different external technological effects.

Also, to date, most of the research on the subject is in regard to the social qualities of welfare: size and especially market share is researched based on the perspective of monopolistic/oligopolistic industry structure and its effect on firms' intra-industry behaviour (e.g. pricing). This research views the relationship between firm size and innovation from a different perspective, not in regard to whether small or large firms are more innovative, nor whether firm R&D contributes to macroeconomic growth. This study examines the above relationship from the point of view of an individual firm. That is, how a firm's R&D stock of knowledge and associated knowledge spillovers affect firm performance measured by its market indicator: size (in both absolute and relative to its industry size terms), which has not been investigated widely and conclusively.

Our results do not support the hypothesis that R&D stock of knowledge is positively associated with firm size. Using a dataset of 956 UK firms which are R&D active and an econometric approach, we find no significant relationship between R&D stock of knowledge and firm size (in both absolute terms and in terms, relative to its industry), in all models.

The rest of this chapter is organised as follows. In Section 3.2 we review the literature on the topic while in Section 3.3 we discuss the hypotheses to be tested. Section 3.4 describes the baseline specifications and estimation methodology. Section 3.5 presents the descriptive statistics. Thereafter, Section 3.6 describes and interprets the results while Section 3.7 concludes, and highlights, the implications of our findings.

3.2 Literature review

The literature reviewed in this section tests the Schumpeterian (1942) hypothesis that innovation increases with firm size, hence larger firms are more innovative than smaller ones.

3.2.1 The arguments in regard to innovation and large versus small firms

The early empirical studies on the above Schumpeterian hypothesis are generally based on a linear regression of R&D inputs or/and outputs on a measure of firm size. They find a positive relationship between R&D and firm size and explain their findings in terms of the benefits associated with the R&D such as scale economies, complementarities of R&D and other business functions, R&D cost-spreading (Kamien & Schwartz 1982, Cohen & Levin 1989).

The findings of the early research encouraged further studies, which also incorporate other firms' characteristics (e.g., vertical integration, diversification, financial health) in models with size and innovation (Cohen & Levin 1989).

Some researchers, (e.g. Cohen *et al.* 1987, Lee & Sung 2005) provide another perspective on the Schumpeterian hypothesis. According to this view, the relationship between firm size and R&D depends on industry characteristics, such as technological opportunities and appropriability (of innovation) conditions. The assumption is that the relationship between firm size and innovative activities is stronger for firms, operating in industries with higher technological opportunities ('technology-push' hypothesis: high technological opportunity leads to increased innovative activities), higher market opportunities ('demand-pull' hypothesis: high market opportunity leads to increased innovative activities) and appropriability conditions. Other researchers also find such intra-industry differences, e.g. Pavitt (1984), Levin *et al*. (1987), Freeman & Lourca (2001), Malerba (2002, 2005). In addition, Phillips (1966, 1971) provides an evidence of the 'first-mover advantage' theory in that the firm that first sells a new, innovative product gains a competitive advantage over its rivals (who are trying to catch-up), which allows this firm to persistently dominate their market in terms of increasing its market share. However, Blair (1972) and Geroski & Pomroy (1990) cast doubt on this theory, as a uniform tendency. For summaries, see Kamien & Schwartz (1982), Baldwin & Scott (1987), Cohen & Levin (1989), Scherer & Ross (1990), Cohen & Klepper (1996) and Lee & Sung (2005).

According to the above literature, the research findings are diverse, providing controversial views on the subject with many unanswered questions remaining. Although using different types of econometric approaches, modelling the relationship between firm size and innovative activities in different ways with different variables, and employing a diverse range of estimation techniques, the findings of the early econometric studies on the subject can be summarised in terms of the argument of whether larger or smaller firms are more innovative.

3.2.1.1 Larger firms are more innovative than smaller ones

- Larger firms gain more advantages from innovation than smaller firms, e.g. larger sales volumes assure higher returns on R&D and recuperation of 'lumpy' R&D costs, mitigating risks of failures (Galbraith 1952, Kraft 1989, Cannolly & Hirschey 2005).

- Larger firms are more diversified than smaller ones allowing them to appropriate more and better the benefits coming from innovation, e.g. more easily utilise unforeseen, and unanticipated goods or/and services or enter new markets (Nelson 1959, Scott & Pascoe 1987). However, diversified R&D can preclude firms from exploiting economies of scale which are linked to the R&D and can also increase managerial costs (Asakawa 2001, Cincera & Ravet 2011).

- Larger firms benefit more from the economies of scale associated with the R&D process than small ones. e.g. higher R&D expenditures, more researchers and facilities are associated with greater R&D productivity (Kamien & Schwartz 1982, Baldwin & Scott 1987, Cohen & Levin 1989).

- Larger firms are in a better position in both generating internal funds for their R&D and borrowing money for it (larger size provides stability and confidence for creditors), (Baldwin & Scott 1987, Cohen & Levin 1989).

- There are economies of scope in the R&D process, especially in the vertically integrated industries, which follow the technology life-cycle (Malerba 1985). Large firms can develop and commercialise a new product or service faster, more effectively and efficiently than smaller ones as they benefit from the complementarities between their R&D department and the other departments in terms of financial planning, production, and marketing (Kamien & Schwartz 1982, Cohen & Levin 1989).

3.2.1.2 Smaller firms are more innovative than larger ones

- Critics argue that smaller firms have more incentives to innovate as they are hungrier for profits than larger firms. For example, researching the countries in transition, Aghion & Schaffer (2002) find that innovation is led by new, smaller in size firms.

- Large firms have bureaucratic and 'heavy' structure which may stifle innovative activities as a result of 'red-tape' issues (Schumpeter 1942, Baldwin & Gellatly 2003, Kim *et al.* 2009). Firm growth decreases R&D efficiency as management control is diluted and the R&D staff incentives diminish, as the pay-off from their work decreases (Oster 1982).

- As a cohort, in some industries (e.g. low-concentrated or 'young' industries), small firms are accountable for a greater proportion of innovations and employment growth than the large ones (Acs & Audretsch 1988, 1991; Davidsson *et al.* 1994; Audretsch 2002).

- Smaller firms are better at generating radical innovation while larger ones may be better at their commercialisation (Henderson 1993).

- The relationship between innovation and firm size depends on industry characteristics, particularly, on market structure. For example, larger firms are more innovative than smaller ones in monopolistic/oligopolistic sectors with high barriers to entry; however, smaller firms are more innovative in low-concentrated, young industries (Acs & Audretsch 1987, Dorfman 1987).

3.2.2 A historical overview of the studies on the firm size and innovation

The next two sections review the literature on the topic historically. Section 3.2.2.1 reviews the early studies on the relationship between firm size and innovation while Section 3.2.2.2 reviews the more recent studies.

3.2.2.1 Early studies on the relationship between firm size and innovation

The early studies on the subject provide mixed and contradictory results. Some researchers, (e.g., Horowitz 1962, Hamberg 1964, Comanor 1967, Pavitt 1983) use simple regression techniques and find that the relationship between firm size and innovation, however measured, is positive but weak. Others, such as Mansfield (1964) and Grabowski (1968), argue that such positive link is evident only in some sectors. Furthermore, some economists find that this relationship is positive and monotonic (Link 1980, Loeb 1983, Meisel & Lin 1983).

Other studies report even more diversified results. For example, Scherer (1965a,b,c), Philips (1971) and Link (1981) provide evidence of non-linearity in the relationship between firm size and R&D. They both increase following the same trajectory up to a certain level and then, after some monotonicity, they decrease in some industries, yet, the researchers note that this pattern is not evident in all sectors. In his book, which is a collection of 16 essays, Scherer (1984) provides further evidence that the size impact does not exist in all industries. In line with the above studies, Bound *et al.* (1984) provide evidence that the relationship is non-linear. The authors employ the largest (at that time) cross-sectional dataset of US firms (2595) during 1976 and use an econometric approach. However, contrary to the above studies, they find that initially the R&D intensity declines and then increases with the scale of the firm. They also observe that smallest and largest firms are more R&D intense than the middle-sized firms. Like Bound *et al.* (1984), Acs & Audretsch (1991) also find a non-linear, U-shaped relationship between innovation and firm size, using a cross-sectional dataset of 1695 US firms during 1982, and applying an econometric approach.

Utilising a dataset of more than 4000 significant innovations commercialised in the UK between 1945 and 1983, Pavitt *et al*. (1987) confirm the findings of Bound *et al.* (1984) that the firms on both ends of the size distribution are more R&D intense than the firms in between. They also confirm that industry specific effects, e.g. appropriability conditions, are important in the relationship between firm size and R&D.

Arguing that the early studies on the topic use simple models and aggregated data, not properly controlling for industry effects, Cohen *et al.* (1987) find that firm size, however measured, does not affect R&D intensity, if fixed industry effects and other industry characteristics are taken into account. They use an empirical approach and data from the US Federal Trade Commission's Line of Business Program. The authors also utilise a survey indicators of technological opportunity and appropriability conditions. They conclude that industry specific effects explain, on average, half of the variance between R&D intensity and firm size.

Reviewing a number of studies across countries, mainly empirical and based on firm-level datasets, Dosi (1988) in his essay finds, on average, a log-linear relationship within industries between firm size and its R&D expenditure. He notes that the firm size distribution within industry depends on industry technological conditions. He also finds that there is a difference between the 'empirical stories' provided by the econometricians and the 'analytical stories' of the theoreticians in terms of the relationship between firm size and R&D expenditure.

For further discussions in regard to the literature on the relationship between firm size and R&D see the survey by Hall *et al*. (2010), which contains a large literature from the past 50 years.

3.2.2.2 Recent studies on the relationship between firm size and innovation

Using a dataset of US firms during 1974-77 and empirical approach, Cohen & Klepper (1996) report that R&D and firm size are positively correlated within industries and that R&D increases proportionately with firm size in most industries. They find insufficient evidence of economies of scale in the R&D utilisation. The evidence provided by Crepon *et al.* (1998) is similar to the Cohen & Klepper's (1996) findings. Using a dataset of French manufacturing firms and an empirical approach, the researchers account for both 'demand-pull' and 'technology-push' hypotheses. They provide evidence that the likelihood of a firm undertaking R&D grows with both firm absolute size (number of employees), as well as its size relative to its industry (market share), diversification and some industry technological characteristics: 'demand-pull' and 'technology-push' variables.

Employing a dataset of 126 Taiwanese manufacturing firms during 1994-2000 and a production function technique, Tsai & Wang (2005) analyse the relationship between firm size and R&D output elasticity. They find a 'U' type relationship, in line with Bound *et al.* (1984) and Acs & Audretsch (1991), supporting the Schumpeterian hypothesis that innovation increases with firm size, hence larger firms are more innovative than smaller ones.

Employing a dataset of 5755 firms from the US National Cooperation Research Act during 1985-1999, Duso *et al.* (2010) use a regression technique controlling for endogeneity to analyse the effect of R&D on market share. They find that R&D positively affects firm market share, but emphasise that this influence is weak.

Contrary to the above studies, the findings of Ortega-Argiles & Brandsma (2010) do not support the above Schumpeterian hypothesis. Analysing a dataset of the top R&D investors from *The 2006 EU IRI Scoreboard*, the authors report that the average size of the top R&D firms among US-based investors is smaller in relation to the size of the EU-based firms. However, their R&D intensity is higher than in the EU-based firms. Using an econometric approach, they evidence that firm size plays an important role, independent of the sectoral construction of R&D. They conclude that, in both US and EU, smaller firms spend, on average, a higher proportion of their sales revenue on R&D.

Exploring the relation between firm size and innovation Revilla & Fernandez (2012) use a balanced panel of 588 Spanish firms during 1998-2000 and employ an econometric approach. They find that the link between firm size and innovation is dependent on the level of technology. Smaller firms benefit from an environment where the intellectual property rights can be used as a means of appropriation, or where there is a low knowledge cumulativeness. However, the larger firms benefit from an environment where there is a limited use of intellectual property rights.

3.2.3 Concluding remarks

The literature reviewed in this section in regard to the Schumpeterian (1942) hypothesis that innovation increases with firm size, remains empirically inconclusive, providing conflicting evidence (Kamien & Schwartz 1982, Cohen & Levin 1989, Symeonidis 1996, Van Dijk *et al.* 1997, Klette & Griliches 2000, Mazzucato 2000, Ortega-Argiles & Brandsma 2010, Revilla & Fernandez 2012). While some studies evidence a positive relationship, others find no significant relationship at all or even a negative association.

Some researchers use non-random samples, without taking into consideration the ‘selection’ biases, other do not account for firm and industry specific effects, except for firm size (Scott 1984). Other do not control for potential collinearity between firm and industry effects, and firm size. Only a few studies take into consideration the inter-industry differences in the relationship between innovative activities and firm size. According to Arvanitis (1997), the inconclusive and conflicting results might be due to the lack of recognised theories and empirical models to account for the determinants of R&D at a firm-level and their association with firm size. For Mazzucato (2000), the inconclusive and conflicting results of the studies might be because they do not account for the fact that firm size and R&D may be simultaneously determined, that is, they may both affect each other.

To date, most of the research is in regard to the social qualities of welfare: size, especially market share, is researched based on the perspective of monopolistic/oligopolistic industry structure and its effect on firms' intra-industry behaviour (e.g. pricing). This research views the relationship between firm size and innovation from a different perspective, not in regard to whether small or large firms are more innovative, or whether firm R&D contributes to macroeconomic growth. This study examines the above relationship from the point of view of an individual firm. That is, how a firm's R&D stock of knowledge and associated knowledge spillovers affect firm performance, measured by its market indicator: size, which has not been investigated widely and conclusively.

The next section describes the hypotheses to be tested, in relation to both literature review and the different perspective taken in this study - from the point of view of an individual firm.

3.3 Hypotheses to be tested

This chapter aims to empirically explore the relationship between R&D stock of knowledge and firm performance in the UK economy, measured by its size and accounting for a broad range of firms' heterogeneity. The literature reviewed in Section 3.2 tests the Schumpeterian (1942) hypothesis that innovation increases with firm size, hence larger firms are more innovative than smaller ones. Here, we modify the hypothesis from the viewpoint of an individual firm in order to provide justification for the firm investment in R&D.

Therefore, the hypotheses to be tested are:

H1(Ch.3, H1): A firm's R&D stock of knowledge is positively associated with its absolute size.

Under this hypothesis, we measure firm absolute size by its value-added and as an alternative measure, we use the total sales.

H2(Ch.3, H2): A firm's R&D stock of knowledge is positively associated with its market share.

Under this hypothesis we measure firm size, relative to its industry, as the share of value-added and as an alternative measure, we use a firm's share of total sales.
Both hypotheses are in levels, emphasising the direction of the relationships, not the exact magnitude.

Historically, the empirical studies on the relationship between firm size and innovation (however innovation is measured) provide contradictory and inconclusive results. While some studies evidence a positive relationship, others find no significant relationship at all or even a negative association.

The next section describes and supports the baseline specifications and the econometric approach used, in relation to both literature review, and the different perspective taken in this study - from the point of view of an individual firm.

3.4 Baseline specifications and estimation methodology

This part of Chapter 3 focuses on our baseline specifications - Section 3.4.1 and estimation methodology - Section 3.4.2.

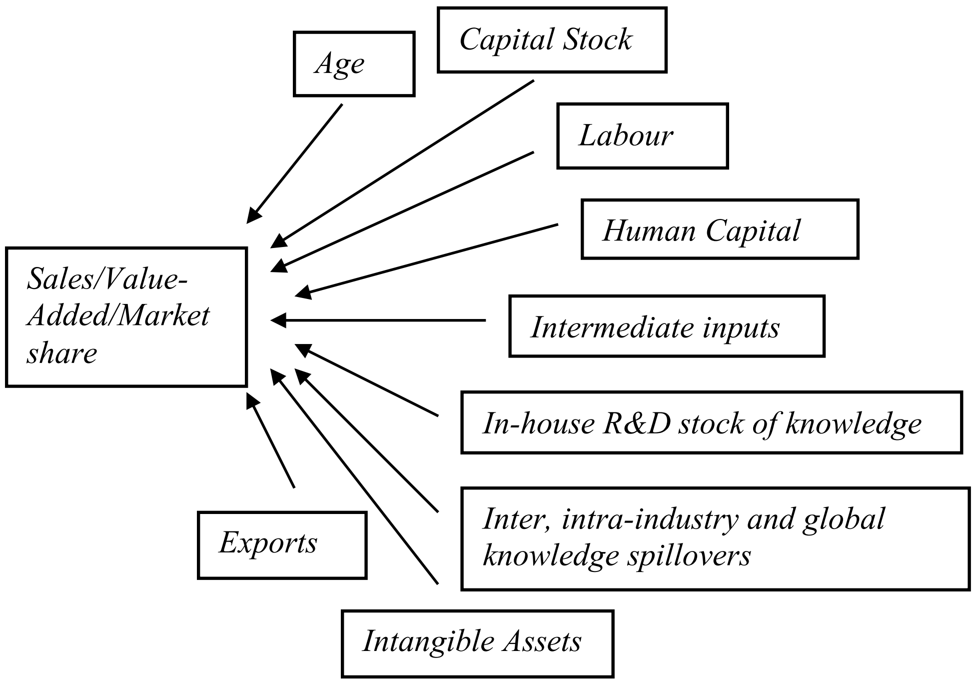
3.4.1 Baseline specifications

This section describes and justifies the conceptual framework envisioned for answering the research question: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market performance indicator - size?

Historically, the contribution of R&D expenditure to macroeconomic growth has been studied using case studies (e.g. Griliches 1958, Mansfield *et al.* 1977), surveys (e.g. Griliches 1973), and production function models including R&D among the explanatory variables (Griliches 1979). Surveys and case-studies are time- and data-consuming, focusing on significant innovation and areas; however, the evidence obtained is not generalisable for all firms. For this reason, this study will employ an empirical econometric approach based on a modified production function technique, which directly links theory and data, to examine the validity of a theory. In this research, we take a different, not widely studied perspective. We will not focus on whether firms' R&D contributes to macroeconomic growth or whether large or small firms are more innovative. This study will examine instead the above relationship from the point of view of an individual firm. In particular, we will investigate how R&D stock of knowledge and associated knowledge spillovers affect firm performance measured by its both absolute size and size, relative to its industry, using the same dataset.

We employ the conventional Cobb-Douglas production technology to represent the firm's output as a function of inputs (Figure 5).

Figure 5: Firm size and R&D stock of knowledge conceptual framework



Source: Adapted from Stoedinova (2011)

Most researchers (e.g. Griliches 1992, Hall & Mairesse 1995) use this technique as the most appropriate when the aim is to quantify the R&D effect in the production process, as it does not generate biased estimates of R&D elasticities when controlling for permanent firm effects. There are concerns that the R&D stock of knowledge coefficient may be understated due to failure to control for the double-counting of R&D expenditure[15] (Wakelin 2001). As R&D inputs are also included in the conventional inputs, e.g. capital, labour, intermediate inputs, their coefficients account for the normal returns to R&D inputs (Schankerman 1981). Therefore, the R&D stock of knowledge

[15] Counting R&D expenditure as a regressor together with capital and labour means that double counting is present, as capital equipment and R&D researchers will be incorporated in the capital and labour variables (Wakelin 2001). Some studies claim that the bias is substantial (e.g. Schankerman 1981, Cuneo & Mairesse 1984, Hall & Mairesse 1995), while others argue that the bias is trivial (e.g. the Australian Industry Commission 1995, Verspagen 1995).

coefficient will account only for the returns associated with R&D stock of knowledge, not for the total return on R&D expenditure (Griliches 1992, Hall & Mairesse 1995).

The conceptual framework (Figure 5), incorporates the key findings from the literature review, taking into account the two-way causality between R&D stock of knowledge and firm size. Identifying the factors of the production function, the study employs the 'sources of growth' theory, which links increases in a firm's output with increases in a firm's inputs of capital, labour, human capital, intermediate inputs and other factors, such as R&D expenditure, intangible assets and spillovers (Griliches 1979, Katayama *et al*. 2005, Cincera & Ravet 2011).

This study employs R&D stock of knowledge as a measure of innovation input, as this most closely corresponds to the objectives of the research: measuring the effect of R&D expenditure on an individual firm performance, not on economic growth. Our study investigates the return on investment in R&D to an individual firm: does it improve firm performance, measured by its size? The research aims to justify firm investment in R&D when the objective of the firm is to increase its size. A definition of R&D and in-house R&D stock of knowledge is provided in the introductory chapter.

In our model, we also include intra- and inter-industry as well as global spillovers to account for the external R&D/innovation effects (Griliches 1992, Guellec & Van Pottelsberghe 2004). Intra-industry, inter-industry and global spillovers can exercise positive as well as negative effects on firm performance. While the positive effects are clear, the negative effects are less researched and somehow avoided. The negative spillover effects, namely poorer firm profits and a greater depreciation rate of knowledge, are first evidenced by Jaffe (1986). As the evidence in regard to firm size and R&D spillover effects is scarce, we explain the spillover effects in general terms of their effects on firm performance.

According to Griliches (1990), other 'innovation spending', not counted as R&D, is also important for firm performance. Accounting for such spending, we include firm intangible assets (derived from firms' financial statements in *FAME*), which incorporate patents, brand names, copyrights, customer lists, franchises, customer and supplier relationships and marketing rights, licenses, operating rights record masters, secret processes, trademarks, and trade names (IAS 38). According to Mohnen & Hall (2013), there is complementarity between R&D/innovation and intangibles. By creating brand loyalty, product differentiation and barriers to entry, intangible assets are complimentary to a firm's R&D stock of knowledge accounting for both the 'demand-pull' and 'technology-push' sides of the innovation activities, and prospective complementarities between them. Marketing is also an instrument of appropriability as it reduces product/service price-elasticity, thus permitting firms to increase prices while keeping customers (Lee 2005, Bagwell 2007). According to the literature reviewed, cross-industry variations in technological opportunities and appropriability conditions are the main factors accounting for cross-industry variations in the relationship between R&D expenditure and firm size, expected to be found in the empirical analysis (Crepon *et al.* 1998, Revilla & Fernandez 2012). Therefore, firm intangible assets are accounted for when we estimate the effect of R&D stock of knowledge on firm size.

Human capital affects a firm's capability to innovate and its absorptive capacity (Griliches 1964, Anon-Higon & Sena 2006). The 'absorptive-capacity' hypothesis advocates that the firm's ability to capture, assimilate and use external knowledge depends on the firm's prior R&D and human capital (Cohen & Levinthal 1990). Furthermore, according to Rammer *et al.* (2009) findings, to some extent, in-house R&D activities can be either combined with or even substituted by different management practices, e.g. training of employees, creating human capital and networking. Accounting for the above effects, we include a human capital variable in our models.

Although there are no formal theories on the relationship between innovation and international trade at a firm-level, historically, the researchers have applied the macroeconomic theoretical framework (e.g. Wakelin 1998a, Roper & Love 2002). This framework is centred around the 'neo-endowment' theory and the 'technology-based' theories such as Posner's (1961) 'technology-gap' model of trade and Vernon's (1966) 'life-cycle' model of trade (Wakelin 1998a). According to the 'neo-endowment' theory, firms' competitive advantage comes from factor-based advantages, e.g. materials, labour, capital, human and knowledge capital (Wakelin 1998a, Roper & Love 2002).

According to the 'technology-based' theories of trade, innovation and technological differences are the main determinants of the pattern of trade (Posner 1961; Vernon 1966; Krugman 1979, 1986). Therefore, firm export activities are accounted for when measuring the effect of R&D stock of knowledge on firm size. Most of the researchers find a positive, non-linear relationship between firm export activities and its size (Kumar & Siddharthan 1994, Wagner 1995, Bernard & Wagner 1997, Wakelin 1998a, Bernard & Jensen 1999, Sterlacchini 1999).

Age could exercise both positive and negative effects on firm size (Loderer & Waelchli 2010). The empirical results are diverse as their theoretical justifications. On one hand, with age, firms learn what they can do well and also, how to perform better (Arrow 1962, Jovanovic 1982, Ericson & Pakes 1995). On the other hand, age can render firm knowledge and skills obsolete, and lead to firm decline as it becomes trapped in 'red tape' bureaucracy (Agarwal & Gort 1996, 2002), and the Schumpeterian 'perennial gale of creative destruction' (Loderer & Waelchli 2010). Therefore, age certainly has a place in our equations.

The models, outlined in the following Section 3.4.1.1 and Section 3.4.1.2, will be applied to both the 'All-Firms' (the entire dataset) and the subset of the high and medium-high R&D intensity firms - the 'Innovators'.

3.4.1.1 Modelling the effect of R&D stock of knowledge on firm absolute size

The first estimation model aims to provide evidence on the research question: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its absolute size?'.

It tests the first hypothesis in this chapter:

H1(Ch.3, H1): A firm's R&D stock of knowledge is positively associated with its absolute size.

Under this hypothesis, we measure firm absolute size by its value-added and as an alternative measure, we use the total sales. The hypothesis is in levels, showing the direction of the relationship, not the exact magnitude.

The study employs the standard production function approach. Our model assumes that a firm's output - $Y_{i,t}$, can be presented with a conventional Cobb-Douglas production function. Equation (1) presents our first model, where firm i's real gross output - $Y_{i,t}$ (i.e. value-added - $VA_{i,t}$, and as a robustness test we use deflated total sales - $TS_{i,t}$) is a function of its age - $Q_{i,t}$, capital stock - $C_{i,t}$ (proxied by the real value of the firm's fixed assets and calculated using the perpetual inventory method), labour - $L_{i,t}$ (i.e. the number of employees), human capital - $E_{i,t}$ (proxied by the firm's per-employee remuneration), real cost of intermediate inputs - $M_{i,t}$, intangible assets - $A_{i,t}$ (proxied by the firm's intangible assets intensity - the firm's intangible assets divided by its total assets), R&D capital stock - $K_{i,t}$, export intensity - $EI_{i,t}$ (proxied by the firm's exports over its total sales), intra-industry - $K_{t,1}$, inter-industry - $K_{t,2}$, and global spillovers - $K_{t,f}$.

Expressed in a logarithmic form, our model in terms of value-added output - $VA_{i,t}$, is presented in Equation (1),

$$\begin{aligned} lnVA_{i,t} = \ & a_0 + a_1 lnVA_{i,t(t-1)} + a_2 lnC_{i,t} + a_3 lnL_{i,t} + a_4 lnM_{i,t} + a_5 lnE_{i,t} \\ & + a_6 lnEI_{i,t} + a_7 lnA_{i,t} + a_8 lnQ_{i,t} + a_9 lnK_{i,t} + a_{10} lnK_{t,1} + a_{11} lnK_{t,2} \\ & + a_{12} lnK_{t,f} + Ind.D. + TimeD. + v_i + \varepsilon_{i,t} \end{aligned}$$

(Equation 1)

where the subscripts *i* and *t* represent firm and time respectively, and the *a'*s are the input's *j* elasticity (some of the parameters we are interesting in estimating).

The error term, in general, includes stochastic, omitted or unobservable variables. It contains two components. The first one is the firm-specific component - v_i, which accounts for any time-invariant firm characteristics which may influence the firm size and also, any time-invariant components of the measurement error, which may influence any variable in our model. The second one denotes the idiosyncratic *i.i.d.* element - $\varepsilon_{i,t}$.

The inclusion of industry dummies controls for factors which are different for different industry and which are omitted in the econometric model. This way, the estimates capture the effect of the regressors on firm size within each industry instead of firms in different industries (Wakelin 2001). Odagiri & Iwata (1986) evidence important effects of sector dummies, emphasising the significance of the inter-industry heterogeneity in the level of the exogenous technical progress. However, Mairesse & Cuneo (1985) and Mairesse & Sassenou (1991) advocate that industry specific effects are better accounted for by including variables in the model which have been omitted, e.g. the level of technological opportunity in the industry, and inter-industry spillovers, rather than industry dummies. However, still, most of the empirical studies in this area (e.g. Wakelin 2001, Jefferson *et al*. 2006) include industry dummies to capture industry-specific effects (e.g. technological opportunities). Technological opportunities in this study are proxied by industry classifications (industry dummies) and also, by including intra- and inter-industry spillovers as well as global spillovers.

This study also includes time dummies to capture business-cycle effects.

As the main interest of this research is the contribution of the R&D stock of knowledge, and to avoid a double counting of R&D expenditure in the model, firm *i*'s R&D expenditure is removed from that of the other firms total R&D expenditure, in line with Wakelin (2001) and Cincera *et al*. (2003). That is, it is removed from firm *i*'s own industry total R&D expenditure in the case of intra-industry spillovers - $K_{t,1}$. It is also removed from the firm *i*'s inter-industry spillovers - $K_{t,2}$. In regard to the inter-industry spillovers variable - $K_{t,2}$, each researched industry R&D expenditure - $K_{t,1}$, is also removed for the same reason - to avoid double counting, as $K_{t,1}$ enters our right-hand side model separately. The global R&D spillovers are represented by the term $K_{t,f}$. The intra-industry spillovers variable is expressed in its intensity form - per industry turnover while the inter-industry spillovers variable is also expressed in intensity form, however, per employee, to minimise the collinearity between both variables. Due to the lack of data, the global spillovers figures are not scaled.

Employing our alternative measure of firm absolute size - total sales, we use the same model, substituting value-added with total sales. The justification for the variables included in the model is provided in the previous section.

3.4.1.2 Modelling the effect of R&D stock of knowledge on firm market share

This estimation model aims to provide evidence on the research question: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market share?'

It tests the second hypothesis in this chapter:

H2(Ch.3, H2): A firm's R&D stock of knowledge is positively associated with its market share.

Under this hypothesis, we measure firm size, relative to its industry size as the firm share of value-added in its industry, and as an alternative measure, we use the firm's share of its industry's total sales. The hypothesis is in levels, emphasising the direction of the relationships, not the exact magnitude.

In regard to the firm value-added and total sales, the estimations are straightforward following Equation 1. In terms of the market share, the model is modified, measuring market share as a dependent variable. While the total firm market share is linked to all production factors, an effort is made to statistically estimate the fraction of it due to in-house R&D.

Dividing both sides of Equation (1) in its static design by the industry's totals of each variable (except the exogenous variables age - $Q_{i,t}$, intra-industry - $K_{t,1}$, inter-industry - $K_{t,2}$, and global spillovers - $K_{t,f}$, as well as the endogenous variable - R&D stock of knowledge - $K_{i,t}$,) and assuming the inputs elasticity across all firms are the same, the left-hand side of the basic model - Equation (2), represents firm *i*'s market share - $MS_{i,t}$.

$$\frac{Y_{i,t}}{Y_t} = MS_{i,t} = \left(\frac{C_{i,t}}{C_t}\right)^{\beta_C} \left(\frac{L_{i,t}}{L_t}\right)^{\beta_L} \left(\frac{M_{i,t}}{M_t}\right)^{\beta_M} \left(\frac{E_{i,t}}{E_t}\right)^{\beta_E} \left(\frac{EI_{i,t}}{EI_t}\right)^{\beta_{EI}} \left(\frac{A_{i,t}}{A_t}\right)^{\beta_A} Q_{i,t}^{\beta_{Q_{i,t}}} \cdot K_{i,t}^{\beta_{K_{i,t}}} \cdot K_{t,1}^{\beta_{K_{t,1}}} \cdot K_{t,2}^{\beta_{K_{t,2}}} \cdot K_{t,f}^{\beta_{K_{t,f}}}$$

Equation (2)

Division of the term expressing firm *i*'s share of R&D activities into the firm's R&D stock of knowledge - $K_{i,t}$, and those of the other firms in its industry - $K_{t,1}$, allows us to still control for firm *i*'s share of R&D activities by controlling for the R&D activities of the other firms in its industry. Moreover, the division enables us to interpret the R&D activities of the other firms as intra-industry spillover effects - $K_{t,1}$, and thus, to compare the results of Equation (1) and Equation (3). Equation (3) is the modified production function, linking a measure of the firm's market share - $MS_{i,t}$ at the micro-level, to the stated inputs and the disturbance term,

$$lnMS_{i,t} = \beta_0 + \beta_1 lnMS_{i,t(t-1)} + \beta_2 lnc_{i,t} + \beta_3 lnl_{i,t} + \beta_4 lnm_{i,t} + \beta_5 lne_{i,t} + \beta_6 lnei_{i,t} + \beta_7 lna_{i,t} + \beta_8 lnQ_{i,t} + \beta_9 lnK_{i,t} + \beta_{10} lnK_{t,1} + \beta_{11} lnK_{t,2} + \beta_{12} lnK_{t,f} + Ind.D. + TimeD. + u_i + \epsilon_{i,t}$$

Equation (3)

where the subscripts *i* and *t* represent firm and time respectively, and the β's represent the input's *j* elasticity. The lower-case letters indicate firm *i*'s share of each input within its industry. The rest of the variables are as per Equation (1). The error term contains two components. The first one is the firm-specific component - u_i, which accounts for any time-invariant firm characteristics, which may influence firm market share and also, any time-invariant component of the measurement error, which may influence any variable in our model. The second one denotes the idiosyncratic *i.i.d.* element - $\epsilon_{i,t}$.

The inclusion of time and industry dummies is as per Section 3.4.1.1. Employing our alternative measure of market share - the firm's total sales over its industry's total sales, we use the same model. The justification for the variables included in the model is provided in Section 3.4.1.

This model assumes separability of the conventional inputs from the series of past and current R&D expenditure. It also assumes that firm and industry prices do not differ. In that sense, we measure market share in nominal terms.

In regard to both Equation (1) and Equation (3), assumed are constant returns in the firm's own inputs which simplify the models. The assumption of constancy in the other parameters is not too offensive as the scope of the research will be confined to the sectors in the *R&D Scoreboard* industry classification. The issue of multicollinearity (e.g. the time-series of R&D expenditure are correlated from year to year) is controlled for by assuming a functional form for the lag-distribution on the grounds of past knowledge and broad considerations (Griliches 1967). In regard to both models, there is an issue of simultaneity. This is due to the loop causality in the link between firm size and R&D stock of knowledge: future firm size may depend on past R&D while current R&D may depend on both previous and future firm size (Mazzucato 2000). Also, there is an issue of interdependencies: the present firm size may depend on the firm's size in the previous time-period. We control for these issues by estimating dynamic models, which also account for any other dynamic effects.

3.4.1.3 Expectations

Although the general findings of the literature on the topic are controversial and confusing, we expect the coefficient on R&D stock of knowledge - $K_{i,t}$ to be positive and significant in all our models, in line with the findings of Cohen & Klepper (1996), Crepon *et al.* (1998); Tsai & Wang (2005).

The circumstances for positive and negative spillovers differ between firms, and theory alone is not able to forecast which effect may emerge (Kafouros & Buckley 2008). Therefore, we have no conclusive expectations; however, we expect some diversity in the results in terms of both models.

In regard to firm intangible assets - $A_{i,t}$, as there are some complementarities between them and the R&D stock of knowledge - $K_{i,t}$, (Mohnen & Hall 2013), we expect its coefficient to be positive and significant in all our cases.

As human capital - $E_{i,t}$ positively affects a firm's capability to innovate and its absorptive capacity (Griliches 1964; Anon-Higon & Sena 2006), we expect the human capital estimate to be positive and significant in terms of both our datasets.

In line with the majority of the research on the topic (e.g. Kumar & Siddharthan 1994, Wagner 1995, Bernard & Wagner 1997, Wakelin 1998a, Bernard & Jensen 1999, Sterlacchini 1999), we expect the coefficient on firm exports - $EI_{i,t}$, to be positive and significant in both models.

However, we expect some diversity in our results in regard to both measures of firm size - firm absolute size, and market share. We also expect some variety in the results in regard to the 'All-Firms' dataset and the 'Innovators' subset.

The next section describes and justifies the estimation methodology used to test the hypotheses.

3.4.2 Estimation methodology

In order to allow for comparability of the results and to maintain consistency throughout the entire thesis, our econometric strategy involves a comprehensive system of empirical approaches, within which there are different options. Therefore, as a standard technique, in Chapters 3 to 5 we employ the pooled Ordinary Least Squares (OLS), the Fixed Effects (FE), and the dynamic, robust, one-step GMM, followed by the GSEM approach in Chapters 4 and 5.

This chapter employs and compares different estimation methodologies using the same logarithmic-specifications (Equation1 and Equation 3) of the model strategy: pooled OLS, FE, and dynamic, robust, one-step GMM. The GMM models are estimated with the 'xtabond2' command (see Roodman 2006, 2008). Controlling for industry effects, separate regressions are performed for the 'All-Firms' dataset and the 'Innovators' subset.

The OLS estimator does not control for the heterogeneity bias (resulting from the likely correlation between firm-specific fixed effects and the explanatory variables), and the possible endogeneity of the regressors (resulting from the likely correlation between the inputs and the error term). In the presence of endogeneity, both OLS and

FE can produce biased and inconsistent parameter estimates. The FE estimator controls for unobserved differences across the firms but not for the endogeneity issues, which would affect its consistency. This research assumes that firm capital, value-added, total sales, market share, labour, human capital, intermediate inputs, intangible assets and exports are potentially endogenous, as they may be correlated with the firm-specific effects, productivity shocks and measurement errors, all of which are included collectively in the error term of the models. R&D stock of knowledge is also potentially endogenous as there may be a double causality between market share/absolute size and R&D stock of knowledge (Mazzucato 2000). The strictly exogenous variables are the industry and year dummies, firm age, intra-, inter-industry and global spillovers.

The GMM model controls for unobserved heterogeneity across firms and endogeneity (Arellano & Bond 1991, Blundell & Bond 1998). It also accounts for measurement errors in the regressors when instruments are uncorrelated with the errors in measurement, but they may be due to 'a weak instruments' problem (Roodman 2009). The GMM, first introduced by Hansen (1982) employs the orthogonality conditions to permit for efficient estimation when there is heteroskedasticity of unidentified form. GMM estimators are derived from so-called moment conditions.

We chose the System GMM as it is superior to the Difference GMM in regard to minimising the finite sample bias (Blundell & Bond 1998, Blundell *et al.* 2000). Also, the System GMM is more robust to 'weak instruments' than the Difference GMM (Roodman 2009). In addition, the Difference GMM magnifies gaps in an unbalanced panel, as in our case, as one period of missing data is substituted with two missing differences (Baum 2013).

The model is estimated by the one-step, System GMM with robust standard errors[16]. The System GMM involves a system of two equations: the first-differenced and the level equations. This estimator uses lagged values of the endogenous variables for the first differences equation while it uses lagged differences of the endogenous variables for the equation in levels (Arellano & Bond 1991, Blundell & Bond 1998). First-differencing targets the unobserved heterogeneity. Lagged values of the regressors are employed as instruments to account for the potential endogeneity of the regressors (Bond *et al.* 2001, Baum 2006, Roodman 2006).

The GMM estimators are designed for cases as in this study where: (1) the dependent variable is not strictly exogenous but dynamic; (2) the explanatory variables are also not strictly exogenous; (3) fixed firm effects exist; and (4) where suspected heteroskedasticity and autocorrelation within firms but not across them is present.

In order for the GMM estimators to be valid, the instruments must be exogenous to fulfil the orthogonality conditions. This is assured by performing the Hansen (1982) test. As the validity of the instrument set is subject to the error structure, we also perform the Arellano & Bond (1991) *AR(2)* test (or *M2* test), which identifies second-order autocorrelation of the error in the first-differences model.

The tests performed in regard to all our GMM models and their associated hypotheses are described as follows.

AR(1) and *AR(2)* are Arellano-Bond tests for serial correlations.

[16] As our model is dynamic, the inclusion of the lagged dependent variable on the right-hand side of the equation leads to a serial correlation of the error term. The lagged dependent variable, in addition, is also stochastic as the dependent variable. This contravenes the classical conventions of the linear regression model according to which both the independent variable and error term have to be independent. Therefore, the pooled OLS estimator will produce biased and inconsistent estimators (Maeshiro 1996, 1999).

AR(1) tests the hypothesis: *H0 There is no first-order serial correlation in residuals.* As there is a negative first order serial correlation by construction (because of the mathematical link concerning the first difference and the first lag of difference), rejection of the null hypothesis is expected (Roodman 2006).

AR(2) (or *M2*) is a test for second-order correlation in differences. It tests for first-order serial correlation in levels (Roodman 2006). In regard to *AR(2),* the hypothesis tested is: *H0 There is no second-order serial correlation in residuals*. The hypothesis should not be rejected.

Hansen's *J* statistic checks for the validity of the overidentifying restrictions. The *Hansen J* statistic follows a Chi-square distribution where the value of degrees of freedom is the same as the number of over-identifying restrictions (the number of instruments minus the number of parameters). The hypothesis tested is: *H0 Model specification is correct, and all overidentifying restrictions (all overidentified instruments) are correct (exogenous).* The null hypothesis should not be rejected, as this would mean that the instruments do not fulfil the required orthogonality conditions. That is, it would mean that the instruments are correlated with the error term, or they are inaccurately incorporated in the equation. The power of the *Hansen J* test decreases with the number of instruments. Using too many moment conditions makes Sargan/Hansen test unuseful (Bowsher 2002). Therefore, the number of instruments should not be greater than the number of groups (as the literature does not suggest when there are too many instruments), (Roodman 2008, 2009).

In terms of the GMM model lag structure, only lags 2 and 3 are employed for different time-periods. Using initially the second lag, when estimations do not satisfy the requirements of the model, lag 3 structure was applied. This was based on the trade-off between efficiency gains from adding more information and the over-fitting of the data because of the inclusion of lagged instruments for each variable.

As we have discussed earlier, in a dynamic panel model, the pooled OLS estimator does not properly control for the unobserved firm-specific characteristics and the possible endogeneity of the regressors, while the FE estimator does not handle the endogeneity issues. Therefore, the coefficient on the lagged dependent variable computed by the pooled OLS estimator will be upwards biased, while the one received from the FE estimator will be downwards biased (Baum 2013). Using the GMM approach allows us to check the validity of our estimates: the GMM estimated coefficient on the lagged dependent variable should lie between the estimates computed by the FE estimator and the pooled OLS (Bond *et al.* 2001).

3.5 Data, variables of interest and descriptive statistics

The data, as well as the data sources, are described in Chapter 2. Both our panel datasets are unbalanced with data missing for some firms. The total number of firms included in our 'All-Firms' dataset is 956; of these, 772 firms belong to the high and medium-high R&D intensity sectors (the 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity sectors.

3.5.1 Variables of interest

In Section 3.5.1, we provide a description of the variables used in both models as well as justification for their estimation.

3.5.1.1 R&D stock of knowledge

In-house R&D stock of knowledge - $K_{i,t}$, is estimated employing Griliches (1979) perpetual inventory method, with data on both accumulated 'stock of knowledge' and R&D expenditure in the current period, accounting also for the rate of stock depreciation, widely used in such type of research (Coe & Helpman 1994, Blundell *et al*. 1999, Cameron *et al.* 2005).

Employing the above method, in-house R&D stock of knowledge - $K_{i,t}$, is calculated from deflated R&D expenditure (R) as follows:

$$K_{i,t} = (1 - \delta)K_{i,t-1} + R_{i,t}$$

Equation (4)

where δ is the depreciation rate, in general, assumed to be constant.

The industry-specific R&D depreciation rates within each nation and across nations vary, however, developing a consistent methodology to estimate them is problematic (Mead 2007, Li & Hall 2016). Appendix 2 provides a summary of the issues encountered in calculating the R&D depreciation rates. The first set of constant R&D depreciation rates for the main US high-tech industries has been developed by Li & Hall (2016). They compare their results with the results for Japan (calculated on limited datasets) and find significant differences. However, the authors state that no direct measurements can validate any estimate of R&D depreciation rates. Therefore, most of the R&D studies use a constant depreciation rate of 15%[17] (Hall & Mairesse

17 The depreciation rate is not critical for the results as the R&D expenditure within a firm does not fluctuate significantly (Hall & Mairesse 1995). Griliches & Mairesse (1984) explore a sample of 133 firms to determine the impact of several ways of defining and estimating physical and R&D stocks. They find no definitive estimates of the depreciation rate and the lag. However, some researchers use 20% depreciation in regard to the R&D expenditure (e.g. Pakes & Schankerman 1984, Goto & Suzuki 1989, Kafouros & Buckley 2008, Bravo-Ortega & Marin 2011). Re-estimating their initial results using also 15% and 25%, Kafouros & Buckley (2008) find that the rate of depreciation does not significantly affect the results, which is in line with other studies (e.g. Harhoff 2000, Guellec & de la Potterie 2004).

1995, Wakelin 2001, Guellec & de la Potterie 2004, Parisi *et al.* 2006). Recent studies also use this rate. For example, examining the relationship between market value and innovation, using data for Indian firms during 2001-2010, Kanwar & Hall (2015) employ a constant depreciation rate of 15%. Experimenting with a higher rate of 30%, they conclude that a depreciation rate of 15% is more suitable, as it is more in line with the expected value of the coefficient, and is more useful for comparison to prior work by others. Investigating the effect of R&D stock of knowledge on firm productivity in the UK economy, Solomon *et al.* (2015) use a growth rate of 5% for R&D investment and a constant depreciation rate of 15% (as per our study), based on the general consensus in the literature that rates of growth or depreciation do not change the elasticity coefficients (Hall *et al.* 2010, Solomon *et al.* 2015)[18]. For the same reasons Cincera *et al.* (2015) also employ the classical depreciation rate of single 15% when they estimate the sensitivity of R&D investments to cash flows, comparing EU and US innovative firms.

To our knowledge, to date, there are no estimated industry-specific R&D depreciation rates in regard to the UK economy. The scarce R&D data is insufficient to allow their calculation without imposing very strong identifying assumptions, which may prove unverifiable, as Mead (2007) suggests. Therefore, we use the traditional, constant rate of 15%.

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18 Hall *et al.* (2010) show that the estimated elasticity is not sensitive to the choice of depreciation rate. If R&D increases over a long period at a constant, firm-specific rate g_i and R&D stock ($K_{i,t}$) depreciates at a firm-specific rate δ_i, then:

$$K_{i,t} \cong \frac{R_{i,t}}{g_i + \delta_i} \quad or \quad ln\, K_{i,t} \cong ln\, R_{i,t} - ln\,(g_i + \delta_i)$$

That is, if the depreciation and the growth rates do not vary significantly within firm over time, they will be built into the firm effects, and the calculated elasticity of output with respect to both $K_{i,t}$ and $R_{i,t}$ will be the same: $K_{i,t}$ will not be sensitive to the choice of depreciation rate (Hall *et al.* 2010).

The stock of R&D is lagged 1 year[19], in line with most of the literature, suggesting that the most significant effect of R&D on productivity occurs with a 1-year lag (e.g. Pakes & Schankerman 1984, Hall *et al*. 1986, Coe & Helpman 1995, Hall & Mairesse 1995, Klette & Johansen 1998, Guellec & de la Potterie 2004, Lokshin *et al*. 2008).

The estimation of the initial R&D stock of knowledge for each firm is constructed on the first observation of the annual flow. Assuming that real R&D expenditure have been growing since minus infinity at a certain rate (e.g. at a rate g), the initial observed year's flow is divided by $(g + \delta)$. As this study uses a depreciation rate of 15%, then this corresponds to $(g + 0.15)$. The benchmark for the initial R&D stock of knowledge - K_0 is estimated following Griliches (1980) procedure as:

$$K_0 = R_0/(g + \delta)$$

Equation (5)

where g is the average compound annual growth rate of R&D expenditure over the time period for which published R&D data is available. In this study, we assume it is equal to 0.05, in line with generally accepted practice in such cases, discussed in Hall (1993). R_0 is the value of R&D expenditure of the initial year for which the data is available.

Appendix 3 reports a table of detailed descriptive statistics in regard to our R&D stock of knowledge variable for each industry and year. The table reports the number of observations, mean, median, standard deviation, minimum and maximum

[19] The lag structure of R&D has an inverted V-shape, the peak benefits from R&D flows are at five- to eight-year lags; impact from R&D expenditure at lags more than 10 -16 years is very low (Evenson 1968). The lags are smaller for industrial R&D, echoing the applied character of private R&D expenditures (Wagner 1968).

values of the variable studied. The statistics are in line with the sector level *ICB* classification of firms, according to their R&D intensity, presented in Chapter 2, Table 1.

3.5.1.2 R&D spillovers

Technological spillovers are the non-appropriable quantity of knowledge, generated by an innovative firm (Cincera *et al*. 2003). Even when the knowledge-creator firm has an effective strategy in place to prevent knowledge leakages (e.g. via patent, copy rights), information leaks and other firms can benefit from this knowledge without paying the full price of the newly created knowledge. The existence of different types of technological spillovers has been confirmed by most of the empirical studies [20] (for surveys see Griliches 1992, 1995; Nadiri 1993; Mohnen 2001; Sveikauskas 2007). According to the 'endogenous growth' theory, external R&D positively affects firms' performance (Romer 1986, 1990; Lucas 1988; Krugman 1991; Grossman & Helpman (1991a,b). For more information and discussions on this matter, see Griliches (1992) and Kaiser (2002b).

Technological spillovers are generally classified as intra-, inter-industry and foreign/global spillovers. The intra-industry spillovers indicate the extent of technological opportunity and the size of the pool of technological knowledge accessible (Wakelin 2001). Employing the R&D expenditure of the other firms in the industry as a proxy for intra-industry spillovers may reflect knowledge availability in this industry, but not all of it may spill over to each firm, and not all the firms within

[20] There are vertical or rent/market spillovers (the inability of the innovator to sell its product at prices that fully capture all quality improvements) and horizontal or knowledge spillovers (associated with the flows of knowledge without economic transaction, e.g. exports, FDI, R&D co-operation, technology payments), (Griliches 1979, 1992). Rent/market spillovers might be controlled for by employing perfect price deflators (Wakelin 2001). However, knowledge and network spillovers are difficult to measure as they are also linked to economic transactions (Cincera *et al*. 2003).

this industry may benefit from it. Intra-industry spillovers are generally proxied by the total R&D expenditure of all firms in the industry (which does not vary for the firms within the same industry), excluding the firm studied (Wakelin 2001, Cincera *et al*. 2003). This research will use the same approach in measuring firm intra-industry spillovers - $K_{t,1}$. The variable intra-industry spillovers $K_{t,1}$, is used in this study in its intensity form - per total industry sales.

Inter-industry spillovers are the technological spillovers from the other industries in the economy. The knowledge that firms can use via inter-industry spillovers requires information of the direction of these inter-industry relations, which is usually unavailable (Cincera *et al*. 2003), as in our case. Estimations of spillovers are based on aggregated R&D expenditure in the whole industry/economy or on weighted by the R&D stocks of each industry/economy, depending on their proximity to the first firm or industry[21] (Mohnen 1991, 1996). Different researchers use different weighting systems to estimate the inter-industry spillovers. The weighting is based on economic, technological or trade associations: the closer the innovator and the recipient are, the higher the spillovers (Cincera *et al.* 2003).

However, in recent years many researchers use the aggregated unweighted sum of the R&D expenditure of each industry (e.g. Keller 1998, Cincera *et al*. 2003, Wei & Liu 2006, Bravo-Ortega & Garcia 2011) as their inter-industry spillovers variable. Their argument is that different measures of spillovers yield different outcomes, not

[21] There is a lively debate in regard to which measure of spillovers is most appropriate. One of the methods assumes that technological spillovers track the pattern of economic transactions (e.g. supplier-customer link), and it is based on input-output tables, measuring in practice the rent spillovers (Griliches 1979), (for more information see Terleckyj 1974, 1980; Sterlacchini 1989; Coe & Helpman 1995). Patent-citations, employed to locate geographical clusters also can identify and measure spillovers (e.g. Jaffe *et al*. 1993) or technological proximity between firms, based of the technological overlap between different firms' patents (e.g. Jaffe 1986). Other studies directly calculate spillover impacts using the adjustment-cost model of investment and factor demand, instead of measuring spillovers (e.g. Bernstein & Nadiri 1988).

definitely capturing a particular channel of knowledge transfusion, therefore they are not robust (Kaiser 2002a, Cincera *et al*. 2003). This study will use this approach in measuring inter-industry spillovers - $K_{t,2}$,. As a proxy for inter-industry spillovers, we employ the UK total R&D expenditure (which does not vary for all the firms within the sample set) of all firms, excluding the firm studied, in line with the above studies. In order to avoid double counting, the total R&D expenditure of each industry studied - $K_{t,1}$, is also excluded (as it already appears in the model as a regressor). The variable inter-industry spillovers - $K_{t,2}$, is used in this study in its intensity form - per employees.

The UK total R&D expenditure includes not only R&D from Business Enterprise (BERD) but also, the R&D expenditure in the other segments of the economy, namely, Higher Education (HERD), Government (GovERD), which also includes Research Councils, and Private Non-Profit (PNP) organisations, as defined in the *'Frascati Manual*'. The above sectors' R&D data are recognised collectively as GERD, which indicates the gross domestic expenditure on R&D in the UK and is the preferred measure of R&D activity in international comparisons.

As the countries of the global economy are becoming progressively open and interdependent (e.g. international trade, FDI), promoting new ideas and their dissemination, external knowledge may also come from outside the domestic borders (Eaton & Kortum 1999, Keller 2001, Cincera *et al*. 2003). Hence, the nations may take advantage of the international pool of R&D stock of knowledge. Both 'endogenous growth' and 'trade' theories support the view that trade/exports and FDI stimulate knowledge flows and technology transfer between trading partners (e.g. Nadiri 1993, Barba & Tarr 2000, Tybout 2000, Keller & Yeaple 2003). Some studies (e.g.

Branstetter 2001, Luintel & Khan 2004, McVicar 2002, Anon-Higon 2007) find that foreign spillovers are not beneficial to advanced economies. Other studies (e.g. Huggins *et al.* 2010) find that a significant proportion of technology-based firms source knowledge from abroad. For surveys on evaluations of international spillovers see Mohnen (2001) and Sveikauskas (2007). There are different conflicting views[22] when measuring foreign spillovers. Many researchers (e.g. Keller 1998, 2000; Kaiser 2002a; Cincera *et al*. 2003) argue that different measures of spillovers produce different results, not necessarily measuring a particular channel of knowledge transfusion; hence they are not robust. In regard to this research, for each firm, the global R&D spillovers variable - $K_{t,f}$, is proxied by simply the sum of the domestic R&D expenditure of the rest of the world (as captured by *UNESCO* and *OEDC* datasets, described in Chapter 2) in line with Keller (1998), Lumenga-Neso *et al*. (2001), and Bravo-Ortega and Garcia (2011). We exclude the UK total R&D expenditure, to avoid a double counting. The reason for using this measurement is that the UK is one of the most developed countries, which has access to almost all inputs available in the world economy. UK companies can procure an input and use it in their production process anywhere the input is made in the world.

The technological spillovers are associated with the 'absorptive capacity' theory. First, they may directly stimulate firm innovative activities. Second, they may indirectly raise firm knowledge base and absorptive capacity, increasing technological awareness of employees, thus, leveraging firm innovative performance (Rosenberg

[22] Guellec & de la Potterie (2001) measure the foreign R&D stock of knowledge as the weighted sum of the national corporate R&D capital stocks of the other nations. The weights reflect the bilateral technological distances between states. They reason this by the argument that technology circulates directly, without exchange of goods. This is different from Coe & Helpman's (1995) proxy for foreign spillovers. Coe & Helpman (1995) estimate the effect of domestic and foreign R&D on TFP in OECD states creating an index of foreign R&D as the import-weighted sum of the R&D created in each of the other OECD states. However, Edmond (2001), arguing that the spillover impact via imports is not clearly demonstrated by the research evidence, uses a measure of spillovers via exports, instead of imports.

1982; Jaffe 1986; Cohen & Levinthal 1989; Romer 1990; Grossman & Helpman 1991a, b; Segestrom 1991; Geroski *et al*. 1993; Neary & Leahy 1999; Guellec & de la Potterie 2001; Griffith *et al*. 2004a). Spillovers are also associated with the firm human capital created: firms with a high level of human capital possess a higher absorptive capacity to assimilate new knowledge (Cohen & Levinthal 1989). Most of the empirical literature (e.g. Jaffe 1986, 1988; Griliches 1979, 1992; Cincera 2005; Harhoff 2000; Kaiser 2002a; Aldieri & Cincera 2009) claim that absorptive capacity depends on firms' technological proximity in technological space: the closer a couple of firms are, the higher the gains from each other's innovative activities. However, the technological proximity of each couple of firms depends on how related the firms are in regard to technology adopted and activities undertaken to adopt new 'know-how' (Cardamone 2012).

3.5.1.3 Other variables of interest

- **Physical capital stock**

While some researchers use the firm total fixed assets as a proxy for their capital variable (e.g.Wakelin 2001), others use the stock of physical capital (Basant & Fikkert 1996, Hall & Jones 1999, Aiello & Cardamone 2005, Parisi *et al*. 2006, Bos *et al*. 2013). In this research, firm capital is measured using the book value of the firm's fixed assets to estimate the physical capital stock by the perpetual inventory technique, as per R&D knowledge capital. For full details of this method see Blundell *et al.* (1992).

Following Blundell *et al.* (1992), physical capital stock - $C_{i,t}$, is calculated from deflated fixed assets (*I*):

$$C_{i,t} = (1-\delta)C_{i,t-1} + I_{i,t}$$

Equation (6)

where δ is the depreciation rate, in general, assumed to be constant and in this case of 6% per year, as per Basant & Fikkert (1996); Vandenbussche *et al.* (2004) and Kumbhakar *et al*. (2010). Other researchers assume a constant capital depreciation rate of 5% per year (Blundell *et al.* 1992, Aiello & Cardamone 2005, Parisi *et al.* 2006) while others, (e.g. Bos *et al*. 2013) use the average service life (ASL) of capital per industry.[23]

The replacement cost values of the capital stock are not available; therefore, they have to be calculated from historic cost data. In order to obtain the starting values for the perpetual inventory method, this study assumes, as per Blundell *et al.* (1992), equality of replacement cost and historic cost valuations of the capital stock in the first year of data - 2003/4, subsequently updated, employing the perpetual inventory method. To minimise the effect of the starting assumption on the research results, we do not use data for the earliest three years in our estimations, to address the potential concerns in regard to the estimation of the replacement value of the capital stock. However, other studies evidence that the results are not significantly sensitive to the specific measure of the capital stock employed. Given positive rates of depreciation and sufficiently long investment series, the perpetual inventory method is not sensitive to the level of capital employed to initialize the series (Bond & Devereux 1989, Blundell *et al.* 1992, Liao *et al.* 2009).

[23] Doraszelski & Jaumandreu (2008) calculate physical and domestic R&D capital stocks using depreciation rate of 10% for physical capital stock, and 20% for R&D capital stock. The R&D capital stock depreciation rate is higher than the one used to calculate the physical capital as the economic life-cycle of technology becomes shorter. They find that this pattern is not fundamental and employing different alternative arrangements of depreciation rates did not significantly alter their study's results.

New knowledge is generally embedded in capital investments (Hulten 2001). However, there is no consensus in the literature on the short-run relationship between firms' R&D investment, inventions, and physical capital investments, while the long-run link is evidenced (De Jong 2007).

- **Labour**

As a proxy for our variable labour - $L_{i,t}$, we use the total number of employees, as per many other studies, as a size control variable (Shan *et al.* 1994, Rothaermel & Deeds 2004, Quintana-Garcia & Benavides-Velasco 2004).

- **Human capital**

In this study, human capital - $E_{i,t}$, will be proxied by the firm's remuneration per employee. The data available does not offer a breakdown by skill type, but the average wage operates as a proxy for the average level of human capital per employee, as per O'Mahony & de Boer (2002). It is assumed that *all things being equal*, companies with high employment costs per employee are more knowledge and skill intensive than companies where the average cost is lower (Kodama 1995, Kim 1997, George *et al.* 2001).

- **Intangible assets**

According to Mohnen & Hall's (2013) survey, there is complementarity between R&D/innovation and intangibles. According to Griliches (1990), other 'innovation spending', not counted as R&D, is also important for firm performance. This study will employ intangible assets intensity - $A_{i,t}$, as a proxy for firm 'other innovation spending', not reported as R&D expenditure. The international standards for intangible assets accounting are very complex. Paragraph 8 of IAS 38, and IFRS 3 (January 2008) defines an intangible asset as *'an identifiable non-monetary asset without physical substance.'* For example, patents, brand names, copyrights, customer lists, franchises, customer and supplier relationships and marketing rights, licenses, operating rights record masters, secret processes, trademarks, and trade names (IAS 38). The reporting of intangible assets is detailed in the IAS 38 *Intangible assets,* IFRS 3 *Business Combinations* and IAS 36 *Impairment of Assets* standards. However, still, there are great discrepancies in the reported firm 'intangibles' due to the different accountancy practices and concepts of 'intangibles'.

Intangible assets intensity is measured by the ratio of the intangible assets to the total assets reported by the firms at the end of the financial year.

- **Exports**

As a proxy for the firm exports variable, this study employs export intensity - $EI_{i,t}$, (exports as a proportion of total sales), as per Helpman *et al.* (2008); Lawless & Whelan (2008). Most of the researchers find a positive, non-linear relationship between firm export activities and its size (Kumar & Siddharthan 1994, Wagner 1995, Bernard & Wagner 1997, Wakelin 1998a, Bernard & Jensen 1999, Sterlacchini 1999).

- **Material costs (intermediate inputs)**

As a proxy for the firm intermediate inputs, we will use the 'cost of sales' variable - $M_{i,t}$, from the *FAME* database. Material costs are input in the Cobb-Douglas production process. They can also be calculated by the difference between nominal gross output and nominal value-added.

- **Age**

The variable age - $Q_{i,t}$, is measured in years (current year minus incorporation year) and is included as a control variable. Some studies evidence a significant role of age on firm size (Evans 1987a,b; Dunne *et al.* 1989; Dunne & Hughes 1994). The justification is that with age, firms learn what they can do well and also, how to perform better (Arrow 1962, Jovanovic 1982, Ericson & Pakes 1995). However, others, such as Glancey (1998), Wijewardena & Tibbits (1999), Almus & Nerlinger (2000) and Davidsson *et al*. (2002) evidence an inverse relationship between firm age and size, proposing that older firms grow slower than younger firms. A possible explanation for this is that age can render firm knowledge and skills obsolete, and lead to firm decline as it becomes more bureaucratic (Agarwal & Gort 1996, 2002).

- **Value-added and Total sales**

The variable value-added - $VA_{i,t}$, will be measured by the total firm sales less intermediate inputs. Value-added is generally accepted as a measure of the firm's contribution to society. However, Mairesse & Hall (1996) use both total sales and value-added in their research, and report that sales as dependent variable performs relatively well. Therefore, in order to conduct robustness tests, this study will use total sales - $TS_{i,t}$, as an alternative measure of firm output.

- **Market share**

Firm relative size, market share - $MS_{i,t}$, enables measurement of firm performance against its peers and direct rivals. As a proxy for firm market share, this study will use the share of the firm's value-added relative to its industry's total value-added. In order to conduct robustness tests this study will use, as an alternative measure, the share of the firm's total sales relative to its industry's total sales.

- **Variables unaccounted for** in these models are: government policies, management proficiencies, pure luck, efficiency and other unobservable inputs, as well as other measures of the parameters of the stochastic process. For example, the level of technological risk, entry barriers, historical chance.

3.5.2 Descriptive statistics

Chapter 3 explores the relationship between R&D stock of knowledge and firm size measured in both absolute size (value-added/total sales) and relative to its industry's size (market share), controlling for firms' heterogeneity. The total number of firms included in our 'All-Firms' dataset is 956; of these, 772 firms belong to the high and medium-high R&D intensity industries (the 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity industries.

Regarding firm absolute size, Table 3.1 and Table 3.2 summarise the descriptive statistics of the variables in both 'All-Firms' (Table 3.1) and 'Innovators' (Table 3.2) analysis. Table 4.1 and Table 4.2 summarise the equivalent statistics in terms of firm market share for both datasets. Both tables report the number of observations, mean, median, standard deviation, minimum and maximum values of the variables studied. Data is presented in levels.

As the 'Innovators' represent, on average, 81% of the whole dataset in terms of both measure of firm size, while the low and medium-low R&D intensity firms - on average, 19%, high heterogeneity in firms' characteristics is expected. Firms' heterogeneity per *ICB* industry classification in terms of value-added and exports is shown in Appendix 4. The great heterogeneity of the firms' characteristics between firms belonging to different technological groups and level of knowledge is recently confirmed by Baum *et al.* (2015). Using the same *IRI* classification of the firms according to their R&D intensity as in this research, however, at the level of the *EU R&D Scoreboard*, Montresorb & Vezzania (2015) find a great firms' heterogeneity in terms of all their reported economic activities in both within and across different sectors.

3.5.2.1 Descriptive statistics: firm absolute size

In regard to Table 3.1, 'All-Firms' analysis, as the majority of the firms are from high and medium-high R&D intensity sectors, it is expected that the mean of the R&D stock of knowledge (*65179.01)* will be high with a high standard deviation (*190446.1).*

In terms of their size, the firms are large with an average mean of value-added - 84574.47 and total sales - 244430.8, and high standard deviations of 374293.1 and 765102.4, respectively.

The firms from the 'All-Firms' dataset, on average, export 39% of their total sales, while their intangible assets represent 21% of their total assets. The average human capital (*52.489*) and physical capital stock (*1656583*) are also at high levels. The firms in this data sample are also, on average, mature firms (*30.483*). The intra-industry R&D expenditure, on average, is 8% of the total intra-industry sales.

Table 3.1: Descriptive statistics: firm absolute size, 'All-Firms'

Descriptive Stat.	*'All-Firms'*					
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Value Added	*7927*	*84574.47*	*(374293.1)*	*10234*	*1.063*	*6399609*
Total Sales	*9494*	*244430.8*	*(765102.4)*	*25628.83*	*2.125*	*8986890*
Export Intensity	*5558*	*.387*	*(.362)*	*.504*	*.00003*	*1*
R&D Stock of Knowledge	*7350*	*65179.01*	*(190446.1)*	*10463.46*	*5*	*1466876*
Intangible Assets Intensity	*5740*	*.205*	*(.223)*	*.116*	*1.51e-06*	*.987*
Human Capital	*9518*	*52.489*	*(22.188)*	*48.730*	*2.126*	*139.782*
Physical Capital Stock	*7563*	*1656583*	*(6394232)*	*41977.21*	*3*	*4.66e+07*
Labour	*9869*	*1216.099*	*(4017.864)*	*179*	*10*	*38400*
Cost of Sales	*8324*	*153264.1*	*435509.6*	*14811.5*	*.897*	*4234460*
Age	*10516*	*30.483*	*(24.947)*	*22*	*5*	*147*
Intra-Ind.Spillovers /Total Sales	*10516*	*.077*	*(.059)*	*.068*	*.0001*	*.200*
Inter- Ind.Spillovers /Labour	*10516*	*823.583*	*(102.729)*	*856.468*	*565.589*	*960.467*
Global Spillovers	*10516*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*

Note: All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form.

In regard to Table 3.2, 'Innovators' analysis, the high mean of the R&D stock of knowledge (*70458.93)* is expected. However, the standard deviation is also high - (*200720*). The firms that belong to the high R&D intensity sectors in this subset are: Aerospace & Defence, Pharmaceuticals & Biotechnology, Software & Computer Services, and Technology Hardware & Equipment. The R&D intensity in these sectors is above 5%. The medium-high R&D intensity sectors in this sample are: Automobiles & Parts and Personal Goods. The R&D intensity in this group is between 2% and 5%. The firms are of reasonable, however, not very large size, with the average mean of value-added of 49660.9 and total sales of 170344.

Table 3.2: Descriptive statistics: firm absolute size, 'Innovators'

Descriptive Stat.			*'Innovators'*			
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Value Added	*6386*	*49660.9*	*(183502.3)*	*8863.172*	*1.063*	*4544173*
Total Sales	*7656*	*170344*	*(579173.5)*	*20111.73*	*2.235*	*8986890*
Export Intensity	*4682*	*.448*	*(.362)*	*.581*	*.00003*	*1*
R&D Stock of Knowledge	*6497*	*70458.93*	*(200720)*	*11811.85*	*5*	*1466876*
Intangible Assets Intensity	*4609*	*.227*	*(.229)*	*.144*	*.00002*	*.987*
Human Capital	*7571*	*54.833*	*(22.180)*	*51.663*	*2.126*	*138.859*
Physical Capital Stock	*6115*	*436508.6*	*(1677145)*	*30318.72*	*3*	*3.73e+07*
Labour	*7871*	*854.308*	*(3088.546)*	*154*	*10*	*38400*
Cost of Sales	*6725*	*123830.5*	*378435.8*	*11333.72*	*1.117*	*4148400*
Age	*8492*	*28.096*	*(22.561)*	*20*	*5*	*147*
Intra-Ind.Spillovers /Total Sales	*8492*	*.094*	*(.052)*	*.076*	*.001*	*.200*
Inter- Ind.Spillovers /Labour	*8492*	*802.406*	*(102.836)*	*842.816*	*565.589*	*957.256*
Global Spillovers	*8492*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*

Note: All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form.

In regard to the 'Innovators' subset, on average, the firms export 45% of their total sales, while their intangible assets are 23% of their total assets. The average human capital (*54.833*) and the average physical capital stock (*436508.6*) are also at high levels. The firms in this sample are, on average, mature firms (*28.096*). The intra-industry R&D expenditure is, on average, 9% of the total intra-industry sales.

Looking at the descriptive statistics, on average, it seems that the firms with high mean values for R&D stock of knowledge are also those associated with larger firm size. This relationship is expressed more strongly in regard to the 'All-Firms' dataset than the 'Innovators' subset, where the firms are, on average, smaller in size. This, in general, supports our hypothesis that R&D stock of knowledge is positively associated with firm absolute size. In Section 3.6 we will see if after controlling for other factors this relationship is confirmed.

The correlation matrix of the variables, reported in Appendix 5, does not indicate any intolerable multicollinearity issues.

3.5.2.2 Descriptive statistics: firm market share

Table 4.1 and Table 4.2 provide the descriptive statistics of the firms in both datasets in terms of their market share.

In regard to the 'All-Firms' analysis (Table 4.1), the mean value of the R&D stock of knowledge (*65179.01),* as well as its standard deviation (*190446.1)*, are the same as per Section 3.5.2.1. Division of the term expressing firm i's share of R&D activities into the firm's R&D stock of knowledge - $K_{i,t}$, and those of the other firms in its industry - $K_{t,1}$, allows us to still control for firm *i*'s share of R&D activities by controlling for the R&D activities of the other firms in its industry. The mean of all exogenous variables: age - $Q_{i,t}$, intra-industry - $K_{t,1}$, inter-industry - $K_{t,2}$, and global spillovers - $K_{t,f}$, are also the same as per Section 3.5.2.1, (based on the model, built in Section 3.4.1.2). The same applies for the analysis of the 'Innovators' subset.

In terms of their size, the firms in the 'All-Firms' dataset are large with an average mean value of their market share in regard to their value-added - (*.013*) and in terms of total sales - (*.009*). On average, the firms from the 'All-firms' data sample have high mean values of their export intensity share - (*1.144*), intangible assets intensity share - (*1.250*), and human capital share - (*1.146*). Their share of physical capital stock is also high, with a mean value of .015.

Table 4.1: Descriptive statistics: firm market share, 'All-Firms'

Descriptive Statistics			*'All-Firms'*			
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max***
Value Added /Ind.	*7839*	*.013*	*(.037)*	*.002*	*1.13e-07*	*.398*
Total Sales/Ind.	*9494*	*.009*	*(.035)*	*.001*	*2.02e-08*	*.375*
Export Intensity/Ind.	*5422*	*1.144*	*(1.146)*	*1.040*	*.0001*	*4.970*
R&D Stock of Knowledge	*7350*	*65179.01*	*(190446.1)*	*10463.46*	*5*	*1466876*
Intangible Assets Intensity/Ind.	*5689*	*1.250*	*(1.440)*	*.707*	*.00002*	*8.791*
Human Capital/Ind.	*9665*	*1.146*	*(.524)*	*1.046*	*.001*	*3.973*
Physical Capital Stock/Ind.	*7562*	*.015*	*(.055)*	*.001*	*5.47e-08*	*.304*
Labour/Ind.	*9770*	*.011*	*(.027)*	*.002*	*.00001*	*.269*
Cost of Sales/Ind.	*8253*	*.013*	*.038*	*.001*	*1.11e-07*	*.375*
Age	*10516*	*30.483*	*(24.947)*	*22*	*5*	*147*
Intra-Ind. Sp. /Total Sales	*10516*	*.077*	*(.059)*	*.068*	*.0001*	*.200*
Inter-Ind. Sp./Labour	*10516*	*823.583*	*(102.729)*	*856.468*	*565.589*	*960.467*
Global Spillovers	*10516*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*

Note: All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form

In regard to Table 4.2, 'Innovators' analysis, we can see that the firms in this group are of reasonable, however, not very large size with an average mean of their market share in terms of value-added of .009 and in terms of total sales of .006. The high mean of the R&D stock of knowledge (*70458.93)* is expected as the firms in this group are the UK top investors in R&D. The 'Innovators' also have high mean values of their export intensity share - (*1.278*), intangible assets intensity share - (*1.314*), and human capital share - (*1.098*). Their share of physical capital stock is also high, with a mean value of .008.

Table 4.2: Descriptive statistics: firm market share, 'Innovators'

Descriptive Statistics			***'Innovators'***			
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max***
Value Added /Ind.	*6369*	*.009*	*(.026)*	*.002*	*1.13e-07*	*.379*
Total Sales/Ind.	*7656*	*.006*	*(.021)*	*.001*	*4.33e-08*	*.342*
Export Intensity/Ind.	*4631*	*1.278*	*(1.141)*	*1.110*	*.0001*	*4.945*
R&D Stock of Knowledge	*6497*	*70458.93*	*(200720)*	*11811.85*	*5*	*1466876*
Intangible Assets Intensity/Ind.	*4595*	*1.314*	*(1.436)*	*.804*	*.0001*	*8.760*
Human Capital/Ind.	*7687*	*1.098*	*(.469)*	*1.025*	*.001*	*3.973*
Physical Capital Stock/Ind.	*6115*	*.008*	*(.034)*	*.001*	*5.47e-08*	*.290*
Labour/Ind.	*7840*	*.007*	*(.017)*	*.001*	*.00001*	*.267*
Cost of Sales/Ind.	*6723*	*.010*	*.030*	*.001*	*1.11e-07*	*.376*
Age	*8492*	*28.096*	*(22.561)*	*20*	*5*	*147*
Intra-Ind. Sp. /Total Sales	*8492*	*.094*	*(.052)*	*.076*	*.001*	*.200*
Inter-Ind. Sp./Labour	*8492*	*802.406*	*(102.836)*	*842.816*	*565.589*	*957.256*
Global Spillovers	*8492*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*

Note: All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form

Looking at the descriptive statistics, on average, it seems that the firms with high mean values for R&D stock of knowledge are also those associated with larger market shares. This relationship is expressed more strongly in the 'All-Firms' analysis than in the 'Innovators' analysis, as per Section 3.5.2.1, where the firms are, on average, smaller in size. This, in general, supports our hypothesis that R&D stock of knowledge is positively associated with firm market share. In the next section, we will see whether after accounting for other factors this correlation is confirmed.

3.6 Results: description and interpretation

Section 3.6 provides the results of our econometric analysis and discusses the findings, and their both statistical, and economic significance. First, we discuss the results in terms of the relationship between firm absolute size and R&D stock of knowledge - Section 3.6.1, followed by the results in terms of the alternative measure of firm size, market share - Section 3.6.2.

3.6.1 Results: firm absolute size

Here, we report the results of both 'All-Firms' - Section 3.6.1.1 and 'Innovators' subset analysis - Section 3.6.1.2.

3.6.1.1 Results: firm absolute size – 'All-Firms' analysis

Table 5 provides the results of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions of our dynamic model of the determinants of firm value-added, outlined in Equation (1). Model 4 reports the GMM results of our alternative measure of firm absolute size - total sales.

Table 5: Firm absolute size and R&D stock of knowledge: 'All-Firms' analysis

Firm absolute size and R&D stock of knowledge: 'All-Firms' analysis				
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***
Constant	*3.994** *(2.452)*	*-4.123* *(3.217)*	*Omitted*	*Omitted*
ln (Value Added $_{t-1}$)	*.739**** *(.038)*	*.170**** *(.050)*	*.655**** *(.070)*	
ln (Total Sales $_{t-1}$)				*.320**** *(.105)*
ln (R&D Stock of Knowledge)	*.005* *(.010)*	*-.080** *(.047)*	*-.023* *(.050)*	*-.040* *(.064)*
ln (Intangible Assets Intensity)	*-.004* *(.007)*	*-.012* *(.016)*	*.016* *(.031)*	*-.017* *(.039)*
ln (Human Capital)	*.141**** *(.044)*	*.409**** *(.112)*	*.314** *(.195)*	*.144* *(.229)*
ln (Export Intensity)	*.005* *(.010)*	*.070*** *(.033)*	*.086*** *(.042)*	*.067** *(.037)*
ln (Age)	*-.028** *(.018)*	*Omitted*	*.006* *(.040)*	*.034* *(.039)*
ln (Physical Capital Stock)	*.043**** *(.014)*	*-.009* *(.058)*	*.025* *(.060)*	*.023* *(.066)*
ln (Labour)	*.157**** *(.035)*	*.556**** *(.091)*	*.148** *(.093)*	*.332**** *(.018)*
ln (Cost of Sales)	*.037*** *(.016)*	*.115**** *(.042)*	*.118** *(.064)*	*.320**** *(.087)*
ln (Intra-Ind./Sales Spillovers)	*-.023* *(.047)*	*-.011* *(.054)*	*-.049* *(.045)*	*.005* *(.034)*
ln (Inter-Ind./Labour Spillovers.)	*-.300* *(.336)*	*.039* *(.347)*	*-.629** *(.426)*	*-.193* *(.310)*
ln (Global Spillovers)	*-.089* *(.123)*	*.333*** *(.167)*	*.200** *(.137)*	*.154** *(.106)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.019*	*0.011*
AR(2) Test			*0.260*	*0.175*
Hansen's J test			*0.376*	*0.315*
Obs.(groups)	*1678*	*1678 (390)*	*1678 (390)*	*1732(397)*
Instruments (lags)			*137, (3 3)*	*137,(3 3)*
R^2	*0.929*	*0.369*		
F	*F(29,389)= 744.45****	*F(17,389)= 34.48****	*F(37, 389)= 18744.03 ****	*F(37,396)= 19827.13****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 presents the pooled OLS coefficients, which are based on cluster-robust standard errors. The OLS accounts for arbitrary heteroscedasticity and intra-cluster correlation. The model explains, on average, 93% of the variation in firms' value-added, according to the adjusted R-square. The coefficients associated with the lagged value-added, and conventional inputs such as physical capital stock, labour and human capital variables, are all positive and significant at the 1% level of significance. The coefficient on the cost of sales variable is also positive and significant at the 5% level. The results are in line with the 'sources of growth' theory, which links increases in a firm's output with increases in a firm's inputs of capital, labour, human capital, intermediate inputs (Griliches 1979, Katayama *et al*. 2005, Cincera & Ravet 2011). The variable age has a negative coefficient, though, only marginally significant at the 10% level. However, as discussed in the estimation methodology (Section 3.4.2), the pooled OLS parameters tend to be biased due to the unobserved firm-specific heterogeneity and likely endogenous regressors.

Column 2 displays the fixed effects estimates. The FE model removes the effect of time-invariant firm characteristics. The coefficient, associated with the R&D stock of knowledge is negative, however, only marginally significant at the 10% level of significance. The coefficients, associated with the lagged value-added, labour, human capital, and cost of sales variables are all positive and significant at the 1% level. The coefficients on both export intensity and global spillovers variables are positive and significant at the 5% level. However, Model 2 accounts for unobserved differences across firms but does not account for the endogeneity issues which affects its consistency, hence, the coefficients are likely to be biased.

Column 3 reports our preferred one-step dynamic GMM estimates. The model controls simultaneously for the two potential biases - unobserved heterogeneity and endogeneity. All our test statistics are within the requirements, as discussed in Section 3.4.2 - Estimation methodology. Statistical diagnostics conducted do not reject the null hypothesis of instruments' validity and/or model specification, meaning that the coefficients derived from the one-step, robust, system GMM regression are credible.

The GMM coefficient on the lagged dependent variable - (*0.655*) is positive and significant at the 1% level of significance. It lies precisely within the range for dynamic stability achieved by the FE (*0.170*), (lower bound) and the pooled OLS (*0.739*), (upper bound) estimators. The positive and strongly significant coefficient suggests that firm size (measured by its value-added) in the current year depends on its size in the previous year, in line with Mazzucato's (2000) predictions. This means that firms' absolute size fluctuations are sluggish and smooth.

The coefficient, associated with the R&D stock of knowledge is negative but not significant while the coefficient on the intangible assets intensity variable is positive, however, also not significant. Contrary to our expectations, the results of this analysis do not support our first hypothesis in Chapter 3 that R&D stock of knowledge is positively associated with firm size, measured by value-added, in the 'All-Firms' dataset. Our results, that there is no significant relationship between R&D stock of knowledge and firm size, are in line with the study of Cohen *et al.* (1987) and contrary to the results of Cohen & Klepper (1996), Crepon *et al.* (1998), Vivero (2002) and Tsai & Wang (2005), who all find a positive link between firm size and R&D activities.

The coefficients associated with the inter-industry and global spillovers, as well as human capital variables are all marginally significant at the 10% level. However, only the coefficients on the human capital and global spillovers variables are positive.

In terms of the human capital, the results show a very weak support for the 'absorptive capacity' theory - firms with a high level of human capital are also those associated with a higher absorptive capacity in order to assimilate new knowledge (Cohen & Levinthal 1989). The positive effects of the global spillovers are confirmed in the findings of Guellec & de la Potterie (2001), Griffith *et al*. (2004b), Luintel & Khan (2004), Huggins *et al*. (2010), Chyi *et al*. (2012). However, in our case, the effects are very weak.

There are many arguments in regard to the positive and negative spillover effects. A possible interpretation of the negative inter-industry spillovers effect might be viewed in terms of McGahan & Silverman (2006) arguments. They claim that external innovations can negatively affect firm performance directly through the market-stealing effects or through indirect appropriation via licensing. They also claim that the strength of such an impact is subject to whether innovation has come from a prospective competitor or not.

The coefficient associated with the export intensity variable (*0.086*) is positive and significant at the 5% level. It means that when other variables are held constant, a 10% increase in the priority given by a firm to its export intensity is associated with an increase of its value-added by, on average, 0.8 %. The results are expected and they are in line with the general view that a firm's export activities increase its size (Kumar & Siddharthan 1994; Wagner 1995; Bernard & Wagner 1997; Wakelin 1998a; Bernard & Jensen 1999, 2004; Sterlacchini 1999; Aw *et al*. 2000; Greenaway & Kneller 2004).

Column 4 reports the one-step, dynamic GMM estimates using an alternative measure of firm absolute size - the total firm sales. All our test statistics in regard to this GMM model are within the norms, specified in Section 3.4.2. The GMM coefficient on the lagged dependent variable - (*0.320*) has the same sign and level of significance, as the coefficient on the lagged dependent variable in Model 3.

The coefficients on both R&D stock of knowledge and intangible assets intensity variables are negative, however not significant. Similarly to the results in Model 3, our findings do not support the hypothesis that R&D stock of knowledge is positively associated with firm size.

In regard to the technological spillovers, only the coefficient associated with the global spillovers is marginally significant at the 10% level of significance and positive. In terms of the human capital variable, in comparison to Model 3, its coefficient ceases to be significant, although it is still positive. The coefficient associated with the export intensity variable (*0.067*) is still positive as per Model 3; however, its significance decreases and its value is smaller.

Conventional inputs such as labour and cost of sales are positively associated with firm value-added, however, in contrast to Model 3, their coefficients' level of significance is at the 1% level.

3.6.1.2 Results: firm absolute size – 'Innovators' analysis

Table 6 provides the results of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions of our dynamic model of the determinants of firm value-added, outlined in Equation (1) in terms of the 'Innovators' subset. Model 4 reports the GMM results of our alternative measure of firm absolute size - total sales.

Table 6: Firm absolute size and R&D stock of knowledge: 'Innovators' analysis

Firm absolute size and R&D stock of knowledge: 'Innovators' analysis				
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***
Constant	*3.952**	*-2.489*	*Omitted*	*Omitted*
	(2.555)	*(3.045)*		
ln (Value Added $_{t-1}$)	*.761****	*.195****	*.660****	
	(.033)	*(.050)*	*(.069)*	
ln (Total Sales $_{t-1}$)				*.311****
				(.104)
ln (R&D Stock of Knowledge)	*.007*	*-.082**	*-.035*	*-.049*
	(.010)	*(.045)*	*(.052)*	*(.065)*
ln (Intangible Assets Intensity)	*-.005*	*-.017*	*.016*	*-.030*
	(.008)	*(.017)*	*(.032)*	*(.040)*
ln (Human Capital)	*.122****	*.368****	*.261*	*.122*
	(.041)	*(.111)*	*(.188)*	*(.221)*
ln (Export Intensity)	*.004*	*.060**	*.076**	*.060**
	(.010)	*(.032)*	*(.043)*	*(.038)*
ln (Age)	*-.032**	*Omitted*	*.012*	*.031*
	(.019)		*(.040)*	*(.040)*
ln (Physical Capital Stock)	*.035****	*.016*	*.040*	*.044*
	(.014)	*(.055)*	*(.064)*	*(.066)*
ln (Labour)	*.145****	*.512****	*.127**	*.328****
	(.031)	*(.081)*	*(.084)*	*(.019)*
ln (Cost of Sales)	*.038***	*.115****	*.119**	*.323****
	(.016)	*(.042)*	*(.064)*	*(.087)*
ln (Intra-Ind./Sales Spillovers)	*-.033*	*-.024*	*-.067*	*-.012*
	(.050)	*(.060)*	*(.055)*	*(.041)*
ln (Inter-Ind./Labour Spillovers)	*-.332*	*-.028*	*-.716**	*-.267*
	(.352)	*(.365)*	*(.449)*	*(.332)*
ln (Global Spillovers)	*-.073*	*.269**	*.238**	*.159*
	(.131)	*(.169)*	*(.145)*	*(.112)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.020*	*0.011*
AR(2) Test			*0.255*	*0.191*
Hansen's J test			*0.337*	*0.496*
Obs. (groups)	*1538*	*1538 (347)*	*1538 (347)*	*1592(354)*
Instruments (lags)			*131, (3 3)*	*131,(3 3)*
R^2	*0.929*	*0.370*		
F	*F(23,346)= 827.04****	*F(17,346)= 37.40****	*F(29, 346)= 15443.81 ****	*F(29,353)= 19234.99****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 presents the pooled OLS coefficients. All variables in Model 1, (Table 5) with statistically significant coefficients, maintain their coefficients' sign and level of significance, correspondingly, in this model. However, the pooled OLS estimates are prone to biases due to the unobserved firm-specific heterogeneity and likely endogenous regressors.

Column 2 reports the fixed effects estimates. All variables in Model 2, (Table 5) with statistically significant coefficients, maintain their coefficients' sign and level of significance, correspondingly in this model, except for the coefficients on the global spillovers and export intensity variables, which decrease their significance from 5% in Table 5 to 10% level in Table 6. However, although Model 2 accounts for unobserved variances across firms, it does not control for the endogeneity issues in our model, which affects its consistency.

Column 3 reports our preferred, one-step, dynamic GMM estimates. The model controls for the unobserved heterogeneity and endogeneity biases simultaneously. The test statistics in terms of this GMM model are within the requirements, as reviewed in Section 3.4.2 - Estimation methodology. The GMM coefficient on the lagged dependent variable (*0.660*) is positive and significant at the 1% level of significance. Also, it lies within the range for dynamic stability achieved by the FE (*0.195*), (lower bound) and the pooled OLS (*0.761*), (upper bound) estimators. The positive GMM coefficient on the lagged dependent variable suggests that a firm's value-added in the current year depends on its value-added in the previous year, as per Model 3 in Table 5.

The coefficient on R&D stock of knowledge is negative but not significant while the coefficient on the intangible assets intensity variable is positive, however, also not significant. In line with our findings in regard to Table 5, (Model 3) and contrary to our expectations, the results do not support our first hypothesis that R&D stock of knowledge is positively associated with firm size, measured by value-added in the ‘Innovators’ subset.

The coefficients associated with the inter-industry and global spillovers are both marginally significant at the 10% level, however, only the coefficient on the global spillovers variable is positive, similarly to the equivalent results of the ‘All-Firms’ analysis (Table 5, Model 3).

The coefficient associated with the export intensity variable (*0.076*) is positive, however, in this analysis, its significance, as in comparison to the ‘All-Firms’ analysis (Table 5, Model 3), decreases to 10%.

Column 4 displays the one-step, dynamic GMM estimates using an alternative measure of firm absolute size - firm total sales. All our test statistics in regard to this GMM model are within the requirements, specified in Section 3.4.2.

The GMM coefficient on the lagged dependent variable is positive and significant at the 1% level of significance, in line with the results of Model 3, the same table, associated with the lagged dependent variable.

The coefficients on both R&D stock of knowledge and intangible assets intensity variables are negative but not significant.

The coefficients associated with the intra- and inter-industry, as well as global spillovers, although maintaining their sign as per Model 3 of the same table, are not significant.

The coefficient on export intensity variable (*0.060*) is still positive and marginally significant at the 10% level, as per Model 3, however, its value is lower.

Conventional inputs such as labour and cost of sales are positively associated with firm total sales, however, in contrast to Model 3, the significance of their coefficients is strong - at the 1% level.

3.6.2 Results: firm market share

In Section 3.6.2 we report the results of both 'All-Firms' analysis - Section 3.6.2.1 and 'Innovators' subset analysis - Section 3.6.2.2. The columns in grey display the results presented as a robustness test, discussed in Section 3.6.4.

3.6.2.1 Results: firm market share – 'All-Firms' analysis

Table 7 provides the results of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions of our dynamic model of the determinants of a firm's market share, measured by its share of value-added, relative to its industry's total value-added and specified in Equation (3). Model 4 reports the GMM results of our alternative measure of a firm's market share - the share of its industry's total sales (Model 4).

Table 7: Firm market share and R&D stock of knowledge: 'All-Firms' analysis

Firm market share and R&D stock of knowledge: 'All-Firms' analysis					
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***	***5. GMM (lnTotal Sales)***
Constant	*6.942* (2.520)*	*-6.057** (2.994)*	*Omitted*	*Omitted*	*Omitted*
ln (Value Added /Ind. $_{t-1}$)	*.722*** (.033)*	*.155*** (.047)*	*.473*** (.074)*		
ln (Total Sales /Ind. $_{t-1}$)				*.176** (.074)*	*.363*** (.076)*
ln (R&D Stock of knowledge)	*.009 (.011)*	*-.084* (.049)*	*-.022 (.052)*	*-.028 (.061)*	*-.019 (.057)*
ln (Intang. Assets Int. /Ind.)	*-.009 (.008)*	*-.014 (.018)*	*-.014 (.031)*	*-.031 (.024)*	*-.006 (.034)*
ln (Human Capital /Ind.)	*.136*** (.042)*	*.416*** (.110)*	*.410*** (.146)*	*-.028 (.189)*	*-.017 (.210)*
ln (Export Intensity /Ind.)	*-.001 (.010)*	*.023 (.027)*	*.031 (.043)*	*.037 (.043)*	*.013 (.037)*
ln (Age)	*-.024 (.020)*	*Omitted*	*-.008 (.046)*	*.043 (.041)*	*.027 (.038)*
ln (Physical Capital Stock/Ind.)	*.051*** (.014)*	*.053 (.055)*	*.120* (.072)*	*.090 (.068)*	*.027 (.058)*
ln (Labour/Ind.)	*.147*** (.031)*	*.440*** (.086)*	*.205** (.091)*	*.409*** (.101)*	*.293*** (.089)*
ln (Cost of Sales/Ind.)	*.049*** (.017)*	*.157*** (.043)*	*.168*** (.062)*	*.340*** (.061)*	*.302*** (.071)*
ln (Intra-Ind./Sales Spillovers)	*.492*** (.065)*	*.736*** (.089)*	*.590*** (.098)*	*.701*** (.082)*	*.619*** (.069)*
ln (Inter-Ind./Labour Spillovers)	*1.402*** (.374)*	*2,920*** (.454)*	*1.712*** (.523)*	*2.265*** (.446)*	*2.039*** (.399)*
ln (Global Spillovers)	*-.688*** (.136)*	*-.570*** (.151)*	*-.420*** (.160)*	*-.688*** (.139)*	*-.634*** (.130)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.008*	*0.001*	*0.000*
AR(2) Test			*0.290*	*0.465*	*0.799*
Hansen's J test			*0.122*	*0.254*	***0.036***
Obs. (groups)	*1642*	*1642 (385)*	*1642 (385)*	*1697(392)*	*1697(392)*
Instruments (lags)			*235, (3 5)*	*378,(2 8)*	*235,(3 5)*
R^2	*0.929*	*0.403*			
F	*F(28,384)= 24.11****	*F(17,384)= 33.35****	*F(37, 384)= 173.45 ****	*F(37,391)= 959.89****	*F(37,391)= 1411.86****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 details the coefficients obtained using the pooled OLS estimator. The coefficients associated with the firm's share of its value-added, physical capital stock, labour, human capital and cost of sales, relative to its industry's total, respectively, are all positive and significant at the 1% level - in line with the 'sources of growth' theory. The coefficients associated with intra-, inter-industry and global spillovers variables are all significant at the 1% level. While the coefficients on intra- and inter-industry spillovers are positive, the coefficient on the global spillovers is negative. However, although the model accounts for arbitrary heteroscedasticity and intra-cluster correlation, the pooled OLS parameters are likely to be biased, as argued in the previous sections.

Column 2 reports the fixed effects estimates. All variables with significant coefficients in Model 1 maintain the same sign and level of significance, correspondingly in this model, except for the coefficient on the firm share of physical capital stock, which is still positive as per Model 1, however, not significant. The coefficient on R&D stock of knowledge is negative, but only marginally significant at the 10% level. However, the FE estimator does not account for endogeneity issues which makes its coefficients inconsistent.

Column 3 outlines the results of our preferred one-step, dynamic GMM model. The model controls simultaneously for both unobserved heterogeneity and endogeneity. All our test statistics in regard to this GMM model are within the requirements, as discussed in Section 3.4.2. Statistical tests conducted do not reject the null hypothesis of instruments' validity and/or model specification, meaning that the estimates produced by the one-step, robust, system GMM regression are credible.

The GMM coefficient on the lagged dependent variable - (*0.473*) is positive and significant at the 1% level of significance. It lies precisely within the range for dynamic stability achieved by the FE (*0.155*), (lower bound) and the pooled OLS (0*.722*), (upper bound) estimates. The positive GMM coefficient on the lagged dependent variable suggests that a firm's market share in the current year depends on its market share in the previous year. This may also suggest that 'success breeds success' in terms of the 'first-mover advantage' theory, associated with Philips (1966, 1971). The firm that first sells a new, innovative product gains a competitive advantage over its rivals (who are trying to catch-up), which allows this firm to persistently dominate its industry in terms of increasing or maintaining its market share. However, Blair (1972) and Geroski & Pomroy (1990) cast doubt on this theory as a uniform tendency. Therefore, without further investigations, we cannot conclusively put forward such an interpretation.

The coefficients on both R&D stock of knowledge and a firm's share of intangible assets intensity, relative to its industry's total*,* are negative but not significant. Similarly to both our analysis in Section 3.6.1 and contrary to our expectations, the findings do not support the hypothesis that at a firm-level, R&D stock of knowledge is positively associated with market share, measured by the firm's share of value-added, relative to its industry's total, in the 'All-Firms' dataset.

The coefficients associated with the intra and inter-industry spillovers are both positive and strongly significant at the 1% level of significance. In regard to the intra-industry spillovers, our findings are in general, in line with the findings of Jaffe (1986, 1988), Jaffe *et al.* (1993), Acs *et al*. (1994), Adams & Jaffe (1996), Audretsch & Feldman (1996) and Cincera (2005), who report that the effects of the R&D/innovation spillovers between firms belonging to the same technological cluster are positive. Our evidence is contrary to Geroski's (1991) findings, who finds that in regard to the UK, the effects of the knowledge spillovers from technological neighbours are very modest.

In regard to the positive effects of the inter-industry spillovers, our findings are in line with the studies of Wei & Liu (2006), Aldieri & Cincera (2009), Chyi *et al.* (2012), Cardamone (2012).

Both our intra- and inter-industry coefficients are not only statistically significant but also, economically significant. Although according to Griffith *et al.* (2006), rivals are not a vital source of information, in our case, the coefficient on the intra-industry spillovers has an important economic significance - its value is large (*.590*). It means that when other variables are held constant, a 10% increase in the intra-industry spillovers is associated with an increase in the firm's market share by, on average, 5.8 %. The value of the inter-industry coefficient is even larger - (*1.712*). This means that when other variables are held constant, a 10% increase in the inter-industry spillovers is associated with an increase in the firm's market share by, on average, 17.7%. The economic significance of these coefficients has important policy implications as according to the 'endogenous growth' theory, which links macro-economic growth to firms' R&D, innovation leads to economic growth (Romer 1986, 1990; Lucas 1988).

Although the coefficient on the global spillovers is also strongly significant at the 1% level, it is negative. This is in line with the view of Branstetter (2001), McVicar (2002), Luintel & Khan (2004) and Anon-Higon (2007), who all find that global spillovers are not beneficial to the advanced economies. Some studies even report that international spillovers are statistically insignificant or if they exercise positive effects, these effects benefit mostly less developed countries (e.g. Keller 1998, 2000, 2002;

Kao *et al.* 1999). According to all editions of the *IRI, EU R&D Scoreboards*[24], UK is one of the top R&D investors in the world. In such terms, the above suggestions are supported by our results. The coefficient is not only statistically significant but also has an important economic significance - its value is large *(-.420*). It means that when other variables are held constant, a 10% increase in the global spillovers is associated with a decrease in the firm's market share by, on average, 3.9 %.

In terms of the coefficient on the firm's share of its human capital, taken together with the estimates of the intra- and inter-industry spillovers, the findings show strong support for the 'absorptive capacity' theory. Firms with a higher level of human capital can better absorb and assimilate other firms' 'know-how' (Cohen & Levinthal 1989). Its coefficient is positive (*.410*) and strongly significant at the 1% level meaning that when other variables are held constant, a 10% increase in the priority given by a firm to its share of the human capital in its industry, is associated with an increase in its share of value-added, relative to its industry's total, by, on average, 4%. It looks like the firms in this dataset substitute their investment in R&D for investment in human capital. This could be interpreted in terms of Rammer's *et al*. (2009) findings, who evidence that, to some extent, in-house R&D activities can be either combined with or even substituted by, different management practices, e.g. training of employees, creating human capital and networking.

Column 4 reports the one-step, dynamic GMM estimates using an alternative measure of firm market share - a firm's share of its total sales relative to its industry's total sales. All our statistics in regard to this GMM model are within the norms. The

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[24] http://iri.jrc.ec.europa.eu/scoreboard.html

GMM coefficient on the lagged dependent variable - (*0.176*) is positive and significant at the 5% level of significance.

The coefficients on both R&D stock of knowledge and firm share of intangible assets intensity variables are negative but not significant, as in Model 3 of the same table.

The coefficients on intra- and inter-industry spillovers variables, as well as global spillovers, maintain their sign and significance level as per Model 3, however, their values are much higher than in Model 3, (Table 7).

The coefficient on the firm's share of its human capital variable, in comparison to Model 3, ceases to be significant, and it becomes negative.

Conventional inputs such as labour and cost of sales, represented in their share of industry's total, respectively, are positively associated with firm market share, at the 1% level. However, the coefficient on the firm's share of its physical capital stock although still positive, as per Model 3, is not significant in Model 4.

3.6.2.2 Results: firm market share – 'Innovators' analysis

Table 8 details the outcomes of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions of our dynamic model of the determinants of a firm's market share, measured by its share of value-added, relative to its industry's total value-added, and outlined in Equation (3). Model 4 reports the GMM results of our alternative measure of market share - a firm's total sales relative to its industry's total sales (Model 4).

Table 8: Firm market share and R&D stock of knowledge: 'Innovators' analysis

Firm market share and R&D stock of knowledge: 'Innovators' analysis					
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***	***5. GMM (lnTotal Sales)***
Constant	*6.295** (2.616)*	*-5.551** (2.984)*	*Omitted*	*Omitted*	*Omitted*
ln (Value Added /Ind. $_{t-1}$)	*.740*** (.032)*	*.177*** (.048)*	*.459*** (.077)*		
ln (Total Sales /Ind. $_{t-1}$)				*.164** (.075)*	*.367*** (.075)*
ln (R&D Stock of knowledge)	*.010 (.011)*	*-.089* (.048)*	*-.031 (.049)*	*-.039 (.058)*	*-.018 (.054)*
ln (Intang. Assets Int. /Ind.)	*-.010 (.008)*	*-.020 (.019)*	*-.018 (.033)*	*-.043* (.026)*	*-.018 (.033)*
ln (Human Capital /Ind.)	*.122*** (.041)*	*.378*** (.107)*	*.386*** (.143)*	*-.061 (.197)*	*-.018 (.217)*
ln (Export Intensity /Ind.)	*.003 (.010)*	*.045* (.029)*	*.055 (.049)*	*.060 (.047)*	*.031 (.038)*
ln (Age)	*-.030* (.020)*	*Omitted*	*-.009 (.050)*	*.053 (.045)*	*.028 (.038)*
ln (Physical Capital Stock/Ind.)	*.049*** (.014)*	*.067 (.056)*	*.128* (.068)*	*.106* (.072)*	*.034 (.056)*
ln (Labour/Ind.)	*.140*** (.031)*	*.442*** (.087)*	*.215** (.091)*	*.405*** (.109)*	*.301*** (.090)*
ln (Cost of Sales/Ind.)	*.042*** (.017)*	*.135*** (.040)*	*.172*** (.060)*	*.342*** (.063)*	*.287*** (.071)*
ln (Intra-Ind./Sales Spillovers)	*.533*** (.060)*	*.798*** (.088)*	*.643*** (.096)*	*.803*** (.089)*	*.714*** (.069)*
ln (Inter-Ind. /Labour. Spillovers)	*1.571*** (.355)*	*3,110*** (.445)*	*1.928*** (.500)*	*2.631*** (.453)*	*2.398*** (.391)*
ln (Global Spillovers)	*-.752*** (.134)*	*-.648*** (.143)*	*-.532*** (.153)*	*-.780*** (.145)*	*-.721*** (.127)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.011*	*0.001*	*0.000*
AR(2) Test			*0.570*	*0.593*	*0.920*
Hansen's J test			*0.232*	*0.443*	***0.029***
Obs.(groups)	*1533*	*1533 (347)*	*1533 (347)*	*1588(354)*	*1588(354)*
Instruments (lags)			*229, (3 5)*	*351,(2 7)*	*229,(3 5)*
R^2	*0.929*	*0.426*			
F	*F(23,346)= 840.95****	*F(17,346)= 36.86****	*F(29, 346)= 4083.79 ****	*F(29,353)= 4983.13****	*F(29,353)= 8858.68****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 reports the results of the pooled OLS model. The significant coefficients on all variables in Model 1, (Table 7) maintain their sign and level of significance, correspondingly here. The coefficient on the variable age is negative but, only marginally significant at the 10% level of significance. However, as mentioned previously, the pooled OLS parameters tend to be biased due to the unobserved firm-specific heterogeneity and likely endogenous regressors.

Column 2 reports the coefficients obtained using the FE estimator. The coefficients on the firm's share of its lagged value-added*,* labour, human capital and cost of sales variables, are all positive and significant at the 1% level. The coefficients on the intra-, inter-industry and global spillovers maintain their sign and level of significance, as per Model 1 of the same table. The coefficient on R&D stock of knowledge is negative, but only marginally significant at the 10% level. The coefficient associated with the firm's share of its export intensity is positive and only marginally significant at the 10% level. However, the model does not control for endogeneity issues which may affect its consistency.

Column 3 displays the one-step, dynamic GMM estimates. All our test statistics in regard to this GMM model are within the requirements, as considered in Section 3.4.2. - Estimation methodology.

The GMM coefficient on the lagged dependent variable - (*0.459*) is positive and significant at the 1% level, and lies precisely within the range for dynamic stability achieved by the FE (*0.177*), (lower bound) and the pooled OLS (*0.740*), (upper bound) estimators. The positive GMM coefficient on the lagged dependent variable suggests that a firm's market share in the current year depends on its market share in the previous year.

The coefficients on R&D stock of knowledge and firm share of its intangible assets intensity variables are both negative but not significant. In line with our findings in Table 7, (Model 3) and contrary to our expectations, the results do not support the hypothesis that at a firm-level, R&D stock of knowledge is positively associated with market share, in terms of the 'Innovators' dataset.

The coefficients on intra and inter-industry spillovers as well as global spillovers maintain their sign and level of significance as per Model 3, (Table 7), however, here their values are higher. The coefficients are not only statistically significant but also have an important economic significance - their values are large.

In terms of the firm's share of its human capital, its coefficient is positive and strongly significant, and its interpretation is the same as per Model 3, (Table 7).

The coefficients on conventional inputs such as labour, cost of sales and physical capital stock, represented by their share of industry's total, respectively, are positive and significant at the 5%, 1% and 10% levels, respectively, providing support for the 'sources of growth' theory.

Column 4 reports the one-step, dynamic GMM estimates using an alternative measure of market share - the firm's share of its total sales relative to its industry's total sales. All our test statistics in regard to this GMM model are within the requirements. The GMM coefficient on the lagged dependent variable is 0.164 (positive and significant at the 5% level).

The coefficients on both R&D stock of knowledge and firm share of intangible assets intensity variables are negative, however, only the coefficient on the intangible assets intensity is significant, but marginally - at the 10% level.

The coefficients on intra- and inter-industry spillovers, as well as global spillovers, maintain their sign and significance level as per Model 3, of the same table, however, here they are much larger than in Model 3. As per Table 7, (Model 4), the coefficients are not only statistically significant but they also have an economic significance and their economic significance is greater than in Table 7, (Model 4).

In terms of the firm's share of its human capital, in comparison to Model 3, its coefficient ceases to be significant, and it becomes negative.

3.6.3 Summary of results and general considerations

3.6.3.1 Summary of results

Contrary to our expectations, the results of all our GMM models do not support the hypothesis that R&D stock of knowledge is positively associated with a firm's size, measured in terms of both absolute size and relative to its industry's size, in both the 'All-Firms' dataset and the 'Innovators' subset. In terms of the other variables, there are some variations in the results.

In regard to the firm absolute size analysis (Section 3.6.1), the coefficients on the inter-industry spillovers are negative and marginally significant (at the 10% level) in the GMM models with value-added as a dependent variable: Table 5, (Model 3) and Table 6, (Model 3). The coefficients on the intra-industry spillovers are not significant in all GMM cases while the coefficients on the global spillovers are positive, however, weakly significant (at the 10% level) except in Table 6, (Model 4) where the coefficient is still positive, however, not significant.

This is in contrast to the analysis of the firm market share (Section 3.6.2) where the coefficients on both intra- and inter-industry spillovers are positive and significant at the 1% level in all GMM models in Tables 7 and 8. The same applies to the coefficients on the global spillovers variable, however, their effects are negative. The effects of all above spillovers, in regard to Section 3.6.2 also have a great economic significance as all coefficients are large, especially in both models where the dependent variable is measured as the firm's share of its industry's total sales.

The coefficients on human capital variable in the analysis of the market share (3.6.2), are positive and significant at the 1% level in both 'All-Firms' and 'Innovators' GMM models, where we measure a firm's market share in terms of its share of value-added, relative to its industry's total value-added (Table 7, Model 3 and Table 8, Model 3). In terms of firm absolute size (Section 3.6.1), the human capital coefficient is positive only in Table 5, (Model 3), but weakly significant at the 10% level.

The coefficients on the firm export intensity in the analysis of firm absolute size are, in general, positive but marginally significant at the 10% level in both 'All-Firms' and 'Innovators' GMM models except in Table 5, (Model 3) where the coefficient is significant at the 5% level. In regard to the analysis of firm market share, the coefficient on firm export intensity has no significant effect on market share in all GMM models.

In regard to the conventional inputs, our findings are, in general, in line with the 'sources of growth' theory: in the long-terms, increasing conventional inputs increases firm size.

However, there are some considerations about the interpretation of our findings.

3.6.3.2 General considerations

There are some considerations which have to be taken into account when interpreting the results.

The literature review reveals that the association between R&D activities and firm size is prone to variations across industries due to cross-industry variations in technological opportunities, appropriability conditions, and strategic focus of innovation (Scherer 1980, Kamien & Schwartz 1982, Baldwin & Scott 1987, Cohen & Levin 1989, Cohen & Klepper 1996, Lee & Sung 2005). This research explores the above relationship only in terms of the firms belonging to the high and medium-high R&D intensity sectors in the UK, and in regard to the whole dataset, described comprehensively in Chapter 2. However, the 'Innovators' represent, on average, 81% of the 'All-Firms' dataset in terms of both measure of firm size, while the low and medium-low R&D intensity firms represent, on average, 19%, with high heterogeneity in firms' characteristics observed. Medium-low and low R&D intensity sectors are not analysed separately for the reasons discussed in Chapter 2, (Section 2.2.2). However, we account for the variances in technological levels by including inter- intra-industry and global spillovers.

Furthermore, R&D stock of knowledge, calculated from R&D inputs (R&D expenditure in this study), does not account for the entire firm innovative activities. However, we account for firms' 'other spending' on innovative activities, not reflected in their R&D expenditure - the intangible assets. In-house R&D is related to a number of market failures such as uncertainty, inappropriability, and indivisibility (Spence, 1984). These simultaneous market failures are different in different industries at different levels, affecting the relationship between R&D inputs and outputs.

In addition, in our research, we investigate if firms aim their in-house R&D at increasing their size. However, some firms may have different strategies. For example, a smaller firm trading in frequently purchased, differentiated consumer products may gain satisfactory rewards with a smaller market share, e.g., by maintaining a higher rate of return than larger firms (Jackson 2007). Other smaller firms may sidestep going head-to-head with bigger, more powerful rivals, deploying their investments into market segments where the dominant players do not participate.

3.6.4 Robustness tests

The results could be questioned in potentially two bases of biases. First, the datasets are likely to be biased and second, value-added is not an appropriate proxy for firm output. Therefore, robustness tests are performed to check the validity of results.

We check whether both datasets are likely to suffer from a possible 'selection' bias caused by our decision to include only the R&D active firms in 'All-Firms' dataset where the majority of the firms are from the high and medium-high R&D intensity sectors, and only the firms on the *R&D Scoreboard* in regard to the 'Innovators' subset. Accordingly, we have to check whether the likelihood of these firms decision to invest in R&D (and consequently emerge in the R&D Scoreboards) is not randomly distributed but the outcome of firms' common characteristics. We perform a generalised Heckman's (1976, 1979) two-step procedure (Appendix 6) which accounts for a firm's decision to engage in R&D expenditure. Following Cincera *et al.* (2003), we check for 'sample selection bias' in both the 'All-Firms' and 'Innovators' datasets. The first stage involves determining the firm probability of investing in R&D, employing a Probit model. From the first stage, we obtain the 'inverse Mill's ratio' which we incorporate in the equation from the first stage as a proxy variable, accounting for the omitted effect of the R&D investment decision (the second stage). The insignificant coefficients on 'lambda' ('Mill's ratio') in all cases mean that both datasets do not suffer under 'selection' bias. That is, we do not need to make corrections for 'selectivity' bias.

In regard to our second possible bias, to check the validity of our estimates we use the same econometric strategy employing firm total sales instead of value-added in regard to all GMM models. The results are similar.

In summary, the validity of this study's results is confirmed in both cases of potential biases.

Furthermore, all GMM equations in terms of firm absolute size (Section 3.6.1), employ the same set of instruments. In terms of firm market share (Section 3.6.2), as a robustness test, in addition to the main results, we also report the results with the same GMM instrument set (the columns in grey). However, in both cases (Model 5, Table 7 and Model 5, Table 8), the null hypothesis associated with the Hansen test: *H_0 Model specification is correct, and all overidentifying restrictions (all overidentified instruments) are correct (exogenous),* is rejected. That is, the instruments do not fulfil the required orthogonality conditions, discussed in Chapter 3, Section 3.4.2. Therefore, these results are not analysed.

In addition, most R&D studies (e.g. Crepon *et al.* 1998, Kumbhakar *et al.* 2012, Mairesse *et al*. 2012, Baum *et al*. 2015) use logarithmically transformed variables in regard to both continuous variables and ratios (including, in most cases, industry adjusted variables). For the sake of analytical tractability and ease of interpretation, we use the same approach[25]. As an additional robustness check, Appendix 7 presents a set of the same models, using the logarithmic transformations only on continuous variables. In terms of firm absolute size, the GMM regression results obtained from this investigation (Appendix 7.1 and Appendix 7.2) are, generally, qualitatively similar to the GMM results reported in Table 5 and Table 6. In terms of firm market share (Appendix 7.3 and Appendix 7.4), the null hypothesis associated with the Hansen test: *H_0 Model specification is correct, and all overidentifying restrictions (all overidentified instruments) are correct (exogenous),* is rejected in regard to all GMM models. This means that the instruments do not fulfil the required orthogonality conditions, explained in Chapter 3, Section 3.4.2.

3.7 Conclusions and implications

This section summarises the results of Chapter 3 and discusses policy implications. It also outlines opportunities for future research.

Although according to the 'endogenous growth' theory, which links macro-economic growth to firms' R&D, innovation leads to economic growth (Romer 1986, 1990; Lucas 1988), at a firm-level, this is not so widely and conclusively investigated so that to confidently back up firms' increasing R&D expenditure. This research provides evidence in regard to the research question: 'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its market performance indicator: size? The study uses an unbalanced panel of 956 UK firms (our 'All-Firms' dataset) during 2003/4-2013/14, of which 772 firms belong to

25 According to Section 3.5.2 Descriptive statistics, (Tables 3.1 - 3.2 and Tables 4.1 - 4.2), our datasets do not suffer from the issue of 'zeros/negative values' (the data cleaning processes have removed the insignificant number of these values), which would have caused the loss of a large number of observations.

the high and medium-high R&D intensity sectors (our 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity sectors.

The study provides an important addition to the current literature in the UK context. Historically, the studies on this topic investigate the effect of a firm's R&D/innovation on either its absolute size or on its market share. Contrary to these studies, this chapter explores the effect of the R&D stock of knowledge on both firm absolute size and market share, using the same dataset. Another contribution is that this study employs a comprehensive set of variables, accounting for both firm-level R&D/innovation as well as for different external technological effects and firms' heterogeneity. Also, to date, most of the research on the subject is in regard to the social qualities of welfare: size and especially market share is researched based on the perspective of monopolistic/oligopolistic industry structure and its effect on firms' intra-industry behaviour (e.g. pricing). This research views the relationship between firm size and innovation from a different perspective, not in regard to whether small or large firms are more innovative, nor whether firm R&D contributes to macroeconomic growth. This study examines the above relationship from the point of view of an individual firm.

Contrary to our expectations, the results of all our GMM models do not support the hypothesis that a firm's R&D stock of knowledge is positively associated with its size, measured in terms of both its absolute size and size, relative to its industry, in regard to both datasets.

In terms of the other variables, the most important results are as follows.

In the analysis of firm market share (Section 3.6.2), the effects of both intra- and inter-industry spillovers are positive and highly significant in all GMM models. The effects of the global spillovers are negative, however, highly significant also in all GMM models. The effects of all types of spillovers in Section 3.6.2 are also economically significant as all their coefficients are large.

The effects of the human capital variable in the analysis of market share, (Section 3.6.2) are positive and highly significant only in Table 7, (Model 3) and Table 8, (Model 3).

The effects of export intensity in the analysis of firm absolute size (Section 3.6.1), are positive but only weakly significant in all our GMM models, except in Table 5, (Model 3), where the coefficient is significant at the 5% level of significance.

The study findings are important from both micro- and macroeconomic perspectives. At a microeconomic level, the study aims to provide justification for the firms' investment in R&D. At a macroeconomic level, it contributes to the current literature debate, which casts doubt that firms' R&D expenditure translates into satisfactory macroeconomic growth rates (Andersson *et al.* 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011).

According to Edquist & Mckelvey (1998), the reason for the above paradox might be due to the failure of national innovation systems in converting firms' R&D investment into macroeconomic growth. According to the above policy-debate researchers, the paradox may be due to the initial 'endogenous growth' theory models being too optimistic, which in turn have raised idealistic expectations that macroeconomic growth is proportional to R&D expenditure (e.g. Romer 1990, Aghion & Howitt 1992, Grossman & Helpman 1994). This prompted many researchers to amend their studies and downgrade the role of firms' R&D expenditure in economic growth (Jones 1995, 2002; Aghion & Howitt 1998; Ejermo *et al.* 2011). The results of our research show that at the micro-level, there is no significant relationship between firm size and R&D stock of knowledge. This study offers evidence of and insights into the firm-level R&D investment, which according to the 'endogenous growth' theory is the source of macroeconomic growth. Thus, on one hand, this study may facilitate policy-makers to fine-tune their policy mechanisms for encouraging firms' R&D activities to promote sustainable economic growth. On the other hand, this research may help policy makers to strengthen the ability of the national innovation system of converting firms' R&D investment into macroeconomic growth.

The limitations of this research provide opportunities for future research. This study can be extended in different ways so that the relationship between firm size and R&D/innovation can be more fully explained. A follow-up study, modelling the proposition that firm size and R&D activities are simultaneously determined, accounting for firms' heterogeneity, would be of great interest to a wide range of audiences. Furthermore, employing more modern econometric approaches, e.g. the GSEM in computing such simultaneous systems of equations may produce different outcomes, than the outcomes produced by more traditional approaches, controlling for different dynamics and interdependencies between the variables researched.

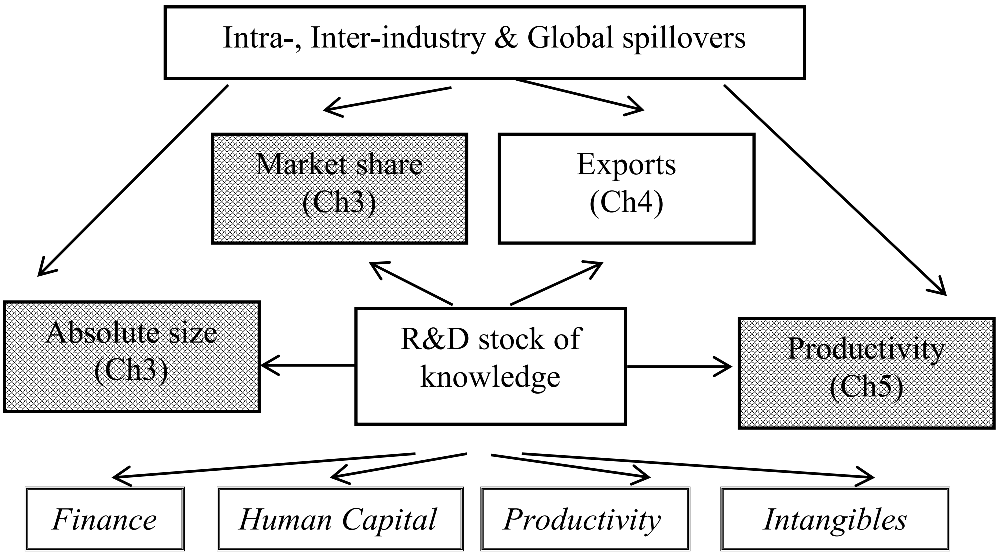
Chapter 4: The Relationship between R&D Stock of Knowledge/Innovation and Firm Exports

Investigating the link between a firm's R&D stock of knowledge and its exports, we use both traditional technique (GMM) and a new econometric approach in this area: Generalised Structural Equation Modelling (GSEM). Our findings support both *'innovating by exporting*' (higher export activities lead to intensified R&D/innovation) and *'exporting by innovating'* (higher R&D/innovation leads to intensified export activities) hypotheses. Furthermore, we evidence that there is two-way causality between a firm's R&D stock of knowledge and its exports, both affecting each other positively, depending on firm productivity.

4.1 Introduction

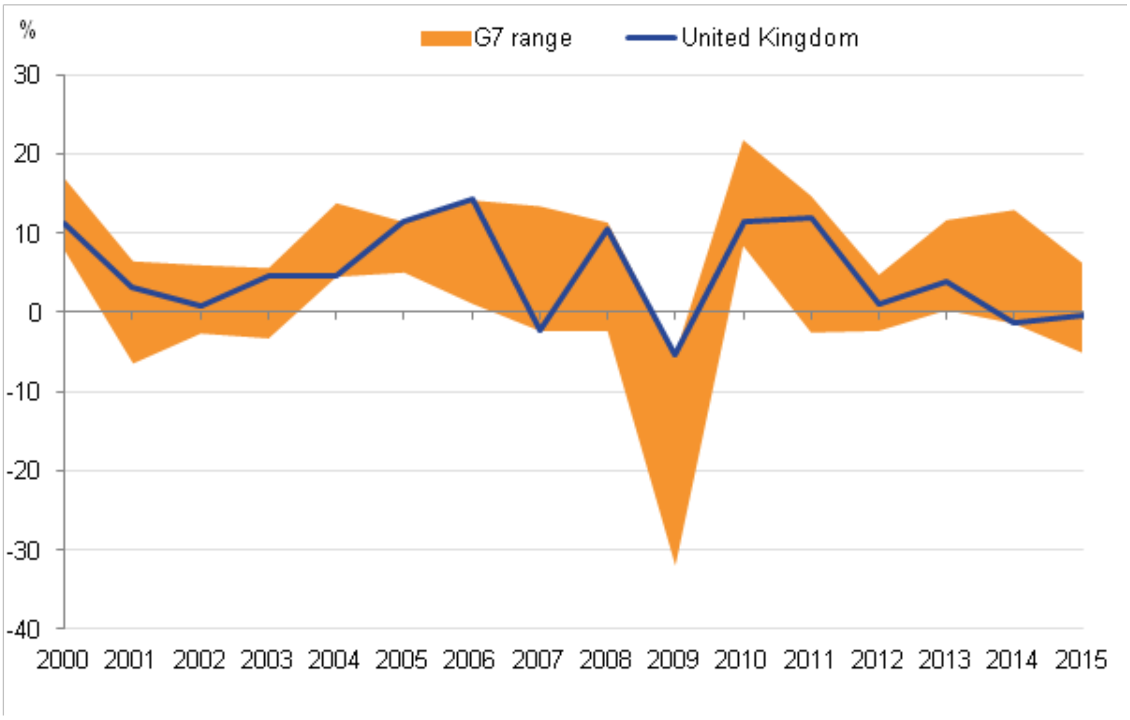
The subject researched in Chapter 4, the relationship between a firm's export activities and its R&D stock of knowledge, is a part of the thesis' general investigation on the effects of a firm's R&D stock of knowledge on several performance indicators - size (Chapter 3), exports (Chapter 4), and productivity (Chapter 5). The scheme is presented in Figure 6.

Figure 6: Research structure: Chapter 4.



At a micro-level, the relationship between a firm's investment in R&D and its export activities is an important subject due to the fact that they both affect firm productivity (Clerides *et al*. 1998; Bernard & Jensen 1999, 2004; Aw *et al*. 2000; Greenaway & Kneller 2004). Furthermore, at a macro-level, according to the 'endogenous growth' theory, firms' R&D leads to economic growth (Romer 1986, 1990; Lucas 1988). In line with the 'endogenous growth' theory, recent literature focuses on the microeconomic perspective to trade, linking firms' export activities to their productivity, and thus, reinforcing the importance of exports for national productivity growth (Bernard *et al*. 2003; Melitz 2003; Bernard & Jensen 2004a,b,c; Helpman *et al*. 2004a; Bernard *et al*. 2005; Harris & Li 2009). This has significant implications for policy-makers, as according to Figure 7, the export growth in the UK in the last 3 years of the time-period captured has been at the bottom of the G7 range. In particular, in 2014 the UK export growth was seventh of the G7 range (*ONS* 2016).

Figure 7: Total exports of goods and services of G7 nations (2000-2015), (current price in national currency)



Source: Office for National Statistics[26], Statistical bulletin: UK Trade: 2016

Therefore, this study is important from a policy perspective. The findings of this chapter indicate that integrated R&D and export promotion policies can be advantageous to the UK economy, as both R&D and exports lead to economic growth. It is envisaged that this study will enable policy-makers to enhance their policy instruments as there are numerous advantages of firm-level studies on the relationship

[26] https://www.ons.gov.uk/economy/nationalaccounts/balanceofpayments/bulletins/uktrade/mar2016

between innovation/R&D stock of knowledge and export activities, conditioning on productivity. Therefore, policy actions encouraging R&D and export activities, e.g. subsidy or tax-relief, supporting exports and innovative collaborations or backing up innovative management practices, are justifiable (Ortega-Argiles *et al*. 2009).

From a theoretical viewpoint, initially, empirical studies were based on the 'neo-endowment theory', which advocates that firms' competitive advantage comes from factor-based advantages, e.g. materials, labour, capital and human capital (Wakelin 1998a, Roper & Love 2002), thus, incorporating them in equations, determining firms' export activities.

Later on, subsequent studies incorporate 'innovation' variables in the models, in line with 'technology-based' theories of trade, which claim that innovation and technological differences are the key determinants of the pattern of trade (Posner 1961, Vernon 1966), examining also the reverse causation.

Recently, some researchers (e.g. Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011, Harris & Moffat 2012) forwarded a theoretically sound framework, based on the relationship between innovation and export activities, in line with the 'endogenous growth' theory. According to Harris & Moffat (2012), *'theoretical efforts have been made to endogenise firm heterogeneity'*, (p3). It is based on the requirements of the firms to employ productivity enhancing processes (e.g. R&D/innovations) before entering export markets and to use productivity enhancing feedback after engaging with export activities. This defines the two-way causal relationship between exports and R&D/innovation (Harris & Moffat 2012). On the one hand, firms' gains from engaging in R&D/innovation activities and exports grow with firms' underlying productivity. Therefore, firms with greater productivity will be prone to a 'self-selection' bias, engaging in further R&D/innovation activities and exports. On the other hand, R&D/innovation activities and exports also have a direct impact on the firms' future productivity, thus, reinforcing endogeneity via the 'self-selection' process. However, this modern theoretical framework has not been widely and conclusively investigated. As Chapter 5 deals explicitly with the link between firm productivity and R&D/innovation, this theoretical framework will be comprehensively reviewed there.

This study's contribution to the literature is that it uses different econometric techniques (e.g. pooled OLS, FE, GMM and GSEM) to investigate the relationship between firm R&D stock of knowledge and export intensity, conditioning on firms' heterogeneity.

First, it explores the one-way causality between a firm's R&D stock of knowledge and its export activities, accounting for both firm-specific and technological heterogeneity, using more traditional econometric approaches. The results support the first hypothesis in this chapter - *'exporting by innovating'*.

Second, this research follows Atkeson & Burstein (2010), Aw *et al*. (2011), Bustos (2011) and Harris & Moffat (2012) by looking at the relationship between firm export activities and R&D stock of knowledge as a simultaneous process. Therefore, it tests all three hypotheses of this chapter simultaneously. For this, it uses the GSEM econometric approach based on the work of Rabe-Heskesh & Pickles (2004) and elaborately discussed by Roodman (2011) in his 'cmp' STATA approach. The idea of estimating the two-way causality between R&D stock of knowledge and exports, conditioning on firms' productivity, is motivated by Baum *et al.* (2015).

Both 'cmp' and GSEM are built on the generalised linear model framework. However, STATA GSEM also handles multiple equation systems and latent variables

(Baum *et al.* 2015). Furthermore, it allows us to model the two-way causality between a firm's R&D stock of knowledge and its exports, their interdependencies, dynamics, endogeneity and potential simultaneity while accounting for firms' characteristics. Using this approach, the results also support the first hypothesis. Moreover, the results support the less researched, second hypothesis of this chapter: *'innovating by exporting'*. In addition, the findings, to a great extent, support the modern strand of the literature which endogenises firm heterogeneity. R&D stock of knowledge and firm exports are endogenous, they both affect each other positively, depending on firms' characteristics.

The third contribution to the literature, in a UK context, is that the dataset used in this research is unique in that it contains information from several data sources with manually matched variables. It includes data on firm exports, R&D expenditure, intangible assets, intra-, inter-industry and global spillovers.

The research question is worthy of investigation as the relationship between firm exports and R&D activities is of vital importance at both micro- and macro-levels in terms of firm productivity and economic growth, respectively. The subject is contemporary, and the evidence provides support to both traditional 'neo-endowment' and 'technology-based' theories. Additionally, in the UK context, it provides support to the modern framework which endogenises firm heterogeneity.

The remaining of this chapter is organised as follows. In Section 4.2, we provide the theoretical background of the relationship between firm export activities and R&D/innovation. In Section 4.3, we discuss the hypotheses to be tested, while in Section 4.4 we describe the baseline specification and estimation methodology. Section 4.5 presents the dataset and summary statistics. Thereafter, Section 4.6 describes and interprets the results, while Section 4.7 concludes the research and highlights the implications of our findings.

4.2 Literature review

4.2.1 Theoretical framework

Although there are no formal theories on the relationship between innovation and international trade at the firm-level, historically, researchers (e.g. Wakelin 1998a, Roper & Love 2002) applied a macro-economic theoretical framework. This framework is centred around the 'neo-endowment' theory and the 'technology-based' theories, such as Posner's (1961) 'technology-gap' model of trade and Vernon's (1966) 'life-cycle' model of trade (Wakelin 1998a). Recent developments of the 'endogenous growth' theory also shed light on the subject.

4.2.1.1. The 'neo-endowment' theory

According to the 'neo-endowment' theory, a firm's competitive advantage comes from factor-based advantages, e.g. materials, labour, capital and human capital (Wakelin 1998a, Roper & Love 2002). Therefore, they were included in models of the determinants of firms' export activities. This is specifically important if the firm is a natural monopolist of a specific factor or if the firm is situated in a geographical area where a particular factor is available at a low cost (Ganotakis & Love 2011), e.g. China's labour-cost advantage.

4.2.1.2. The 'technology-based' theories of trade

According to the 'technology-based' theories of trade, innovation and technological differences are the main determinants of the pattern of trade. Posner's

(1961) 'technology-gap' perspective, (extended by Hufbauer 1966) advocates that countries with high level of innovation will have an export advantage in the development of innovative products. However, this advantage is transitory: as knowledge creation has a public good quality, it is prone to spillovers. Therefore, it can be freely transferred to technologically less advanced nations. Vernon's (1966) 'product-cycle' perspective (extended by Hirsch 1974) advocates that innovative products, developed in technologically advanced countries, go through different maturity stages during their life-cycle: introduction, growth, maturity and decline. When the product, initially developed in the innovator nation, reaches its maturity stage it becomes standardised and forwarded for production to developing countries with low labour-costs. Krugman (1979, 1986) extends the 'technology-gap' models reaching similar conclusions, emphasising that the diffusion of technological advances will benefit both exports and the terms of trade in less advanced nations.

4.2.1.3. The 'endogenous growth' theory

The early research on the relationship between international trade and innovation (e.g. the 'product-cycle' frameworks of Vernon 1966) finds evidence that, at the macro-level, exogenous innovation affects export activities in a positive and significant way (Ganotakis & Love 2011). Later research, based on the 'endogenous growth' theory where innovation is regarded as endogenous (Grossman & Helpman 1991a,b), although also considering the reverse causation, find similar results (Ganotakis & Love 2011).

The 'endogenous growth' theory advocates that international trade enables the creation, transfer and diffusion of new technological advances (Rivera-Baits & Romer 1991a,b; Coe & Helpman 1995; Coe *et al*. 1997; Wei & Liu 2006). In line with the 'endogenous growth' theory, recent literature focuses on the microeconomic perspective to trade, linking firms' export activities to their productivity, and thus, reinforcing the importance of exports for national productivity growth (Bernard *et al*. 2003; Melitz 2003; Bernard & Jensen 2004a,b,c; Helpman *et al*. 2004a; Bernard *et al*. 2005; Harris & Li 2009). Export activities increase productivity by enabling efficient use of resources, better capacity utilisation and economies of scale in regard to the large international markets (Bhagwati 1978, Krueger 1978, Obstfeld & Rogoff 1996). Furthermore, according to Greenaway *et al*. (2007), exporters are financially healthier than non-exporters.

4.2.1.4. Firm exports, start-up costs and heterogeneity in firm productivity

Although there are benefits of exporting, not all firms engage in export activities. According to recent studies (e.g. Roberts & Tybout 1997, Bernard *et al*. 2003, Melitz 2003, Campa 2004, Helpman *et al*. 2004b, Greenaway & Kneller 2007, Greenaway *et al*. 2007; Chen & Guariglia 2013), this may be due to the sunk start-up costs (associated with the research of international markets, R&D of goods and services suitable for the destination countries, survival and success in foreign business environment and government legislation) and the heterogeneity in firm productivity (Bleaney & Wakelin 1999). The largest and most productive firms are the ones that engage in export activities, as only they can rely on profits, sufficient to absorb the sunk entry costs (Clerides *et al.* 1998; Bernard & Jensen 1999, 2004c; Aw *et al.* 2000; Greenaway & Kneller 2004; Greenaway *et al*. 2007).

Studies on the effect of innovation on aggregate exports are scarce. One main exception is Fagerberg (1988), who establishes that innovation is a vital factor accounting for competitiveness within 15 OECD nations. The majority of the research on the relationship between innovation and exports at the macro-level adopts the 'technology-based' theories of trade, finding a positive link between innovation and exports (Dosi *et al.* 1990, Greenhalgh *et al.* 1994, Magnier & Toujas-Bernate 1994, Wakelin 1998b, Roper & Love 2002).

As the focus of our research is at a firm-level, the following sections will review the literature in regard to the relationship between R&D/innovation and firm exports, in terms of the proposition of the 'endogenous growth' theory according to which the causality of this relationship runs in both directions.

4.2.2 Firm-level studies: the effect of R&D/innovation on exports

Most evidence at the firm-level is empirics-led (Harris & Li 2009). Generally, the models include a number of variables, in line with both 'neo-endowment' and 'technology-based' theories, to analyse the relationship between R&D/innovation and firm exports.

4.2.2.1. Firm-level studies, in line with the 'neo-endowment' theory

According to the 'neo-endowment' model, a firm's comparative advantage may be based on a variety of endowment factors. Covering 320 UK firms during 1988 - 1992, employing various Probit, Tobit and truncated regression techniques, Wakelin (1998a) analyses the relationship between innovation and firm export behaviour. She finds a positive relationship between firm exports and the average capital intensity. Focusing on a similar subject and using econometric techniques similar to Wakelin's (1998a) research, Sterlacchini (1999) analyses the impact of innovation on 143 small Italian firms' export behaviour. He employs data from direct interviews at the end of

1997. The firms in his research belong to industries with low R&D intensity. He evidences a positive relationship between a firm's technological level and its export propensity.

As this research will not focus explicitly on the 'neo-endowment' theory, only a summary of the general findings is provided to justify the variables used herein. Most of the researchers find a positive, non-linear relationship between export propensity and plant size (Kumar & Siddharthan 1994, Wagner 1995, Bernard & Wagner 1997, Wakelin 1998a, Bernard & Jensen 1999, Sterlacchini 1999). Other common findings are that older and larger firms are more likely to be exporters (Roberts & Tybout 1997, Barrios *et al.* 2003). Furthermore, more productive and skill-intensive firms are more likely to be exporters (Bernard & Jensen 2001, Barrios *et al.* 2003). Modern research, based on Melitz (2003), employs empirical models which link international trade to firm heterogeneity by including different variables representing firms' characteristics, e.g. productivity, financial variables, ownership (Redding 2011, Wagner 2012).

4.2.2.2. Firm-level studies, in line with the 'technology-based' theory

At the firm-level, 'technology-based' theories of international trade argue that R&D/innovation leads to market power which in turn increases export activities. This is generally referred to as the '*exporting by innovating'* hypothesis (Roper & Love 2002).

- **Studies, based on countries other than the UK**

Most of the studies on this subject, outside the UK, are in line with the above thought. For example, employing a dataset of 111 Israeli innovative companies during 1975-1981, Hirsch & Bijaoui (1985) study the relationship between R&D expenditure and firm export behaviour. They find that R&D expenditure plays a key role in explaining the firm-level change in export activities. However, Kumar & Siddharthan (1994) find that R&D has a positive impact on export propensity only in low and medium technology industries. To reach this conclusion, they examine the effect of R&D expenditure on firm export propensity, using a dataset of 640 Indian firms during 1988-1990**.** Similar to Kumar & Siddharthan (1994), Sterlacchini (1999) finds that in low R&D intense industries, innovation is positively and significantly correlated with the small firms' export activities. However, using a large sample of US manufacturing firms during 1983-1992, Bernard & Jensen (1999) provide evidence that firms introducing new products are more likely to become exporters.

Analysing a firm-level panel dataset of over 2000 Spanish firms during 1990-98, Barrios *et al*. (2003) explore the role of firm R&D and intra-industry spillovers on both the probability of a firm to export and its export intensity. They report that for both domestic and foreign firms, R&D intra-industry spillovers are positively associated with firms' export ratios.

Contrary to the above studies, several researchers provide evidence of inconsistent results. Analysing the exports and imports of multinational companies in Brazil, Willmore (1992) finds that R&D has no impact on exports. Ito & Pucik (1993) provide evidence that R&D intensity does not have a significant explanatory power in regard to Japanese firms' export propensity. Similar inconsistent results for Italy are found by Becchetti & Rossi (1998) and for Canada by Lefebvre *et al.* (1998). According to these researchers, some innovation proxies (e.g. R&D intensity) do not have any explanatory power in regard to firm export propensity in comparison to other innovation indicators.

- **UK studies**

In regard to the UK, Wakelin (1998a), in the same study, as described in the previous section, finds that the factors determining the export propensity for innovative and non-innovative firms are different. However, her analysis across all firms provides evidence that being an innovative firm, decreases firm export activities in terms of both the probability to export and export intensity. Wakelin's analysis of only innovative firms shows that the higher the level of innovations, the greater the likelihood of the firm being an exporter.

Employing a dataset of 110 UK firms during 1988-1992, Bleaney & Wakelin (2002) use an econometric model, incorporating both 'neo-endowment' and 'technology-based' variables as factors determining firm export activities. Their analysis confirms that the firm-specific determinants of the 'neo-endowment' theory are important for firm export activities. However, they stress that the key variable determining firm export activities is the 'technology-based' variable of innovation.

- **Comparative studies**

Using comparable plant-level surveys, Roper & Love (2002) show that there are great differences between the determinants of export activities of UK and German manufacturing firms. Operating with a variety of indicators, measuring firm innovative activities, they conclude that product innovation, however measured, is positively and significantly associated with firm probability to export in both UK and Germany. Yet, they evidence that in Germany, although the levels of innovation intensity are greater, the fraction of sales associated with new products is lower. They find some evidence of a negative link between the scale of innovation activity and export performance, and a great variety between innovative and non-innovative plants in their absorption of technological spillovers. The UK innovative plants are better at exploiting intra-industry spillovers, while in Germany, the non-innovative firms are better at absorbing regional and supply-chain spillovers.

Based on datasets from *OECD* countries innovation surveys, the '*OECD Innovation Micro-data'* study (Onodera 2008) finds that the percentage of innovative firms trading internationally is higher than the percentage of innovative firms operating domestically only. Thus, supporting the view that innovation positively affects firm export activities (Onodera 2008). The study also provides evidence that trade and investment can influence innovation in several ways: as sources of technology, via their competition effects and via the scale economies. Onodera (2008) stresses that although the effects of trade and investment are mainly positive, (e.g. technology transmission via imports, greater incentives through competition, positive impact of exports on scale economies), in some cases, their effects on innovation are negative (e.g. negative impact of imports on scale economies, declined rent available for innovation).

- **Service sector studies**

According to Ganotakis & Love (2011), most of the studies on the relationship between a firm's exports and its innovative activities are in regard to the manufacturing sector with only a few studies on the service sector. Analysing a panel data of 1468 UK firms in the service sector during 1988-2001, Gourlay *et al.* (2005) find that a firm's R&D intensity is positively associated with its probability of exporting and export intensity. In line with Gourlay *et al.* (2005), Love & Mansury (2007), researching a dataset of 206 US service firms during 2001-2003, also find that a firm's innovative activities are positively associated with its probability of exporting. Yet, contrary to Gourlay *et al.*

(2005), they find that within exporters, innovation is negatively associated with export intensity. Exploring the same subject, Chiru (2007) uses a set of 913 Canadian firms during 2001-2003 and cross-sectional multinomial logit regressions. He finds that highly innovative behaviour is linked to export orientation.

4.2.2.3. Summary of the literature in Section 4.2.2.

The studies in this section, generally, focus on investigating the effects of innovation on firm export activities (except Onodera's 2008 comparative study, which also looks at the effect of exports on innovation). Although most of the research, to date, finds that innovation affects firm export activity positively, the evidence in support of this is still not conclusive (Pla-Barber & Alegre 2007, Harris & Li 2009). In fact, several researchers provide evidence of inconsistent results (e.g. Willmore 1992, Ito & Pucik 1993, Lefebvre *et al*. 1998, Becchetti & Rossi 2000).

The next section reviews the literature in regard to the effects of firm export activities on innovation.

4.2.3 Firm-level studies: the effect of exports on R&D/innovation

According to the theoretical predictions of the 'endogenous growth' literature (e.g. Romer 1990; Grossman & Helpman 1991a,b; Young 1991; Aghion & Howitt 1998), the causality between innovative activities and exports may run from exports to innovation (Harris & Li 2009). The reasons are as follows:

- As competition at the level of international markets is stronger than the competition at the level of domestic markets, firms engaged in export activities are forced to invest in R&D, in order to develop products/services that meet the requirements of the customers in the foreign target market and thus, to remain competitive (Ganotakis & Love 2011).

- Through '*learning by exporting'*, firms can gain access to foreign knowledge and skills, advanced technologies, R&D of foreign firms and thus, improve their business processes, depending on the level of their *'absorptive capacity'* (the ability to identify and acquire new knowledge), (Harris & Li 2009). In turn, this will improve their productivity and efficiency (Kobrin 1991, Grossman & Helpman 1991a, Kraay 1999, Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Girma *et al*. 2004, Greenaway & Yu 2004, Salomon & Shaver 2005). In order to test the *'learning by exporting'* hypothesis, researchers employ performance-related variables (e.g. labour productivity, total factor productivity) to measure firms' learning behaviour (Ganotakis & Love 2011). However, the existing evidence on this perspective is scarce and weak (Girma *et al*. 2008). According to Harris & Li (2005), this may be due to the use of highly-aggregated data.

- There are economies of scale associated with exports. Firms' export activities expand the market, allowing for the 'lumpy' R&D fixed-costs to be recovered by the higher sales volume. In turn, this enhances firm productivity and encourages the firm to further invest in R&D (Ganotakis & Love 2011).

The literature on the effect of firm export activities on R&D/innovation is scarce. The majority of research is in regard to emerging or developing countries. This is because these nations are assumed to have more incentives, in terms of technological catch-up, economic convergence and *'learning by exporting'* (Ben-David & Loewy 1998, Guillen 2001, Ganotakis & Love 2011).

Studying the 'technology-gap' between the developed and developing countries, Hobday (1995) uses case studies of latecomer firms in regard to the East-Asian electronics sector. He provides evidence that innovation rates are increased by international consumer demand and by firms' exports. Hobday's (1995) study illustrates that knowledge is cumulative and that its evolution follows a firm's growth path. Analysing the Taiwanese electronics sector in 1986, 1991 and 1996, Aw *et al.* (2007) find a link between firms' exports and their innovative activities. In particular, firms' exports increase productivity, conditional on R&D expenditure and/or the provision of employee training in terms of creating human capital.

Researching the effect of exports on innovation by analysing cross-sectional data of 2019 firms in Germany's service sector during 1996-1998, Blind & Jungmittag (2004) show that exports positively affect the probability of being both product and process innovator.

In conclusion, the studies in this section investigate the effects of firm export activities on R&D/innovation. The next section evaluates the literature on the view that the relationship between R&D/innovation and exports is endogenous, both affecting each other positively, depending on firms' characteristics.

4.2.4 Firm-level studies on the endogenous relationship between R&D/innovation and exports

4.2.4.1. Historical studies

Most of the early research did not consider the possibility of endogeneity between firm innovative activities and exports (Veugelers & Cassiman 1999). However, some of the early researchers (e.g. Mansfield *et al.* 1979, Walker 1979, Levin & Reiss 1984) suggest that R&D and exports are jointly determined. Recent studies take into consideration the prediction of the 'endogenous growth' theory, which supports the two-way causality between exports and innovation (e.g. Cassiman & Martinez-Ros 2004, Lachenmaier & Wößmann 2006, Girma *at al*. 2008, Harris & Li 2009).

There is an increasing interest in conducting such studies in regard to the emerging economies, for the reasons explained in the previous section. Examining the relationship between R&D and both export propensity and growth, using a large dataset of China's manufacturing firms, Zhao & Li (1997) employ logistic and simultaneous empirical models. They find that R&D positively affects both export propensity and growth. Their simultaneous model also shows that the relationship between R&D and exports is reciprocal and that other factors, in line with the 'neo-endowment theory', such as capital intensity, profitability and relative firm size, also affect both export propensity and growth in different ways. The study provides strong support for the 'technology-based' theories.

Examining a sample of 981 German manufacturing firms in 2001, Lachenmaier & Wößmann (2006) employ an instrumental variable model in their empirical analysis of exports, with innovation as an endogenous determinant. As instruments, they use a number of 'impulses'/push factors and impediments to innovation. Controlling for endogeneity, they provide evidence that the export share of innovative firms is about 12.6% higher than those of non-innovative firms and that over half of this difference is associated with the impact of innovation on export activities.

In their comparative analysis of UK firms during 1996-2003 and of Irish firms during 2000-2004, Girma *et al.* (2008) initially employ a bivariate Probit analysis to simultaneously model firms' R&D and export decisions. As a next stage, they replace the dichotomous variables export and R&D with their truncated counterpart variables (e.g. intensities) and model these simultaneously, employing a 3SLS estimation technique. Their results provide evidence that, in regard to the Irish firms, export activities encourage R&D, but this is not the case in regard to the UK firms, where what matters is being an exporter, not the export intensity. According to Girma *et al.* (2008), the difference may be because Irish firms' exports are directed to more advanced nations in comparison to the UK firms, benefiting from *'learning by exporting'*. However, there are potential issues with their analysis as both datasets may not be directly comparable (Ganotakis & Love 2011).

Analysing both manufacturing and services sectors in the UK in a dataset from the *CIS,* 2001 and the '2000 Annual Respondents Database for the UK', Harris & Li (2009) examine the relationship between exports and R&D expenditure. They use an empirical approach that allows them to account for the joint endogeneity of R&D and exports: a two-stage Heckman's technique and simultaneous estimation. The authors provide evidence that endogenous R&D is important for encouraging firms to become exporters, however, R&D expenditure does not have an effect on the export intensity of the exporters.

Examining the relationship between R&D, product innovation and exports Ganotakis & Love (2011) use a cross-sectional dataset of new technology-based UK firms. They employ a recursive system of three equations to analyse the relationship between R&D-innovation and exports, allowing for endogeneity and sample 'selection' bias between innovation and exports. Similar to Lachenmaier & Wößmann (2006) and Harris & Li (2009), they use instrumental variable techniques. Their findings are in line with those of Harris & Li (2009), providing evidence that the likelihood of engaging in export activities is higher for innovative firms than for non-innovative ones. However, increased innovation does not have an effect on the export intensity of the exporters.

4.2.4.2. Modern theoretical developments

A new strand of the literature on the relationship between innovation and export activities, in line with the 'endogenous growth' theory, has put forward a theoretically sound framework that endogenises firm heterogeneity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011, Harris & Moffat 2012). It is based on the needs of the firms to engage in productivity enhancing processes (e.g. R&D/innovations) before becoming exporters, and to use productivity enhancing feedback after becoming exporters. This defines the two-way causal relationship between exports and R&D/innovation (Harris & Moffat 2012). According to Harris & Moffat (2012) on the one hand, as the firms' benefits from engaging in R&D/innovation and export activities increase with firms' underlying productivity, firms with greater productivity will be prone to 'self-selection' bias. That is, they will engage in further R&D/innovation activities and exports. On the other hand, firms' R&D/innovation and export activities also have a direct impact on the future firms' productivity, thus, reinforcing endogeneity via the 'self-selection' process.

The research on this subject is scarce. The general findings are that a firm's decisions on whether to innovate or to export are interdependent and that they both may endogenously influence the firm's future productivity (Damijan *at al.* 2008, Aw *et al*. 2011, Harris & Moffat 2012). As the link between R&D stock of knowledge and firm productivity is a subject of the next chapter, we will evaluate the literature on the topic in Chapter 5. In Chapter 4 we will only consider to what extent our econometric model and findings are in line with the above theoretical framework in terms of the relationship between R&D stock of knowledge and firm export activities.

4.3 Theory: hypotheses to be tested

Following the literature review in Section 4.2, in this section, we describe the hypotheses to be tested.

4.3.1 Does a firm's R&D stock of knowledge positively affect its export activities?

In line with the literature review in Section 4.2.2, the first hypothesis in this chapter is outlined as:

H3(Ch.4, H1): A firm's R&D stock of knowledge positively affects its export activities ('exporting by innovating' hypothesis).

At a firm level, 'technology-based' theories of international trade argue that R&D/innovation leads to market power, which in turn increases export activities

(Roper & Love 2002). In this sense, the general consensus of the literature is that the causality of the relationship between firm innovation and exports flows from innovation to exports. Most of the studies, to date, find that innovation positively affects firms' export activity (Wakelin 1998a, Sterlacchini 1999, Bleaney & Wakelin 2002, Gourlay *et al.* 2005, Chiru 2007). However, the evidence in support of this is still not conclusive (Pla-Barber & Alegre 2007, Harris & Li 2009).

4.3.2 Does a firm's export activities positively affect its R&D stock of knowledge?

The second hypothesis to be tested is derived from the literature in Section 4.2.3:

H4(Ch.4, H2): A firms' export activities positively affect its R&D stock of knowledge, ('*innovating by exporting'* hypothesis).

According to the theoretical predictions of the 'endogenous growth' literature (e.g. Romer 1990; Grossman & Helpman 1991a,b; Young 1991; Aghion & Howitt 1998), the causality between firms' innovative activities and exports may run from exports to innovation (Harris & Li 2009). Through *'learning by exporting'*, firms can have access to foreign knowledge and skills, advanced 'know-how', R&D of foreign firms, and thus, improve their business processes, conditioning on their level of '*absorptive capacity'* (Haris & Li 2009). Furthermore, firms' export activities expand the market, permitting for the 'bulky' R&D fixed-costs to be retrieved by the greater sales volume. In turn, this boosts firm productivity and efficiency gains, and encourages firms to further invest in R&D (Ganotakis & Love 2011).

4.3.3 Endogeneity of firm exports and R&D stock of knowledge

Section 4.2.4. is a source of the third hypothesis to be tested:

H5(Ch.4, H3): A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics.

The hypothesis is in line with the new strand of the literature on the correlation between innovation and export activities, linked to the 'endogenous growth' theory, which endogenises firm heterogeneity (Atkeson & Burstein 2010, Aw *et al.* 2011, Bustos 2011, Harris & Moffat 2012), the mechanism of which is explained in Section 4.2.4.2. Modern theoretical developments.

The general findings are that firms' decisions on whether to innovate and whether to export are interdependent and that they both may endogenously affect firms' future productivity (Aw *et al*. 2008, Damijan *at al*. 2008, Aw *et al*. 2011, Harris & Moffat 2012).

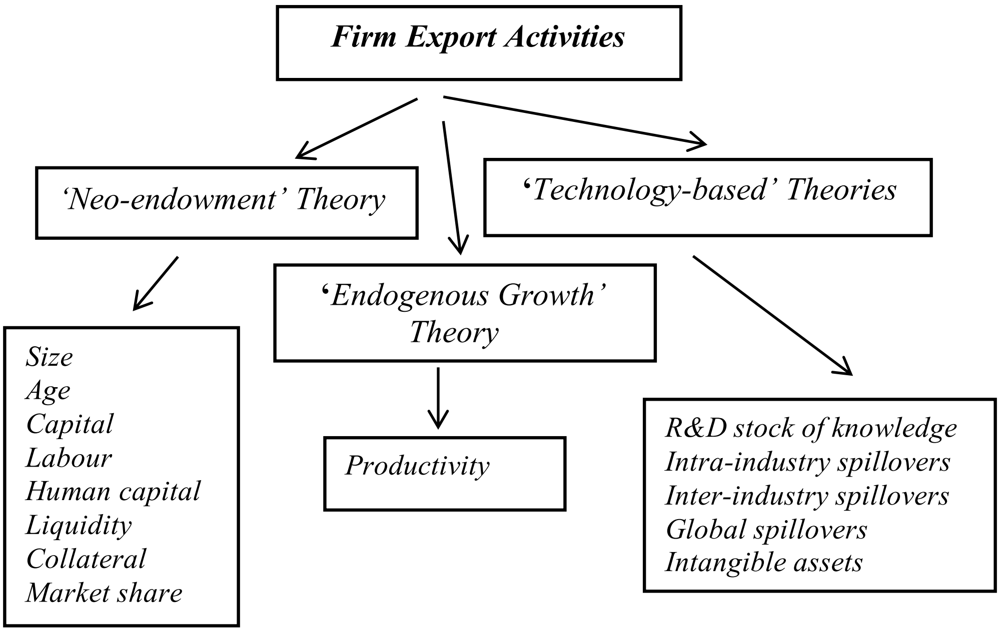
The next section describes the baseline specifications and the estimation methodologies this chapter employs to test the above hypotheses.

4.4 Baseline specifications and estimation methodology

Accounting for the key theoretical models ('neo-endowment', 'technology based' and 'endogenous growth' theories) and recognising the two-way causality between R&D and exports, this chapter's strategy is to employ a comprehensive system of similar empirical models, within which there are different options. The aim is to investigate, in a comprehensive and reliable manner, the links between firm export activities and R&D stock of knowledge, their interdependencies, dynamics, endogeneity and potential simultaneity, while accounting for firms' characteristics.

The conceptual framework is based on the literature reviewed. The variables used are identified by the 'neo-endowment', 'technology-based' and 'endogenous growth' theories (Figure 8).

Figure 8: List of variables according to the 'neo-endowment', 'technology-based' and 'endogenous growth' theories of firm export activities



In Section 4.4.1 we provide the baseline specification and estimation methodology for testing our first hypothesis in this chapter, while in Section 4.4.2 we describe the baseline specification and estimation methodology for testing all hypotheses in Chapter 4 simultaneously.

4.4.1. Baseline specification and estimation methodology for testing the 'exporting by innovating' hypothesis

In this section, first, we outline our model in regard to the first hypothesis in this chapter: *'exporting by innovating'* - Section 4.4.1.1 and second, we describe our estimation methodology - Section 4.4.1.2.

4.4.1.1. Modelling the effect of a firm's R&D stock of knowledge on export activities

The first estimation model aims to provide evidence on the research question: *'Does an increase in a firm's R&D stock of knowledge lead to an increase in firm performance, measured by its exports?'* It tests the first hypothesis in this study:

H3(Ch.4, H1): A firm's R&D stock of knowledge positively affects its export activities.

In this model, we include a comprehensive set of firms' heterogeneity dimensions, discussed in the literature review, as determinants of firms' export activities. In terms of the 'neo-endowment' theory, all variables listed in Figure 9, ('*Neo-endowment' Theory*), are included. In regard to the 'technology-based' theories, also included are all variables as per Figure 9, ('*Technology-based' Theories*). Accounting for the 'endogenous growth' theory, we include firm productivity in our model.

Addressing the hypothesis discussed in the literature review, (Section 4.2.2), we include firm R&D stock of knowledge in our model as a measure of firm innovation as well as intra- and inter-industry spillovers. The different types of spillovers account for different intra- as well as inter-industry heterogeneity dimensions in terms of technology levels. We also include firm intangible assets intensity as complementary to firm investment in R&D. The sum of the total global spillovers is also included. The variables are in line with the 'technology-based' theories of trade.

In their empirical framework, Clerides *et al*. (1998), Bernard & Jensen (1999, 2004a), Aw *et al*. (2000) and Greenaway & Kneller (2004) all include 'size' and 'productivity' variables, evidencing that firms which export are, in general, more productive and larger than firms which do not export. Therefore, we include firm labour productivity in our model. The inclusion of the number of employees as a size control variable also features in similar studies (Love & Roper 2001, Ruane & Sutherland 2005, Lachenmaier & Wößmann 2006). In this research, we include two measures of firm size: firm absolute size - the number of employees and firm market share. Firm market share also accounts for the competitive environment, faced by the firm, in line with the 'neo-endowment' theory (Wakelin 1998a, Roper & Love 2002).

Although productivity and firm size are considered the key dimensions of firms' heterogeneity included in the models of determining firms' export activities, some other dimensions have also been explored. For instance, Yeaple (2005) considers heterogeneity in terms of different technologies used, while Davidson *et al.* (2005) permit for different salaries to be paid. Our R&D associated variables, as well as our human capital (measured by the firm's remuneration per employee relative to its industry's remuneration per employee), could also be seen in such terms. High wages are positively linked to the probability of a firm becoming an exporter (Bleaney & Wakelin 2002; Bernard & Jensen 2004a,b,c; Ruane & Sutherland 2005; Davidson *et al.* 2005). Employing wage as a proxy for skills of employees is based on Mincer's (1974) human capital theory, which advocates that human capital (education, experience and personal characteristics) is the main determinant of wage rates (Willis 1999).

In line with Greenaway *et al.* (2007), the model includes a financial dimension of firms' heterogeneity to test whether there is an association between a firm's financial health and its export activities. In this research, financial health is measured by firm liquidity ratio (as per Chaney 2005, Greenaway *et al.* 2007) and collateral, (as per Carpenter & Petersen 2002, Almeida *et al*. 2004, Spaliara 2008, Chen & Guariglia 2009). The greater the liquidity ratio, the better the firm's financial health. Similarly, more tangible assets attract more external financing, as tangibility augments the money that can be recovered by creditors in a case of insolvency. Although maintaining more liquid assets may be seen as less risky by creditors, it may lead to high opportunity costs for the firm (Chen & Guariglia 2013). Furthermore, a very high liquidity ratio may downgrade the credibility of a firm to its creditors: such high liquidity ratio unlocks, in fact, numerous trading strategies that may be unfavourable to creditors' interests (Myers & Rajan 1998). Therefore, excessive liquidity ratio may, in some cases, decrease a firm's ability to obtain external finance.

Greenaway *et al.* (2007) find that exporters are financially healthier than non-exporters. According to them, the inclusion of financial health variables is based on the literature exploring the influence of capital market imperfections on firms' undertakings. More specifically, on the view that financial constraints affect firm employment, investment, and R&D (for surveys on the subject, see Hubbard 1998 and Bond & van Reenen 2005). There are also theoretical views that financial health influences firms' decisions to export (Chaney 2005, Van Biesebroeck 2006, Blalock & Roy 2006).

In line with the above literature, our model of the determinants of firm export activities (proxied by the firm's export intensity - $EI_{i,t}$ and measured by the firm's exports over its total sales) in terms of the 'technology-based' theories are: the firm's R&D stock of knowledge - $K_{i,t}$, (calculated as per Chapter 3, Section 3.5.1.1), the firm's intangible assets - $A_{i,t}$ (proxied by the firm's intangible assets intensity - the firm's intangible assets divided by its total assets), intra-industry - $K_{t,1}$, inter-industry - $K_{t,2}$, and global spillovers - $K_{t,f}$ (calculated as per Chapter 3, Section 3.5.1.2).

In terms of the 'endogenous growth' theory, the firm's labour productivity - $LP_{i,t}$ (measured by the firm's value-added divided by the number of employees) is included.

Accounting for the 'neo-endowment' theory, we include in our model the firm's age - $Q_{i,t}$, capital stock - $C_{i,t}$ (proxied by the real value of the firm's fixed assets and calculated using the perpetual inventory method, as per Chapter 3, Section 3.5.1.3), labour - $L_{i,t}$ (i.e. the number of employees, controlling for firm size), human capital - $E_{i,t}$ (proxied by the firm's per-employee remuneration, divided by its industry's per employee remuneration). Accounting for the firm's financial health, we include in our model the firm's liquidity ratio - $LiqR_{i,t}$, (proxied by the firm's current assets minus its current liabilities, divided by its total assets) and collateral - $COL_{i,t}$, (measured by the firm's tangible assets over its total assets). Accounting for the firm's competitive environment, the firm's market share - $MS_{i,t}$, (measured by the firm's share of its industry's total sales) is also included.

In line with the existing studies (Roberts & Tybout 1997; Bernard & Jensen 1999, 2004a, Greenaway *et al.* 2007), all right-hand side explanatory variables are lagged once[27], except time and year dummies. Expressed in a logarithmic form, our

[27] Firm age - $Q_{i,t}$, entering the model either lagged once or in its contemporaneous form, does not alter the outcomes significantly.

dynamic model in terms of the determinants of the firm's export intensity - $EI_{i,t}$, is presented in Equation (7),

$$
\begin{aligned}
lnEI_{i,t} = \; & a_0 + \; a_1 lnEI_{i,t(t-1)} + \; a_2 lnC_{i,t(t-1)} \\
& + a_3 lnE_{i,t(t-1)} + a_4 lnLP_{i,t(t-1)} + a_5 lnL_{i,t(t-1)} + a_6 lnMS_{i,t(t-1)} \\
& + a_7 lnCOL_{i,t(t-1)} + a_8 lnLiqR_{i,t(t-1)} + a_9 lnA_{i,t(t-1)} + a_{10} lnQ_{i,t(t-1)} \\
& + a_{11} lnK_{i,t(t-1)} + a_{12} lnK_{t(t-1),1} + a_{13} lnK_{t(t-1),2} + a_{14} lnK_{t(t-1),f} \\
& + Ind.D. + TimeD. + v_i + \varepsilon_{i,t}
\end{aligned}
$$

(Equation 7)

where the subscripts *i* and *t* represent firm and time respectively, and the *a'*s are the input's *j* elasticity (some of the parameters we are interested in estimating).

The error term contains two components. The firm-specific component - v_i, controls for any time-invariant firm characteristics which may affect firm export intensity, and also, any time-invariant components of the measurement error which may affect any variable in our model. The second component - $\varepsilon_{i,t}$, symbolises the idiosyncratic *i.i.d.* element.

As most of the empirical studies in this area (e.g. Wakelin 2001; Jefferson *et al.* 2006), we include industry dummies in order to capture industry-specific effects. However, Mairesse & Cuneo (1985) and Mairesse & Sassenou (1991) claim that industry-specific effects are better controlled for by including variables in the model which have been omitted, e.g. the level of technological opportunity in the industry, and inter-industry spillovers, rather than industry dummies. Technological opportunities in this model are proxied by industry classifications (industry dummies) and also, by including intra- and inter-industry spillovers as well as global spillovers.

This model also includes time dummies to control for the likely impact of business cycles and the changes in interest and exchange rates.

Dynamic models are in line with the literature which emphasises the presence of significant hysteresis in export market participation (Bernard & Jensen 2004c, Campa 2004, Greenaway *at al.* 2007).

In line with most of the literature reviewed in Section 4.2.2, (e.g. Hirsch & Bijaoui 1985, Bernard & Jensen 1999, Bleaney & Wakelin 2002, Roper & Love 2002, Gourlay *et al.* 2005, Love & Mansury 2007, Chiru 2007), we expect the coefficient on R&D stock of knowledge to be positive and significant. Wakelin's (1998a) analysis of only innovative firms shows that the higher the level of innovation, the greater the likelihood of the firm being an exporter. Therefore, we expect to find similar results in our analysis of the 'Innovators' subset. Accounting for the fact that there are complementarities between firm R&D stock of knowledge and intangible assets, according to Mohnen & Hall's (2013) survey, we also expect the coefficient on intangible assets intensity variable to be positive and significant. In line with Roper & Love (2002) and Barrios *et al*. (2003) who evidence that intra-industry spillovers are positively associated with firms' export ratios, we expect the coefficients on our intra-industry spillovers to be positive and significant. The environments for positive and negative spillovers differ between firms, and theory alone cannot forecast which effect may emerge (Kafouros & Buckley 2008). Therefore, we have no conclusive expectations in regard to the effects of inter-industry and global spillovers.

According to the literature review, firms which export are generally more productive and larger than firms which do not export (Clerides *et al*. 1998; Bernard &

Jensen 1999, 2004a; Aw *et al*. 2000; Greenaway & Kneller 2004). Therefore, we expect to find similar results.

High wages are positively linked to firms' export activities (Bleaney & Wakelin 2002; Bernard & Jensen 2004a,b,c; Ruane & Sutherland 2005; Davidson *et al.* 2005). In these terms, we expect the coefficient on the human capital variable to be positive and significant.

In line with the view that exporters are generally financially healthy (Greenaway *et al.* 2007, Spaliara 2008, Chen & Guariglia 2009), we expect the coefficient on the liquidy ratio to be positive while the coefficient on collateral to be negative.

However, we expect some diversity in the results in regard to both 'All-Firms' and 'Innovators' datasets.

4.4.1.2. Estimation methodology

In order to facilitate comparability of the results and to provide consistency throughout the entire thesis, our econometric strategy encompasses a comprehensive system of empirical approaches, within which there are different options. Therefore, following our standard econometric approach in regard to Chapters 3 to 5, we use the pooled OLS, the FE, and the dynamic, robust, one-step System GMM, comprehensively described in Chapter 3, (Section 3.4.2).

In order to account for firms' heterogeneity, in our model, we include age, productivity, intangible assets intensity, financial variables, human capital and market share. We also account for firms' heterogeneity by including intra-, inter-industry and global spillovers. Export intensity, productivity, capital, labour, market share, human capital, intangibles and the financial variables are potentially endogenous as they are all likely to be correlated with the firm-specific effects, productivity shocks and measurement errors, all of which are included collectively in the error term of the models. The R&D stock of knowledge is also potentially endogenous as there may be a double causality between firm export activities and R&D stock of knowledge. The strictly exogenous variables are the industry and year dummies, firm age, intra-, inter-industry and global spillovers.

Our preferred one-step, System GMM with robust standard errors controls for unobserved heterogeneity across firms and endogeneity (Arellano & Bond 1991, Blundell & Bond 1998). In order for our GMM estimators to be valid, the instruments must be exogenous to fulfil the orthogonality conditions. Therefore, we perform a number of tests, which are elaborately explained in Chapter 3, (Section 3.4.2 - Estimation methodology).

4.4.2 Endogeneity of firm exports and R&D stock of knowledge: baseline specification and estimation methodology

This section tests all hypotheses in Chapter 5 simultaneously, namely:

H3(Ch.4, H1): A firm's R&D stock of knowledge positively affects its export activities.

H4(Ch.4, H2): A firm's export activities positively affect its R&D stock of knowledge.

H5(Ch.4, H3): A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics.

The first hypothesis has been comprehensively reviewed in Section 4.2.2. and Section 4.4.1. Section 4.2.3. provides the foundation of the second hypothesis, while Section 4.2.4 details the background of the third hypothesis to be tested.

4.4.2.1. Baseline specification

To account for the new developments in the literature that firm R&D stock of knowledge and exports are endogenous, they both affect each other positively, depending on firms' characteristics, and to better understand the linkages between these variables, this research uses a simultaneous, multi-equation system (Equation 8). Thus, we test all three hypotheses in this chapter concurrently. In line with the modern theoretical developments in this area, we model the two-way causality between a firm's R&D stock of knowledge and its exports, conditioning on productivity. When testing all hypotheses in this chapter, due to the more complex technique used - i.e. the GSEM, a reduced, but still a comprehensive number of variables are included, as per 'neo-endowment', 'technology-based' and 'endogenous growth' theories (Figure 6)[28].

First, we employ a Probit selection model, Equation (8/1), to establish the likelihood that a firm will become an exporter. Second, the Probit model is combined with three linear regression models representing a firm's export intensity - Equation (8/2), R&D stock of knowledge - Equation (8/3), and its productivity - Equation (8/4).

Expressed in a logarithmic form, our system of equations is presented in Equation (8),

$$DE_{i,t} = \alpha_0 + \alpha_1 lnLP_{i,t} + \alpha_2 lnK_{i,t} + \alpha_3 lnCOL_{i,t} + \alpha_4 lnL_{i,t} + Ind.D. + TimeD. + \mathcal{L} + \varepsilon_{i,t}$$

Equation (8/1)

[28] To our knowledge, to date, there is no other study which uses the GSEM approach in this area of research. Therefore, this study represents a modest attempt to apply the GSEM technique in order to investigate the two-way causal relationship between firm R&D stock of knowledge and export activities, conditioning on productivity.

$$lnEI_{i,t} = \gamma_0 + \gamma_1 lnLP_{i,t(t-1)} + \gamma_2 lnK_{i,t(t-1)} + \gamma_3 lnCOL_{i,t(t-1))} + \gamma_4 lnE_{i,t(t-1)} + \gamma_5 lnMS_{i,t(t-1)} + \gamma_6 lnQ_{i,t(t-1)} + \gamma_7 \mathcal{L} + Ind.D. + TimeD. + \gamma_i + v_{i,t}$$

Equation (8/2)

$$lnK_{i,t} = \delta_0 + \delta_1 lnLP_{i,t(t-1)} + \delta_2 lnEI_{i,t(t-1)} + \delta_3 lnMS_{i,t(t-1))} + \delta_4 lnE_{i,t(t-1)} + \delta_5 \mathcal{L} + Ind.D. + TimeD. + \delta_i + u_{i,t}$$

Equation (8/3)

$$lnLP_{i,t} = \lambda_0 + \lambda_1 lnEI_{i,t(t-1)} + \lambda_2 lnK_{i,t(t-1)} + \lambda_3 lnC_{i,t(t-1))} + \lambda_4 lnMS_{i,t(t-1)} + \lambda_5 lnE_{i,t(t-1)} + \lambda_6 \mathcal{L} + Ind.D. + TimeD. + \lambda_i + \xi_{i,t}$$

Equation (8/4)

where the subscripts *i* and *t* denote firm and time, respectively.

In the first equation, $DE_{i,t}$ is a dummy variable equivalent to 1 if a firm *i* exported in year *t*, and 0 if not, $L_{i,t}$ is the number of employees, (a size control variable), $LP_{i,t}$ is a labour productivity (proxied by a firm's value-added divided by the number of employees), $COL_{i,t}$ - a firm's collateral (measuring the firm's financial health, proxied by the firm's tangible assets over its total assets), and $K_{i,t}$ denotes the firm's R&D stock of knowledge (proxied by the firm's R&D stock of knowledge per employees).

In the second equation, $EI_{i,t}$ is the firm's export intensity (the ratio between the firm's exports and its total sales), $MS_{i,t}$ is the firm's market share (measured as the firm share of total sales divided by its industry's total sales), $E_{i,t}$ signifies human capital (proxied by the firm's per-employee remuneration relative to its industry's per employee remuneration), and $Q_{i,t}$ is the firm's age (measured in years - current year minus incorporation year).

In the third equation, all variables are symbolised in the same way as per Equations (8/1) and (8/2). In the fourth equation, the only new variable introduced is the firm's physical capital stock, denoted by $C_{i,t}$ (proxied by the firm's physical capital stock per employee). In contrast to the model of Section 4.4.1, in this GSEM model the variables R&D stock of knowledge - $K_{i,t}$ and physical capital stock - $C_{i,t}$ are expressed in intensity form (per employee).

Equations (8/1) to (8/4) also include time dummies, which control for the likely impact of business cycles and changes in interest and exchange rates. Industry dummies are also incorporated into all equations to capture industry fixed effects.

The error term contains two components. The first one is the firm-specific component and the second one denotes the idiosyncratic component. The idiosyncratic error terms of Equations (8/1), (8/2), (8/3), and (8/4) are symbolised as ε, ν, υ and ξ, respectively. The firm-specific fixed effects of Equations (8/2) to (8/4) are symbolised as γ, δ and λ. The latent variable - $\mathcal{L}$, included in all equations, deals with the issue of selectivity, as in the second equation $EI_{i,t}$ is measured only for the exporters.

In line with existing studies (Roberts & Tybout 1997; Bernard & Jensen 1999, 2004a, Greenaway *et al.* 2007), all time-variant, right-hand side explanatory variables of the Equation (1/2) are lagged once[29]. In line with the modern research in this area, e.g. Girma *et al*. (2008) and Damijan *et al.* (2010), who estimate simultaneously firms' decisions to enter export markets and engage in R&D activity, conditioned on productivity, we include only the one-period lagged values of all time-variant, right-hand side variables in Equations (1/3) and (1/4) to account for endogeneity. In line with

[29] Firm age - $Q_{i,t}$, entering the model either lagged once or in its contemporaneous form, does not alter the outcomes significantly.

Harris & Moffat (2012), all right-hand side variables of Equation (8/1) - the Probit selection equation, are contemporaneous.

Equations (8/1) and (8/2) address the hypothesis of *'exporting by innovating'* as discussed in Section 4.4.1. Estimating them simultaneously, we account for the likely 'selection' bias. The two 'export' equations, derived from the literature reviewed, consider a firm's export propensity and export intensity as functions of variables, which are derived from 'neo-endowment', 'technology-based' and 'endogenous growth' theories. The variables included, as well as the justification for their inclusion, are as per Section 4.4.1. In regard to the 'Export intensity' equation, in terms of the 'neo-endowment' theory, also included are both firm absolute size, $L_{i,t}$ - the number of employees and its market share, $MS_{i,t}$, (accounting also for the firm's competitive environment), collateral - $COL_{i,t}$, human capital - $E_{i,t}$, and the firm's age - $Q_{i,t}$, all listed in Figure 9, (*'Neo-endowment' Theory*). In regard to the 'technology-based' theories, included is the R&D stock of knowledge - $K_{i,t}$, listed in Figure 9, (*'Technology-based' Theories*). Accounting for the 'endogenous growth' theory, we include firm productivity - $LP_{i,t}$. In both equations, we expect the coefficients on the R&D stock of knowledge, productivity and both size variables to be positive and significant.

Equation (8/3) addresses explicitly the *'innovating by exporting'* hypothesis, namely that, exports lead to intensified R&D (Girma *et al.* 2008, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013), which has not been so widely researched as the first hypothesis. Section 4.2.3 of the literature review addresses specifically this hypothesis.

The R&D Equation (8/3) is in line with the relevant literature in regard to the determinants of firms' R&D (Griliches 1984, Hall 2002, Lynskey 2004, Aw *et al*. 2007, Girma *et al.* 2008, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013). Research on the determinants of R&D emphasises the effects of firm size, and other firm-specific factors such as productivity, exports and human capital (Griliches 1984, Hall 2002; Lynskey 2004), all included in Equation (8/3). As rivalry at the level of overseas markets is tougher than the rivalry at the level of national markets, firms engaged in export activities are forced to invest in R&D in order to create products and services that meet the demand of the customers of the foreign target market, and thus, stay competitive (Ganotakis & Love 2011). Firms' export activities expand the market, allowing for the R&D fixed-costs to be recovered by the higher sales volume (Ganotakis & Love 2011). Therefore, we include both firm export intensity and a measure of competition - firm market share (also controlling for firm size). Firm market share is also included in many firm-level studies as an important factor influencing R&D (e.g. Crepon *et al*. 1998, Baum *et al.* 2015).

Through *'learning by exporting'*, firms can access the pool of foreign knowledge and skills, new 'know-how', R&D of foreign firms and thus, improve their business processes, depending on the level of their 'absorptive capacity', (Harris & Li 2009). (Therefore, we also include in this model the human capital variable.) In turn, this will improve their productivity and efficiency (Kobrin 1991, Grossman & Helpman 1991a, Kraay 1999, Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Girma *et al*. 2004, Greenaway & Yu 2004, Salomon & Shaver 2005). In order to test the *'learning by exporting'* hypothesis, researchers employ performance-related variables (e.g. labour productivity) as proxies for firms' learning behaviour (Ganotakis & Love 2011). Therefore, in our model, we also include firm productivity.

Similar discussions are also found in the 'endogenous growth' and 'trade' literature, accounting for the firms' export activities as determinants of R&D/innovation (e.g. Rivera & Romer 1991a; Grossman & Helpman 1990, 1991a,b, 1994; Aghion & Howitt 1992, 1998; Ericson & Pakes 1995; Klette & Griliches 2000; Atkeson & Berstein 2010). Generally, they find that firms' exports lead to technology exchange, expanded scale of production and intensified innovation, which in turn, lead to lower costs, higher variety of products/services and higher productivity gains for the firm (Bravo-Ortega *et al.* 2013).

Therefore, we expect the coefficients on the export intensity, productivity and human capital variables to be positive and significant.

Equation (8/4) is a labour productivity model, used by many researchers. The effects of R&D on productivity has been recently surveyed by Hall *et al*. (2009); Hall (2011); and Mohnen & Hall (2013). The general agreement in the literature is that the impact of R&D on productivity is positive. Therefore, the R&D stock of knowledge is included in this equation. The justification for the inclusion of the R&D stock of knowledge also comes from the *'learning by exporting'* hypothesis, addressed in this model. The literature on the view that firms' exports improve productivity in several ways, according to Greenaway & Kneller (2007), provides the justification for incorporating firm export intensity in this equation. The exposure to the international markets and interactions with foreign competitors and customers makes firms more aware of products and processes, thus reducing their costs while increasing quality. Exporting also allows access to bigger markets, increasing production. The fierce competition from foreign markets forces firms to become more efficient, increasing their R&D expenditure. These arguments are also found in 'endogenous growth' and 'trade' literature (e.g. Rivera & Romer 1990; Aghion & Howitt 1992, 1998; Klette & Griliches 2000; Atkeson & Berstein 2007). Essentially, they find that technology exchange, expanded scale of production and intensified innovation lead to lower costs, higher variety of products/services, and higher productivity gains for the firm (Bravo-Ortega *et al.* 2013). For a comprehensive literature summary on productivity and exports see Wagner (2007) and Greenaway & Kneller (2007). For a summary on '*learning by exporting*', see Girma *et al.* (2004).

In line with this hypothesis is the 'absorptive capacity' theory linked to the 'human capital' theory. Firms with a higher level of human capital can better absorb and assimilate other firms' knowledge (Cohen & Levinthal 1990). Therefore, we include the human capital variable in this model. The physical capital variable is a conventional input in the production function, while market share is a size control variable, also accounting for the firms' competitive environment.

Therefore, we expect the coefficients on the R&D stock of knowledge, export intensity and market share variables to be positive and significant.

Estimating both Equation (8/1) and Equation (8/2) simultaneously, we address the 'self-selection' bias hypothesis, that high productivity generates exports. This hypothesis is based on the literature reviewed, according to which there are fixed and sunk costs associated with the entry into export markets. Therefore, more productive firms are more likely to export (Melitz 2003, Greenaway & Kneller 2004, Arnold & Hussinger 2005, Alvarez & Lopez 2005, Harris & Li 2009). Hence, firms 'self-select' to export.

In line with the theoretical framework, our general expectations are as follows. We expect to find support for all our hypotheses. In particular, in regard to both 'exports' equations, we expect in both models to find the coefficients on the R&D stock of knowledge positive and significant, showing support for our *'exporting by innovating'* hypothesis. In regard to our 'R&D stock of knowledge' equation, we expect to find that the firm's export activities positively affect its R&D stock of knowledge, in support of our *'innovating by exporting'* hypothesis. Modelling the two-way causality between a firm's R&D stock of knowledge and exports, conditioning on its productivity, we expect to find support for the new developments in the literature that, a firm's R&D stock of knowledge and exports are endogenous, they both affect each other positively, depending on firm productivity.

4.4.2.2. Estimation methodology

The econometric model in Section 4.4.1.1 represents the one-way relationship between firm R&D stock of knowledge and exports, based on the relevant literature, not accounting appropriately for the simultaneity and interdependency issues, different dynamics between the variables of interest, and the 'self-selection' bias. As we want to test all hypotheses in Chapter 4 simultaneously, we need an econometric approach which can account for the two-way causality between a firm's R&D stock of knowledge and its exports, depending on firm characteristics.

Using an econometric technique, the Asymptotic Least Squares (ALS), new in this area, Bravo-Ortega *et al.* (2013) explore the above links in Chilean plants. The benefits of this approach, according to the authors, are that the multi-equation system can be estimated simultaneously, taking into considerations the discrete characteristics of some of the variables and the simultaneity of different interactions, having better statistical properties in comparison to other estimation techniques, such as 2SLS or

GMM (Bravo-Ortega *et al*. 2013). However, recently another approach, i.e. the GSEM has been developed, which proves to be very useful in such situations.

This research will use a simultaneous multi-equation system to account for the two-way causality between R&D stock of knowledge and exports, conditioning on firms' characteristics. Therefore, it employs the GSEM - a unified estimation approach with which both a firm's propensity to become an exporter as well as the observable consequences of being an exporter (in terms of export intensity) can be modelled simultaneously. In particular, we estimate the two-way causality between a firm's R&D stock of knowledge and its exports, conditioning on productivity by employing the GSEM method with a full-information maximum likelihood estimator. That is, the GSEM technique estimates the above relationship as one system of simultaneous, non-recursive equations. The equations are non-recursive as there are feedback loops running in both directions between a firm's export activities and its R&D stock of knowledge, conditioned on productivity. GSEM is a multivariate method that tolerates estimation of a system of equations. This approach accounts for the dynamics in the relationship between firm R&D stock of knowledge, exports and productivity. Each dependent variable enters the equations of the other two dependent variables. The GSEM is very appropriate for this type of modelling, allowing for an accounting of several potential issues, unaccounted for by the single-equation modelling.

The empirical strategy, in this case, involves a GSEM procedure consisting of four regressions - Equation (8). The GSEM model, as a whole, addresses all three hypotheses in Chapter 4. Equations (8/1) and (8/2) - the export activities equations, address the first hypothesis - *'exporting by innovating'*. Equation (8/3) addresses our second hypothesis - '*innovating by exporting'*. Equation (8/4) is the labour productivity model. Taken together, all four equations account for the modern theoretical developments, which endogenise firm heterogeneity, summarised in our third hypothesis: *A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics*.

To date, some of the studies dealt with endogeneity by using instrumental variable in regard to their measure of innovation/R&D[30]. Dealing with the selection bias, some researchers (e.g. Becker & Egger 2009) compare firm performance of export activities for innovating and non-innovating firms, while other researchers (e.g., Girma *et al*. 2008, Damijan *et al.* 2010) estimate simultaneously firms' decisions to enter the export markets and engage in R&D activity, including only the one-period lagged values of the hypothetically endogenous variables in each equation.

In GSEM, by including the same unobserved component in all our equations, we can handle endogeneity[31]. In our case, $\mathcal{L}$ is the shared, unobserved latent variable, that gives rise to the endogeneity. This is the second way we account for endogeneity in our model, in addition to using only lagged time-varied variables on the right-hand side of the equations, except in the Probit Model. The study normalises the latent variable by constraining its variances to be 1. In this case, when variances are equal to 1, covariances are equal to correlations (StataCorp 2015).

[30] For example, Cassiman & Martinez-Ros (2004) employ industry and time dummies as instruments, Caldera (2009) - whether the firm was awarded public fund for undertaking R&D, while Harris & Li (2009, 2010) use firm size, age, absorptive capacity, locality, industry, and ownership.

[31] According to Drukker (2014), there are two STATA commands that deal more generally with solutions to endogeneity: 'gsem' and 'gmm'.

Models with latent variables need normalisation constraints as the latent variables do not have natural scale[32].

In this model, we assume that all variables are potentially observed endogenous variables, except age, industry and time dummies which are observed, exogenous. The latent variable - $\mathcal{L}$, is the shared, unobserved element which handles endogeneity. The GSEM also adds error variables - latent exogenous variables with fixed-unit path coefficients, which are linked to each of the dependent variables (StataCorp 2015).

This study uses a single, mixed-process simultaneous system of equations comprising four structural equations. The GSEM modelling permits different observations to be used in each equation of the whole model. The GSEM can deal with endogeneity, expressed in a simultaneous system of equations - the full-information maximum likelihood (FIML) estimates, computed by GSEM can manage this type of simultaneity (Roodman 2011). Using a single equation system, modelling the two-way causality between R&D stock of knowledge and exports, conditioning on productivity, we can test all three hypotheses in Chapter 4 at the same time.

4.5 Data, variables of interest and descriptive statistics

The dataset and the data sources are described comprehensively in Chapter 2. Both our panel datasets are unbalanced with data missing for some firms. The total number of firms included in our 'All-Firms' dataset is 956; of these, 772 firms belong to the high and medium-high R&D intensity sectors (the 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity sectors. Yet, the number of

[32] Without normalisation the model would be treated by STATA GSEM in the same way as a model with a fundamental absence of identification; the estimation procedure would iterate endlessly without reaching a solution (StataCorp 2015).

firms with sufficient R&D data regarding the medium-low and low R&D intensity sectors is not sufficient to satisfy the requirements of our econometric approach - the GMM. All our experiments produced invalid parameters due to the 'weak instruments' problem (described in Chapter 2, Section 2.2.2). Therefore, we analyse the firms at the 'All-Firms' level and at the 'Innovators' sub-sample level when testing only the first hypothesis: *'exporting by innovating'*, described in Section 4.4.1.

Testing all our hypotheses (described in Section 4.4.2) simultaneously, the GSEM approach is applied at the 'All-Firms' level only. This is because we were not able to apply the same model to both 'Innovators' and the firms from the medium-low and low R&D sectors[33].

4.5.1 Variables of interest

All variables of interest in Chapter 3, (Section 3.5.1) are also used in this chapter. Value-added and total sales variables are utilised to calculate firm labour productivity and market share. In regard to the GSEM approach, the firm's physical capital stock and R&D stock of knowledge are in their intensity form (per employee), as per GSEM manual guidance[34]. For the same reasons, the human capital variable is calculated as a firm's remuneration per employee, relative to its industry's remuneration per employee, used throughout the Chapter 4 analysis.

The additional variables included are as follows.

Labour productivity - $LP_{i,t}$: the firm's value-added divided by the number of employees.

[33] All our tests produced error results 'r (1400): initial values not feasible', even when using different starting values in line with the GSEM procedure, described in the STATA manual. The GSEM approach is relatively new and still there is not enough information on how different issues could be resolved.

[34] http://www.stata.com/manuals13/sem.pdf

Liquidity ratio - $LiqR_{i,t}$: the firm's current assets minus its current liabilities, divided by its total assets.

Collateral - $COL_{i,t}$: the firm's tangible assets divided by its total assets.

4.5.2 Descriptive statistics

This chapter explores the relationship between firm export activities and R&D stock of knowledge, accounting for firms' characteristics. The initial summary statistics as well as firms' classification are provided in Chapter 2, (Section 2.2.2, Tables 1 and 2).

Table 9.1 and Table 9.2 summarise the descriptive statistics of the variables in both 'All-Firms' (Table 9.1) and 'Innovators' (Table 9.2) datasets, reporting the number of observations, mean, median, standard deviation, minimum and maximum values of the variables studied. Data is presented in levels.

As the 'Innovators' represent, on average, 81% of the whole dataset, while the low and medium-low R&D intensity firms - on average 19%, high heterogeneity in firms' characteristics is expected. Firms' heterogeneity per *ICB* industry classification in terms of exports and labour productivity are shown in Appendix 4.2 and Appendix 11, respectively.

In regard to Table 9.1, 'All-Firms' analysis, as the majority of firms are from high and medium-high R&D intensity sectors, it is expected that the mean value of the R&D stock of knowledge (*65179.01)* will be high with a high standard deviation (*190446.1).* In terms of their size, the firms are large with average mean values of labour (*1216.099*), physical capital stock (*1656583*) and market share (*.009*) quite high, and high standard deviations. Viewed in their intensity forms, per employee, both mean values of R&D stock of knowledge (*696.686*) and physical capital stock (*7138.233*) are still high.

Table 9.1: Descriptive statistics: Chapter 4, 'All-Firms'

Descriptive Stat.	***'All-Firms'***					
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Export Intensity	*5558*	*.387*	*(.362)*	*.504*	*.00003*	*1*
Labour Productivity	*7858*	*103.856*	*(235.053)*	*59.962*	*.011*	*6205.674*
R&D Stock of Knowledge	*7350*	*65179.01*	*(190446.1)*	*10463.46*	*5*	*1466876*
Intangible Assets Intensity	*5740*	*.205*	*(.223)*	*.116*	*1.51e-06*	*.987*
Human Capital/Ind.	*9665*	*1.146*	*(.524)*	*1.046*	*.001*	*3.973*
Physical Capital Stock	*7563*	*1656583*	*(6394232)*	*41977.21*	*3*	*4.66e+07*
Labour	*9869*	*1216.099*	*(4017.864)*	*179*	*10*	*38400*
Age	*10516*	*30.483*	*(24.947)*	*22*	*5*	*147*
Intra-Ind.Spillovers /Total Sales	*10516*	*.077*	*(.059)*	*.068*	*.0001*	*.200*
Inter- Ind.Spillovers /Labour	*10516*	*823.583*	*(102.729)*	*856.468*	*565.589*	*960.467*
Global Spillovers	*10516*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*
Market share	*9494*	*.009*	*(.035)*	*.001*	*2.02e-08*	*.375*
Liquidity Ratio	*7395*	*.339*	*(.237)*	*.296*	*.00003*	*.998*
Collateral	*9733*	*.193*	*(.216)*	*.107*	*.00002*	*.999*
Export dummy	*7017*	*.792*	*(.406)*	*1*	*0*	*1*
R&D Stock of Knowledge/L.	*6995*	*696.686*	*(11027.51)*	*61.171*	*.015*	*731105.5*
Physical Capital Stock/L.	*7217*	*7138.233*	*(152465.4)*	*236.390*	*.250*	*1.06e+07*

Note: Data is presented in levels. All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form. The last three variables are used in the GSEM model only

Firms from the 'All-Firms' dataset, on average, export 39% of their total sales, while their intangible assets represent 21% of their total assets. The average human capital (*1.146*) is also at a high level. The mean value of their labour productivity is 103.856, however, with a high standard deviation (*235.053*), confirming the great heterogeneity in terms of firms' characteristics, as discussed in Chapter 3, (Section

3.5.2). The firms in this data sample are also, on average, mature firms (*30.483*). The intra-industry R&D expenditure, on average, is 8% of the total intra-industry sales. In terms of their financial variables, the mean value of the firm collateral *(.193*) seems low; the mean value of the liquidity ratio is .339.

In regard to Table 9.2, 'Innovators' analysis, the high mean value of the R&D stock of knowledge (*70458.93)* is expected. However, the standard deviation is also high - (*200720*). The firms are of reasonable, however, not very large size, with average mean values of labour of 854.308, physical capital stock of 436508.6 and market share of .006, and high standard deviations of 3088.546, 1677145 and .021, respectively.

In regard to the 'Innovators' subset, on average, the firms export 45% of their total sales, while their intangible assets are 23% of their total assets. The average human capital (*1.098*) is also at a high level. The firms in this sample are, on average, mature firms (*28.096*). The intra-industry R&D expenditure is, on average, 9% of the total intra-industry sales.

The mean value of their labour productivity is 90.705, however, with a high standard deviation (*191.471*), confirming the great heterogeneity in terms of firms' characteristics, not only between different sectors of technological levels but also, within the same sector, as discussed in Chapter 3, (Section 3.5.2). In terms of their financial variables, the mean value of the firm collateral *(.142*) seems low; the mean value of the liquidity ratio is .365.

Table 9.2: Descriptive statistics: Chapter 4, 'Innovators'

Descriptive Stat.	***'Innovators'***					
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Export Intensity	*4682*	*.448*	*(.362)*	*.581*	*.00003*	*1*
Labour Productivity	*6324*	*90.705*	*(191.471)*	*59.459*	*.011*	*6205.674*
R&D Stock of Knowledge	*6497*	*70458.93*	*(200720)*	*11811.85*	*5*	*1466876*
Intangible Assets Intensity	*4609*	*.227*	*(.229)*	*.144*	*.00002*	*.987*
Human Capital/Ind.	*7687*	*1.098*	*(.469)*	*1.025*	*.001*	*3.973*
Physical Capital Stock	*6115*	*436508.6*	*(1677145)*	*30318.72*	*3*	*3.73e+07*
Labour	*7871*	*854.308*	*(3088.546)*	*154*	*10*	*38400*
Age	*8492*	*28.096*	*(22.561)*	*20*	*5*	*147*
Collateral	*7757*	*.142*	*(.163)*	*.077*	*.00003*	*.999*
Intra-Ind.Spillovers /Total Sales	*8492*	*.094*	*(.052)*	*.076*	*.001*	*.200*
Inter- Ind.Spillovers /Labour	*8492*	*802.406*	*(102.836)*	*842.816*	*565.589*	*957.256*
Global Spillovers	*8492*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*
Market share	*7656*	*.006*	*(.021)*	*.001*	*4.33e-08*	*.342*
Liquidity Ratio	*6055*	*.365*	*(.239)*	*.327*	*.0003*	*.998*

Note: Data is presented in levels. All relevant variables are measured in thousands from which the ratios are calculated. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form.

Looking at the descriptive statistics, on average, it seems that the firms with high mean values for R&D stock of knowledge are also those associated with higher firms' export activities. This relationship is expressed more strongly in regard to the 'Innovators' subset than in regard to the 'All-Firms' dataset. This, in general, provides support for our hypotheses in terms of that R&D stock of knowledge and firm export activities are positively correlated. However, in Section 4.6 we will see if, after controlling for other factors, this relationship is confirmed in terms of each of our hypothesis.

The correlations between the variables are reported in Appendix 8, showing that there is no intolerable multicollinearity among the variables.

4.6 Results: description and interpretation

In this section, first, we provide evidence in regard to the '*exporting by innovating'* hypothesis only, using traditional econometric approaches (Section 4.6.1) and second, we report and discuss the results of our GSEM approach, testing all three hypotheses in this chapter simultaneously (Section 4.6.2).

4.6.1 Evidence in support of 'exporting by innovating' hypothesis, using traditional econometric approaches

This section tests the first hypothesis in this chapter: *A firm's R&D stock of knowledge positively affects its export activities.* Section 4.6.1.1. provides evidence in regard to the 'All-Firms' dataset while Section 4.6.1.2 reports the findings in regard to the 'Innovators' only subset.

4.6.1.1 'All-Firms' analysis

Table 10 reports the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) estimates of our dynamic model of the determinants of firm export intensity, outlined in Equation (7), in terms of the 'All-Firms' dataset.

Table 10: Firm exports and R&D stock of knowledge: 'All-Firms' analysis

'All-Firms' analysis			
Model/Dependent Variable	***1. Pooled OLS (lnExp.Int.)***	***2. Fixed Effects (lnExp.Int.)***	***3. GMM ((lnExp.Int.)***
Constant	*3.714*	*-16.019**	*Omitted*
	(4.607)	*(8.383)*	
ln (Export Intensity $_{t-1}$)	*.868****	*.294***	*.780****
	(.027)	*(.125)*	*(.062)*
ln (Age $_{t-1}$)	*-.089****	*Omitted*	*-.104***
	(.029)		*(.044)*
ln (Physical Capital Stock $_{t-1}$)	*-.019* *(.021)*	*-.132** *(.069)*	*-.030* *(.045)*
ln (Labour Prod. $_{t-1}$)	*.052*	*.088*	*.138*
	(.052)	*(.066)*	*(.111)*
ln (Labour $_{t-1}$)	*.040*	*.054*	*.091*
	(.064)	*(.128)*	*(.142)*
ln (Human Capital $_{t-1}$)	*-.036*	*-.091*	*.075*
	(.052)	*(.108)*	*(.201)*
ln (Collateral $_{t-1}$)	*-.028**	*.009*	*-.027*
	(.015)	*(.039)*	*(.041)*
ln (Intangible Assets Intensity $_{t-1}$)	*.010* *(.012)*	*-.026* *(.029)*	*.016* *(.031)*
ln (Liquidity Ratio $_{t-1}$)	*-.059****	*-.043**	*-.118***
	(.022)	*(.028)*	*(.049)*
ln (Market Share $_{t-1}$)	*-.044*	*-.002*	*-.127*
	(.061)	*(.108)*	*(.150)*
ln (R&D Stock of Knowledge $_{t-1}$)	*.036** *(.020)*	*.259* *(.194)*	*.102** *(.054)*
ln (Intra-Ind./Sales Spillovers $_{t-1}$.)	*-.001* *(.067)*	*.094* *(.079)*	*.267** *(.176)*
ln (Inter-Ind./Labour Spillovers $_{t-1}$)	*.291* *(.458)*	*.840*** *(.435)*	*1.623** *(.964)*
ln (Global Spillovers $_{t-1}$)	*-.305**	*.399*	*-.572**
	(.197)	*(.435)*	*(.357)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.012*
AR(2) Test			*0.374*
Hansen's J test			*0.485*
Observations (groups)	*1104*	*1104(328)*	*1104(328)*
Instruments (lags)			*323, (2 5)*
R^2	*0.832*	*0.127*	
F	*F(29,327)= 428.40****	*F(18,327)= 3.27****	*F(39, 327)= 356.11 ****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 details the coefficients obtained using the pooled OLS estimator, which is based on cluster-robust standard errors, controlling for arbitrary heteroscedasticity and intra-cluster correlation. The model explains, on average, 83% of the variation in firms' export intensity. The coefficients associated with the lagged export intensity, age and liquidity ratio variables are all significant at the 1% level of significance, although, only the coefficient on the lagged dependent variable is positive. The coefficient on the lagged R&D stock of knowledge is positive, however, only marginally significant at the 10% level. The coefficients on the firm collateral and global spillovers are also marginally significant at the 10% level but negative. However, the pooled OLS parameters tend to be biased due to the unobserved firm-specific heterogeneity and likely endogenous regressors.

Column 2 reports the coefficients obtained using the FE estimator. The coefficients on the lagged export intensity and inter-industry spillovers variables are both positive and significant at the 5% level. The coefficients on the lagged physical capital and liquidity ratio variables are both negative but only marginally significant at the 10% level. The coefficients on remaining variables are not statistically significant. However, although the FE model removes the impact of time-invariant firm characteristics, it does not take into account the endogeneity issues, specified in Section 4.4.1.2, which affects its consistency.

Column 3 presents our preferred one-step, system GMM estimates. The model accounts for unobserved heterogeneity and endogeneity simultaneously. Statistical tests performed do not reject the null hypothesis of instruments validity and/or model specification, meaning that the coefficients derived from the one-step, robust, system GMM regression are credible.

The GMM coefficient on the lagged dependent variable - (*0.780*) is positive and significant at the 1% level. It lies within the range for dynamic stability attained by the FE (*0.294*), (lower bound) and the pooled OLS (*0.868*), (upper bound) estimators. The positive GMM coefficient on the lagged dependent variable suggests that a firm's export intensity in the current year depends on its export intensity in the previous year. This means that firm export intensity fluctuations are sluggish and smooth.

The coefficient on R&D stock of knowledge - (*.102*) is positive and marginally significant at the 10% level, while the coefficient on intangible assets intensity variable is positive, however, not significant. In line with our expectations, the evidence of this investigation provides some support, although weak, for our first hypothesis in this chapter namely, that a firm's R&D stock of knowledge positively affects its export intensity, in the 'All-Firms' dataset. It means that when other variables are held constant, a 10% increase in the priority given by a firm to its investment in R&D, is associated with an increase in its export intensity by, on average, 1%. The results are in line with most of the literature reviewed in Section 4.2.2 (e.g. Hirsch & Bijaoui 1985, Bleaney & Wakelin 2002, Roper & Love 2002, Chiru 2007) that R&D/innovation positively affects export activities.

Our results in terms of intra-, inter-industry and global spillovers are similar to the equivalent results in Chapter 3, (Section 3.6.2) in regard to the effect of R&D stock of knowledge on market share. However, while in Section 3.6.2 the coefficients are strongly significant, here, they are all only marginally significant. The positive coefficients associated with intra-industry spillovers although only marginally significant at the 10% level are in line with the findings of Roper & Love (2002) and

Barrios *et al.* (2003), who report that intra-industry spillovers are positively associated with firm export activities. The coefficient on global spillovers is also significant at the 10% level, however, it is negative. This is in line with the evidence provided by Branstetter (2001), McVicar 2002; Luintel & Khan (2004) and Anon-Higon (2007), who report that global spillovers are not beneficial to firms in advanced economies.

The coefficients on firm age and liquidity ratio variables are both negative and significant at the 5% level. The coefficient on liquidity ratio is -.118. It means that when other variables are held constant, a 10% increase in the priority given by a firm to its liquidity ratio, is associated with a decrease in its export intensity by, on average, 1%. Maintaining more liquid assets may lead to high opportunity costs for the firms (Chen & Guariglia 2013).

The coefficients on the remaining variables are not statistically significant.

4.6.1.2 'Innovators' analysis

Table 11 provides the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) estimates of our dynamic model of the determinants of firm export activities, outlined in Equation (7), in terms of the 'Innovators' subset. The column in grey shows the results used as a robustness test, discussed in Section 4.6.3.

Column 1 presents the coefficients obtained using the poled OLS estimator. The coefficients, associated with all significant variables in Model 1, (Table 10) maintain their sign and level of significance also in this model. However, the pooled OLS coefficients are likely to be biased due to the unobserved firm-specific heterogeneity and likely endogenous regressors.

Table 11: Firm exports and R&D stock of knowledge: 'Innovators' analysis

'Innovators' analysis				
Model/Dependent Variable	***1. Pooled OLS (lnExp.Int.)***	***2. Fixed Effects (lnExp.Int.)***	***3. GMM (lnExp.Int.)***	***4. GMM (lnExp.Int.)***
Constant	*4.344*	*-12.719**	*Omitted*	*Omitted*
	(4.935)	*(8.438)*		
ln (Export Intensity $_{t-1}$)	*.868****	*.301***	*.636****	*.787****
	(.028)	*(.129)*	*(.091)*	*(.062)*
ln (Age $_{t-1}$)	*-.095****	*Omitted*	*-.203***	*-.115****
	(.032)		*(.084)*	*(.043)*
ln (Physical Capital Stock $_{t-1}$)	*-.020*	*-.112**	*-.115**	*-.036*
	(.023)	*(.068)*	*(.066)*	*(.045)*
ln (Labour Prod. $_{t-1}$)	*.060*	*.086*	*.065*	*.149*
	(.056)	*(.068)*	*(.121)*	*(.115)*
ln (Labour $_{t-1}$)	*.046*	*.017*	*.216*	*.101*
	(.069)	*(.129)*	*(.213)*	*(.136)*
ln (Human Capital $_{t-1}$)	*-.041*	*-.075*	*.079*	*.073*
	(.054)	*(.109)*	*(.147)*	*(.194)*
ln (Collateral $_{t-1}$)	*-.027**	*.017*	*-.117***	*-.024*
	(.016)	*(.039)*	*(.057)*	*(.045)*
ln (Intangible Assets Intensity $_{t-1}$)	*.007*	*-.043**	*-.008*	*-.001*
	(.013)	*(.027)*	*(.042)*	*(.024)*
ln (Liquidity Ratio $_{t-1}$)	*-.066****	*-.052**	*-.099**	*-.134****
	(.024)	*(.028)*	*(.067)*	*(.051)*
ln (Market Share $_{t-1}$)	*-.050*	*.007*	*-.073*	*-.132*
	(.065)	*(.110)*	*(.179)*	*(.146)*
ln (R&D Stock of Knowledge $_{t-1}$)	*.037**	*.262*	*.163***	*.096**
	(.022)	*(.192)*	*(.081)*	*(.058)*
ln (Intra-Ind./Sales Spillovers $_{t-1}$.)	*-.003*	*.063*	*.605**	*.266**
	(.075)	*(.089)*	*(.385)*	*(.180)*
ln (Inter-Ind./Labour Spillovers $_{t-1}$)	*.282*	*.736**	*2.873**	*1.672**
	(.480)	*(.471)*	*(1.732)*	*(.930)*
ln (Global Spillovers $_{t-1}$)	*-.342**	*.269*	*-.978**	*-.638**
	(.207)	*(.447)*	*(.634)*	*(.370)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.009*	*0.018*
AR(2) Test			*0.245*	*0.316*
Hansen's J test			*0.659*	*0.775*
Observations (groups)	*1027*	*1027(300)*	*1027(300)*	*1027(300)*
Instruments (lags)			*200, (3 4)*	***318, (2 5)***
R^2	*0.816*	*0.134*		
F	*F(24,299)= 193.31****	*F(18,299)= 3.07****	*F(31, 299)= 59.29 ****	*F(31, 299)= 163.09 ****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 2 reports the FE coefficients. Contrary to the results of Model 1 in both Tables 10 and 11, which are similar, the FE models in the same tables show some differences. While the coefficients on the lagged dependent variable, physical capital stock and liquidity ratio maintain their sign and level of significance, the significance level of the coefficient on the inter-industry spillovers decreases from 5% in Table 10 to 10% in Table 11. In addition, the coefficient, associated with the intangible assets intensity variable although negative in both tables, here, in Table 11 is also marginally significant at the 10% level. However, the FE model does not take into account the endogeneity issues in our model which makes its estimates not consistent.

Column 3 details our preferred one-step, system GMM estimates. The model controls for unobserved heterogeneity and endogeneity simultaneously. The tests performed in terms of this GMM model are within the requirements of the diagnostic statistics, as reviewed in Chapter 3, (Section 3.4.2).

The GMM coefficient on the lagged dependent variable - (*0.636*) is positive and significant at the 1% level. It lies within the range for dynamic stability reached by the FE (*0.301*), (lower bound) and the pooled OLS (*0.868*), (upper bound) estimators. The positive GMM coefficient on the lagged dependent variable suggests that firm export intensity fluctuations are sluggish and smooth, as per Section 4.6.1.1.

The coefficient on R&D stock of knowledge - (*.163*) is positive and significant at the 5% level. In line with our expectations, the evidence provided by this analysis supports our first hypothesis in this chapter, namely, that a firm's R&D stock of knowledge positively affects its export intensity, in terms of the 'Innovators' dataset. The support for this hypothesis is stronger in regard to the 'Innovators' subset than in regard to the 'All-Firms' dataset, as per our preliminary results (Section 4.5.2, Descriptive statistics).

The coefficients, associated with the spillover variables maintain their sign and level of significance as per Model 3 in Table 10, however, here their values are larger.

The coefficient on the variable age is negative and significant at the 5% level, as per Model 3 in Table 10. Contrary to Model 3, (Table 10), here, the coefficient on the physical capital stock is not only negative as per Table 10 but also, marginally significant. The coefficient on the firm collateral - (-*.117*) is negative and significant at the 5% level, contrary to its equivalent in Model 3, (Table 10), where it is also negative but not significant. This means that when other variables are held constant, a 10% increase in the priority given by a firm to its collateral, is associated with a decrease in its export intensity by, on average, 1%. It seems that, in this case, when firms invest more in tangible assets their export activities suffer.

The coefficient associated with liquidity ratio maintains its sign as per Model 3, (Table 10), however, here its significance decreases to the 10% level. The coefficients on the remaining variables are not statistically significant.

4.6.1.3 Summary of results

Summarising the findings of Section 4.6.1, our results support the *'exporting by innovating'* hypothesis. At the firm-level, 'technology-based' theories of international trade suggest that R&D/innovation leads to market power, which in turn increases export activities (Roper & Love 2002). In this sense, the general consensus of the literature is that the causality of the relationship between firm innovation and exports runs from innovation to exports (Wakelin 1998a, Sterlacchini 1999, Bleaney & Wakelin 2002, Gourlay *et al.* 2005, Chiru 2007). Our results, in general, are in line with this literature.

4.6.2 A firm's R&D stock of knowledge and its exports are endogenous, both positively affecting each other, depending on firm characteristics

4.6.2.1 GSEM results, description and interpretation

This section tests all hypotheses in this chapter simultaneously.

H3(Ch4, H1): A firm's R&D stock of knowledge positively affects its export activities or, in other words, *'exporting by innovating'* hypothesis.

H4(Ch4, H2): A firm's export activities positively affect its R&D stock of knowledge or, in other words, *'innovating by exporting'* hypothesis.

H5(Ch4, H3): A firm's R&D stock of knowledge and its exports are endogenous, both affecting each other positively, depending on firm characteristics.

The results of the GSEM model are presented in Table 12, (Models 1 to 5).

Columns 1 and 2 report the outcomes of the selectivity equation - the Probit Model, where the marginal effects are presented in Model 2 (*GSEM Probit* (*2*)). Column 3 reports the results of the 'Export intensity' equation. Column 4 details the results of the 'R&D stock of knowledge' model, while Column 5 presents the results of the 'Productivity' equation.

In addition, to check to what extent the GMM technique captures the results in regard to Model 3, we perform a GMM estimation (Column 6), with the same variables as per Model 3.

Table 12: Firm exports and R&D stock of knowledge: GSEM results

	Firm exports, productivity and R&D stock of knowledge					
Model	***1.GSEM Probit(1)*** *a/SE*	***2.GSEM Probit(2)*** *Mfx*	***3. GSEM Exports***	***4. GSEM R&D***	***5.GSEM Prod.***	***6.GMM Exports***
Constant	*19.707 (2379.97)*		*31.286*** (5.150)*	*-2.686*** (.382)*	*4.117*** (.418)*	*.528 (1.527)*
ln (Export Intensity)				*.136*** (.015)*	*-.114*** (.013)*	
ln (Labour. Productivity)	*-1.531*** (.160)*	*-.136*** (Om.)*	*-7.699*** (.909)*	*.751*** (.022)*		*-.244* (.143)*
ln (R&D Stock of Knowledge)	*1.511*** (.134)*	*.134*** (Om.)*	*6.519*** (.745)*		*.840*** (.022)*	*.201* (.120)*
ln (Physical Capital Stock)					*-.001 (.001)*	
ln (Collateral)	*.149*** (.047)*	*.013*** (Om.)*	*-.002 (.010)*			*-.011 (.064)*
ln (Labour)	*.595*** (.075)*	*.053*** (Om.)*				
ln (Market Share)			*1.745*** (.228)*	*-.210*** (.014)*	*.225*** (.013)*	*.201*** (.077)*
ln (Human Capital)			*-3.338*** (.531)*	*.788*** (.052)*	*-.426*** (.050)*	*.277* (.179)*
ln (Age)			*-.033* (.019)*			*-.215** (.101)*
Latent	*3.340*** (.246)*		*10.635*** (1.238)*	*-1.319*** (.022)*	*1.376*** (.030)*	
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test						*0.030*
AR(2) Test						*0.156*
Hansen's J test						*0.582*
var(e.lnProd.)					*.001** (.001)*	
var(e.lnR&D)				*.328** (.014)*		
var(e.lnExport)			*.198** (.058)*			
Observations (Groups/equation)	*4139 (3815)*		*4139 (2209)*	*4139 (3193)*	*4139 (2343)*	*2880 (603)*
F						*F(31,602)= 314.6****

Notes: Robust standard errors are reported in parentheses. Robust standard errors in GSEM, Probit 2 are omitted by STATA when calculating the 'fixedonly' marginal effects with the latent variable set to zero. For AR(1), AR(2) and Hansen test reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

The results of Model 2 (*GSEM Probit* (*2*)) equation address the 'selectivity' bias and show that the probability of being an exporter is positively related with firm R&D stock of knowledge, collateral and labour. Furthermore, it is negatively associated with firm labour productivity. Firms need to be financially healthy, in order to become exporters, which is in line with the financial constraints literature (Chaney 2005, Van Biesebroeck 2006, Blalock & Roy 2006, Greenaway *et al.* 2007). The results are also in line with the modern literature that endogenises firm heterogeneity, in the sense that in order to become exporters, firms participate in innovative activities so that to be able to break the entry barriers shielding the very competitive overseas markets (Harris & Moffat 2012).

Column 3 reports the estimates of the 'Export intensity' equation. Estimating the model, we were not able to enter the equation with lagged labour productivity (even when using different starting values, in line with the GSEM procedure). Although we did not experience this issue in regard to the 'R&D stock of knowledge' equation; therefore, we used the contemporaneous values. However, Greenaway *et al.* (2007) find that their results were robust to employing contemporaneous variables instead of lagged variables on the right-hand side of a similar 'export' equation.

The coefficient associated with the R&D stock of knowledge is positive and statistically significant at the 1% level of significance. The coefficient is not only statistically significant but also has an important economic significance - its value is huge *(6.519*). It means that when other variables are held constant, a 10% increase in the priority given by a firm to its R&D stock of knowledge, is associated with an increase in its export intensity by, on average, 86 %. This supports the findings of the majority of traditional literature in regard to the first hypothesis in this chapter:

'*exporting by innovating'* (Wakelin 1998a, Sterlacchini 1999, Bleaney & Wakelin 2002, Gourlay *et al.* 2005, Chiru 2007). The results from this equation are in line with our results in Section 4.6.1. The results are also in line with the modern literature, in the sense that maintaining the level of innovative activities after becoming an exporter assures a firm's continuing existence in the foreign markets (Bernard & Jensen 2004a,b,c; Greenaway & Kneller 2007; Haris & Moffat 2012).

The coefficient associated with the market share is positive and strongly significant at the 1% level. The coefficient also has an important economic significance - its value is large *(1.745*). It means that when other variables are held constant, a 10% increase in the priority given by a firm to its market share, is associated with an increase in its export intensity by, on average, 18 %. Our findings in terms of the market share are in line with the majority of research in this area, which reports that exporters are, in general, more productive and larger than firms which do not export (Clerides *et al*. 1998; Bernard & Jensen 1999, 2004a; Aw *et al*. 2000; Greenaway & Kneller 2004). However, contrary to the above studies, our results show that increasing labour productivity tends to decrease firm export intensity, which is unexpected. The coefficient associated with the labour productivity is also economically significant - its value is very large *(-7.699*). This means that when other variables are held constant, a 10% increase in the priority given by a firm to its labour productivity, is associated with a decrease in the firm's export intensity by, on average, 52%. This result is perplexing, prompting as to further investigate the matter - a subject of Chapter 5.

Furthermore, although for most of the researchers (e.g. Bleaney & Wakelin 2002; Bernard & Jensen 2004a,b,c; Ruane & Sutherland 2005; Davidson *et al.* 2005), high wages are positively linked to firms' exporting activities, in our case, the coefficient associated with the human capital variable is negative and strongly significant at the 1% level, which is unexpected. The coefficient is not only statistically significant but also, it is economically significant - its value is very large (*-3.338*). This means that when other variables are held constant, a 10% increase in the priority given by a firm to its remuneration per employee, relative to its industry's remuneration per employee, is associated with a decrease in the firm's export intensity by, on average, 27%. Many studies, using panel data (e.g. Benhabib & Spiegel 1994, Islam 1995, Hamilton & Monteagudo 1998), also find that the effects of human capital (measured in different ways) are close to zero or negative and statistically significant, even when the GMM approach is used (Arcand & D'Hombres 2007). However, still, there are no conclusive explanations in regard to such findings (Arcand & D'Hombres 2007). In our case, the negative and strongly significant effect of human capital on export intensity may indicate that increasing remuneration per employee, in comparison to industry's average remuneration per employee, increases firms' remuneration costs but decreases export intensity.

The coefficient, associated with the age variable is also negative but marginally significant at the 10% level. The coefficient on the latent variable is strongly significant and positive, indicating that some unobservable factors contribute positively to firms' export intensity.

Column 4 reports the GSEM estimates of the 'R&D stock of knowledge equation'. The effects of firm export intensity variable are strongly significant and positive. The 'R&D stock of knowledge' equation (Column 4) provides convincing evidence in support of the '*innovating by exporting'* hypothesis, which is not widely researched. According to the theoretical predictions of the 'endogenous growth' literature (e.g. Romer 1990; Grossman & Helpman 1991a,b; Young 1991; Aghion & Howitt 1998), the causality between firm innovative activities and exports may run from exports to innovation (Harris & Li 2009). Our results are in line with these studies.

Furthermore, according to the results of Model 2 (*GSEM Probit* (*2*)), R&D stock of knowledge positively affects a firm's decision to engage in export activities, while in turn, is affected by the *'learning by exporting'* experience (Haris & Moffat 2012). This means that a firm's R&D stock of knowledge and its exports are endogenous, they both positively affect each other, depending on firm characteristics (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011).

The coefficient associated with the human capital variable is positive and strongly significant. Firms with a high level of human capital possess a greater absorptive capacity to assimilate new knowledge (Cohen & Levinthal 1989). Through *'learning by exporting'* firms can access overseas knowledge and skills, cutting-edge 'know-how' and thus, improve their business processes, depending on the level of their *'absorptive capacity'* (Haris & Li 2009). In turn, this will improve their productivity and efficiency (Kobrin 1991, Grossman & Helpman 1991a, Kraay 1999, Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Girma *et al*. 2004, Greenaway & Yu 2004, Salomon & Shaver 2005). Our results support this view: the coefficient associated with the firm productivity is strongly significant and positive.

The effect of market share is also strongly significant but negative. This could be interpreted in terms of our Chapter 3 discussions that larger firms have a 'heavy' structure which may stifle innovative activities as a result of 'red-tape' issues (Schumpeter 1942, Baldwin & Gellatly 2003, Kim *et al.* 2009).

Only in this model, the coefficient on the latent variable is negative and strongly significant, meaning that some unobservable factors contribute negatively to firm R&D stock of knowledge.

Column 5 reports the results of the 'Productivity equation'. The effect of R&D stock of knowledge estimate is strongly significant and positive, as well as the effect of market share. This is in line with the majority of literature which evidence that in general, the impact of R&D and size on firm productivity is positive (Hall *et al*. 2009, Hall 2011, Mohnen & Hall 2013). In addition to Model 2, (*GSEM Probit* (*2*)), this model provides support for the modern hypothesis which states that firms not only need productivity enhancing activities (e.g. R&D/innovation) in order to become exporters but also, they need productivity enhancing feedback (e.g. R&D/innovation) after becoming exporters. This defines the two-way causal relationship between exports and R&D/innovation (Harris & Moffat 2012).

The effect of human capital is strongly significant, but negative, contrary to most of the literature in this area which evidence that human capital contributes greatly to firm productivity growth (e.g. Engelbrecht 1997, Frantzen 2000, Griffith *et al*. 2004b, Guellec & Van Pottelsberghe de la Potterie 2004).

The effect of export intensity estimate is strongly significant at the 1% level, however, negative. This is in contrast to the *'learning by exporting*' hypothesis which advocates that the presence in foreign markets increases firm productivity. This result is unexpected and contrary to the general literature in this area (Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Aw *et al.* 2007, Aw *et al.* 2008, Damijan *at al.* 2008, Harris & Moffat 2012).

Comparing the outcome of the GSEM 'Export intensity' equation with the similar one-step, system GMM equation, the main difference is in the variable human capital, where the coefficient is positive and marginally significant at the 10% level. In regard to the other variables with significant coefficients, the difference is only in the level of significance and the size of the estimates.

4.6.2.2 Summary of Section 4.6.2.

In summary, in each of the GSEM equations, we find an indication of heterogeneity in the main variables estimates connecting the model, and also, in other explanatory variables.

The 'Export intensity' equation (Model 3) provides support for the '*exporting by innovating'* hypothesis. The results of Model 2 (*GSEM Probit* (*2*)) equation show that the probability of being an exporter is positively related with firm R&D stock of knowledge.

The 'R&D stock of knowledge' equation (Model 4) provides evidence in support of the '*innovating by exporting'* hypothesis, which is not widely researched.

Looking at the results of all models together, we find evidence in support of our third hypothesis that: *A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics.* First, prior to exporting, firms engage in innovative activities to be able to break the entry barriers guarding the highly competitive international markets (Harris & Moffat 2012), accounted for by Model 2 (*GSEM Probit* (*2*)). Second, maintaining the level of innovative activities assures firms' continuing existence in these markets (Models 3 to 5), (Bernard & Jensen 2004a,b,c; Greenaway & Kneller 2007; Haris & Moffat 2012). Third, firms achieve further productivity gains post-entry (Aw *et al*. 2011). Firm R&D stock of knowledge, as a measure of innovation in our case, also is likely to affect a firm's decision to engage in export activities while in turn, it is affected by the *'learning by exporting'* experience (Haris & Moffat 2012). That is, a firm's R&D stock of knowledge and its exports are endogenous, they both positively affect each other, depending on firm productivity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011). As firm innovative and export activities intensify with the firms' underlying productivity, the most productive firms will 'self-select' into more innovative and export activities. Furthermore, the firm's innovative and export activities have a direct impact on its future productivity, thus, reinforcing endogeneity via the 'selection' bias (Aw *et al*. 2011).

However, the scarce research on this subject find that a firm's decisions on whether to innovate and whether to export are interdependent and that they both may endogenously influence the firm's future productivity (Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Aw *et al.* 2007, Aw *et al.* 2008, Damijan *at al.* 2008, Aw *et al*. 2011, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013). The next chapter will explore the firm's productivity in a more comprehensive way, and perhaps, it will provide evidence on how exactly the 'self-selection' bias process works.

4.6.3 Robustness tests

The results could be questioned on the ground that the datasets are likely to be biased, e.g. prone to 'sample selection' bias. We check whether both datasets are likely to suffer from a possible bias caused by our decision to include only the R&D active firms in the 'All-Firms' dataset and only the firms on the *R&D Scoreboard* in regard to the 'Innovators' subset. The procedure is described in Chapter 3, (Section 3.6.4). The results are reported in Appendix 6. The insignificant coefficients on 'lambda' ('Mill's ratio') in all cases mean that we cannot reject the null hypothesis of independence of the second-stage equations from the Probit selection equations. This means that we do not need to make corrections for 'selectivity' bias.

Furthermore, for robustness tests, reported in Table 11 ('Innovators analysis', Model 4) are the GMM results with the same set of instruments, as per Model 3 (Table 10). The results displayed in Model 3 (Table 11) and Model 4 (Table 11) are qualitatively similar. However, the number of instruments in Model 4 (Table 11) is higher than the number of groups which makes the estimates potentially biased (Bowsher 2002; Roodman 2008, 2009). The reason is that using too many moment conditions makes Sargan/Hansen test not useful (Bowsher 2002). According to Roodman (2008, 2009), the number of instruments should not be greater than the number of groups (as the literature does not suggest when there are too many instruments).

In line with Chapter 3, in Chapter 4 we use the logarithmic transformation on both continuous variables and ratios, for the same reasons stated in Chapter 3, Section 3.6.4. As a robustness check, Appendix 9 presents a set of the same models, using the logarithmic transformations only on continuous variables. In terms of the 'All-Firms', GMM analysis (Appendix 9.1), the null hypothesis associated with the Hansen test: H_0 *Model specification is correct, and all overidentifying restrictions (all overidentified instruments) are correct (exogenous),* is rejected as per Appendix 7.3 and Appendix 7.4. That is, the instruments do not fulfil the required orthogonality conditions. In terms of the 'Innovators', GMM analysis (Appendix 9.2), the number of instruments is higher than the number of groups which makes the estimates potentially biased (Bowsher 2002; Roodman 2008, 2009), explained in the previous paragraph.

In regard to the GSEM equation, the model did not converge although we have explored different specifications, following very strictly the suggested problem-solving guidance, provided in the STATA manual (StataCorp 2015). We have applied all three possible solutions: 'the improved-starting-values technique', 'the alternative-starting-values method' and 'the alternative-software-logic procedure'. However, the estimation procedure iterated endlessly without reaching a solution. The GSEM technique is new, and there is not sufficient information on how different problems could be resolved. To our knowledge, to date, there are only a few studies which employ the GSEM technique. The most prominent one is the study of Baum *et al*. (2015), which we have followed: the authors use the logarithmic transformation on both continuous variables and ratios.

Additionally, the 'Export intensity' equation of the GSEM model (Column 3) was also used in a one-step, system GMM regression. The results, in general, show to be robust.

In summary, the validity of this study's results is confirmed in the above cases of potential biases.

4.7 Conclusions and implications

This chapter explores the link between firm R&D stock of knowledge and export activities, conditioning on firms' characteristics. It uses an unbalanced panel of 956 UK firms during 2003/4-2013/14, of which 772 belong to the high and medium-high R&D intensity sectors and 184 to both medium-low and low R&D intensity sectors.

The study adds to both traditional and modern literature by providing evidence on the above relationship by using different econometric techniques. Initially, it explores the one-way causality between a firm's R&D stock of knowledge and its export activities, accounting for both firm-specific and technological heterogeneity, by using more traditional econometric approach (e.g. GMM). The results support the first hypothesis in this chapter - *'exporting by innovating'*.

Next, this research follows Atkeson & Burstein (2010), Aw *et al*. (2011), Bustos (2011) and Harris & Moffat (2012) by looking at the relationship between firm export activities and R&D stock of knowledge as a simultaneous process. Therefore, it tests all three hypotheses of this chapter simultaneously. For this, it uses the GSEM econometric approach, which accounts for both 'selectivity' bias and endogeneity issues, to handle our multiple equation system with latent variables (Baum *et al.* 2015). Using the GSEM technique, we are able to account for the key theoretical models ('neo-endowment', 'technology based' and 'endogenous growth' theories). The GSEM method also allows us to model the two-way causality between R&D stock of knowledge and exports, their interdependencies, dynamics, endogeneity and potential simultaneity while controlling for firms' characteristics. Employing the GSEM approach, the results also support the first hypothesis of this chapter. Furthermore, the results support the less researched, second hypothesis in this chapter: *'innovating by exporting'*. In addition, the findings are also in line with our third hypothesis, namely that a firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics (in this case, on productivity).

The research question is worthy of investigation as the relationship between firms' exports and R&D activities is of vital importance at both micro- and macro-levels. The subject is contemporary, and the evidence provides support, in the UK context, to both traditional 'neo-endowment' and 'technology-based' theories, as well as to the modern framework which endogenises firm heterogeneity. The study's findings are important from a policy perspective. At a micro-level, the relationship between a firm's investment in R&D and its export activities is an important subject due to the fact that they both affect firm productivity (Clerides *et al*. 1998; Bernard & Jensen 1999, 2004; Aw *et al*. 2000; Greenaway & Kneller 2004). Furthermore, at a macro-level, according to the 'endogenous growth' theory, firms' R&D leads to economic growth (Romer 1986, 1990; Lucas 1988). In line with the 'endogenous growth' theory, recent literature focuses on the microeconomic perspective to trade, linking a firm's export activities to its productivity, and thus, reinforcing the importance of exports for national productivity growth (Bernard *et al*. 2003; Melitz 2003; Bernard & Jensen 2004a,b,c; Helpman *et al*. 2004a; Bernard *et al*. 2005; Harris & Li 2009). This chapter's findings suggest that R&D and export promotion policies can be beneficial to the economy, as they both lead to economic growth. It is hoped that this research will help policy-makers to fine-tune their policy instruments as there are several advantages of firm-level studies on the relationship between innovation/R&D stock of knowledge and export activities. Therefore, policy measures supporting R&D and export activities, e.g. subsidy or tax-relief, facilitating exports and innovative collaborations or supporting innovative management practices, are justifiable (Ortega-Argiles *et al*. 2009).

As the hypothesis of endogenising firm heterogeneity is relativity new, this research can be extended in different ways such that, the relationship between a firm's R&D/innovation and its export activities, conditioning on firm heterogeneity, can be explained more fully. For example, it would be interesting to see whether the results hold for other similar GSEM models in the UK context. In addition, subject to data availability, it would be noteworthy to see how firms from different technological groups behave and whether there are differences in the relationship between firm R&D activities and exports. Finally, it would be interesting to compare the results from different countries and identify lessons to be learnt.

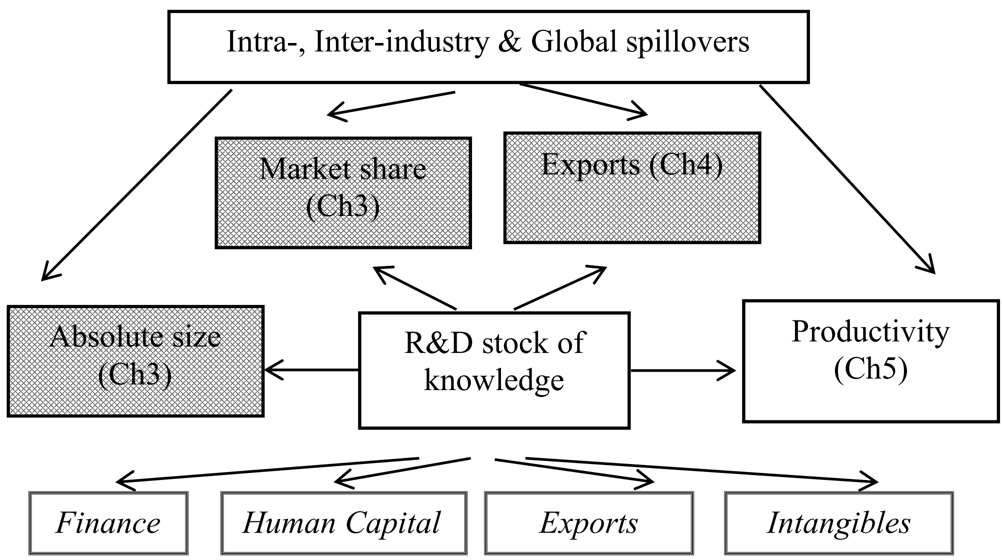
Chapter 5: The Relationship between R&D Stock of Knowledge/Innovation and Firm Productivity

Examining the link between a firm's R&D stock of knowledge and its productivity, in line with Bravo-Ortega *et al.* (2013), we find that at a firm-level, R&D stock of knowledge affects productivity by two channels: directly and indirectly through export levels. However, we find no evidence of 'selection' bias in both export (more productive firms are more likely to become exporters) and R&D activities (more productive firms are more likely to engage in investment in R&D). Contrary to the *'learning by exporting'* hypothesis, (i.e. exporting increases firm productivity), we evidence a negative relationship between a firm's labour productivity and its export intensity (running in both directions).

5.1 Introduction

The aim of this research is to explore the extent to which an increase in a firm's R&D stock of knowledge is associated with increased firm productivity in the UK economy, accounting for firm heterogeneity. This is a part of the thesis' general investigation on the relationship between a firm's R&D stock of knowledge and its performance indicators – size (Chapter 3), exports (Chapter 4) and productivity (Chapter 5). The scheme is presented in Figure 9. Productivity is the quantity of output that a firm can produce utilising a given level of inputs: this definition is free from any assumption of optimality or efficiency in the firm's production process (Hall 2011).

Figure 9: Research structure: Chapter 5



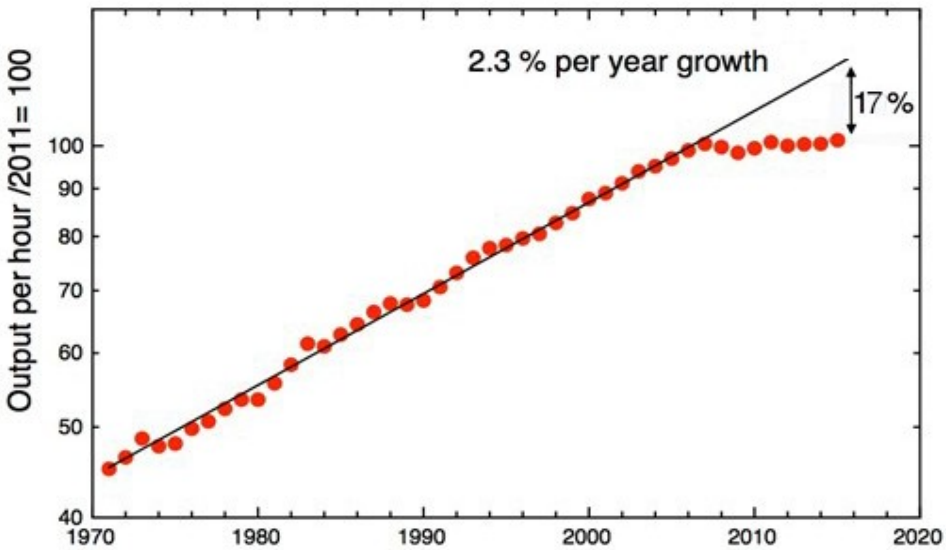
The study uses an unbalanced panel of 956 UK firms during 2003/4-2013/14, of which, 772 belong to the high and medium-high R&D intensity industries and 184 to both medium-low and low R&D intensity industries.

This research is important for both micro- and macro-economic purposes as it investigates one of the most important performance indicators at both firm- and economy-levels. Its importance is summarised in the Nobel Laureate Professor Krugman's powerful sentence:

> ***'Productivity isn't everything, but in the long run it is almost everything'***
>
> (Paul Krugman, *The Age of Diminishing Expectations,* 1994)

However, how has the UK's labour productivity performed in the long run? Figure 10 shows that the UK's labour productivity (the orange dotted line), measured as the GDP produced per hour worked, has followed a trajectory (the black solid line) of constant growth of 2.3% per year during 1971-2008. However, the 2008 financial crisis has sharply distorted the steady evolution of productivity and from that point onwards, the UK's labour productivity growth has effectively ceased (Jones 2016).

Figure 10: UK's labour productivity as the GDP produced per hour worked (1971-2016)



Source: Jones, R., 2016. Innovation, research and the UK's productivity crisis. SPERI Paper No. 28.[35]

[35] The trajectory is a least-squares fit to the period 1970- 2007 of an exponential function equivalent to constant growth of 2.3% a year. ONS Labour Productivity Dataset, 7 April 2016, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/datasets/labourproductivity

A firm's R&D activity and innovation are fundamental to its technological progress and productivity growth, which is in turn, a major driving force of economic growth (Romer 1986, 1990, 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Jones 2005; Cameron *et al*. 2005). According to Bloom & Griffith (2001), as corporate R&D and innovation are the main drivers of economic growth and vital for increasing UK productivity, policies aimed at encouraging R&D and productivity are on the government's agenda. It is envisaged that this study will assist policy-makers to adjust their policy mechanisms as there are several benefits to be derived from firm-level studies on the relationship between R&D/innovation and productivity. For example, it could help them better understand how firms' productivity trajectories can be translated into aggregate productivity, which is in fact, the policy-makers' fundamental challenge. Chapter 5 findings suggest that this could be done by examining the degree to which various integrated policy frameworks (taking into account the interdependencies between firm productivity, exports and R&D) can improve firm productivity.

The overarching theory of this research is the 'endogenous growth' theory, which advocates that a firm's R&D activity and innovation are fundamental to its technological progress and productivity growth (Romer 1986, Lucas 1988). The vast majority of research in this area supports the view of the 'endogenous growth' theory, that increased corporate R&D increases productivity growth (Romer 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Cameron *et al*. 2005; Jones 2005).

In line with the 'endogenous growth' theory, a new strand of the literature on the links between firm productivity, innovation and exports has advanced a theoretically sound framework that endogenises firm heterogeneity (Atkeson &

Burstein 2010, Aw *et al*. 2011, Bustos 2011, Harris & Moffat 2012), discussed in Chapter 4. In Chapter 4 we have evidenced that a firm's R&D stock of knowledge and its exports are endogenous, they both influence each other positively, depending on firm productivity. In this chapter, we will take a different perspective, exploring the relationship between firm productivity and R&D stock of knowledge.

The contributions of this study to the current literature are summarised in the following points.

First, unlike other studies, this research uses the same unique dataset, described in Chapter 2, to investigate a number of firm performance indicators, such as size, export activities and productivity and how they are affected by firms' investment in R&D. This provides a coherent and comprehensive way of analysing firm productivity, accounting for any interdependencies, dynamics, and interrelations between the above indicators.

Second, the study accounts for the effects of a number of firm characteristics (e.g. human capital, financial health, competitive environment, intangibles, exports) on a firm's productivity and on its relationship with R&D stock of knowledge. It also accounts for intra- and inter-industry characteristics measured in terms of intra- and inter-industry spillovers, as well as for global technological characteristics, measured in terms of global spillovers.

Third, productivity is analysed in both traditional terms - as a one-way process, from R&D stock of knowledge to productivity, as well as a simultaneous process, together with a firm's R&D stock of knowledge and its export activities. This is in line with the modern theoretical developments, which analyse interdependencies between firm exports and R&D stock of knowledge, conditioning on firm productivity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011).

Fourth, in regard to the above, the study employs both traditional econometric techniques (e.g. pooled OLS, FE, GMM) in estimating variations of the classical Cobb-Douglas production function, as well as a modern technique (e.g. GSEM) in estimating a system of simultaneous equations involving firm productivity, exports and R&D stock of knowledge.

The traditional techniques are applied using two alternative but complementary approaches to measuring firm productivity. The first one is based on the estimation of a production function (the direct approach) while the second one employs the Total Factor Productivity (TFP) as a dependent variable (the indirect approach). They are applied to both the 'All-Firms' dataset and the subset made up by the 'Innovators'. Using the traditional econometric techniques, we find no direct evidence to support the hypothesis that a firm's R&D stock of knowledge positively affects its labour productivity. We also test the modern development hypothesis which endogenises firm heterogeneity. In order to provide coherence throughout the thesis and comparability of our results, we extend the GSEM model in Chapter 4 by adding a firm propensity to invest in R&D equation and enhance the R&D stock of knowledge equation with a financial variable. Using a GSEM approach, we test both hypotheses simultaneously. The GSEM results are contrary to the outcomes of the traditional approaches - they support the hypothesis that a firm's R&D stock of knowledge positively affects its productivity. The GSEM model also supports the hypothesis based on the new strand of the literature according to which at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels (Bravo-Ortega *et al.* 2013). However, we find no evidence of 'selection' bias, in terms of both export (more productive firms are more likely to become exporters) and R&D activities (more productive firms are more likely to engage in investment in R&D). Moreover, contrary to the *'learning by exporting'* hypothesis, accounted for in our productivity equation, we evidence a negative relationship between a firm's labour productivity and its export intensity (running in both directions), indicating that there are other factors at play. We find that the same latent variable, included in all equations, positively affects firm export intensity and productivity, while it negatively affects firm R&D stock of knowledge.

The rest of the chapter is organised as follows. Section 5.2 provides the theoretical background of the relationship between a firm's productivity and its R&D/innovation. Section 5.3 discusses the hypotheses to be tested, while Section 5.4 describes the baseline specifications and estimation techniques. Section 5.5 discusses the dataset and presents the descriptive statistics. Section 5.6 reports and interprets the results, while Section 5.7 concludes and highlights the policy implications.

5.2 Literature review: the relationship between firm R&D/innovation and productivity

This section critically reviews how the literature on the subject has historically evolved in economics, identifying gaps in the literature and justifying the contribution of this research to it. Section 5.2.1 provides the economic background and the theoretical framework employed in this chapter. Section 5.2.2 briefly reviews the early studies on the relationship between firm R&D/innovation and productivity, while Section 5.2.3 reviews the more recent studies on the subject. Section 5.2.4 summarises the literature review.

5.2.1 Economic background

In this section, we provide the theoretical framework employed in Chapter 5 - the 'endogenous growth' theory (Section 5.2.1.1), the modern theoretical development (Section 5.2.1.2), the 'absorptive capacity' theory (Section 5.2.1.3) and the technological spillovers effects (Section 5.2.1.4).

5.2.1.1 The 'endogenous growth' theory

The main theory of the entire research is the 'endogenous growth' theory, which advocates that a firm's R&D activity and innovation are vital to its technological progress and productivity growth (Romer 1986, Lucas 1988). Since the classic 'Solow residual' study (Solow 1957), which establishes that the rates of factor accumulation do not account for most of the economic growth, there is a general consensus that innovation, especially commercially orientated R&D, is a major driving force of economic growth (Romer 1986; Lucas 1988; Grossman & Helpman 1991a,b, 1994; Coe & Helpman 1995; Coe *et al*. 1997; Aghion & Howitt 1998, 2005; Mohnen 2001; Cameron *et al*. 2005; Jones 2005).

In addition, firms learn from exporting ('*learning by exporting'* hypothesis), thus increasing their productivity, which is in line with the literature on the 'endogenous growth' and 'trade' (Rivera & Romer 1990; Grossman & Helpman 1990, 1991, 1994; Aghion & Howitt 1992, 1997; Ericson & Pakes 1995; Klette & Griliches 2000; Atkeson & Berstein 2007. According to Greenaway & Kneller (2007), productivity increases can materialise via three channels. First, firms' interactions with foreign rivals and customers enhance their awareness of products and processes, thus helping them to cut costs and improve quality. Second, export activities are associated with economies of scale in the production process due to access to larger markets.

Third, the fierce rivalry in foreign markets is likely to pressurise firms to become more efficient and intensify their investment in innovation. However, this hypothesis is not widely researched. The first studies in this area by Clerides *et al*. (1998) and Bernard & Jensen (1999), do not find evidence that productivity improves more quickly after a firm becomes an exporter. Later studies employed mainly an econometric technique, known as 'propensity score matching', first applied by Wagner (2002). It is based on the notion that for each exporter there is a non-exporter 'twin' with whom productivity after entry into foreign markets is compared. In regard to the German companies, Wagner (2002) evidences no significant effects of *'learning by exporting'*. Employing UK firm-level data, Girma *et al.* (2004) use the same technique examining firms that enter or exit foreign markets during 2000. They report significant effects of *'learning by exporting'*. Using similar econometric technique on data for Slovenia, De Loecker (2007) evidences positive impacts on productivity of newly becoming exporters, which rise over time. In terms of the developing nations, Alvarez & Lopez (2005) report significant learning effects from exporting in regard to Chilean firms, while Fernandez & Isgut (2005) report similar evidence for Colombian firms.

5.2.1.2 Modern theoretical development

The modern view of the literature on the relationship between firm productivity, innovation and export activities, in line with the 'endogenous growth' theory, have promoted a theoretically sound framework that endogenises firm heterogeneity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011, Harris & Moffat 2012) (discussed in Chapter 4, Section 4.2.4.2 Modern theoretical developments). It is built on the needs of the firms to participate in productivity enhancing activities (e.g. R&D/innovations) before entering foreign markets and to use productivity enhancing feedback after becoming exporters (Harris & Moffat 2012). As the firms' returns from participating in R&D/innovation activities and exports flourish with the firms' underlying productivity, firms with greater productivity are prone to 'self-selection' bias, undertaking more R&D/innovation activities and increasing exports (Aw *et al*. 2011, Harris & Moffat 2012). Firm R&D/innovation and export activities also have a direct impact on firm future productivity, thus, reinforcing endogeneity via the 'self-selection' mechanism. Studies, examining the two-way causality between firm R&D and exports, conditioning on productivity, find that a firm's decisions on whether to innovate and export are interdependent; they both may endogenously impact its future productivity (Baldwin & Gu 2004; Damijan *at al.* 2008, Aw *et al.* 2008, Harris & Moffat 2012). Furthermore, Bravo-Ortega *et al.* (2013) suggest that at a firm-level, R&D/innovation influences productivity by two channels: directly and indirectly through export levels.

5.2.1.3 The 'absorptive capacity' theory

Many studies claim that R&D has a 'dual nature'. First, it directly encourages firm innovative activities. Second, it may indirectly enhance firms' knowledge base and absorptive capacity, increasing technological awareness of the workforce, consequently leveraging firm innovative performance (Griffith *et al*. 2004b). Griffith *et al*. (2004a) outlines the theoretical framework of the 'absorptive capability' hypothesis: R&D intensifies technology transfer by facilitating firms to acquire and absorb new knowledge and technology, in line with the work of Rosenberg (1982); Jaffe (1986); Cohen & Levinthal (1989); Romer (1990); Grossman & Helpman (1991a,b); Segestrom (1991); Geroski *et al*. (1993); Neary & Leahy (1999); Guellec & Van Pottelsberghe (2001).

Most of the empirical literature (e.g. Jaffe 1986, 1988; Griliches 1979, 1992; Cincera 2005; Harhoff 2000; Kaiser 2002a; Aldieri & Cincera 2009) finds that absorptive capacity depends on firms' technological proximity in technological space: the closer a couple of firms are, the larger the benefits from each other's innovative activities. However, the technological proximity of each couple of firms depends on how related the firms are in terms of technology adopted and activities undertaken to adopt new 'know-how' (Cardamone 2012).

5.2.1.4 Technological spillovers

Technological spillovers (discussed in Chapter 3, Section 3.5.1.2) are the non-appropriable amount of knowledge, created by an innovative firm or 'co-operative' (Cincera *et al*. 2003). Even when the innovator has an effective strategy in place to block knowledge leakages (e.g. via patent, copyrights, licenses), information leaks and other firms can take advantage of this without paying the full price of the newly created knowledge. According to the 'endogenous growth' theory, external R&D positively and significantly affects firms' productivity growth (Romer 1986, 1990; Lucas 1988; Krugman 1991; Grossman & Helpman 1991b). For more information and discussions on technological spillovers, see Griliches (1992) and Kaiser (2002b).

The presence of technological spillovers has been established by most of the empirical research (for surveys see Nadiri 1993; Griliches 1992, 1995; Mohnen 2001; Sveikauskas 2007). However, the evidence of their impact on firm performance is inconclusive and diverse.

5.2.2 Early studies on the relationship between firm R&D/innovation and productivity

From early days, the effect of corporate R&D on productivity has been examined in numerous empirical studies, conducted at the business unit, firm, industry and country levels. Most of these studies support the hypothesis that firm R&D/innovation is positively associated with productivity, however, other studies provide some conflicting results. Some of the earliest prominent work on the subject includes Griliches (1957, 1958, 1964) and Mansfield's (1961, 1965) studies on the role of R&D in agriculture and manufacturing industries. They make an attempt to endogenise most of the technological change. Subsequent studies provide evidence on the impact of public and private R&D and their spillovers on productivity growth, by extending the definition of capital to include R&D capital and calculating its effects (for discussions on this literature see Griliches 1979, 1992; Mairesse & Sassenou 1991; Nadiri 1993; Mairesse 1995).

Using cross-sectional data from a sample of French manufacturing firms during 1980-1987, Hall & Mairesse (1995) calculate the R&D elasticity in a number of cases. The authors explore how the estimates react when underlying assumptions change (e.g. the R&D depreciation rate, the constant returns to scale in estimating the production function, the correction for double counting of R&D expenditures in the labour and capital variables). They provide evidence, in line with the literature employing 1970s datasets: R&D elasticity is significantly positive, in the range of 0.20 to 0.25. Recalculating the equations with time-series data, the estimate of the elasticity decreased abruptly, while the statistical significance almost disappeared. Recalculating again the equations with data in levels, depending on the underlying assumptions, the estimates of the elasticity are between around 0 to 0.07 either statistically insignificant or hardly significant. Yet, again recalculating the equations with growth rates, the estimates of the R&D elasticity are between 0.02 and 0.05, statistically insignificant. Furthermore, the time-series estimates provided some implausible results, e.g. a negative estimate of the elasticity of the labour variable, and a shallow estimate of the elasticity of physical capital input.

5.2.3 Recent studies on the relationship between firm R&D/innovation and its productivity

Most of the recent studies also support the hypothesis that a firm's R&D/innovation is positively associated with its productivity, whether they look at the relationship as a one-way process (Section 5.2.3.1), as an interdependent process (Section 5.2.3.2), or even when the relationship is interacted with firm export activities (Section 5.2.3.3).

5.2.3.1 Firm-level studies on the relationship between R&D/innovation and productivity

Wakelin's (2001) research is the first study in the UK, which explores the relationship between firm R&D expenditure and productivity growth. She employs a Cobb–Douglas production function augmented with R&D intensity. Her dataset consists of a sample of 170 UK firms during 1988-96 with exception of the R&D data which is for the period of 1988-92. She finds that a firm's own R&D expenditure positively and significantly affects its productivity growth. Intra-industry spillovers contribute to the productivity of the firms belonging to some sectors that are 'net-users' of innovations. In contrast to many firm-level studies (e.g. Goto & Suzuki 1989), which report the existence of important R&D inter-industry spillovers, Wakelin (2001) finds that spillovers from innovation-supplying industries have no significant effects. This is in line with Geroski (1991), who evidences that the impact of the neighbouring industries' innovations on the TFP growth, in the UK industries, is marginal.

Examining the link between output, physical capital, employment and R&D capital, Wang & Tsai (2004), in line with Wakelin (2001), use an augmented Cobb-Douglas production function. The model is applied on a balanced panel dataset of 136 large firms from Taiwan during 1994 - 2000. They find that R&D investment is a significant determinant of firm productivity growth, again, in line with Wakelin's (2001) findings.

Similarly to the above studies, Parisi *et al.* (2006) employ a Cobb-Douglas production function to investigate the impact of innovations on productivity in increasing the likelihood of introducing firm-level innovations. Their panel dataset consists of 465 Italian firms during 1992–1997. They find that process innovation has a positive effect on productivity and that R&D expenditure increases the probability of introducing a new product. The results indicate that R&D can impact on productivity growth by enabling the absorption of new technologies.

However, Doraszelski & Jaumandreu (2008) report that the relationship between R&D and productivity is subject to uncertainty, nonlinearity, and firm heterogeneity. They evidence that R&D appears to be the key determinant of the variances in firm productivity and the changes of the firm-level productivity over time. They employ a dynamic investment model, similar to the knowledge capital model of Griliches (1979), applied on an unbalanced panel of over 1800 Spanish manufacturing firms during the 1990s.

Empirically investigating whether the impact of innovation on productivity growth varies across the distribution of firms, Damijan *et al*. (2012) employ a large sample of Slovenian firms during 1996 - 2002. They report that only manufacturing firms with less than average productivity growth are most likely to gain from innovation. High productivity performers do not receive additional gains from innovating. Unlike Parisi *et al*. (2006), they conclude that the reaction of productivity growth to successful innovation does not seem to be heterogeneous in terms of the type of innovation. Indeed, the impact of innovation on productivity growth varies across the distribution of firms.

5.2.3.2 Firm-level studies on the interdependencies between R&D/innovation and productivity

First to add structure to the above relationship are Crépon *et al*. (1998), (CDM model). They use a system of three equations, where each of the three endogenous variables - R&D, innovation output and productivity, can have both idiosyncratic and common determinants. The system was tested on a cross-section of French firms during 1986-90, and calculated by the Asymptotic Least Squares (ALS - minimum distance estimator) method. Crépon *et al*. (1998) report that causality runs from higher R&D to higher innovative activity (propensity to innovate) and consequently from higher innovative activity to higher productivity growth**.** They find that firm probability of getting involved in R&D grows with its size, market share, diversification, 'demand-pull' and 'technology-push' indicators. The research efforts of the firm involved in R&D intensifies with the same variables excluding firm size.

However, the CDM method and alike have some limitations. Theoretically, this 'input-output-performance' method is created on the linear understanding of the innovative process. This does not provide a realistic conceptualisation of the links and multifaceted feedback mechanisms between firms' innovative strategies, their economic performance, and the sector-specific characteristics of the industry in which they operate (Von Tunzelmann *et al*. 2008; Castellacci & Zheng 2010). Another potential limitation of the CDM is that it uses a cross-sectional dataset which means that the estimates do not account for the timing of the innovation and its effect on firm productivity (Hall 2011).

The relationship between R&D expenditure and productivity in China is analysed by Hu (2001), using a cross-sectional dataset of 813 enterprises which report data for 1995. Examining the determinants of private and government R&D and the relationship between the two, he employs a system of three equations: the production function, a private R&D equation and a government R&D equation. He reports a strong relationship between private R&D and firm productivity. However, similarly to Crépon *et al*. (1998), his cross-sectional dataset does not allow for the construction of knowledge capital which is a drawback as R&D is a path-dependent process.

Comparing four European countries, France (3625 firms), Germany (1123 firms), Spain (3588 firms), and the UK (1904 firms), Griffith *et al*. (2006) explore the impact of innovation on firm productivity. They employ data from the *CIS* 3 during 1998-2000 and use a modification of the CDM model. The authors report that the drivers of innovation and productivity across these countries are similar. However, there are differences, especially in the variation in productivity related to more or less innovative activities. Internationally operating firms and larger ones are more inclined to invest in R&D, as well as firms which belong to industries where there are strong strategies in place to protect innovation. They find that rivals are not a vital source of information in comparison to firm suppliers and customers. However, their dataset also does not allow for the calculation of knowledge capital.

Using an unbalanced panel of 7375 Italian manufacturing SMEs during 1995-2003, Hall *et al*. (2009) focus on R&D-performing ones and study the relationship between R&D activities, a firm's innovative performance, and its productivity. They use a modified version of the CDM model and find that international competition increases R&D intensity, particularly for high-tech firms. Firm size, R&D intensity and investment in equipment increase the probability of introducing both process and product innovations, both of which positively affect firm productivity. They report that larger and older firms are less productive and that R&D is positively correlated to productivity.

Raymond *et al*. (2013) introduce some dynamics in the links from R&D to innovation and from innovation to productivity by using a system of four maximum likelihood, nonlinear, dynamic simultaneous equations. The system estimation accounts for individual effects employing two unbalanced panels of Dutch (1639 firms) and French (2505 firms) manufacturing firms from the *CIS* during three periods: 1994-1996, 1998-2000 and 2002-2004. Contrary to most of the other studies, they report a robust unidirectional causality coming from innovation to productivity with no feedback weight.

In a groundbreaking study, using an econometric approach new in this area - the GSEM, Baum *et al.* (2015) analyse the relationship between firm R&D, innovation and productivity. They employ a panel of 7083 Swedish firms during three consecutive *CIS*s - 2008, 2010 and 2012. First, they employ a Probit selection model to identify the firms with both innovation input and innovation output. The second equation represents the determinants of R&D expenditures. The third equation shows the determinants of innovation sales, and the last equation is the conventional productivity equation. They include a latent variable accounting for 'selectivity'. Their results are in line with the main findings of Crépon *et al.*(1998), confirming the effect of R&D expenditure on innovation sales and of innovation sales on labour productivity. They evidence significant heterogeneity across technology and knowledge levels, observing that the effects of the other explanatory variables also vary significantly across sectors. The authors suggest that their findings cast doubt on previous studies, which do not account for such heterogeneity.

5.2.3.3 Firm-level studies on the interdependencies between R&D/innovation, productivity and firm exports

The studies reviewed in this section are based on the new strand of the literature, linked to the 'endogenous growth' theory, which endogenises firm heterogeneity (Atkeson & Burstein 2010, Aw *et al.* 2011, Bustos 2011, Harris & Moffat 2012).

Studying a firm-level dataset of Slovenian firms during 1996-2002, Damijan *et al.* (2008) find that firms' productivity and export decisions are closely linked to their innovative activities. Their econometric approach is based on matching techniques. They suggest that the link coming from product innovation to firm productivity and to its choice of becoming an exporter can explain how a firm's choice to invest in R&D and to innovate pushes its productivity and encourages it to become an exporter.

Investigating the relationship between exporting, productivity/profitability, and investments in R&D, Aw *et al*. (2008) use a dataset of Taiwanese electronics industry firms from 2000 to 2004 with a total of 7772 observations. Their empirical model incorporates firms' heterogeneity in their productivity and that each firm's return to R&D expenditure, physical capital, and exporting depends on its productivity level. Consequently, these investments provide feedback effects with the ability to modify the future productivity path of a firm. They find that prior exporting is significantly and positively related to current R&D expenditure, which is in line with the models of Constantini & Melitz (2007) and Lileeva & Trefler (2010) that larger export market offers higher returns to R&D.

Using a matched dataset from the UK component of the *CIS* 4, 2005, and the Annual Business Inquiry for Northern Ireland, Love *et al.* (2010) explore how Northern Ireland service firms' innovative activities are linked to firms' productivity and exports. They employ a variety of estimation techniques including a 'knowledge production function'. The authors find that, although the relationships between innovative activities, exports and productivity are complicated, innovative activities alone are not enough to improve firms' productivity. However, if firms' innovative activities are conducted together with increased exports, then productivity improvements become apparent.

Utilising a balanced plant-level panel data of 1237 plants for the Taiwanese electronics industry during 2000-2004, Awl *et al*. (2011) develop a dynamic structural model of a producer's decision to engage in R&D and export activities, with both choices endogenously influencing the future path of firm productivity. They estimate three pathways relating exporting, R&D expenditure and productivity. In the first one, the return to exports and R&D grows with the producer's underlying productivity: this leads high-productivity producers to 'self-select' into both R&D and export activities.

In the second one, both export and R&D activities directly affect a firm's future productivity; this reinforces the 'selection' bias. In the third one, policy alterations that modify the future return to one activity, e.g. a decrease in trade costs, R&D grant, influence the probability of both export and R&D activities. They find that the 'self-selection' of high productivity performers is the key path driving exports and R&D expenditure, which in turn, is reinforced by the impact of each activity on future productivity. The authors report that both exports and R&D are significantly and positively correlated with the plant's future productivity, which is endogenous. As a consequence, more plants are 'self-selecting' into both activities, leading to further productivity increases.

Harris & Moffat (2012) explore the contemporaneous links in the relationship between firm R&D activities, innovation and exports, emphasising that these activities underline the general understanding of productivity differences between firms. The authors use three consecutive waves of the UK *CIS* during 2005, 2007 and 2009. They employ Probit regressions for these activities and instrument the endogenous dichotomous variables utilising other variables of their dataset to account for endogeneity. They find that in manufacturing, firms with higher labour productivity are more likely to invest in R&D, while firms with higher capital intensity are more likely to become exporters. However, this is not the case in regard to the non-manufacturing firms where labour productivity is not significant in determining firms' investment in R&D.

Analysing the link between labour productivity, innovation input and innovation output Mairesse *et al*. (2012) employ a sample of 13245 firms from China during 2005 to 2006. They use an approach, similar to CDM with a sequential IV. Mairesse *et al*. (2012) find that firm-level innovation input is the main driver in improving labour productivity. Firm characteristics, (e.g. market share, subsidy, size and other), explain the significant difference in firm involvement in innovation and production. The innovation input depends not on export activities, but on the competitive advantage of the industry in the global market. Hence, gaining a competitive advantage in 'know-how' is as vital as, or even more vital than, the competitive advantage gained from exporting.

Employing a sample of Chilian plant-level data during 1997-2004, Bravo-Ortega *et al*. (2013) investigate the link between productivity, exports and R&D expenditure. They use a multi-equation system, encompassing three processes. The first one represents a plant's decision to engage in R&D expenditure and its amount. The second one captures the decision of a firm to export and its amount. The third process describes the determinants of a firm's productivity. The system is estimated by the ALS technique. The authors report that firms engaged in R&D expenditure are more inclined to export, but the reverse does not hold. Both exports and R&D jointly act to enhance productivity. R&D impacts productivity directly and indirectly through exports. These findings are contrary to the predominant view in the literature, that the same firms 'self-select' for both activities - R&D (more productive firms are more likely to engage in investment in R&D) and export (more productive firms are more likely to become exporters). However, in line with the literature (e.g. Alvarez & Lopes 2005; Van Beveren *et al*. 2010; Cassiman *et al*. 2010), they report that firms engage in 'conscious self-selection'. That is, firms invest in R&D to increase productivity before they become exporters. However, a drawback of this study is that it does not account for the fact that R&D is a path-dependent process.

The authors point out that although their research is a major breakthrough, there are many challenges opened for future research, e.g. not only about the determinants of investment in exports, R&D and productivity but also about possible complementarities with other investments, e.g. physical and human capital. This research aims to address these challenges.

5.2.4 Concluding remarks

The majority of the studies reviewed use econometric approaches which do not account for endogeneity, simultaneity and 'self-selection' biases, as well as different dynamics and interdependencies between the variables, and firm's heterogeneity. Using a CDM approach means, with some exceptions, that the estimates are cross-sectional, and do not account for the timing of the innovation and its impact on firm productivity (Hall 2011). This is because they use *CIS* surveys, which capture data from the past three years only, and there is not sufficient overlap between surveys to create a time-series or a panel dataset. Even researchers who report a great number of firms in their dataset, only have a small number of R&D active firms. For instance, Criscuolo & Haskell (2003) employ a sample of 1596 companies in their *CIS* 2 and 4567 in their *CIS* 3 dataset, but only 509 R&D active companies are entered in both surveys. Examining the effect of R&D cooperation on firms' productivity on a sample of Belgian firms during 1995-1999, Cincera *et al.* (2003) report 599 firms of which only 222 are R&D active. Hall *et al.* (2008) report 9462 enterprises in their dataset drawn from three surveys of which only 608 R&D active enterprises appear in all three of them. Contrary to most of the research in this area, which reports a great number of companies in their datasets, but only a small number of which are R&D active, in this research, we incorporate only R&D active firms in our datasets.

Due to the nature of the innovation surveys, most of the researchers use R&D intensity, a dummy for whether the firm undertakes R&D or other measures of innovation instead of R&D stock of knowledge. Using R&D intensity and dummy variables as proxies for innovation makes the research outcomes not fully applicable for policy-makers as these proxies offer only an indication of the differential impact of various types of innovation on productivity (Hall 2011, Mohnen & Hall 2013). Both variables - R&D intensity and innovation dummy do not perform satisfactorily as normally they account only for the three-year period of the *CIS* survey, therefore, they do not account for the precise timing (Mohnen & Hall 2013). Moreover, these proxies reflect various projects without controlling for their level of success (the most successful projects are mixed with barely successful ones) and do not account for firm size - larger firms with a greater number of projects have a better opportunity to deliver a successful innovative product/service, with at least one of them (Hall 2011, Mohnen & Hall 2013). Contrary to most of the above studies, this research uses R&D stock of knowledge, accounting for the fact that R&D is a path-dependent process.

Taking into consideration the literature review, the following Section 5.3 describes the hypotheses to be tested.

5.3 Theory: hypotheses to be tested

5.3.1 A firm's R&D stock of knowledge positively affects its productivity

The first hypothesis in this chapter tests the predominant view that:

H6(Ch.5, H1): A firm's R&D stock of knowledge positively affects its labour productivity.

At the firm-level, most of the studies are in line with this hypothesis. They find that firms' R&D/innovation positively affects their productivity (Griliches 1980, Griliches & Mairesse 1990, Nadiri 1993, Hall & Mairesse 1995, Wakelin 2001, Damijan *et al*. 2012).

Various authors examine this link using a variety of system equations thus, adding more structure to the relationship (Crepon *et al.* 1998, Hu 2001, Griffith *et al.* 2006, Hall *et al.* 2009). The general finding is that the relationship between R&D/innovation and productivity is positive, depending on firms' characteristic such as human capital, innovation sales, market share, size, exports, diversification, whether it is a process or product innovation and other firms' characteristics.

5.3.2 A firm's R&Dstock of knowledge is an important factor in its productivity-exports relationship

The second hypothesis in this chapter is in line with the modern theoretical developments, namely that:

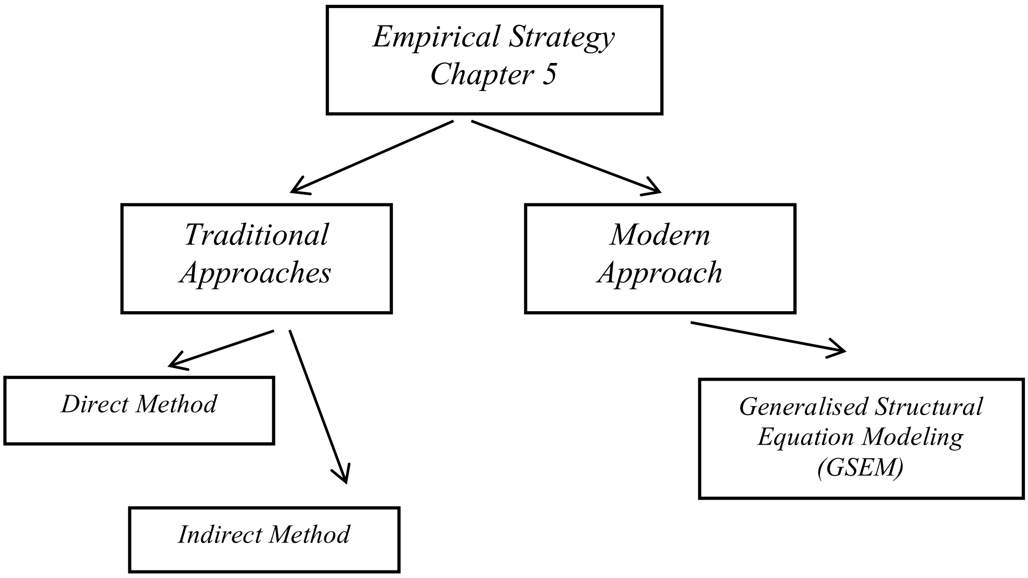
H7(Ch.5, H2): At a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels.

The studies that are in line with this hypothesis are based on the current strand of the literature, linked to the 'endogenous growth' theory, which endogenises firm heterogeneity (Aw *et al.* 2011, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013). Testing our hypothesis, in terms of this theoretical framework, we hope to provide evidence in support of the modern strand of the literature. While in Chapter 4 we have analysed, to some extent, this framework in terms of the relationship between firm R&D stock of knowledge and exports, here, we will take a different perspective, looking mainly at the relationship between firm productivity and R&D stock of knowledge. In particular, in Chapter 4 we have evidenced that a firm's R&D stock of knowledge and its exports are endogenous, they both influence each other positively, conditioning on firm productivity. In Chapter 5, we examine whether at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels, as suggested by Bravo-Ortega *et al.* (2013). This perspective, also in line with the modern theoretical developments, is less researched.

5.4 Baseline specifications and estimation methodology

Accounting for the key theoretical models discussed in the literature review, our strategy in Chapter 5 is to employ a system of empirical approaches, with different options in regard to modelling firm productivity. The aim is to examine in a comprehensive and consistent way the links between R&D stock of knowledge and productivity and their interdependencies, taking into account different dynamics, endogeneity and potential simultaneity. We also account for the interdependencies of R&D stock of knowledge and productivity with other variables such as exports, human capital, market share, finance variables, intangibles and other firms' characteristics. The empirical strategy of Chapter 5 is illustrated in Figure 11.

Figure 11: Empirical strategy of Chapter 5



In this chapter, firm productivity is investigated in both traditional terms - as a one-way process, flowing from R&D stock of knowledge to productivity, as well as a simultaneous process, together with firm R&D stock of knowledge and export activities.

The econometric strategy also includes both traditional and modern approaches. First, in line with most studies on the subject, more traditional econometric approaches will be applied. They will test the first hypothesis that R&D stock of knowledge is associated with an increase in firm productivity. The traditional techniques are applied using two alternative but complementary models to measuring firm productivity. More specifically, intially, we will follow the traditional approaches similar to those used in Damijan *et al.* (2012), who also investigate the effects of R&D/innovation on firm productivity. The first one is based on the estimation of a production function (the direct approach) while the second one employs the TFP as a dependent variable (the indirect approach). The direct approach measures the effect of R&D stock of knowledge and spillovers on labour productivity, making use of a variation of the standard growth accounting approach. Next, we employ the classical indirect method involving obtaining a firm-level measure of TFP (by Levinsohn & Petrin's 2003 method, Appendix 10), which is subsequently regressed on firm R&D stock of knowledge, knowledge spillovers, exports, financial variables, market share and various control variables. They are applied to both the 'All-Firms' dataset and the subset made up by the 'Innovators'.

Second, the GSEM methodology will be applied to test the second hypothesis, according to which at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels, in line with the modern theoretical developments incorporated in the studies of Aw *et al*. (2011) and Bravo-Ortega *et al.* (2013). In fact, applying the GSEM model, we are able to test both hypotheses in Chapter 5 simultaneously.

In Section 5.4.1 we provide the baseline specifications and estimation methodology used for testing the first hypothesis in this chapter, while in Section 5.4.2 we describe the baseline specification and estimation methodology used for testing both Chapter 5 hypotheses simultaneously.

5.4.1 Traditional approaches: baseline specifications and estimation methodology

In this section, first, we outline our models - Section 5.4.1.1 and second, we describe the estimation methodology - Section 5.4.1.2.

5.4.1.1 Traditional approaches: baseline specifications

Following past literature (Griliches 1979, 1992; Scherer 1982) and the literature reviewed in this chapter, the direct method is based on the estimation of an extended Cobb-Douglas production function. Griliches (1992) and Hall & Mairesse (1995) recommend Cobb-Douglas production function as the most appropriate when the objective is to quantify the importance of R&D in the production process. This is because the production function does not yield biased estimates of R&D elasticity when controls for permanent firm effects are incorporated. We use the 'sources of growth' theory, which links increases in output with increases in inputs of capital, labour, human capital and other factors, such as R&D expenditure, intangible assets and spillovers (Griliches 1979, Katayama *et al*. 2005, Cincera & Ravet 2011).

In order to test this hypothesis in a traditional way, we use variations of the augmented growth accounting approach used in Damijan *et al.* (2012) as a direct method. In other words, we estimate the following model:

$$
\begin{aligned}
lnLP_{i,t} = {} & a_0 + a_1 lnLP_{i,t(t-1)} + a_2 lnEI_{i,t} + a_3 lnC_{i,t} + a_4 lnK_{i,t} + a_5 lnL_{i,t} \\
& + a_6 lnCOL_{i,t} + a_7 lnMS_{i,t} + a_8 lnE_{i,t} + a_9 lnQ_{i,t} + a_{10} lnLqR_{i,t} \\
& + a_{11} lnA_{i,t} + a_{12} lnROCE_{i,t} + a_{13} lnK_{t,1} + a_{14} lnK_{t,2} + a_{15} lnK_{t,f} \\
& + Ind.D. + TimeD. + \omega_i + \varepsilon_{it}
\end{aligned}
$$

Equation (9).

Next, following the indirect method, we estimate the alternative but complementary to Equation (9) model - Equation (10):

$$lnTFP_{i,t} = \beta_0 + \beta_1 lnTFP_{i,t(t-1)} + \beta_2 lnEI_{i,t} + \beta_3 lnK_{i,t} + \beta_4 lnL_{i,t} + \beta_5 lnCOL_{i,t} + \beta_6 lnMS_{i,t} + \beta_7 lnE_{i,t} + \beta_8 lnQ_{i,t} + \beta_9 lnLqR_{i,t} + \beta_{10} lnA_{i,t} + \beta_{11} lnROCE_{i,t} + \beta_{12} lnK_{t,1} + \beta_{13} lnK_{t,2} + \beta_{14} lnK_{t,f} + Ind.D. + TimeD. + \omega_i + \varepsilon_{it}$$

Equation (10)

The subscripts i and t signify firms and time respectively. The dependent variables are labour productivity ($LP_{i,t}$, proxied by firm value-added divided by the number of employees), and firm TFP ($TFP_{i,t}$, calculated using the Levinsohn & Petrin's (2003) approach)). Lagged dependent variables are included on the right-hand side of their respective equations to account for firm dynamics. In line with Damijan *et al.* (2012), both right-hand side specifications are the same, except that in the $TFP_{i,t}$ equation we do not include firm physical capital stock - $C_{i,t}$, as it is used in calculating the firm $TFP_{i,t}$ in the Levinsohn & Petrin's (2003) approach, as per Damijan *et al.* (2012). Labour - ($L_{i,t}$), controls for firm size and is measured by the number of employees, while capital - ($C_{i,t}$), is measured by physical capital stock. Firm export intensity - ($EI_{i,t}$), is measured by the ratio of exports to total sales. The financial variables, measuring firm financial health are collateral - ($COL_{i,t}$) and liquidity ratio - ($LiqR_{i,t}$). The return on capital employed - ($ROCE_{i,t}$), measures firm profitability and also, competitive pressure. Market share - ($MS_{i,t}$), is included to account for the firm's competitive environment and also, as a size control variable. In addition, we include human capital - ($E_{i,t}$), measured as a firm's remuneration per employee relative to its industry's remuneration per employee, and firm age - ($Q_{i,t}$), measured by current year minus the year of establishment. Intangible assets intensity - ($A_{i,t}$), measured by the ratio between intangible assets and total assets, is included as complimentary to firm R&D activities, as discussed in Chapter 3, (Section 3.5.1.3). The R&D stock of knowledge is denoted by $K_{i,t}$, the intra-industry spillovers by $K_{t,1}$, the inter-industry spillovers by $K_{t,2}$, and the global spillovers by $K_{t,f}$ (the measurement of which is discussed in Chapter 3, Section 3.5.1.2).

In the alternative equation, first, we obtain a firm-level measure of TFP computed by Levinsohn & Petrin's (2003) technique, according to which firm productivity follows a first-order Markov process. The method accounts for the simultaneity between output and input variables (Petrin *et al*. 2004). Lagged TFP is included on the right-hand side of the equation to also control for serial correlation.

The a_s and β_s are some of the parameters we are interested in estimating. The error term in both equations includes a state-variable transmitted element - ω_t, which influences firms' decision-making process, and an *i.i.d*. element - $\varepsilon_{i,t}$, which does not influence firms' decisions.

The inclusion of industry dummies controls for industry-specific effects (Wakelin 2001; Odagiri & Iwata 1986). In this section, technological opportunities are proxied by intra- and inter-industry spillovers as well as global spillovers, in line with Mairesse & Cuneo (1985) and Mairesse & Sassenou (1991).

Finally, time dummies are included to capture business-cycle effects.

Both indirect and direct models of the traditional econometric approach test whether R&D capital stock positively affects firm productivity. In line with both 'endogenous growth' theory and modern developments, which advocate that the impact of R&D on productivity is positive (summarised in the surveys of Hall *et al.* 2009, Hall 2011, Mohnen & Hall 2013), we expect to observe positive and significant coefficients on R&D stock of knowledge - ($K_{i,t}$), in regard to both direct and indirect approaches in both datasets. Intangible assets - ($A_{i,t}$), as complimentary to R&D stock of knowledge, are also expected to increase firm productivity. Therefore, we expect the coefficients on intangible assets to be positive and significant in all cases.

The 'absorptive-capacity' theory advocates that a firm's ability to capture, assimilate and use external knowledge depends on its prior R&D and human capital (Cohen & Levinthal 1990). Therefore, we expect to find significant and positive effects of human capital - ($E_{i,t}$) on firm productivity. Levin *et al.* (1987) claim that corporate internal research is a way of examining and appropriating competitors' 'know-how'. The literature on spillovers reports that R&D-intensive firms adopt new technologies more rapidly than less R&D-intensive firms (Baldwin & Scott 1987). However, the evidence in regard to the spillover effects is still not conclusive. Therefore, we expect to observe negative intra-industry spillovers - ($K_{t,1}$) effects on firm productivity, to account for the 'stealing' effect within each industry, and positive effects of the global spillovers - $K_{t,f}$, to account for the fact that the UK is one of the most developed countries, which has access to practically all inputs available in the global economy. UK companies can procure an input and utilise it in their production process anywhere the input is produced in the world. In regard to the inter-industry spillovers ($K_{t,2}$) effects on firm productivity, we have no conclusive expectations. The environments for positive and negative spillovers differ between firms and theory alone cannot predict which effect may emerge (Kafouros & Buckley 2008).

A number of studies report that size and age are linked to firms' productivity (Palangkaraya *et al*. 2009, Parisi *et al.* 2006, Guariglia & Cheng 2013). In general, the findings are that firms of larger size and also, older firms are less productive. In line with the work of Gatti & Love (2008), Moreno-Badia & Slootmaekers (2009) and Chen

& Guariglia (2013), we include firm size and age in our models. Similarly to the above findings, we expect the signs of the coefficients associated with firm absolute size (the number of employees - $L_{i,t}$) and age - $Q_{i,t}$ variables to be negative in all cases.

In regard to the remaining variables in our both models, our expectations are set out in the next Section 5.4.1.2 where we describe how we account for firms' heterogeneity in our models.

5.4.1.2 Accounting for firms' heterogeneity

Assessing the impact of both R&D stock of knowledge on firm productivity, we account for the following dimensions of firms' heterogeneity: human capital, firm finances (collateral, liquidity ratio), export behaviour, intangible asset intensity and market share.

- **Human capital**

Human capital contributes greatly to firm productivity growth (Engelbrecht 1997, Frantzen 2000, Griffith *et al*. 2004b, Guellec & de la Potterie 2004). It impacts on a firm's capability to innovate and on its absorptive capacity (Griliches 1964, Anon-Higon & Sena 2006). Human capital - $E_{i,t}$, is proxied by the firm's remuneration per employee divided by the average remuneration per employee of all firms operating in the industry the firm belongs to. The empirical literature supports the view, that in general, human capital increases firm productivity (for surveys, see Blundell *et al.* 1999, Bartel 2000). Conti (2005) for Italian firms and Dearden *et al*. (2006) for British firms both report that R&D is associated with increases in human capital which in turn is linked to greater productivity (for more discussion on the subject see Bartel 1994, 1995; Black & Lynch 1996).

- **Firm finances**

The relationship between finance and firm-level productivity has not been researched comprehensively except in a few studies. Nucci *et al*. (2005) for Italy, Gatti & Love (2008) for Bulgaria, and Moreno-Badia & Slootmaekers (2009) for Estonia report a positive and significant impact of financial variables on firms' TFP.

Chen & Guariglia (2013) use a panel of 130 840 Chinese manufacturing firms during 2001-2007 to estimate a TFP model extended with financial variables. They report that both liquidity and exports are vital determinants of the relationship between internal finance and productivity.

Liquidity - $LiqR_{i,t}$, or the working capital, is the difference between a firm's current assets and current liabilities, divided by the firm's total assets. The higher the liquid assets, the better the firm's ability to raise external funds swiftly (as it is categorised by lenders as low-risk) or to sell some assets quickly. Nucci *et al*. (2005) also report that Italian firms with low liquidity experience a tougher negative impact of leverage on their TFP in comparison to firms with high liquidity. Although maintaining more liquid assets may be seen as less risky by creditors, it may lead to high opportunity costs for the firms (Chen & Guariglia 2013). This happens because excessive liquidity may also encourage various trading strategies, which could be adverse to creditors' interests (Myers & Rajan 1998). Thus, excessive liquidity may ruin the credibility of the firms to their creditors and lower their ability to raise external finance. Our expectations are that the coefficients on our liquidity ratio variable - $LiqR_{i,t}$, will be positive and significant in all cases.

Firm collateral - $COL_{i,t}$, is measured by the ratio of a firm's tangible assets to total assets. More tangible assets can help the firm borrow money externally, as tangibility increases the value that can be recovered by creditors if borrowers default (Carpenter & Petersen 2002, Almeida *et al*. 2004, Spaliara 2008). Productivity-enhancing R&D/innovation involves high risks, uncertainties and bulky investments. High-tech firms are associated with the possession of R&D related intangible assets, which usually are not accepted as collateral (Chen & Guariglia 2013). Therefore, we expect the coefficients on our firm collateral variable to be negative and significant in terms of both 'All-Firms' (as the majority of the firms in this dataset are high-tech firms) and 'Innovators' datasets.

- **Export behaviour**

The general consensus in the international economics literature is that exporters are usually more productive than non-exporters (e.g. Bernard & Jensen 1999). One of the explanations for this is based on the 'self-selection' bias hypothesis: only the most productive firms have the capability to become exporters and operate in international markets (Bernard & Jensen 1999). The other explanation is based on the view that exporting makes it easier for firms to obtain new knowledge and expertise, which increases their productivity (Van Biesebroeck 2006). Furthermore, trade increases firm productivity by enabling more efficient use of resources, better capacity utilisation and scale benefits in terms of large international markets (Bhagwati 1978, Krueger 1978, Obstfeld & Rogoff 1996, Wei & Liu 2006). The 'endogenous growth' theory advocates that international trade facilitates technology creation, transfer and diffusion (Rivera-Baits & Romer 1991a,b; Coe & Helpman 1995; Coe *et al*. 1997). Trade provides firms with knowledge about international best practice, learning and could increase productivity by stimulating the creation of new technologies (Hejazi & Safarian 1999). Atkeson & Burstein (2010) and Constantini & Melitz (2007) explain how trade can intensify the rate of return on a firm's R&D or investment in 'know-how' and consequently improve the productivity benefits. However, some researchers, e.g. Griffith *et al*. (2004a) evidence a trivial effect of trade on firm productivity growth. For a survey on the link between exports and productivity, see Greenaway & Kneller (2007). Therefore, our expectations are that the coefficients on our export intensity variable - $EI_{i,t}$, will be positive and significant in all cases.

- **Intangible assets intensity**

There is complementarity between R&D/innovation and intangibles, both influencing firm productivity (Mohnen & Hall 2013). This study employs intangible assets intensity - $A_{i,t}$, as a proxy for intangibles, discussed in Chapter 3, (Section 3.5.1.3). Intangibles intensity accounts for an appropriation mechanism and a mechanism for erecting barriers against competitors, branding, marketing and product differentiations. By building brand loyalty, product differentiation and barriers to entry, marketing accounts for both the 'demand-pull' (customer preferences) and 'technology-push' (technological opportunities) sides of the innovation activities, and prospective complementarities between them. Marketing is also an instrument of appropriability as it reduces product/service price-elasticity, thus permitting firms to increase their prices while keeping customers (Lee 2005, Bagwell 2007). Many studies evidence that in fast-changing technology-focused sectors, where customer demands are diverse and highly segmented, R&D complementarities can lead to better firm performance and successful innovation efforts (Maidique & Hayes 1984, Gupta *et al*. 1985, Perks *et al.* 2009). Therefore, our expectations are that the coefficient on our intangible assets variable - $A_{i,t}$, will be positive and significant especially in the 'Innovators' subset.

- **Market share**

Researchers use a variety of proxies for competitive pressure: profitability, market share, market concentration, concentration ratio, barriers to entry (Greenhalgh & Rogers 2006). This study employs market share - $MS_{i,t}$, and ROCE - $ROCE_{i,t}$, (return on capital employed, also accounting for firm profitability) as proxies of competitive pressure. ROCE shows the ability of the firm to profit from its existing capital base. The literature advocates that the appropriability conditions (whether a firm can appropriate or not the benefits of its productivity enhancing R&D/innovation activities) may differ depending on competitive conditions (Tang 2006, Kafouros & Buckley 2008). Those firms operating in an R&D-intensive environment can fully appropriate the benefits of their innovation only for a certain time, as their competitors' innovations shorten the life-cycle of technologies, making the innovations obsolete. McGahan & Silverman (2006) evidence that even a major break-through may not have a significant impact on firm performance if it operates in an environment of fierce rivalry. This s because intensified competition prevents the firm from capturing the full benefits of its invention (as the 'know-how' spills over to other firms), while allowing other firms to productively use such external R&D.

Tang (2006) reports that firms with higher market power finance their productivity enhancing R&D activities more easily than other firms as they obtain supranormal profits stemming from such power. In line with the above discussions, we expect the coefficients on both market share - ($MS_{i,t}$) and ROCE - ($ROCE_{i,t}$) to be positive and significant in all our cases.

5.4.1.3 Traditional approaches: estimation methodology

In order to allow for comparability of the outcomes and to deliver consistency throughout the whole thesis, our econometric strategy incorporates a comprehensive system of empirical approaches. Within the system, there are different options for estimating the effects of R&D stock of knowledge on firm performance, measured by a number of indicators, e.g. size - Chapter 3, exports - Chapter 4 and productivity - Chapter 5. Therefore, following our standard econometric approach in regard to Chapters 3 and 4 we use the pooled OLS, the FE, and the dynamic, robust, one-step GMM, described comprehensively in Chapter 3, (Section 3.4.2), and applied to both Equations 9 and 10. In order for our GMM estimators to be valid, the instruments must be exogenous to fulfil the orthogonality conditions. Therefore, we perform a number of tests, which are elaborately explained in Chapter 3, (Section 3.4.2 - Estimation methodology).

According to the previous sections, to account for firms' heterogeneity, we include age, intangible assets intensity, exports, financial variables, human capital and market share in our model. We also account for firms' heterogeneity by including intra-, inter-industry and global spillovers. R&D stock of knowledge, export intensity, productivity, capital, labour, market share, human capital, intangibles and the financial variables are potentially endogenous as they are likely to be correlated with the firm-specific effects, productivity shocks and measurement errors, all of which are collectively included in the error term of the models. The strictly exogenous variables are the industry and year dummies, firm age, intra-, inter-industry and global spillovers.

5.4.2 Modern approach: baseline specification and estimation methodology

The econometric model in Section 5.4.1 represents the one-way relationship between firm productivity and R&D stock of knowledge, based on the relevant literature in Section 5.2.1.1 as well as in Section 5.2.3.1 and Section 5.4.1. The model does not appropriately account for the simultaneity and interdependency issues, different dynamics between the variables of interest and the 'self-selection' bias. This section tests both hypotheses of this chapter simultaneously, namely:

H6 (Ch5, H1): A firm's R&D stock of knowledge positively affects its labour productivity.

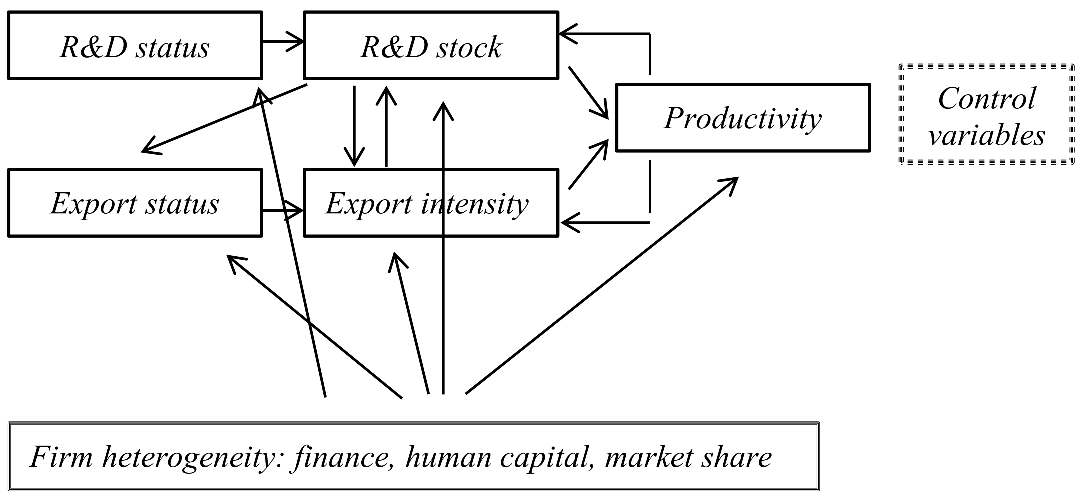
H7(Ch5, H2) At a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels.

The first hypothesis has been comprehensively reviewed in the above stated sections. Section 5.2.1.2, as well as Section 5.2.3.2 and Section 5.2.3.3 of the literature review provide the theoretical foundation of the second hypothesis to be tested.

5.4.2.1 Modern approach: baseline specification

The complexity of the relationship between R&D stock of knowledge, productivity and exports, and underlying firms' heterogeneity is shown in Figure 12.

Figure 12: Modern approaches model (modified from Bravo-Ortega *et al.* 2013)



According to the scarce research, produced in line with the new theoretical developments in this area, the general findings are that a firm's decisions on whether to innovate and whether to export are interdependent; they both may endogenously influence the firm's future productivity (Baldwin & Gu 2004, Aw *et al.* 2008, Damijan *et al.* 2008, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013).

Accounting for the above literature, the objective of our empirical strategy is to define the three firm processes - exports, R&D stock of knowledge and productivity gains, and to identify the structural relationships between these variables. The first process describes the firm's decision to export and the amount exported; the second, the decision to engage in R&D expenditure and the amount invested; and the third, the achievement of productivity gains. Our model includes five equations, estimated simultaneously by the GSEM approach.

Chapter 4 explores these relationships emphasising mainly the link between firm exports and R&D stock of knowledge. Here, our aim is to investigate the effect of R&D stock of knowledge on firm productivity and to test whether at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels. For consistency of results and reliability of our analysis, an approach, similar to Chapter 4, (Section 4.4.2) is followed.

This is because we have seen in Chapter 4 that the coefficient on the latent variable - $\mathcal{L}$, in the 'R&D stock of knowledge' equation is negative but strongly significant. This is the only equation where the latent variable has a negative sign. Therefore, in this chapter we try to further explore the 'R&D stock of knowledge' equation in order to discover other factors which may influence firm investment in R&D. Thus, we add a Probit 'R&D selectivity' equation to the GSEM model in Chapter 4 to account for the 'R&D selectivity' bias.

In this equation, instead of export intensity - $EI_{i,t}$, we include an export growth variable - $EG_{i,t}$, to examine whether a firm's engagement in R&D investment depends on its export growth (estimated as the growth rate in a firm's exports over the 11-year period being studied), accounting for past export activities, not only for the current, or previous year's export activities. Export growth is used widely by research scholars as a complimentary measure of firm export intensity and export propensity (Zou & Simona 1998, Katsikeas *et al.* 2000).

Also, we add a variable - $LPI_{i,t}$, to account for the level of a firm's labour productivity, relative to its industry's average labour productivity because we are interested to explore whether a firm needs to have a higher labour productivity in regard to the industry's average labour productivity, in order to engage in R&D activities. We also account for the level of the firm's physical capital stock, relative to its industry's physical capital stock - $CI_{i,t}$, to examine whether more capital intense firms are more likely to engage in R&D activities. Market share - $MS_{i,t}$, is included to account for the level of competition the firm faces (and also, as a size variable) while the number of employees - $L_{i,t}$, is used as a size variable.

In both R&D equations, we include financial variables to account for the firm's financial health. In the Probit 'R&D selectivity' model, we include the leverage ratio - $LR_{i,t}$, while in the other R&D equation we include the firm collateral - $COL_{i,t}$.

We use firm collateral ($COL_{i,t}$) in the 'R&D stock of knowledge' equation as firms which are already engaged in R&D activities are characterised by a high level of intangible assets (Mohnen & Hall 2013, Griliches 1990). However, the higher tangibility of assets makes it easier for a firm to externally fund its R&D/innovation activities, as the higher the tangibility of the assets, the higher the value recovered by creditors if borrowers default (Carpenter & Petersen 2002, Almeida *et al*. 2004, Spaliara 2008).

In the Probit 'R&D selectivity' equation we use the leverage ratio - $LR_{i,t}$, (calculated by the sum of a firm's current liabilities and non-current liabilities over total assets). This is because firms which aim to invest in R&D are highly dependent on their ability to raise finance. Productivity enhancing R&D processes are associated with high level of risks and uncertainty and require large investments (Chen & Guariglia 2013). Therefore, a firm needs to be financially healthy to undertake such activities. The leverage ratio shows the percentage of a firm's assets that have been financed with (both short-term and long-term) debt. A higher ratio implies a greater level of leverage, and subsequently, financial risk for the lenders in order to lend money to such firms, especially when a borrower wants to invest the money in risky R&D activities (Brown *et al.* 2009).

Employing similar econometric strategies allows us to compare the results of both Chapter 4 and Chapter 5 and thus, to provide more comprehensive and conclusive evidence on the above relationships.

The empirical strategy, in this case, involves a GSEM procedure consisting of five equations (Equation 11). First, we estimate a Probit 'Export selection' equation (Equation 11/1) to establish the likelihood that a firm will become an exporter. Second, we estimate a Probit 'R&D selection' equation (Equation 11/2) to establish the likelihood that a firm will engage in investment in R&D. Third, the two Probit models are combined with three linear regression models showing the determinants of export intensity (Equation 11/3), R&D stock of knowledge (Equation 11/4), and productivity (Equation 11/5).

The two 'export' equations (11/1) and (11/3) derived from the literature reviewed in Chapter 4, consider firm export propensity and export intensity as functions of firm 'neo-endowment', 'technology-based' and 'endogenous growth' theories. Estimating them simultaneously, we account for the likely 'selection' bias. As there are fixed, and sunk costs associated with entry into export markets, more productive firms are more likely to export (Melitz 2003, Greenaway & Kneller 2004, Harris & Li 2009). The variables included are as per Chapter 4, (Section 4.4.2).

However, according to Mairesse *et al*. (2012), the firm's costs associated with becoming R&D active are higher than the costs associated with becoming an exporter. Estimating both 'R&D' equations (11/2) and (11/4) together we account for the other likely 'selection' bias, namely, that the most productive firms are more likely to engage in R&D activities (Girma *et al.* 2008, Damijan *et al.* 2010, Harris & Moffat 2012). The variables included in both R&D equations are the same as per Equation 8/3 in Chapter 4 as well as the justification for their inclusion. However, in the 'R&D selection' Equation (11/2), different proxies are used, based on the same inputs, explained earlier. The 'R&D' equations (11/2 and 11/4) are in line with the relevant literature in regard to the determinants of firms' R&D (Griliches 1984, Hall 2002, Lynskey 2004, Aw *et al*. 2007, Girma *et al.* 2008, Baum *et al*. 2015), discussed in Chapter 4, (Section 4.4.2.1).

The fifth Equation (11/5) is a labour productivity model, used by the majority of the researchers. Equation (11/5) accounts for our first hypothesis, namely, that a firm's R&D stock of knowledge positively affects its productivity. It also accounts for the *'learning by exporting'* hypothesis, discussed in Section 5.2.1.1. The variables included are the same as per the equivalent equation in the GSEM model in Chapter 4. In general, the majority of the studies find that the impact of R&D on productivity is positive (Hall *et al*. 2009, Hall 2011, Mohnen & Hall 2013). The literature on the view that a firm's exports boost its productivity in numerous ways (the '*learning by exporting'* hypothesis, reviewed in Section 5.2.1.1), according to Greenaway & Kneller (2007), validate the inclusion of firms' export intensity in this equation. In line with this hypothesis is the 'absorptive capacity*'* theory linked to the 'human capital' literature. Firms with a higher level of human capital can better absorb and assimilate other firms' knowledge (Cohen & Levinthal 1990). Therefore, incorporated in this model is the human capital variable.

Estimating all five equations together, we account for our second hypothesis in this chapter, that at a firm-level, R&D stock of knowledge influences productivity directly and indirectly through export levels.

In other words, we estimate the following model (Equation 11):

$$DE_{i,t} = \alpha_0 + \alpha_1 lnLP_{i,t} + \alpha_2 lnK_{i,t} + \alpha_3 lnCOL_{i,t} + \alpha_4 lnL_{i,t} + Ind.D. + TimeD. + \mathcal{L} + \varepsilon_{i,t}$$

Equation (11/1)

$$DRD_{i,t} = \beta_0 + \beta_1 lnLPI_{i,t} + \beta_2 lnEG_{i,t} + \beta_3 lnCI_{i,t} + \beta_4 lnL_{i,t} + \beta_5 lnMS_{i,t} + \beta_6 lnLR_{i,t} + Ind.D. + TimeD. + \mathcal{L} + \epsilon_{it}$$

Equation (11/2)

$$lnEI_{i,t} = \gamma_0 + \gamma_1 lnLP_{i,t(t-1)} + \gamma_2 lnK_{i,t(t-1)} + \gamma_3 lnCOL_{i,t(t-1))} + \gamma_4 lnE_{i,t(t-1)} + \gamma_5 lnMS_{i,t(t-1)} + \gamma_6 lnQ_{i,t(t-1)} + \gamma_7 \mathcal{L} + Ind.D. + TimeD. + \gamma_i + v_{i,t}$$

Equation (11/3)

$$lnK_{i,t} = \delta_0 + \delta_1 lnLP_{i,t(t-1)} + \delta_2 lnEI_{i,t(t-1)} + \delta_3 lnMS_{i,t(t-1))} + \delta_4 lnE_{i,t(t-1)} + \delta_5 \mathcal{L} + Ind.D. + TimeD. + \delta_i + u_{i,t}$$

Equation (11/4)

$$lnLP_{i,t} = \lambda_0 + \lambda_1 lnEI_{i,t(t-1)} + \lambda_2 lnK_{i,t(t-1)} + \lambda_3 lnC_{i,t(t-1))} + \lambda_4 lnMS_{i,t(t-1)} + \lambda_5 lnE_{i,t(t-1)} + \lambda_6 \mathcal{L} + Ind.D. + TimeD. + \lambda_i + \xi_{i,t}$$

Equation (11/5)

where the subscripts *i* and *t* represent firm and time respectively.

In the first equation, $DE_{i,t}$ is a dummy variable equivalent to 1 if a firm *i* exported in year *t*, and 0 if not, $L_{i,t}$ is the number of employees, (a size control variable), $LP_{i,t}$ - labour productivity (proxied by a firm's value-added divided by the number of employees), $COL_{i,t}$ - a firm's collateral, measuring the firm financial health (proxied by the firm's tangible assets over its total assets), and $K_{i,t}$ denotes the firm's R&D stock of knowledge (proxied by the firm's R&D stock of knowledge per employee).

In the second equation, $DRD_{i,t}$ is a dummy variable equal to 1 if a firm i invest in R&D in year t, and 0 if not. $LPI_{i,t}$ is the firm's labour productivity relative to its industry's average labour productivity, $EG_{i,t}$ is the firm's export growth, (estimated as the growth rate in the firm's exports over the 11-year period being studied), $CI_{i,t}$ signifies the firm's capital relative to its industry's capital (proxied by the the firm's physical capital stock, relative to its industry's physical capital stock), $L_{i,t}$ is the number of employees, $MS_{i,t}$ is the firm's market share (measured as the firm's share of total sales divided by its industry's total sales), and $LR_{i,t}$ is the firm's leverage ratio (measured as the sum of the firm's current liabilities and non-current liabilities over total assets).

In the third equation, $EI_{i,t}$ is the firm's export intensity (the ratio between the firm's exports and its total sales), $E_{i,t}$ signifies human capital (proxied by the firm's per-employee remuneration relative to its industry's per employee remuneration), and $Q_{i,t}$ is the firm's age (measured in years - current year minus incorporation year).

In the fourth equation, all the variables are denoted in the same way as per the previous equations. In the fifth equation, the only new variable is the firm's physical capital stock, denoted by $C_{i,t}$ (proxied by the firm's physical capital stock per employee). In contrast to the models in Section 5.4.1, here the variables R&D stock of knowledge - $K_{i,t}$ and physical capital stock - $C_{i,t}$ are expressed in intensity form (per employee).

Equations (8/1) to (8/5) also incorporate time dummies, which account for the likely effects of business cycles and the changes in interest and exchange rates. Industry dummies are also incorporated into all equations to capture industry fixed effects.

The error term includes two components. The first component is the firm-specific element and the second one denotes the idiosyncratic component. The idiosyncratic error terms of Equations (11/1), (11/2), (11/3), (11/4) and (11/5) are denoted as ε, ϵ, ν, υ and ξ, respectively. The firm-specific fixed effects of Equations (8/3) to (8/5) are denoted as γ, δ and λ. The latent variable - $\mathcal{L}$, integrated into all equations deals with the issue of selectivity, as $EI_{i,t}$ in the third equation is measured only for the exporters while $K_{i,t}$ in the fourth equation is measured only for the firms which possess R&D stock of knowledge.

As per many studies in this area, (Roberts & Tybout 1997; Bernard & Jensen 1999, 2004a, Greenaway *et al.* 2007), all right-hand side time-varied variables of Equation (11/3) are lagged once[36]. In line with modern research in this area, e.g. Girma *et al*. (2008) and Damijan *et al.* (2010), who simultaneously estimate a firm's decisions to enter export markets and to engage in R&D activity, conditioned on its productivity, we include only the one-period lagged values of all right-hand side time-varied variables in Equations (11/4) and (11/5), to account for endogeneity. In line with Harris & Moffat (2012), all right-hand side variables of Equation (11/1) - the 'Export selection' equation, are contemporaneous while all right-hand side variables of Equation (11/2) – the 'R&D selection' equation are also contemporaneous, in line with Baum's *et al.* (2015) GSEM Probit model.

In line with the literature review and the above theoretical framework, our general expectations are as follows. We expect to find support for both our hypotheses.

[36] Firm age - $Q_{i,t}$, entering the model either lagged once or in its contemporaneous form, does not alter the outcomes significantly.

In regard to our 'Productivity' equation, we expect to find that the coefficients on both R&D stock of knowledge - ($K_{i,t}$) and market share - ($MS_{i,t}$) are positive and significant. In terms of both 'export' equations, we expect in both models to find the coefficients on the R&D stock of knowledge - ($K_{i,t}$) positive and significant. In regard to our 'R&D selectivity' equation, we expect the coefficients on export growth - ($EG_{i,t}$) and labour productivity in relation to industry's labour productivity - ($LPI_{i,t}$), to be positive and significant while the coefficient on firm leverage ratio - ($LR_{i,t}$), to be negative and significant. In regard to our 'R&D stock of knowledge' equation, we expect the coefficients on both export intensity - ($EI_{i,t}$) and labour productivity - ($LP_{i,t}$) to be positive and significant. In terms of our firm collateral variable - ($COL_{i,t}$), we expect its coefficient to be negative and significant. Also, we expect to find that a firm's decision on whether to innovate and export are interdependent; they both may endogenously influence the firm's future productivity.

5.4.2.2 Modern approach: estimation methodology

As per Chapter 4, we use the GSEM econometric technique to estimate our system of equations. The GSEM is a unified estimation approach with which both the propensity to become an exporter, as well as the observable consequences of being an exporter (in terms of export intensity) can be modelled simultaneously. Also, both the propensity to engage in R&D investment, as well as the observable consequences of being engaged in R&D investment (in terms of R&D stock of knowledge) can be modelled simultaneously. In particular, we employ the GSEM method with a full-information maximum likelihood estimator. That is, we estimate the above relationship as a single system of simultaneous equations. This approach accounts for the dynamics in the relationship between firm R&D, exports and productivity.

As per our GSEM model in Chapter 4, by including the same unobserved component in all our equations, we can handle endogeneity. In our case, $\mathcal{L}$ is the shared, unobserved latent variable, handling endogeneity. This is the second way we account for endogeneity in our model, in addition to using only lagged time-varied variables on the right-hand side of the equations, except in the Probit Models. The study normalises the latent variable by constraining its variances to be 1, for the same reasons as per the GSEM model in Chapter 4.

In this model, we assume that all variables are potentially observed endogenous variables, except age, industry and time dummies which are observed, exogenous variables. The GSEM also generates error variables - latent exogenous variables with fixed-unit path coefficients, which are associated with each of the dependent variables (StataCorp 2015).

We use a single, mixed-process simultaneous system of five structural equations. The GSEM model permits different observations to be used in each equation (both Probit models, 'Export intensity', 'R&D stock of knowledge' and 'Productivity') of the whole model. The GSEM can deal with the endogeneity, expressed in a simultaneous system of equations - the full-information maximum likelihood (FIML) estimates, computed by the GSEM can manage this type of simultaneity (Roodman 2011). Using a single equation system, we can test both hypotheses at the same time.

5.5 Data, variables of interest and summary statistics

The dataset and the data sources are presented in Chapter 2. In summary, both our panel datasets are unbalanced with data missing for some firms. The total number of firms included in our 'All-Firms' dataset is 956, of which 772 firms belong to the high and medium-high R&D intensity sectors (the 'Innovators' subset) and 184 firms belong to the medium-low and low R&D intensity sectors.

However, as per Chapter 3 and Chapter 4, the number of firms with sufficient R&D data in terms of the medium-low and low R&D intensity industries is not enough in order for our econometric approach - the GMM, to deliver results which satisfy the requirements of the model. All our experiments produced invalid estimates due to the 'weak instruments' problem (described in Chapter 2, Section 2.2.2). Consequently, we analyse the firms at the 'All-Firms' level and at the 'Innovators' sub-sample level when testing the first hypothesis (described in Section 5.3.1), using the traditional econometric approaches.

Testing simultaneously both of our hypotheses in Chapter 5 (described in Section 5.3), the GSEM approach is applied to the 'All-Firms' dataset only. This is because we were not able to apply the same model to neither the 'Innovators' nor the firms from the medium-low and low R&D sectors[37].

5.5.1 Variables of interest

All variables of interest used in both traditional approaches are the same as per Chapter 3, (Section 3.5.1) and Chapter 4, (Section 4.5.1). The human capital variable is calculated as the firm's remuneration per employee, relative to its industry's

[37] As per similar experiments in Chapter 4, all our tests produced error results 'r (1400): initial values not feasible', even when using different starting values, in line with the GSEM procedure, described in the STATA manual.

remuneration per employee, as per Chapter 4. In addition, we include ROCE - $ROCE_{i,t}$ (return on capital employed), as a measure of the firm's competitive environment/profitability. Measuring firm productivity, we also employ the firm's TFP ($TFP_{i,t}$, estimated by Levinsohn & Petrin's 2003 approach) which is used for performing robustness tests. The variables used in this GSEM model are the same as per the Chapter 4 GSEM model, where physical capital stock and R&D stock of knowledge are expressed in their intensity form (per employee). To more thoroughly investigate the relationship between firm R&D stock of knowledge and productivity, we have incorporated an additional R&D Probit equation with the following variables:

R&D export dummy - $DRD_{i,t}$ is a dummy variable equal to 1 if a firm *i* invest in R&D in year *t*, and 0 if not.

Export growth - $EG_{i,t}$, estimated as the growth rate in a firm's exports over the 11-year period being studied.

Labour productivity per industry - $LPI_{i,t}$, measured by a firm's labour productivity divided by its industry's average labour productivity.

Leverage ratio - $LR_{i,t}$, measuring firm financial health and calculated by the sum of a firm's current liabilities and non-current liabilities over total assets, where current liabilities include bank loans, accounts payable and other current liabilities.

Physical capital stock per industry - $CI_{i,t}$, measured by a firm's physical capital stock in relation to its industry's physical capital stock.

5.5.2 Summary statistics

The initial summary statistics as well as firms' classification are presented in Chapter 2, (Section 2.2.2, Tables 1 and 2). Table 13.1 and Table 13.2 provide the descriptive statistics of the variables in both 'All-Firms' (Table 13.1) and 'Innovators' (Table 13.2) datasets, reporting the number of observations, mean, median, standard deviation, minimum and maximum values of the variables studied. Data is presented in levels.

Table 13.1: Descriptive statistics: Chapter 5, 'All-Firms'

Descriptive Stat.	***'All-Firms'***					
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Labour Productivity	*7858*	*103.856*	*(235.053)*	*59.962*	*.011*	*6205.674*
TFP	*7403*	*20.054*	*(15.172)*	*15.532*	*.003*	*74.857*
Export Intensity	*5558*	*.387*	*(.362)*	*.504*	*.00003*	*1*
R&D Stock of Knowledge	*7350*	*65179.01*	*(190446.1)*	*10463.46*	*5*	*1466876*
Intangible Assets Intensity	*5740*	*.205*	*(.223)*	*.116*	*1.51e-06*	*.987*
Human Capital/Ind.	*9665*	*1.146*	*(.524)*	*1.046*	*.001*	*3.973*
Physical Capital Stock	*7563*	*1656583*	*(6394232)*	*41977.21*	*3*	*4.66e+07*
Labour	*9869*	*1216.099*	*(4017.864)*	*179*	*10*	*38400*
Age	*10516*	*30.483*	*(24.947)*	*22*	*5*	*147*
Intra-Ind.Spillovers /Total Sales	*10516*	*.077*	*(.059)*	*.068*	*.0001*	*.200*
Inter- Ind.Spillovers /Labour	*10516*	*823.583*	*(102.729)*	*856.468*	*565.589*	*960.467*
Global Spillovers	*10516*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*
Market share	*9494*	*.009*	*(.035)*	*.001*	*2.02e-08*	*.375*
Liquidity Ratio	*7395*	*.339*	*(.237)*	*.296*	*.00003*	*.998*
Collateral	*9733*	*.193*	*(.216)*	*.107*	*.00002*	*.999*
ROCE	*6481*	*22.091*	*(22.228)*	*14.91*	*.008*	*130.963*
Export dummy	*7017*	*.792*	*(.406)*	*1*	*0*	*1*
R&D Stock of Knowledge/L.	*6995*	*696.686*	*(11027.51)*	*61.171*	*.015*	*731105.5*
Physical Capital Stock/L.	*7217*	*7138.233*	*(152465.4)*	*236.390*	*.250*	*1.06e+07*
Physical Capital Stock/Ind.	*7562*	*.015*	*(.055)*	*.001*	*5.47e-08*	*.304*
R&D dummy	*10516*	*.699*	*(.459)*	*1*	*0*	*1*
Leverage Ratio	*7578*	*.634*	*(.328)*	*.616*	*.001*	*1.990*
Export growth	*2446*	*.272*	*(.548)*	*.183*	*.0001*	*4.736*
Labour Productivity/ Ind.	*7748*	*1.680*	*(1.799)*	*1.193*	*.0001*	*14.718*

Note: All relevant variables are measured in thousands from which the ratios are calculated except ROCE which is obtained from FAME database. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form. The last eight variables are used in the GSEM model only

As the 'Innovators' represent, on average, 81% of the whole dataset, while the low and medium-low R&D intensity firms - on average, 19%, high heterogeneity in terms of firms' characteristics is expected. Firms' heterogeneity per *ICB* industry classification in terms of firm labour productivity is shown in Appendix 11.

In regard to Table 13.1, 'All-Firms' columns, since most of the firms are from high and medium-high R&D intensity sectors, it is anticipated that the mean value of the R&D stock of knowledge (*65179.01)* will be high with a high standard deviation (*190446.1).* The mean value of their labour productivity is 103.856, however, with a high standard deviation (*235.053*), confirming the great heterogeneity in terms of firms' characteristics, as discussed in Chapter 3, (Section 3.5.2). The mean value of firm labour productivity in relation to the industry's average labour productivity is also high - (*1.680*). The mean value of their TFP is 20.054, though, with a high standard deviation (*15.172*). In regard to their size, the firms are large with average mean values of labour (*1216.099*), physical capital stock (*1656583*) and market share (*.009*), and high standard deviations, (*4017.864*), (*6394232*) and (*.035*), respectively. Viewed in their intensity forms, per employee, both mean values of R&D stock of knowledge (*696.686*) and physical capital stock (*7138.233*) are still high as well as the mean value of the physical capital stock relative to the industry's physical capital stock *(.015*).

The firms from the 'All-Firms' dataset, on average, export 39% of their total sales, while the mean value of their export growth is .272. Their intangible assets represent 21% of their total assets. The average human capital (*1.146*) is also at a high level. The firms in this data sample are also, on average, mature firms (*30.483*). The intra-industry R&D expenditure, on average, is 8% of the total intra-industry sales. The mean value of ROCE (*22.091*) shows a good return on capital employed. In regard to the financial variables, the mean of the leverage ratio (*.634*) is high, while the mean of the firm collateral *(.193*) is low. The mean of the liquidity ratio is .339.

In regard to Table 13.2, 'Innovators' analysis, the high mean value of the R&D stock of knowledge (*70458.93)* is expected. However, the standard deviation is also high - (*200720*).

Table 13.2: Descriptive statistics: Chapter 5, 'Innovators'

Descriptive Stat.			*'Innovators'*			
Variable	***Obs.***	***Mean***	***St. Dev.***	***Median***	***Min.***	***Max.***
Labour Productivity	*6324*	*90.705*	*(191.471)*	*59.459*	*.011*	*6205.674*
TFP	*5976*	*20.666*	*(15.592)*	*16.062*	*.003*	*74.857*
Export Intensity	*4682*	*.448*	*(.362)*	*.581*	*.00003*	*1*
R&D Stock of Knowledge	*6497*	*70458.93*	*(200720)*	*11811.85*	*5*	*1466876*
Intangible Assets Intensity	*4609*	*.227*	*(.229)*	*.144*	*.00002*	*.987*
Human Capital/Ind.	*7687*	*1.098*	*(.469)*	*1.025*	*.001*	*3.973*
Physical Capital Stock	*6115*	*436508.6*	*(1677145)*	*30318.72*	*3*	*3.73e+07*
Labour	*7871*	*854.308*	*(3088.546)*	*154*	*10*	*38400*
Age	*8492*	*28.096*	*(22.561)*	*20*	*5*	*147*
Intra-Ind.Spillovers /Total Sales	*8492*	*.094*	*(.052)*	*.076*	*.001*	*.200*
Inter- Ind.Spillovers /Labour	*8492*	*802.406*	*(102.836)*	*842.816*	*565.589*	*957.256*
Global Spillovers	*8492*	*8.25e+08*	*(1.53e+08)*	*8.24e+08*	*6.17e+08*	*1.15e+09*
Market share	*7656*	*.006*	*(.021)*	*.001*	*4.33e-08*	*.342*
Liquidity Ratio	*6055*	*.365*	*(.239)*	*.327*	*.0003*	*.998*
Collateral	*7757*	*.142*	*(.163)*	*.077*	*.00003*	*.999*
ROCE	*4857*	*23.881*	*(23.563)*	*16.316*	*.008*	*130.963*

Note: All relevant variables are measured in thousands from which the ratios are calculated except ROCE which is obtained from FAME database. Due to lack of reliable data, the Global Spillovers variable is not expressed in intensity form.

The firms in this dataset are characterised by great levels of productivity in terms of both labour productivity and TFP. The mean value of their labour productivity is 90.705, however, with a high standard deviation (*191.471*), confirming the high heterogeneity in terms of firms' characteristics, not only between the sectors with different technological levels but also, within the same technological group, as discussed in Chapter 3, (Section 3.5.2). The mean value of their TFP is 20.666, though, with a high standard deviation (*15.592*).

The firms are of reasonable, however, not very large size, with an average mean value of the physical capital stock of 436508.6*,* market share of .006, and high standard deviations of 1677145 and .021, respectively.

In regard to the 'Innovators' subset, on average, the firms export 45% of their total sales, while their intangible assets are 23% of their total assets. The average human capital (*1.098*) is also at a high level. The firms in this sample are, on average, mature firms (*28.096*). The intra-industry R&D expenditure is, on average, 9% of the total intra-industry sales.

In terms of their financial health, the mean value of the firm collateral (.142) is low; the mean value of the liquidity ratio is .365. However, the firms belonging to this group enjoy a good return on capital employed (*23.881*).

Looking at the descriptive statistics, on average, it seems that the firms with high mean values for R&D stock of knowledge are also those associated with a high level of productivity, in terms of both labour productivity and TFP. This, in general, provides support for our hypothesis that R&D stock of knowledge and firm productivity are positively linked. However, in Section 6.6 we shell see if after accounting for other factors this relationship is confirmed in terms of each of our hypotheses.

The correlations between the variables are shown in Appendix 12, indicating that there are no intolerable multicollinearity problems.

5.6 Results and discussions

This section provides the results of our econometric analysis. First, we report and discuss the outcomes of our 'traditional' econometric approaches - Section 5.6.1, followed by the results of our 'modern' approach' - Section 5.6.2. Finally, we report the robustness tests - Section 5.6.3.

5.6.1 Traditional approaches

The traditional econometric approaches test our first hypothesis of this chapter namely that:

H6 (Ch5, H1): A firm's R&D stock of knowledge positively affects its productivity.

The analysis is performed on both the 'All-Firms' dataset, as well as the 'Innovators' only subset.

5.6.1.1 'All-Firms'analysis

Table 14 provides the results of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions in terms of our dynamic model of the determinants of firm labour productivity, outlined in Equation (9). Model 4 reports the results of our TFP regression - Equation (10). The column in grey displays the results employed as a robustness test, discussed in Section 5.6.3.

Table 14: Firm productivity and R&D stock of knowledge: 'All-firms' analysis

Firm productivity: 'All-Firms' analysis					
Model/Dependent Variable	***1.Pooled OLS(lnLP)***	***2. Fixed Effects(lnLP)***	***3. GMM (lnLP)***	***4. GMM (lnTFP)***	***5. GMM (lnLP)***
Constant	*4.886****	*8.729****	*Omitted*	*Omitted*	*Omitted*
	(1.910)	*(2.026)*			
ln (Labour Prod. $_{t-1}$)	*.626****	*.094***	*.488****		*.481****
	(.036)	*(.046)*	*(.062)*		*(.060)*
ln (TFP $_{t-1}$)				*.595****	
				(.040)	
ln (Export Intensity)	*.016****	*.023*	*.044****	*1.125****	*.046***
	(.006)	*(.017)*	*(.017)*	*(.423)*	*(.019)*
ln (Age)	*-.009*	*Omitted*	*.008*	*.234*	*.010*
	(.015)		*(.025)*	*(.417)*	*(.025)*
ln (Capital Stock)	*.056****	*.085***	*.044**		*.059***
	(.011)	*(.037)*	*(.027)*		*(.030)*
ln (Labour)	*-1.371****	*-1.680****	*-1.515****	*-4.916****	*-1.542****
	(.040)	*(.052)*	*(.078)*	*(1.202)*	*(.096)*
ln (Human Capital)	*.097****	*.252****	*.202****	*.231*	*-.057*
	(.034)	*(.060)*	*(.080)*	*(1.354)*	*(.084)*
ln (Collateral)	*-.003*	*.016*	*.004*	*-.032*	*-.025*
	(.009)	*(.041)*	*(.024)*	*(.405)*	*(.023)*
ln (Intang. Assets Int.)	*.013***	*.007*	*.040***	*-.017*	*.027***
	(.006)	*(.011)*	*(.017)*	*(.269)*	*(.014)*
ln (Liquidity Ratio)	*.026***	*.024**	*.005*	*.655*	*-.012*
	(.012)	*(.017)*	*(.029)*	*(.468)*	*(.028)*
ln (Market Share)	*.241****	*.541****	*.378****	*4.222****	*.402****
	(.031)	*(.066)*	*(.072)*	*(1.091)*	*(.090)*
ln (R&D Stock)	*.020***	*-.057***	*-.003*	*-.213*	*.010*
	(.009)	*(.027)*	*(.022)*	*(.363)*	*(.022)*
ln (ROCE)	*.055****	*.067****	*.072****	*1.083****	*.049***
	(.009)	*(.112)*	*(.020)*	*(.427)*	*(.021)*
ln (Intra-Ind./Sales Spill.)	*-.140****	*-.287****	*-.244****	*-3.133****	*-.240****
	(.039)	*(.046)*	*(.058)*	*(.871)*	*(.055)*
ln (Inter-Ind./ Labour Spill.)	*-.321*	*-.627****	*-.759****	*-10.932**	*-.801****
	(.224)	*(.236)*	*(.283)*	*(5.779)*	*(.284)*
ln (Global Spill.)	*.032*	*.261***	*.579****	*5.632****	*.586****
	(.097)	*(.119)*	*(.125)*	*(1.976)*	*(.140)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.025*	*0.001*	*0.023*
AR(2) Test			*0.955*	*0.165*	*0.767*
Hansen's J test			*0.523*	*0.446*	*0.518*
Obs.(groups)	*974*	*974 (286)*	*974 (286)*	*1061(301)*	*974(286)*
Instruments (lags)			*262, (3 4)*	*212,(2 2)*	*190,(2 2)*
R^2	*0.902*	*0.550*			
F	*F(31,285)= 309.21****	*F(20,285)= 35.31****	*F(40, 285)= 4260.07 ****	*F(39,300)= 252.25****	*F(40,285)= 28086.33****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
In Equations 1,2, 3 and 5 the interpretation of the estimates of ln(Labour) is (a_5 -1) as the dependent variable is stated in 'per employee' terms (VA/L).
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 1 presents the pooled OLS model, which is based on cluster-robust standard errors, controlling for arbitrary heteroscedasticity and intra-cluster correlation. The coefficients associated with the lagged labour productivity, export intensity, capital stock, labour, human capital, market share, ROCE and intra-industry spillovers are all significant at the 1% level of significance. However, only the coefficients on labour productivity, export intensity, capital stock, human capital, market share and ROCE, are positive. R&D stock of knowledge, intangible assets intensity and liquidity ratio are also positively associated with firm labour productivity. However, the pooled OLS parameters tend to be biased due to unobserved firm-specific heterogeneity and likely endogenous regressors.

Column 2 details the coefficients obtained using the FE estimator, which removes the impact of time-invariant firm characteristics. The coefficient on the lagged labour productivity variable is positive and significant at the 5% level, as are the coefficients on the capital stock and global spillovers variables. The R&D stock of knowledge is negatively related to labour productivity, contrary to the result provided by the OLS estimator. The coefficient on the intra-industry spillovers is in line with the OLS estimator in terms of sign and significance level. The coefficients on labour, human capital, market share, inter-industry spillovers and ROCE variables are all significant at the 1% level. They are positive for human capital, market share and ROCE. The coefficient on the liquidity ratio is positive and significant at the 10% level. However, the FE estimator does not take into account the possible endogeneity of the regressors which affects its consistency.

Column 3 details our preferred one-step, system GMM estimates. The model controls for unobserved heterogeneity and endogeneity simultaneously. Statistical tests conducted do not reject the null hypothesis of instrument validity and/or model specification, meaning that the coefficients derived from the one-step, robust, system GMM regression, are credible.

The GMM coefficient on the lagged dependent variable is 0.488 (positive and significant at the 1% level) and lies within the range for dynamic stability achieved by the FE (*0.94*, lower bound) and the pooled OLS (*0.626*, upper bound) estimators. The positive GMM coefficient on the lagged dependent variable suggests that a firm's labour productivity in the current year depends on its labour productivity in the previous year. This means that firms' productivity fluctuations are sluggish and smooth.

The coefficient on the R&D stock of knowledge is negative and not significant, while the coefficient on the intangible assets intensity (*0.040*) is positive and significant at the 5% level, suggesting possible substitution between both inputs. Contrary to the results presented in most other similar papers (Romer 1986, 1990, 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Griffith *et al.* 2004; Cameron *et al*. 2005; Jones 2005), our results do not support the hypothesis that a firm's R&D stock of knowledge positively affects its labour productivity. Conversely, as the intangible assets intensity have positive effects on labour productivity, this may hint that, for firms which substitute their investment in R&D for investment in intangible assets (patents, licenses, marketing contracts), the hypothesis is supported. It is worth noting that the above studies do not account for such a comprehensive range of firms' characteristics as our study in this section does. Also, they do not include such a wide set of variables, associated with ‘innovation’ to account for both internal (i.e. R&D stock of knowledge, intangibles) and external (i.e. intra-, inter-industry and global spillovers) technological effects.

The coefficients associated with intra- and inter-industry spillovers, as well as global spillovers and human capital, are all significant at the 1% level, however, only the coefficients on the human capital and global spillovers are positive.

Bitzer & Geishecker (2006) report that negative intra-industry spillovers are, on average, higher than the intra-industry positive effects. The R&D of a firm competitor in the same industry increases not only this industry pool of knowledge but also it improves the competitor’s own goods, processes and productivity. Increased productivity of the rivals usually negatively impacts on the performance of the researched firm (Kafouros & Buckley 2008). This effect is discussed by Aitken & Harrison (1999), who associate it to the ‘market-stealing’ effect, which can force a firm to strategically shrink output in reaction to competition from more scientifically progressive rivals. As a result, the firm cost curve may move up, which in turn will lead to poorer productivity. De Bondt (1996) stresses that although R&D increases the competitiveness of one firm, it may decrease its rivals’ profits. McGahan & Silverman (2006) claim that external innovations can directly influence firm performance negatively, through the ‘market-stealing’ effects or through indirect appropriation via licensing. Mohnen (1996) argues that, if an innovative product created by another firm substitutes for a firm’s own product, then R&D spillovers can decrease the price that a developer can charge for it. Likewise, McGahan & Silverman (2006) claim that the strength of such an effect is subject to whether innovation has come from a prospective competitor or not. The above arguments show that investment in R&D may inflict negative externalities on competitors, even in the presence of positive knowledge diffusion (De Bondt 1996).

The positive effects of the global spillovers are in line with Guellec and Van Pottelsberghe (2001) and Griffit *et al.* (2004b), who evidence that foreign spillovers positively affect firm productivity.

The coefficient on export intensity is positive and significant at the 1% level. The results are expected, and they are in line with the general view that a firm's export activities increase its productivity. One of the explanations for this is provided by the 'self-selection' bias hypothesis: only the most productive firms have the capability to become exporters and compete in foreign markets (Bernard & Jensen 1999). The other explanation is built on the view that exporting makes it easier for firms to acquire new knowledge and expertise, which raises their productivity (Van Biesebroeck 2006). Exporting firms, investing in R&D also engage in creating a brand name, marketing, licensing and trademarks (the coefficient on the intangible assets intensity is positive and significant), which serves as an appropriation (of new knowledge) mechanism and also as a mechanism for erecting barriers against rivals. The results show support for the 'absorptive capacity' theory - firms with a high level of human capital have a higher absorptive capacity to assimilate new knowledge (Cohen & Levinthal 1989).

The coefficients on liquidity ratio and firm collateral are both positive but not significant. The coefficient on ROCE (*.072*) is positive and strongly significant at the 1% level. The possible explanation is that exporters could raise money in both domestic and international financial markets, allowing them to spread their financial resources and the related risks as the business cycles are not impeccably coordinated between countries.

The coefficient on market share *(.378*) is positive and significant at the 1% level meaning that when other variables are held constant, a 10% increase in the priority given by a firm to its market share is associated with an increase in its labour productivity by, on average, 3.7%. Market share is an important factor in the appropriation (or not) of productivity enhancing R&D/innovation activities (Tang 2006, Kafouros & Buckley 2008). Tang (2006) claims that firms with greater market power finance more easily their productivity enhancing R&D activities than other firms as they gain supranormal profits associated with such power.

The coefficient on labour is negative and strongly significant at the 1% level. This could mean that increasing the number of employees necessitates expenditure on remuneration which does not pay off in terms of increasing labour productivity.

Column 4 reports the results of our TFP regression (Model 4), Equation 10.

The GMM coefficient on the lagged dependent variable is 0.595 (positive and significant at the 1% level). The coefficient on R&D stock of knowledge is negative and not significant. The above results are in line with the estimates of Model 3. However, contrary to the results of Model 3, the coefficient on the intangible assets intensity is negative but not significant.

The coefficients on the spillovers maintain their sign and significance level as per Model 3, except for the coefficient on the inter-industry spillovers, which decreases its level of significance to 10%. The coefficient on human capital is positive as per Model 3, however, it ceases to be significant.

The coefficients on export intensity, ROCE and market share maintain their sign and level of significance as per Model 3, however, here they are much larger.

The coefficient on liquidity ratio is positive as per Model 3 while the coefficient on firm collateral is negative, however, both are not significant, as per Model 3.

The next section describes and discusses the results in terms of the 'Innovators' only subset.

5.6.1.2 'Innovators' analysis

Table 15 provides the results of the pooled OLS (Model 1), FE (Model 2), and system GMM (Model 3) regressions of our dynamic model of the determinants of firm labour productivity, outlined in Equation (9). Model 4 reports the results of our TFP regression - Equation (10).

Column 1 details the pooled OLS coefficients. All variables with significant coefficients in Model 1, (Table 14), maintain their coefficients' sign and significance level also in this model. However, for the reasons stated in the previous section, the estimates are likely to be biased.

Column 2 details the coefficients obtained using the FE estimator. All variables with significant coefficients in Model 2, (Table 14), maintain their coefficients' sign and significance level also in this model except for the coefficient on the labour productivity which decreases its significance to the 10% level, while the coefficient on the liquidity ratio ceases to be significant. However, the FE estimator does not take into account endogeneity which affects its consistency.

Table 15: Firm productivity and R&D stock of knowledge: 'Innovators' analysis

Firm productivity: 'Innovators' analysis				
Model/Dependent Variable	***1.Pooled OLS (lnLP)***	***2. Fixed Effects (lnLP)***	***3. GMM (lnLP)***	***4. GMM (lnTFP)***
Constant	*6.240**** *(1.995)*	*9.917**** *(2.047)*	*Omitted*	*Omitted*
ln (Labour Prod. $_{t-1}$*)*	*.619**** *(.038)*	*.085** *(.048)*	*.466**** *(.059)*	
ln (TFP)				*.576**** *(.04)*
ln (Export Intensity)	*.018**** *(.007)*	*.023* *(.018)*	*.047*** *(.020)*	*1.038**** *(.417)*
ln (Age)	*-.012* *(.016)*	*Omitted*	*.004* *(.027)*	*.208* *(.462)*
ln (Capital Stock)	*.057**** *(.012)*	*.091*** *(.037)*	*.058** *(.031)*	
ln (Labour)	*-1.392**** *(.043)*	*-1.719**** *(.056)*	*-1.52**** *(.095)*	*-5.197**** *(1.201)*
ln (Human Capital)	*.093**** *(.035)*	*.261**** *(.064)*	*-.032* *(.080)*	*.464* *(1.278)*
ln (Collateral)	*.001* *(.010)*	*.020* *(.042)*	*-.033* *(.024)*	*-.055* *(.402)*
ln (Intang. Assets Int.)	*.013*** *(.006)*	*.005* *(.012)*	*.026** *(.014)*	*.067* *(.284)*
ln (Liquidity Ratio)	*.027*** *(.013)*	*.022* *(.017)*	*-.011* *(.029)*	*.702** *(.456)*
ln (Market Share)	*.259**** *(.034)*	*.578**** *(.071)*	*.388**** *(.088)*	*4.730**** *(1.095)*
ln (R&D Stock)	*.020*** *(.009)*	*-.055*** *(.028)*	*.014* *(.024)*	*-.421* *(.374)*
ln (ROCE)	*.052**** *(.010)*	*.062**** *(.112)*	*.056**** *(.021)*	*1.277**** *(.427)*
ln (Intra-Ind./Sales Spill.)	*-.147**** *(.045)*	*-.342**** *(.050)*	*-.256**** *(.061)*	*-3.522**** *(.989)*
ln (Inter-Ind./Labour Spill.)	*-.340* *(.242)*	*-.833**** *(.250)*	*-.834**** *(.310)*	*-12.333*** *(6.133)*
ln (Global Spill.)	*.019* *(.103)*	*.289*** *(.124)*	*.562**** *(.145)*	*6.841**** *(2.168)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.027*	*0.002*
AR(2) Test			*0.741*	*0.161*
Hansen's J test			*0.613*	*0.537*
Observations(groups)	*886*	*886 (254)*	*886 (254)*	*968(270)*
Instruments (lags)			*185, (2 2)*	*207,(2 2)*
R^2	*0.897*	*0.556*		
F	*F(26,253)= 258.29****	*F(20,253)= 36.47****	*F(32, 253)= 3965.83 ****	*F(31,269)= 249.76****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values. In Equations 1 to 3, the interpretation of the estimates of ln(Labour) is (a_5 -1) as the dependent variable is stated in 'per employee' terms (VA/L).
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Column 3 details our preferred system GMM estimates. The model controls for unobserved heterogeneity and endogeneity simultaneously. Statistical diagnostics performed do not reject the null hypothesis of instruments validity and/or model specification, meaning that the coefficients derived from the one-step, robust, system GMM regression are credible.

The GMM coefficient on the lagged dependent variable is 0.466 (positive and significant at the 1% level) and lies within the range achieved by the FE (*0.85*, lower bound) and the pooled OLS (*0.619*, upper bound) estimators. The positive GMM coefficient on the lagged dependent variable indicates that a firm's labour productivity in the current year depends on its labour productivity in the previous year.

The coefficient associated with the R&D stock of knowledge is positive but not significant while the coefficient on the intangible assets intensity is positive and marginally significant at the 10% level, suggesting possible substitution between both variables. In line with our outcomes in regard to the 'All-Firms' dataset, our results in the 'Innovators' subset do not support the hypothesis that a firm's R&D stock of knowledge positively affects its labour productivity. The possible substitution suggested in regard to Table 14 between R&D stock of knowledge and intangible assets intensity is weak in this group of firms.

The results in regard to the coefficients on all spillovers, ROCE, labour and market share are in line with their counterparts in Model 3, (Table 14) in terms of sign and significance level.

The coefficient associated with export intensity is still positive, as per Model 3, (Table 14), however, its significance decreases to the 5% level. The coefficients on both liquidity ratio and collateral change their signs as in comparison to Model 3, (Table 14), from positive to negative, but are still not significant.

Column 4 details the results of our TFP regression (Model 4), Equation 10.

The GMM coefficient on the lagged dependent variable is 0.576 (positive and significant at the 1% level). The coefficient associated with the R&D stock of knowledge is negative but not significant. The coefficient on the intangible assets intensity is positive, however, also not significant.

Intra- and inter-industry spillovers are negatively associated with firm TFP. The effects of the global spillovers on firm TFP are positive and strongly significant at the 1% level.

The coefficients on export intensity, labour, market share, ROCE and collateral maintain their sign and level of significance as per Model 4 in Table 14, while the coefficient on liquidity ratio, here, is positive and marginally significant.

5.6.1.3 Summary and considerations

Taken together, we find no evidence that a firm's R&D stock of knowledge positively affects its productivity in both 'All-Firms' and 'Innovators' groups. The positive impact of the intangible assets intensity on labour productivity may indicate that for firms which substitute their investment in R&D for investment in intangible assets (patents, licenses, marketing contracts and other intangible assets) the hypothesis indeed, may be supported.

Looking at both Table 14 and Table 15, we note that although the subset of the 'Innovators' firms makes up on average 81% of the 'All-Firms' analysis, there are differences in the results for both datasets. For example, the coefficient on human capital from strongly significant at the 1% level and positive in the 'All-Firms' analysis (Model 3, Table 14), becomes negative and not significant in Model 3, (Table 15).

Similarly, the coefficient on the liquidity ratio from not significant, although positive in Model 4, (Table 14), becomes marginally significant in Model 4, (Table 15).

Other variables' coefficients change their significance level. For example, the coefficient on export intensity changes its significance from 1% in Model 3, (Table 14) to 5% in Model 3, (Table 15), while the coefficient on the intangible assets intensity changes its significance level from 5% in Model 3, (Table 14), to 10% in Model 3, (Table 15).

The above results show that although the 'All-Firms' dataset includes only a small number of firms from low and medium-low R&D intensity industries, these firms make a big difference. This illustrates that there is a great heterogeneity in terms of firms' characteristics between the firms belonging to different technological sectors and knowledge levels, in line with Baum *et al.* (2015).

5.6.2 Modern approach

5.6.2.1 Main findings

This section tests both hypotheses in this chapter simultaneously. The results of the GSEM model are presented in Table 16 and Table 17.

Table 16: Firm productivity and R&D stock of knowledge: GSEM - Probit models

GSEM: Firm exports, productivity and R&D stock of knowledge				
Model	***1.Probit Exports*** *a/SE*	***2.Probit Exports*** *Mfx*	***3.Probit R&D*** *β/SE*	***4.Probit R&D*** *Mfx*
Constant	*20.060*		*-.582*	
	(2631.359)		*(2.364)*	
ln (Labour Prod.)	*-1.560****	*-.145****		
	(.162)	*(Om.)*		
ln (Export growth)			*-.032*	*-.001*
			(.064)	*(.002)*
ln (Labour Prod./Ind.)			*-.110*	*-.004*
			(.177)	*(.007)*
ln (R&D Stock/ Labour)	*1.519****	*.141****		
	(.134)	*(Om.)*		
ln (Capital Stock/ Labour)				
ln(Capital Stock/ Ind.)			*.339****	*.013****
			(.103)	*(.004)*
ln (Collateral)	*.152****	*.014****		
	(.047)	*(Om.)*		
ln (LR)			*-.057*	*-.002*
			(.171)	*(.007)*
ln (Labour)	*.613****	*.057****	*.242*	*.010*
	(.077)	*(Om.)*	*(.217)*	*(.009)*
ln (Market Share)			*-.248**	*-.010**
			(.170)	*(.007)*
Latent	*3.404****		*1.417****	
	(.251)		*(.282)*	
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations (Groups/equation)	*4390 (3815)*		*4390 (1267)*	

Notes: Robust standard errors are reported in parentheses. Robust standard errors in GSEM, 2. Probit 'Exports' (Model 2) are omitted by STATA when calculating the 'fixedonly' marginal effects with the latent variable set to zero.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Table 17: Firm productivity and R&D stock of knowledge: GSEM - productivity, R&D stock of knowledge and exports

GSEM: Firm exports, productivity and R&D stock of knowledge				
Model	***5.Productivity***	***6. R&D Stock***	***7.Export Intensity***	***8.GMM Product.***
Constant	*4.052*** (.412)*	*-2.655*** (.381)*	*30.175*** (4.906)*	*7.686*** (.903)*
ln (Labour Prod.)		*.745*** (.022)*	*-7.548*** (.868)*	
ln (Export Intensity)	*-.117*** (.013)*	*.139*** (.015)*		*.147* (.086)*
ln (R&D Stock/ Labour)	*.833*** (.022)*		*6.339*** (.705)*	*-.066 (.090)*
ln (Capital Stock/ Labour)	*-.001 (.001)*			*-.010 (.087)*
ln (Collateral)		*-.029*** (.010)*	*-.001 (.010)*	
ln (Market Share)	*.227*** (.013)*	*-.209*** (.014)*	*1.727*** (.220)*	*.213*** (.085)*
ln (Human Capital)	*-.425*** (.049)*	*.782*** (.051)*	*-3.267*** (.508)*	*.642*** (.256)*
ln (Age)			*-.033* (.019)*	
Latent	*1.382*** (.030)*	*-1.327*** (.022)*	*10.476*** (1.186)*	
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test				*0.014*
AR(2) Test				*0.204*
Hansen's J test				*0.232*
var(e.lnProd.)	*.001** (.001)*			
var(e.lnR&D)		*.327** (.014)*		
var(e.lnExport)			*.189** (.057)*	
Observations	*4390*	*4390*	*4390*	*2848*
(Groups/equation)	*(2343)*	*(3175)*	*(2209)*	*(587)*
F				*F(30,586) =53.22****

Notes: Robust standard errors are reported in parentheses. For AR(1), AR(2) and Hansen test reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Table 16, reports the results of our 'Export selectivity' equation - Probit 1 'Exports' (Model 1) and Probit 2 'Exports' (Model 2), where the marginal effects are reported in Model 2. Columns 3 and 4 display the results of the 'R&D selectivity' equation - Probit 3 'R&D' (Model 3) and Probit 4 'R&D' (Model 4), where the marginal effects are reported in Model 4.

Table 17 reports the results of our 'Productivity' (Model 5), 'R&D stock of knowledge' (Model 6) and 'Export intensity' (Model 7) equations. In addition, to check to what extent the GMM method captures the firms' productivity results (Model 5), we perform a GMM estimation (Model 8) of Model 5 with the same variables.

Looking at the Probit 2 'Exports' (Model 2), the results are similar to the results of Model 2, Table 12 (Chapter 4); however, the values of the marginal effects are larger in this model. The results indicate that the likelihood of being an exporter is positively associated with firm R&D stock of knowledge, collateral and size. The results support the modern theoretical developments: before entering foreign markets, firms need to enhance their productivity by undertaking R&D/innovation activities. This is required in order to strengthen their capability to break through the entry barriers protecting highly competitive overseas markets (Alvarez & Lopez 2005, Van Beveren & Vandenbussche 2010, Cassiman *et al.* 2010, Harris & Moffat 2012). Furthermore, firms with larger size are more likely to become exporters (Melitz 2003, Greenaway & Kneller 2004). The results also support the 'financial constraints' literature: in order to become exporters, firms have to be financially healthy (Chaney 2005, Van Biesebroeck 2006, Blalock & Roy 2006, Greenaway *et al.* 2007).

However, the probability of becoming an exporter is negatively associated with firm labour productivity, which is unexpected. Estimating simultaneously both 'export' equations (Equation 11/1 and Equation 11/3), we control for possible 'selection bias'. Taken together, the results of both models (Model 2 and Model 7) suggest that firm export propensity as well as export intensity, are negatively associated with firm productivity. Contrary to the predominant view that, more productive firms are more likely to export (Melitz 2003, Greenaway & Kneller 2004, Harris & Li 2009), we do not find evidence for this 'self-selection' bias in firm export activities, which is in line with the study of Bravo-Ortega *et al.* (2013). However, the findings that prior to becoming exporters, firms have to engage in productivity enhancing activities (e.g. innovation/R&D), help us to explain the nonappearance of 'self-selection' bias in the propensity to export equation (Model 2). This is because first, firms will engage in investment in R&D to increase their productivity and after that, they will export (Bravo-Ortega *et al.* 2013).

The results of the 'R&D selectivity' equation - Probit 4 'R&D' (Model 4, Table 16) show that the probability of engaging in R&D investment is positively associated with a firm's physical capital stock relative to its industry's physical capital stock (at the 1% level of significance) and negatively related to its market share (at the 10% level). The results indicate that in order to engage in investment in R&D, firms need to be capital intense in relation to the industries in which they operate. For some researchers, e.g. Mairesse *et al.* (2012), the firm's costs associated with becoming R&D active are higher than the costs associated with becoming an exporter. However, increasing firm market share decreases the likelihood of a firm engaging in investment in R&D which, in general, is in line with the theory that smaller firms are more innovative than larger firms, as per Chapter 3 literature review. This is because smaller firms are more incentivised to innovate as they are hungrier for profits than larger firms (Aghion & Schaffer 2002).

Probit 4 'R&D' (Model 4) addresses the 'R&D selectivity' bias, namely that the most productive firms are more likely to engage in R&D activities (Girma *et al.* 2008, Damijan *et al.* 2010, Harris & Moffat 2012). Contrary to this view, we find no evidence that the propensity to engage in R&D investment is positively associated with firm labour productivity, relative to its industry's average labour productivity. That is, similarly to Bravo-Ortega *et al.* (2013) we do not find evidence for the R&D 'self-selection' bias.

In addition, we find no significant association between the firm propensity to become R&D active and its financial health, measured by firm leverage ratio. That is, the percentage of a firm's total assets that have been financed with (both short-term and long-term) debt prove to have no significant effect on whether a firm will become R&D active or not.

Looking at the 'Productivity' equation (Model 5, Table 17), the effect of R&D stock of knowledge is strongly significant and positive, as well as the effect of market share. This provides evidence in support of our first hypothesis in this chapter that a firm's R&D stock of knowledge positively affects its productivity, in line with most studies in this area (Hall *et al*. 2009, Hall 2011, Mohnen & Hall 2013). In addition to the results of Model 2, this offers further support for the modern hypothesis which advocates that firms not only need productivity enhancing activity (e.g. R&D/innovation) prior to entering the foreign markets but also, they need productivity enhancing feedback after becoming exporters. This illustrates the two-way causal link between exports and R&D/innovation (Harris & Moffat 2012). Moreover, firms'

R&D/innovation and export activities can also directly influence the future firms' productivity (Aw *et al.* 2011).

Most studies evidence that firms of larger size are less productive (Palangkaraya *et al*. 2009, Parisi *et al.* 2006). However, their measure of firm size is in terms of absolute size, while here we employ market share which also accounts for the firms' competitive environment. The effect of market share in this equation is strongly significant and positive. We find that the greater the market share, the higher the labour productivity. Market share is a significant factor in the appropriation (or not) of productivity enhancing R&D/innovation activities (Tang 2006, Kafouros & Buckley 2008).

The negative and strongly significant effect of human capital on labour productivity may indicate that hiring more workers increases remuneration expenses without necessarily increasing labour productivity. This is contrary to the results of the majority of studies (e.g. Engelbrecht 1997, Frantzen 2000, Griffith *et al*. 2004b, Guellec & Van Pottelsberghe de la Potterie 2004) which report that human capital contributes greatly to firm productivity.

The effect of export intensity is strongly significant at the 1% level, however, negative. The result is unexpected and is contrary to the majority of findings that export activities improve firm productivity (Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Aw *et al.* 2007, Aw *et al.* 2008, Damijan *at al.* 2008, Harris & Moffat 2012). Unlike Girma *et al.* (2004), who report significant effects of *'learning by exporting'* in regard to UK firms, we do not find support for the *'learning by exporting'* hypothesis (discussed in Section 5.2.1.1), namely that firms learn from exporting and thus increase their productivity. However, Girma's *et al.* (2004) dataset includes firms only during one year - 2000. The initial research in this area (e.g. Clerides *et al*. 1998, Bernard &

Jensen 1999), also does not find evidence that productivity increases more quickly after a firm becomes an exporter. Wagner (2002) evidence no significant effects of *'learning by exporting'* in regard to German firms. Nevertheless, this hypothesis is not widely researched, and the evidence provided is scarce.

A possible explanation of the negative effects, running in both directions between export activities and firm productivity, is that the UK is one of the most technologically advanced nations in the world and one of the top investors in R&D according to all editions of the EU *R&D Scoreboard*. Therefore, it is much more likely that firms in foreign markets, especially those in less developed countries, will benefit more from trading with the UK than UK firms do. This hypothesis mainly finds support for firms in developing countries. For example, Alvarez & Lopez (2005) report significant learning effects from exporting in regard to Chilean firms, while Fernandez & Isgut (2005) report similar evidence for Colombian firms. Our results are in line with Krugman's (1979, 1986) view that technological advances from trade will benefit both exports and the terms of trade in less advanced countries. This is because these countries are assumed to have more incentives, in terms of technological catch-up, economic convergence and *'learning by exporting'* (Ben-David & Loewy 1998, Guillen 2001, Ganotakis & Love 2011).

Model 6 (Table 17) reports the GSEM estimates of the 'R&D stock of knowledge' equation which are similar to the results of Model 4 (Table 12, Chapter 4) with small variations in the size of the coefficients. Taken together, the results of Model (5) and Model (6) of Table 17, indicate that R&D stock of knowledge and productivity positively affect each other. The effect of export intensity on R&D stock of knowledge is also positive and strongly significant; the interpretation is the same as per Model 4 (Table 12, Chapter 4).

The effects of the latent variable are negative and strongly significant at the 1% level as per Model 4, (Table 12, Chapter 4). The same latent variable is positively associated with export intensity and productivity while it is negatively associated with R&D stock of knowledge.

Our finance variable collateral negatively affects firm R&D stock of knowledge and it is strongly significant at the 1% level. It seems that, in this case, when firms invest in more tangible assets, their investment in R&D suffers.

The market share effects are negative and strongly significant. This could be interpreted in terms of our Chapter 3 discussions that larger firms have a more bureaucratic structure which may stifle innovative activities (Schumpeter 1942, Baldwin & Gellatly 2003, Kim *et al.* 2009).

Column 7 (Table 17), reports the coefficients on the final link in the GSEM model - the 'Export intensity'[38] (Model 7) estimates, which have the same sign and level of significance as per Model 3, (Table 12, Chapter 4); however, their size in this model is smaller except for the coefficient on age which is the same in both models.

The coefficients on the R&D stock of knowledge and market share are positive and statistically significant at the 1% level. As per Model 3 (Table 12), the coefficients associated with the R&D stock of knowledge *(6.339*) and market share *(1.727*) are not only statistically significant but also, economically significant - their values are large.

[38] Estimating the equation, as per the GSEM model in Chapter 4, we were not able to compute the model with lagged labour productivity (even with different starting values as per GSEM procedure), although we did not experience this problem in terms of the R&D model. Therefore, we employed the contemporaneous values. According to Greenaway *et al.* (2007) research, their results were robust to using contemporaneous variables instead of lagged variables as regressors in a similar 'export' model.

The results of this equation provide further support to the findings of the majority of researchers in that, R&D/Innovation positively influences export activities (Wakelin 1998a, Sterlacchini 1999, Bleaney & Wakelin 2002, Gourlay *et al.* 2005, Chiru 2007).

The coefficients on the labour productivity and human capital are still strongly significant but negative, as per Chapter 4. In line with the results of Model 3 (Table 12), the coefficients associated with the labour productivity *(-7.548*) and human capital *(-3.267*) are not only statistically significant but also, economically significant - their values are very large. In addition to the interpretation provided in regard to the 'Productivity' equation, the negative effect of the labour productivity variable also could be explained in terms of the global spillovers effects which are more beneficial for firms in developing countries (as per Chapter 3 discussions). Both the 'endogenous growth' and 'trade' theories advocate that trade/exports stimulate knowledge flows and technology transfer between trading partners (e.g. Nadiri 1993, Barba & Tarr 2000, Tybout 2000, Keller & Yeaple 2003). A possible explanation is that by trading with UK firms, it looks like the overseas firms gain more advantages in terms of knowledge transfers and 'know-how' than the UK firms. Some researchers (e.g. Keller 1998, 2000, 2002; Kao *et al.* 1999) report that foreign spillovers are statistically insignificant or, if they have positive effects, these effects benefit mostly less developed countries. Furthermore, some studies (e.g. Branstetter 2001, Luintel & Khan 2004, McVicar 2002, Anon-Higon 2007) find that foreign spillovers are not beneficial to advanced economies. In addition, McGahan & Silverman (2006) advocate that external technological advancements can directly impact on firm performance negatively, through the 'market-stealing' effects or through indirect appropriation via licensing, which might be the case in this situation.

5.6.2.2 Modern approach: summary of results

In summary, as per Chapter 4, in each of our GSEM equations, we find signs of heterogeneity in the estimates of the key variables connecting the model, and also, in other regressors.

Looking at the results of all models of the equation system together, we find evidence in support of our last hypothesis in this thesis, that at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels (Bravo-Ortega *et al.* 2013). The mechanism is described as follows.

We find that prior to becoming exporters firms undertake productivity enhancing activities to be able to break through the entry barriers, associated with overseas markets (Model 2), (Alvarez & Lopez 2005, Van Beveren & Vandenbussche 2010, Cassiman *et al.* 2010, Harris & Moffat 2012). However, contrary to the majority of other studies (e.g. Melitz 2003, Greenaway & Kneller 2004, Harris & Li 2009), but similarly to Bravo-Ortega *et al.* (2013), we do not find 'selectivity' bias in terms of export activities. Moreover, unlike other studies (e.g. Girma *et al.* 2008, Damijan *et al.* 2010, Harris & Moffat 2012), we do not find evidence of 'self-selection' bias in regard to R&D activity (Model 4), which again, is in line with the study of Bravo-Ortega *et al.* (2013). Firms do not 'self-select' into export activities because first, they need to undertake productivity enhancing activities (R&D/innovation). Also, firms do not 'self-select' into engaging in R&D activities because first, they may have to become more capital-intense.

We evidence that a firm's R&D stock of knowledge positively affects its productivity (Model 5), in line with the literature on the topic (Romer 1986, 1990, 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Griffith *et al.* 2004; Cameron *et al*. 2005; Jones 2005). In addition, firms not only need to engage in productivity enhancing activities (e.g. R&D/innovation) prior to becoming exporters, but also to use productivity enhancing feedback after becoming exporters, which assures the firms' continuing existence in these markets (Models 5 to 7), (Bernard & Jensen 2004a,b,c; Greenaway & Kneller 2007; Haris & Moffat 2012). This defines the two-way causal relationships between firms' exports and R&D/innovation (Harris & Moffat 2012). However, we find no evidence of '*learning by exporting'*, (Model 5), contrary to the view that firms' export activities improve their productivity (Rivera & Romer 1990; Grossman & Helpman 1990, 1991, 1994; Aghion & Howitt 1992, 1997; Ericson & Pakes 1995; Klette & Griliches 2000; Atkeson & Berstein 2007).

Firms achieve additional productivity gains post-entry (Aw *et al*. 2011). R&D stock of knowledge is likely to affect a firm's decision to become an exporter while in turn, it is affected by the export experience (Haris & Moffat 2012). That is, a firm's R&D stock of knowledge and its exports are endogenous, they both influence each other positively, depending on firm productivity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011), as per Chapter 4. At a firm-level, R&D/innovation leads to market power which in turn increases export activities (Model 7), (Roper & Love 2002).

At a firm-level, both labour productivity and export intensity positively affect R&D stock of knowledge (Model 6). In turn, R&D stock of knowledge also positively affects both labour productivity (Model 5) and export activities (in terms of both export propensity and export intensity). However, firm labour productivity and export activities are in a negative relationship, running both ways. Yet, the majority of firms in our dataset do export, meaning that there should be some benefits stemming from exports, as firms are profit-seeking entities. According to Love *et al.* (2010), innovative activities alone are not sufficient to improve firms' productivity. However, if firms' innovative activities are undertaken together with increased exports, then productivity improvements become apparent (Love *et al.* 2010). At a firm-level, R&D stock of knowledge is the factor, connecting exports and labour productivity, exercising positive effects on both of them. Therefore, our results imply that firm R&D stock of knowledge influences productivity by two channels: directly (Model 5, Table 17) and indirectly, through export levels (Model 6, Table 17), in line with Bravo-Ortega's *et al.* (2013) suggestions. The indirect effect can be explained in terms of the 'endogenous growth' and 'trade' theories. As competition in overseas markets is tougher than the rivalry in home markets, exporting firms are forced to invest in R&D in order to create products and services that meet the requirements of the customers in the foreign target market, and thus, stay competitive (Girma *et al.* 2008, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013). In addition, there are economies of scale associated with exporting. Firms' exports expand the market, allowing for the 'bulky' R&D fixed-costs to be recuperated by the higher sales volume (Ganotakis & Love 2011). Moreover, firms can access the pool of foreign knowledge and skills, new 'know-how', R&D of foreign firms and thus, improve their business processes, depending on the level of their 'absorptive capacity' (Harris & Li 2009). In turn, this will increase their productivity and efficiency (Kobrin 1991, Grossman & Helpman 1991a, Kraay 1999, Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Girma *et al*. 2004, Greenaway & Yu 2004, Salomon & Shaver 2005).

This shows that at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels, in line with Bravo-Ortega *et al.* (2013).

5.6.3 Robustness tests

The evidence provided by this research can be questioned on two bases of potential biases. First, the dataset is likely to suffer from a 'selection' bias. Second, the labour productivity may not precisely reflect a firm's real productivity. Therefore, robustness tests are performed to check the validity of our results.

We check whether both datasets are likely to suffer from a possible bias caused by our decision to include only the R&D active firms in the 'All-Firms' dataset where the majority of firms are from the high and medium-high R&D intensity sectors, and only the firms on the *R&D Scoreboard* in regard to the 'Innovators' subset. The procedure is described in Chapter 3, (Section 3.6.4). The results are reported in Appendix 6. The insignificant coefficients on 'lambda' ('Mill's ratio') in all models mean that data 'selection' bias is not an issue for our coefficients. Therefore, we could infer that we could continue our research analysis without correcting for 'selectivity' bias.

In regard to our traditional econometric techniques, to check the validity of our estimates we have conducted both the direct and indirect traditional approaches, where we use different proxies for measuring firm productivity - labour productivity in the direct approach while using TFP in the indirect approach. The results are robust.

Furthermore, in Table 14 ('All-Firms' analysis, Model 5), we report the GMM results with the same set of instruments. The results in both Model 3 and Model 5 are qualitatively similar; however, the results provided by Model 3 are more informative. The coefficient on the human capital variable is positive and strongly significant, which is in line with the theoretical expectations (described in the literature review, Section 5.2), as well as with our expectations (outlined in Section 5.4.1.1) in comparison to its equivalent in Model 5, where the coefficient is negative but not significant).

In line with Chapter 3 and Chapter 4, in this chapter we employ the logarithmic transformations on both continuous variables and ratios, for the same reasons stated in Chapter 3, Section 3.6.4. As a robustness check, Appendix 13 presents a set of the same models, using the logarithmic transformations only on continuous variables. In terms of the 'All-Firms' analysis (Apendix 13.1, Table 14, the GMM models), where the dependent variable is labour productivity, the results are qualitatively similar only in regard to the effects of the lagged labour productivity, physical capital stock and labour variables. In terms of the 'Innovators' analysis (Appendix 13.2, Table 15, the GMM models), the results are qualitatively similar in regard to the same variables plus ROCE. In terms of the analysis, where the dependent variable is TFP, the results are, generally, qualitatively similar in both 'All-Firms' and 'Innovators' analysis.

In terms of the GSEM equation, we encountered the same issue as per Chapter 4. The model did not converge: the estimation procedure iterated endlessly without reaching a solution.

Comparing the outcome of the GSEM labour productivity equation in Table 17, (Model 5) with the similar one-step, System GMM equation in Table 17, (Model 8), there are substantive differences in the estimates. In Model 8 the coefficient on export intensity is positive and significant at the 10% level while in Model 5 the coefficient is strongly significant and negative. The effect of R&D stock of knowledge on labour productivity in Model 8 is negative but not significant while in Model 5 the effect is positive and strongly significant. While the effect of market share is the same in both models in terms of sign and level of significance, the effect of human capital on productivity is positive and strongly significant at the 1% level in Model 8, while in Model 5 is also strongly significant, however, negative.

The results of this GMM model of labour productivity are generally, in line with the results of the traditional approach, especially with the results of Model 3 (Table 14) - ‘All-firms’ analysis. This is in contrast to Chapter 4, where we compared the ‘Export intensity’ equation from the GSEM approach with a GMM estimation of the same model and found that the results are robust. The differences in both productivity equations (Model 5 and Model 8, Table 17) could be due to the fact that Model 5 is estimated simultaneously in a system of equations, which more precisely accounts for simultaneity of different interactions as well as interdependencies and diverse dynamics between labour productivity, R&D stock of knowledge and export intensity, accounting for firms’ heterogeneity. More specifically, the GSEM model accounts for the dual effects of R&D stock of knowledge on firm productivity: first, directly and second, indirectly through export levels, which is also found in another simultaneously estimated model of a system of equations, in the study of Bravo-Ortega *et al.* (2013).

5.7. Conclusions and implications

This chapter explores whether R&D stock of knowledge is positively associated with firm productivity. It also examines whether at a firm-level, R&D stock of knowledge influences productivity directly and indirectly through export levels. The research uses an unbalanced panel of 956 UK firms during 2003/4-2013/14, of which 772 belong to the high and medium-high R&D intensity sectors and 184 to both medium-low and low R&D intensity sectors.

The study adds to both traditional and modern literature by providing evidence on the above relationships. Using the direct and indirect traditional approaches on both the ‘All-Firms’ dataset and the ‘Innovators’ only subset, we find no direct evidence to support our first hypothesis in this chapter that a firm's R&D stock of knowledge positively affects its labour productivity. Yet, the positive effect of the intangible assets intensity in both dataset analyses may hint that for firms which substitute their investment in R&D for investment in intangible assets (patents, licenses, marketing contracts), the hypothesis may be indeed, supported.

We also note that although the subset of 'Innovators' firms makes up, on average, 81% of the whole sample, there is a great difference in the results for both datasets. That is, although our sample only contains a small number of firms from low and medium-low R&D intensity sectors, these firms make a big difference. This shows that there is a great heterogeneity in terms of firms' characteristics between the firms belonging to different technological sectors and knowledge levels, in line with Baum *et al.* (2015).

Next, we use a GSEM approach to test both our hypotheses simultaneously. The GSEM results contradict the results from the traditional approaches. They support the hypothesis according to which a firm's R&D stock of knowledge positively affects its labour productivity. The GSEM model also provides evidence for the second hypothesis in this chapter that at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels.

This study's results are important from both micro- and macro-economic standpoints as it investigates one of the most important performance indicators at both firm- and economy-levels: productivity. A firm's innovative activities are central to its technological development and productivity growth, which in turn is the main driving force of economic growth (Romer 1986, 1990, 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Jones 2005; Cameron *et al.* 2005). This indicates that the introduction and exploitation of new 'know-how' is a critical factor when the aim is to improve productivity, at both micro- and macro-levels. As the firm's investment in R&D is associated with a high risk of 'market failure', due to the spillovers effects, without adequate government policies, not a lot of money will be invested in R&D by the firms. As the productivity improvements come mainly from the firms - the focus of such policies should be on making firms and markets more competitive (Bloom & Griffith 2001). It is hoped that this study's findings will help policy-makers adapt their policy mechanisms as there are several benefits of firm-level studies on the relationship between innovation/R&D stock of knowledge and firm productivity. For example, it could help them find out how firms' productivity trajectories can be translated into aggregate productivity, which is the policy-makers fundamental challenge. The findings of this research indicate that this could be done by a combination of integrated policies targeting productivity gains, taking into account the interdependencies between firm productivity, exports and R&D.

The hypothesis of endogenising firm heterogeneity is relatively recent and less researched. This provides opportunities for future research in many and diversified ways. For example, examining the relationship between R&D/innovation, exports and productivity in the UK context, in regard to different sectors of the economy in terms of different R&D intensity levels and comparing the outcomes with those from other countries would be of interest to a variety of audiences. In addition, incorporating external technological effects into the models, e.g. technological spillovers or accounting for a broader range of firms' characteristics may provide interesting results. Furthermore, incorporating a 'public policy' equation into the system of equations may indicate the type and the level of policies needed. A follow-up research, for example covering all UK industries over a longer time-period, might show different outcomes and implications for the strategic decision-making process of managers for their firms' R&D activities.

Chapter 6: Research Conclusions, Policy Implications and Opportunities for Future Research

6.1 Overview

Schumpeter (1942) argues that the corporate pursuit of profits drives the implementation of efficiency improvements coming from innovation. This Schumpeterian concept is incorporated into the 'neo-classical' framework of 'endogenous growth' theory which links macroeconomic growth to firms' R&D (Romer 1986, 1990; Lucas 1988). Yet, there is no comprehensive and conclusive research evidencing how undertaking R&D impacts on individual firm performance to confidently back up firms' increasing R&D expenditure. Indeed, recent policy debates challenge the view that firms' investment in R&D translates into acceptable and sustainable macroeconomic growth rates (Andersson *et al*. 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011). This research aims to empirically investigate the link between R&D stock of knowledge and firm performance in the UK economy, measured by several market indicators such as size (in terms of both absolute size and size relative to its industry), exports and productivity, controlling for a broad range of firms' heterogeneity.

The study employs the R&D stock of knowledge as a measure of innovation, in line with Coe & Helpman (1994), Blundell *et al*. (1999) and Cameron *et al.* (2005), which is based on Griliches (1979) perpetual inventory method. The estimation uses data on both accumulated 'knowledge capital' and current R&D expenditure, accounting for the rate of stock depreciation. The study employs the *OECD* '*Frascati Manual'* definition of 'R&D', in line with the international accounting standards (IAS 38), official statistics and firms' accounting practices (*OECD* 1993).

The contributions of this study to the current literature in the UK context are summarised in the following points.

First, the dataset used throughout the whole thesis is the same and is unique in that it contains information from several data sources with manually matched variables, including data on firm exports, R&D expenditure, finance, intangible assets, inter-, intra-industry, global spillovers and other statistics. The study employs an unbalanced panel of 956 UK firms (presenting our 'All-Firms' dataset) during 2003/4-2013/14, of which 772 firms belong to the high and medium-high R&D intensity sectors (included in our 'Innovators' subset), and 184 firms belong to the medium-low and low R&D intensity sectors.

Second, the study employs a comprehensive set of variables, accounting for both firm-level R&D/innovation as well as for different external technological effects. In addition to the R&D stock of knowledge, other 'innovation spending', not reported as R&D expenditure, however, complementary to them are also employed - intangible assets intensity (e.g. patents, brand names, copyrights, customer lists, franchises, customer and supplier relationships, marketing rights), in line with Griliches (1990) and Mohnen & Hall (2013). The study also includes intra-, inter-industry and global spillovers to account for different external technological effects.

Third, the study uses a single performance measurement framework which contains a comprehensive number of firm performance indicators. The objective is to offer clarification on the current inconclusiveness in the literature by presenting a deeper, more comprehensive and subtle explanation of how R&D stock of knowledge influences firm performance. The idea is widely articulated, organised and interconnected in a way that suggests new theoretical bearings and tactics for practical applications.

Fourth, in Chapter 4 and 5, this research uses an econometric technique, which is new in this field - the GSEM, a unified estimation approach with which the impacts of R&D stock of knowledge on different firm performance indicators are modelled simultaneously. It controls for several potential issues, e.g. simultaneity, interdependencies and different dynamics between the variables researched, which are unaccounted for by single-equation modelling.

This research is applicable to a broad variety of stakeholders such as academics, practitioners, governments, professional bodies, policy-makers, analysts, consultants, shareholders and the general public. It provides answers to the important question: 'Does an increase in a firm's R&D expenditure, proxied by its stock of knowledge, lead to an increased firm performance, measured by its market indicators such as size, exports and productivity, in the UK economy?'

6.2 Summary of main findings

6.2.1 Summary: Chapter 3

In Chapter 3 we explore the link between R&D stock of knowledge and firm size (in both absolute and relative to its industry size terms), accounting for firm heterogeneity. We test the Schumpeterian (1942) hypothesis that innovation increases with firm size. However, the hypothesis is modified from the perspective of an individual firm. That is, we test whether R&D stock of knowledge is positively associated with firm size.

The research conducted on the above Schumpeterian (1942) hypothesis is still empirically inconclusive, offering conflicting evidence (Kamien & Schwartz 1982, Cohen & Levin 1989, Symeonidis 1996, Van Dijk *et al*. 1997, Klette & Griliches 2000, Mazzucato 2000, Cannolly & Hirschey 2005, Kim *et al.* 2009, Ortega-Argiles & Brandsma 2010, Cincera & Ravet 2011, Revilla & Fernandez 2012). This study's objective is to offer credible and comprehensive evidence in regard to the link between R&D stock of knowledge and firm size as the inconclusiveness of the studies on this topic has significant policy implications.

The findings in Chapter 3 offer an important addition to the existing literature in the UK context. First, contrary to most of the studies in this area, which investigate the relationship in either absolute size or market share, Chapter 3 examines the effect of the R&D stock of knowledge on both absolute firm size and on firm size, relative to its industry, using the same dataset. Second, to date, most of the research in this area is in terms of the social qualities of welfare: size, particularly market share is investigated based on the perspective of monopolistic/oligopolistic industry structure and its impact on firms' intra-industry behaviour (e.g. pricing). Chapter 3 analyses the relationship between firm size and innovation from a different perspective, not in regard to whether small or large firms are more innovative, nor whether firm R&D contributes to macroeconomic growth. It analyses the above link from the point of view of an individual firm. That is, how firm R&D stock of knowledge and associated knowledge spillovers influence firm size, which has not been examined widely and conclusively.

Contrary to our expectations, the results of all our GMM models do not support the hypothesis that R&D stock of knowledge is positively associated with firm size, measured in terms of both its absolute size and size, relative to its industry, in both the 'All-Firms' dataset and the 'Innovators' subset. Our results are in line with the study of

Cohen *et al.* (1987) and contrary to the results of Cohen & Klepper (1996), Crepon *et al.* (1998), Vivero (2002) and Tsai & Wang (2005), who all find a positive link between firm size and its R&D activities.

However, in regard to the analysis of market share (Section 3.6.2) the impacts of both intra- and inter-industry spillovers are positive and strongly significant in all GMM models, while the impacts of the global spillovers are negative, but, strongly significant. The effects of all types of spillovers in Section 3.6.2 are not only highly statistically significant, but also they have an important economic significance as all coefficients are large.

The impact of the human capital variable, (Section 3.6.2) is positive and highly significant only in the models where we measure a firm's market share in terms of its share of its industry's value-added (Table 7, Model 3 and Table 8, Models 3).

The impact of export intensity in regard to the analysis of firm absolute size (Section 3.6.1), is positive but only weakly significant in all our GMM models, except in Model 3, (Table 5), where the coefficient is significant at the 5% level of significance.

This chapter's findings have important policy and managerial implications, discussed in Section 6.3. They also provide opportunities for future research, considered in Section 6.4

6.2.2 Summary: Chapter 4

This chapter explores the link between firm R&D stock of knowledge and export activities, conditioning on firms' characteristics.

Historically, empirical studies were, generally, based on the 'neo-endowment theory', which claims that firms' competitive advantage comes from factor-based advantages, e.g. materials, labour, capital and human capital (Wakelin 1998a; Roper & Love 2002), thus, incorporating them in equations, determining firms' export activities.

Subsequent studies include 'innovation' variables in the models, in line with 'technology-based' theories of trade, which advocate that innovation and technological differences are the key determinants of the pattern of trade (Posner 1961, Vernon 1966), exploring also the reverse causation.

Recently, some researchers (e.g. Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011, Harris & Moffat 2012) promoted a theoretically credible framework built on the link between innovation and export activities, in line with the 'endogenous growth' theory. Moreover, according to Harris & Moffat (2012), *'theoretical efforts have been made to endogenise firm heterogeneity'*, (p3).

Chapter 4 research contributes to the literature in that it employs different econometric techniques (e.g. GMM and GSEM) to explore the link between firm R&D stock of knowledge and export activities, depending on firms' heterogeneity.

First, it explores the one-way causality between a firm's R&D stock of knowledge and its export activities, accounting for both firm-specific and technological heterogeneity, by employing more traditional econometric approaches. Summarising the evidence of Section 4.6.1, our findings support the first hypothesis in Chapter 4: *'exporting by innovating'*. At a firm-level, 'technology-based' theories of international trade advocate that R&D/innovation leads to market power, which in turn, increases export activities (Roper & Love 2002). In such terms, the general consensus of the literature is that the causality of the link between firms' innovation and exports runs from innovation to exports (Wakelin 1998a, Sterlacchini 1999, Bleaney & Wakelin 2002, Gourlay *et al.* 2005, Chiru 2007). Our results are in line with this literature.

Second, in line with Atkeson & Burstein (2010); Aw *et al*. (2011); Bustos (2011) and Harris & Moffat (2012) the study in Chater 4 looks at the relationship between firm export activities and R&D stock of knowledge as a simultaneous process. Thus, it tests all three hypotheses in Chapter 4 simultaneously, using a system of four equations. For this, it employs the GSEM approach, based on the work of Rabe-Heskesh & Pickles (2004), which is built on the generalised linear model framework. The GSEM also handles multiple equation systems and latent variables (Baum *et al.* 2015). Furthermore, it allows us to model the two-way causality between R&D and exports, their interdependencies, dynamics, endogeneity and potential simultaneity while accounting for firms' characteristics. Employing the GSEM, the findings also provide support for the first hypothesis. In addition, the results indicate that the probability of becoming an exporter is positively related to a firm's R&D stock of knowledge.

Furthermore, the results support the less researched, second hypothesis in Chapter 4: *'innovating by exporting'.* According to the 'endogenous growth' literature, the causality between firms' innovative activities and exports may run from exports to innovation (e.g. Romer 1990; Grossman & Helpman 1991a,b; Young 1991; Aghion & Howitt 1998). Using the GSEM approach, the results support this hypothesis.

Moreover, looking at the results of all equations in the model together, we find evidence in support of our third hypothesis that: *A firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics.* The mechanism is as follows. First, prior to becoming exporters, firms engage in innovative activities to be able to break through the entry barriers protecting the highly competitive foreign markets (Aw *et al*. 2011, Bravo-Ortega *et al*. 2013). Second, sustaining the level of innovative activities ensures the firms remain in these markets (Bernard & Jensen 2004a,b,c; Greenaway & Kneller 2007; Haris & Moffat 2012). Third, firms acquire additional productivity gains post-entry (Aw *et al*. 2011). Firm R&D stock of knowledge, as a measure of innovation in our case, also is likely to positively influence a firm's decision to become an exporter while in turn it is influenced by the *'learning by exporting'* experience (Haris & Moffat 2012). That is, a firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm characteristics (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011).

However, some links in this model appear rather perplexing, motivating us to continue the research on the subject, though, from a different perspective. According to the modern theoretical strand, which endogenises firm heterogeneity, as firm innovative and export activities grow with the firms' underlying productivity, the most productive firms will 'self-select' into more innovative and export activities. Furthermore, a firm's innovative and export activities can directly influence its future productivity, thus, reinforcing endogeneity via the 'selection bias' (Aw *et al*. 2011). The investigation of these claims is conducted in Chapter 5, a summary of which is provided in the next Section 6.2.3.

6.2.3 Summary: Chapter 5

This chapter investigates whether a firm's R&D stock of knowledge positively affects its firm productivity. It also explores whether at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels, as per Bravo-Ortega's *et al.* (2013) suggestions.

The contributions of the research in Chapter 5 to the current literature, in the UK context, are summarised in the following points.

First, productivity is examined in both traditional terms - as a one-way process, coming from R&D stock of knowledge to productivity, as well as a simultaneous process, together with firm R&D stock of knowledge and export activities.

Second, the study controls for the effects of a wide range of firms' heterogeneity (e.g. human capital, financial health, competitive environment, exports, intangibles) on a firm's productivity and its association with R&D stock of knowledge.

Third, in regard to the above, Chapter 5 research utilises both traditional techniques (e.g. pooled OLS, FE, GMM) in estimating variations of the classical Cobb-Douglas production function, as well as a modern regression technique (e.g. GSEM) in estimating a system of simultaneous equations linking firm productivity, exports and R&D stock of knowledge.

The traditional techniques are applied using two alternative but complementary approaches (direct and indirect) to estimating firm productivity. The direct approach is based on the estimation of a production function while the indirect approach uses the TFP as a dependent variable. Employing traditional econometric techniques, we find no evidence to support the hypothesis that a firm's R&D stock of knowledge positively affects its productivity. This is contrary to most of the research on this topic which, in line with the view of the 'endogenous growth' theory, reports that increased firm R&D increases productivity growth (Romer 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Cameron *et al*. 2005; Jones 2005). Yet, the positive impact of the intangible assets intensity in both datasets may suggest that for the firms which substitute their investment in R&D for investment in intangible assets (patents, licenses, marketing contracts and other intangible assets), this hypothesis may be indeed, supported.

We also observe that although the subset of 'Innovators' firms makes up, on average, 81% of the 'All-Firms' dataset, there is a pronounced difference in the outcomes in regard to both datasets. This illustrates that there is a great heterogeneity in terms of firms' characteristics among the firms belonging to different technological sectors and knowledge levels.

Next, we employ the GSEM approach to test both our hypotheses simultaneously. For consistency of results and reliability of analysis, an approach, similar to Chapter 4, (Section 4.4.2) is followed. We add a Probit R&D equation to account for the 'R&D selectivity' biases. Also in both 'R&D' equations we include financial variables to account for the firm financial health.

The GSEM evidence contradicts the results from the traditional approaches. It supports the hypothesis that a firm's R&D stock of knowledge positively affects its labour productivity.

The GSEM approach also provides support for the second hypothesis in this chapter that at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels, supporting the claims of Bravo-Ortega *et al.* (2013). The mechanism is similar to the one outlined in Chapter 4 to the point where we find evidence that a firm's R&D stock of knowledge and its exports are endogenous, they both affect each other positively, depending on firm productivity (Atkeson & Burstein 2010, Aw *et al*. 2011, Bustos 2011).

According to Aw *et al*. (2011) and Harris & Moffat (2012), as the firms' rewards from engaging in R&D/innovation activities and exports increase with firms' underlying productivity, firms with greater productivity are likely to 'self-select', undertaking further R&D/innovation and export activities. We do not find evidence of 'self-selection' bias neither in regard to export (unlike Melitz 2003, Greenaway &

Kneller 2004, Harris & Li 2009), nor to R&D activities (unlike Girma *et al.* 2008, Damijan *et al.* 2010, Harris & Moffat 2012). However, our findings are in line with the results of Bravo-Ortega *et al*. (2013). Firms do not 'self-select' into export activities because first, they need to undertake productivity enhancing activities (R&D/innovation). Also, our results indicate that firms do not 'self-select' into investment in R&D because first, they may have to become more capital-intense.

At a firm level, both labour productivity and export intensity positively affect R&D stock of knowledge. In turn, R&D stock of knowledge also positively affects both labour productivity and export activities (in terms of both export propensity and export intensity). Yet, firm labour productivity and export activities are in a negative relationship, flowing both ways. Even though, the majority of firms in our dataset do export, hence, there should be some benefits coming from exports, as firms are profit-seeking entities. According to Love *et al.* (2010), innovative activities alone are not enough to improve firms' productivity. However, if firms' innovative activities are performed together with intensified exports, then productivity improvements become apparent. R&D stock of knowledge is the factor, connecting exports and labour productivity, exercising positive effects on both of them. Consequently, our results imply that R&D stock of knowledge affects productivity by two channels: directly and indirectly through export levels, which is in line with Bravo-Ortega's *et al.* (2013) findings.

The 'endogenous growth' and 'trade' theories provide a convincing explanation of the indirect effects. As rivalry in foreign markets is stronger than the rivalry in domestic markets, exporters are forced to participate in R&D activities in order to develop products and services that meet the demands of the customers in the foreign target market, and thus, stay competitive (Girma *et al.* 2008, Harris & Moffat 2012, Bravo-Ortega *et al.* 2013). Furthermore, there are economies of scale linked to exporting. Firms' exports enlarge the market, permitting for the 'lumpy' R&D fixed-costs to be recuperated by the higher sales volume (Ganotakis & Love 2011). Moreover, firms can access the pool of foreign knowledge and skills, new 'know-how', R&D of foreign firms and thus, improve their business processes, depending on the level of their 'absorptive capacity' (Harris & Li 2009). In turn, this will improve their productivity and efficiency (Kobrin 1991, Grossman & Helpman 1991a, Kraay 1999, Hallward-Driemeier *et al*. 2002, Baldwin & Gu 2004, Girma *et al*. 2004, Greenaway & Yu 2004, Salomon & Shaver 2005).

This illustrates that at a firm-level, R&D stock of knowledge influences productivity by two channels: directly and indirectly through export levels (Bravo-Ortega *et al.* 2013).

6.3 Policy and managerial implications

The outcomes of this thesis' research have important policy and managerial implications, discussed in the following sections.

6.3.1 Chapter 3

The results of Chapter 3 that there is no significant relationship between R&D stock of knowledge and firm size are important from both micro- and macroeconomic perspectives.

From a microeconomic perspective, it aims to offer justification for the firms' investment in R&D. In particular, it shows that managers who aim their R&D expenditure at increasing firm size in the UK context, may find that this is not a successful strategy. However, there are some considerations which have to be taken into account.

The literature review in Chapter 3 revealed that the link between R&D activities and firm size is prone to variations across industries due to cross-industry variations in technological opportunities, appropriability conditions, and strategic focus of innovation (Scherer 1980, Kamien & Schwartz 1982, Baldwin & Scott 1987, Cohen & Levin 1989, Cohen & Klepper 1996, Lee & Sung 2005). This research examines the link only in terms of the firms belonging to the high and medium-high R&D intensity sectors in the UK, and in regard to the whole dataset, described comprehensively in Chapter 2. Though, the 'Innovators' represent, on average, 81% of the whole dataset in regard to both measures of firm size, while the low and medium-low R&D intensity firms represent, on average, 19%, with high heterogeneity in firms' characteristics witnessed. Medium-low and low R&D intensity sectors are not analysed separately for the reasons discussed in Chapter 2, (Section 2.2.2). However, we control for the variances in technological levels by incorporating inter- intra-industry and global spillovers in our models.

In addition, R&D stock of knowledge, estimated from R&D inputs (R&D expenditure in this study), does not account for the entire firm innovative activities. Furthermore, firm R&D is linked to a number of market failures such as uncertainty, inappropriability, and indivisibility (Spence, 1984) which are different in different sectors at different levels, influencing the relationship between R&D inputs and outputs.

Moreover, in our research, we explore if firms target their in-house R&D at expanding their size. Though, this may not be the case in terms of different firms in different industries. For instance, a smaller firm trading in regularly purchased, differentiated consumer products may receive satisfactory returns with a smaller market share, e.g., by sustaining a higher rate of return than larger firms (Jackson 2007). Other smaller firms may by-pass direct competition with larger, more powerful competitors, positioning their investments into market segments where the powerful players do not operate.

From a macroeconomic perspective, this study contributes to the current literature debate, which challenges the 'endogenous growth' theory's view that firms' R&D expenditure translates into satisfactory macroeconomic growth rates (Andersson *et al.* 2002, *OECD* 2005, Dosi *et al*. 2006, Ejermo & Kander 2009, Braunerhjelm *et al*. 2010, Ejermo *et al*. 2011).

On one hand, for some researchers, (e.g. Edquist & Mckelvey 1998), the reason for the above paradox is because the national innovation system in translating firm R&D investment into macroeconomic growth has failed. On the other hand, according to the above policy-debate researchers, this paradox may be due to the early 'endogenous growth' theory models being too hopeful, which in turn have elevated idealistic expectations that macroeconomic growth is proportional to R&D expenditure (e.g. Romer 1990, Aghion & Howitt 1992, Grossman & Helpman 1994). These debates urged many researchers to revise their studies and downgrade the role of firm R&D expenditure in economic growth (Jones 1995, 2002; Aghion & Howitt 1998; Ejermo *et al.* 2011). The results of our research indicate that at the micro-level, there is no statistically significant relationship between firm size and R&D stock of knowledge. The study in Chapter 3 provides evidence of, and insights into, the firm-level R&D expenditure, which according to the 'endogenous growth' theory is the basis of macroeconomic growth. Thus, on one hand, this research may assist policy-makers to fine-tune their policy mechanisms for encouraging firm R&D activities to stimulate sustainable economic growth. On the other hand, this study may facilitate policy makers to strengthen the ability of the national innovation system in converting firm R&D investment into macroeconomic growth.

6.3.1 Chapter 4

From a policy perspective, the research question is worthy of investigation as the link between firms' export and R&D activities is of fundamental importance at both micro- and macro-levels. The topic is contemporary, and the evidence offers support to both traditional 'neo-endowment' and 'technology-based' theories, as well as to the modern theoretical framework which endogenises firm heterogeneity, in the UK context. Therefore, this study's findings are important from a policy perspective, especially nowadays as the UK export growth in the last 3 years has been at the bottom of the G7 range (Figure 7, Chapter 4), (*ONS* 2016).

At a micro-level, the link between a firm's investment in R&D and its export activities is an important subject due to the fact that they both influence firm productivity (Clerides *et al*. 1998; Bernard & Jensen 1999, 2004; Aw *et al*. 2000; Greenaway & Kneller 2004). From a managerial perspective, aiming R&D expenditure at increasing firm exports may prove a successful strategy if the two-way causality between R&D stock of knowledge and exports, conditioning on firms' heterogeneity, is taken into account. However, as the analysis of this study is not conducted separately for 'Medium-Tech' and 'Low-Tech' firms, this may not be the case for each and every firm. Although our sample only contains a small number of firms from low- and medium-low R&D intensity sectors, these firms make a big difference to our results.

This demonstrates that there is a great heterogeneity in terms of firms' characteristics between the firms belonging to different technological clusters and knowledge levels.

Moreover, at a macro-level, the 'endogenous growth' theory claims that firms' R&D leads to economic growth (Romer 1986, 1990; Lucas 1988). In line with this view, recent literature focuses on the microeconomic perspective to trade, connecting firms' export activities to their productivity, and thus, reinforcing the significance of exports for national productivity growth (Bernard *et al*. 2003; Melitz 2003; Bernard & Jensen 2004a,b,c; Helpman *et al*. 2004a; Bernard *et al*. 2005; Harris & Li 2009). The evidence of Chapter 4 suggests that R&D and export promotion policies can be advantageous to the economy, as they both lead to economic growth. It is hoped that this research will help policy makers to adjust their policy instruments as there are numerous advantages for policy-makers of firm-level studies on the relationship between innovation/R&D stock of knowledge, export activities and productivity. Thus, policy measures encouraging R&D and export activities, e.g. subsidy or tax-relief, enabling exports and innovative collaborations or supporting innovative management practices, are justifiable (Ortega-Argiles *et al*. 2009).

6.3.1 Chapter 5

Chapter 5 research is important from both micro- and macro-economic perspectives as it examines one of the most important performance indicators at both firm- and economy-levels: productivity. The performance of the UK economy against this indicator is not satisfactory. Figure 10 (Chapter 5) illustrates that the UK's labour productivity has followed a trajectory of constant growth of 2.3% per year during 1971-2008. The 2008 financial crisis has severely distorted the steady productivity growth and from that point onwards, the UK's labour productivity growth has effectively ended (Jones 2016).

A firm's R&D expenditure and innovative activities are fundamental to its technological development and productivity growth, which in turn is a key driving force of economic growth (Romer 1986, 1990, 1994; Lucas 1988; Aghion & Howitt 1998, 2005; Mohnen 2001; Jones 2005; Cameron *et al*. 2005). This implies that the introduction and exploitation of new 'know-how' is the key driver behind improved productivity. However, as we have discussed throughout the whole thesis, firms' innovative activities are associated with high risk of 'market failures', which requires policy solutions. Firm investment in R&D is linked to several interacting, simultaneous market failures, namely uncertainty, inappropriability and indivisibility (investment in R&D are fixed costs, not infinitely divisible), (Spence 1984). R&D is a risky, insecure activity, and its output (e.g. knowledge creation) has the quality of a 'public-good', prone to knowledge spillovers. Additionally, there are increasing returns to scale involved in the use of new technology (Oliveira *et al.* 2006, List & Zhou 2007). Due to the spillovers effects, the knowledge-creator cannot capture all the benefits of its innovation. Therefore, without corrective government actions, in terms of public policies, not much R&D will be conducted from the social efficiency perspective. For these reasons, policies designed at boosting R&D and productivity are on the government's agenda. As most of the productivity improvements come from the firms - the emphasis of policies should be on making firms and markets more competitive (Bloom & Griffith 2001). It is hoped that this chapter's research will assist policy makers to adapt their policy mechanisms as there are several benefits of firm-level studies on the link between innovation/R&D stock of knowledge and firm productivity. For example, it could help them understand better how firms' productivity trajectories can be transformed into aggregate productivity, which is the policy-makers fundamental challenge. This study's findings suggest that this could be done by a combination of integrated policies targeting productivity gains. For example, inspecting the degree to which various integrated policy frameworks (taking into account the interdependencies between firm productivity, exports and R&D) can increase firm productivity. In addition, augmenting the effectiveness of the policies which are already in place by aligning them with the findings of the modern research, e.g. policies reducing barriers to entry into foreign markets, encouraging competition, would be beneficial for the UK economy.

6.4 Opportunities for future research

The limitations of this research provide opportunities for future research.

In regard to Chapter 3, the study can be extended in many ways, so that the relationship between firm size and R&D stock of knowledge/innovation can be more comprehensively investigated. A follow-up research, modelling the proposition that a firm's size and its R&D activities are simultaneously determined, both influencing each other would be of great interest to a broad range of audiences. In addition, controlling for the high heterogeneity of firms' characteristics amongst firms belonging to different technological groups and level of knowledge will add more credibility to the results. Moreover, applying more modern econometric approaches, e.g. the GSEM in estimating such simultaneous systems of equations may provide different results, than the results provided by more traditional approaches, accounting for different dynamics and interdependencies between the variables researched.

In terms of Chapter 4, as the modern theoretical strand of the literature which endogenises firm heterogeneity is relativity new, this study can be enriched in different ways such that, the link between firm R&D/innovation and export activities, conditioned on firms' heterogeneity can be investigated more fully. For example, it would be interesting to see whether the outcomes hold for other similar GSEM models in the UK context. Furthermore, if data is available, it would be noteworthy to see how firms from different technological groups behave, whether there are differences in this link and to what extent. Also, it would be interesting to compare the evidence from different countries and identify lessons to be learnt.

Concerning Chapter 5, the hypothesis of endogenising firm heterogeneity is relativity recent and less researched. This provides opportunities for future research in many and diversified ways. For example, examining the relationship between R&D/innovation, exports and productivity in regard to different sectors of the economy in terms of different R&D intensity levels and comparing the results would be of benefit to a variety of audiences. In addition, incorporating external technological effects into the GSEM models, e.g. technological spillovers or accounting for a broader range of firms' characteristics may provide interesting results. Furthermore, incorporating a 'public policy' equation into the system of equations may indicate the type and the level of policies needed. A follow-up research, for example, covering all UK industries over a longer time-period, might show different outcomes and implications for the strategic decision-making process of managers for their firms' R&D activities.

References

Acemoglu, D., 1997. Training and innovation in an imperfect labor market. Review of Economic Studies 64, 445-464

Ackerberg, D., Caves, K., Frazer, G., 2006. Structural identification of production functions. December 28, 2006. http://folk.uio.no/rnymoen/Ackerberg_Caves_Frazer.pdf

Acs, Z. J., Audretsch, D. B., 1987. Innovation, market structure and firm size. Review of Economics and Statistics 69-4, 567-575

Acs, Z. J., Audretsch, D. B., 1988. Innovation in large and small firms: an empirical analysis. American Economic Review 78, 678-690

Acs, Z. J., Audretsch, D. B., 1991. Innovation and size at the firm level. Southern Economic Journal 57, 739-744

Acs, Z. J., Audretsch, D. B., Feldman, M. P., 1994. R&D spillovers and recipient firm size. Review of Economics and Statistics 76, 336-340

Adams, J. D., Jaffe, A. B., 1996. Bounding the effects of R&D: an investigation using matched establishment-firm data. RAND Journal of Economics 27, 700–721

Adnan, N., Ahmad, M.H., Adnan, R., 2006. A comparative study on some methods for handling multicollinearity problems. Matematika 22, 109-119

Agarwal, R., Gort, M., 1996. The evolution of markets and entry, exit and survival of firms. Review of Economics and Statistics 78, 489-498

Agarwal, R., Gort, M., 2002. Firm product life cycles and firm survival. American Economic Review 92, 184-190

Aghion, P., Harris, C., Howitt, P., Vickerset, J., 2001. Competition, imitation and growth with step-by-step innovation. Review of Economic Studies 68-3, 467-92

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60, 323–351

Aghion, P., Howitt, P., 1998. Endogenous growth theory. Cambridge, MA: MIT Press

Aghion, P., Howitt, P., 2005. Growth with quality-improving innovations: an integrated framework. In Aghion, P. and Durlauf, S., (eds.), Handbook of economic growth. Amsterdam: North Holland

Aghion, P., Schaffer, M., 2002. Competition, innovation and growth in transition: exploring the interactions between policies'. William Davidson Working Paper No.151

Aiello, F., Cardamone, P., 2005. R&D spillovers and productivity growth. Further evidence from Italian manufacturing micro-data. Applied Economics Letters 12, 625-631

Aitken, B. J., Harrison, A. E., 1999. Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. The American Economic Review 89-3, 605-618

Aldieri L., Cincera, M., 2009. Geographic and technological R&D spillovers within the triad: micro evidence from US patents. The Journal of Technology Transfer 34-2, 196-211

Allison, P. D., 1998. Multiple Regression: A Primer (Research Methods and Statistics). 1st Edition. Pine Forge Press

Almeida, H., Campello, M., Weisbach, M., 2004. The cash flow sensitivity of cash. Journal of Finance 59, 1777-1804

Almus, M., Nerlinger, E., 2000. Testing Gibrat's law for young firms-empirical results for West Germany. Small Business Economics 15,1-12

Álvarez, R., López, R.A., 2005. Exporting and performance: evidence from Chilean plants. Canadian Journal of Economics 38-4, 1385-1400

Andersson, T., Asplund, O., Henrekson, M., 2002. The importance of systems of innovation: challenges for politics and society. VINNOVA: Stockholm

Anon-Higon, D., 2007. The impact of R&D spillovers on UK manufacturing TFP: a dynamic panel approach. Research Policy 36, 964-979

Anon-Higon D., Sena, V., 2006. Productivity, R&D spillovers and human capital: an analysis for British establishments using the ARD dataset. Aston University. Report Prepared for the Department of Trade and Industry (DTI)

Antonelli C., 1994. Technological districts localized spillovers and productivity growth. The Italian evidence on technological externalities in the core regions. International Review of Applied Economics 8-1, 18-30

Appleyard, M.M., 1996. How does knowledge flow? Interfirm patterns in the semiconductor industry. Strategic Management Journal 17, 137-154

Arcand, J-L., D'Hombres, B., 2007. Explaining the negative coefficient associated with human capital in augmented Solow growth models. Joint Research Center, Scientific and Technical Reports EUR 22733 EN, EC. Luxembourg: Office for Official Publications

Arellano, M., 2003. Panel Data Econometrics. Oxford University Press

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297

Arnold, J. M., Hussinger, K., 2005. Export behavior and firm productivity in German manufacturing. A firm-level analisis. Review of World Economics 141-2, 219–43

Arrow, K., 1962. The economic implications of learning by doing. American Economic Review 29, 155-173

Arvanitis, S., 1997. The impact of firm size on innovative activity: an empirical analysis based on Swiss firm data. Small Business Economics 9, 473–490

Asakawa, K. 2001 Organizational tension in international R&D management: the case of Japanese firms. Research Policy 30-5, 735-757

Atkeson, A., Burstein, A., 2007. Pricing-to-market in a Ricardian model of international trade. American Economic Review 97-2, 362–367

Atkeson, A., Burnstein, A., 2010. Innovation, firm dynamics and international trade. Journal of Political Economy 118-3, 433-484

Audretsch, D. B., 2002. The dynamic role of small firms – evidence from the US. Small Business Economics 18, 13-40

Audretsch, B.D., Feldman, P.M., 1996. R&D spillovers and the geography of innovation and production. The American Economic Review 86-3, 630-640

Australian Industry Commission 1995. The growth and revenue implications of Hilmer and related reforms. A report by the Industry Commission to the Council of Australian Governments. Canberra: vol.3, app. QA

Aw, B.Y., Chung, S., Roberts, M., 2000. Productivity and turnover in the export market: micro evidence from Taiwan and South Korea. World Bank Economic Review 14, 65–90

Aw, B.Y., Roberts, M. J., Winston, T., 2007. Export market participation, investments in R&D and worker training, and the evolution of firm productivity. The World Economy 30, 83-104

Aw, B. Y., Roberts, M. J., Xu, D. Y., 2008. R&D investment, exporting and the evolution of firm productivity. The American Economic Review 98-2, 451-6

Aw, B. Y., Roberts, M. J., Xu, D. Y., 2011. R&D investment, exporting, and productivity dynamics. American Economic Review 101, 1312–44

Bagwell, K., 2007. The economic analysis of advertising. In Armstrong, M. and Porter, R. Handbook of industrial organization. Amsterdam: Elsevier, 1701-1844

Baldwin, J. R., Gellatly, G., 2003. Innovation strategies and performance in small firms. Edward Elgar Publishing: Cheltenham

Baldwin, J.R., Gu, W., 2004. Trade liberalization: export-market participation, productivity growth, and innovation. Oxford Review of Economic Policy 20-3, 372-392

Baldwin W. L., Scott, J. T., 1987. Market structure and technological change. Harwood: New York

Barba, N., Tarr., D., 2000. International knowledge flows and economic performance: a review of the evidence. World Bank Economic Review 14, 1-15

Barker, V.L., Mueller, G., 2002. CEO characteristics and firm R&D spending. Management Science 48, 782-801

Barney, J.B., 1991. Firm resources and sustained competitive advantage. Journal of Management 17, 99-120

Barrios, S., Gorg, H., Strobl, E., 2003. Explaining firms' export behaviour: R&D, spillovers and the destination market. Oxford Bulletin of Eonomics and Statistics 65-4, 0305-9049

Bartel, A., 1994. Productivity gains from the implementation of employee training programs. Industrial Relations 33, 411-425

Bartel, A., 1995. Training, wage growth, and job performance: evidence from a company database. Journal of Labor Economics 13-3, 401-25

Bartel, A., 2000. Measuring the employer's return on investments in training: evidence from the literature. Industrial Relations 39-3, 502-524

Basant, R., Fikkert, B., 1996. The effects of R&D, foreign technology purchase, and domestic and international spillovers on productivity in Indian firms. Review of Economics and Statistics 78-2, 187-199

Baum, C.F., 2006. An introduction to modern econometrics using Stata. Stata Press, College Station, Texas

Baum, C.F., 2013. Dynamic panel data estimators. Boston College, (BC/DIW)

Baum, C., Lööf, H., Nabavi, P., Stephan, A., 2015. A new approach to estimation of the R&D-innovation-productivity relationship. Boston College Working Papers in Economics 876. Boston College Department of Economics.

Bazzi, S., Clemens, M., 2009. Blunt instruments: on establishing the causes of economic growth. Working Papers 171, Center for Global Development.

Becchetti, L., Rossi, S., 1998. The positive effects of industrial district on the export performance of Italian frms. Luiss Working Paper No. 54

Becker, S., Egger, P., 2009. Endogenous product versus process innovation and a firm's propensity to export. Empirical Economics 1-26

Bellone, F., Musso, P., Nesta, L., Shiavo, S., 2010. Financial constraints and firm export behavior. The World Economy 33-6, 347-73.

Ben-David, D., Loewy, M., 1998. Free trade, growth, and convergence. Journal of Economic Growth 3, 143-170

Benhabib, J., Spiegel, M., 1994. The role of human capital in economic development: evidence from aggregate cross-country data. Journal of Monetary Economics 34-2, 143-174

Berman, N., Héricourt, J., 2010. Financial factors and the margins of trade: evidence from cross-country firm-level data. Journal of Development Economics 93, 206-17

Bernard, A.B., Eaton, J., Jensen, J.B., Kortum, S., 2003. Plants and productivity in international trade. American Economic Review 93,1268-1290

Bernard, A.B., Jensen, J. B., 1999. Exceptional exporter performance: cause, effect, or both?' Journal of International Economics 47-1, 1-25

Bernard, A.B., Jensen, J. B., 2001. Why some firms export. NBER Working Paper No. 8349

Bernard, A.B., Jensen, J.B., 2004a. Exporting and productivity in the USA. Oxford Review of Economic Policy 20, 343-357

Bernard, A.B., Jensen, J.B., 2004b. Entry, expansion, and intensity in the US export boom, 1987-1992. Review of International Economics 12-4, 662-675

Bernard, A.B., Jensen, J.B., 2004c. Why some firms export. Review of Economics & Statistics 86-2, 561-569.

Bernard, A.B., Redding, S., Schott, P.K., 2005. Comparative advantage and heterogeneous firm. NBER Working Paper 10668

Bernard, A.B., Wagner, J., 1997. Exports and success in German manufacturing. Weltwirtschaftliches Archiv 133, 134-157

Bernstein, J. I., 1988. Costs of production, intra- and interindustry R&D spillovers: Canadian evidence. Canadian Journal of Economics XXI - 2, 324-347

Bernstein, J.I., Mamuneas, T.P., 2006. R&D depreciation, stocks, user costs, and productivity growth for US R&D intensive industries. Structural Change and Economic Dynamics 17, 70-98

Bernstein, J.I., Nadiri, I., 1988. Interindustry R&D spillovers, rates of return, and production in high-tech industries. American Economic Review 78-2, 429-34

Bernstein, J. I., Nadiri M. I., 1989. R & D and intra-industry spillovers: an empirical application of dynamic duality. Review of Economic Studies 56, 249-269.

BERR (2009) UK Company Statistics Reconciliation Project. Available at: http://www.bis.gov.uk/files/file50753.pdf

Bhagwati, J., 1978. Foreign trade regimes and economic development: anatomy and consequences of exchange control regimes. Ballinger: Cambridge, MA

Bitzer, J., Geishecker, I., 2006. What drives trade-related R&D spillovers? Decomposing knowledge-diffusing trade flows. Economics Letters 93-1, 52-57

Black, S., Lynch, L., 1996. Human capital investments and productivity. American Economic Review (Papers and Proceedings) 86-2, 263–67

Blair, J., 1972. Economic Concentration. Harcourt, Brace and Jovanovich, New York.

Blalock, G., Roy, S., 2006. A firm-level examination of the exports puzzle: Why East Asian exports didn't increase after the 1997-1998 financial crisis? The World Economy

Bleaney, M., Wakelin, K., 1999. Sectoral and firm-specific determinants of export performance: evidence from the United Kingdom'. Centre for Research on Globalisation and Labour Markets Research Paper 99/12

Bleaney, M., Wakelin, K., 2002. Efficiency, innovation and exports. Oxford Bulletin of Economics and Statistics 64, 3-15

Blind, K., Jumgmittag, A., 2004. Foreign direct investment, imports and innovations in the service industry. Review of Industrial Organisation 25, 205-227

Bloom, N., Griffith, R., 2001. The internationalisation of UK R&D. Fiscal Studies 22-3

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115-143

Blundell, R., Bond, S., Devereux, M., Schiantarelli, F., 1992. Investment and Tobin's Q. Journal of Econometrics 51, 233-257

Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in dynamic panel data models: improving on the performance of the standard GMM estimators. The Institute of Fiscal Studies, Working Paper No. 00/12

Blundell, R., Dearden, L., Meghir, C., Sianesi, B., 1999a. Human capital investment: the returns from education and training to the individual, the firm and the economy. Fiscal Studies 20-1, 1-24

Blundell, R., Griffith, R., van Reenen, J., 1999b. Market share, market value and innovation in a panel of British manufacturing firms. The Review of Economic Studies 66, 529-554

Bond, S.R., 2002. Dynamic panel data models: a guide to micro data methods and practice. Portuguese Economic Journal 1, 141–162

Bond, S.R., Devereux, M.P., 1989. Testing the sensitivity of q investment equations to measurement of the capital stock. In M. Funke, (eds.), Factors in business investment. Springer, Berlin

Bond, S.R., Hoeffler, A., Temple, J., 2001. GMM estimation of empirical growth models. Discussion paper No. 3048. CEPR, London

Bond, S., Van Reenen, J., 2005. Microeconometric models of investment and employment. forthcoming in J. Heckman and E. Leamer (eds) Handbook of Econometrics. Volume 6, Elsevier, North Holland

Bos, J.W.B., Economidou, C., Sanders, M.W.J.L., 2013. Innovation over the industry life-cycle: evidence from EU manufacturing. Journal of Economic Behavior and Organization 86, 78-91

Bound, J., Cummins, C., Griliches, Z., Hall, B.H., Jaffe, A., 1984. Who does R&D and who patents? In Z. Griliches, (eds.), R&D patents, and productivity. Chicago: University of Chicago Press for the National Bureau of Economic Research

Bowsher, C.G., 2002. On testing overidentifying restrictions in dynamic panel data models. Economics Letters 77, 211–220

Branstetter, L., 2001. Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the United States and Japan. Journal of International Economics 53, 53–79

Braunerhjelm, P., Acs, Z.J., Audretsch, D.B., Carlsson, B., 2010. The missing link: knowledge diffusion and entrepreneurship in endogenous growth. Small Business Economics 34, 105–125

Bravo-Ortega, C., Garcia, M. A., 2011. R&D and productivity: a two-way avenue? World Development 39-7, 1090-1107

Bravo-Ortega, C., Benavente, J. M., González, A., 2013. Innovation, exports and productivity: learning and self selection in Chile'. Working Papers WP371. University of Chile, Department of Economics

Brown, S., Eisenhardt, K., 1997. The art of continuous change: linking complexity theory and time-paced evolution in relentlessly shifting organizations. Administrative Science Quarterly 42, 1-34

Brown, J. R., Petersen, B. C., 2009. Why has the investment-cash flow sensitivity declined so sharply? Rising R&D and equity market developments. Journal of Banking and Finance 33-5, 971-84

Business Enterprise Research and Development Statistical bulletins, Office for National Statistics,http://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/bulletins/businessenterpriseresearchanddevelopment/previousReleases

Bustos, P., 2011. Trade liberalization, exports, and technology upgrading: evidence on the impact of MERCOSUR on Argentinian firms. American Economic Review 101, 304-40

Caldera, A., 2009. Innovation and exporting: evidence from Spanish manufacturing firms. ECARES Working Paper Series 2009-014

Cameron, G., Proudman, J., Redding, S., 2005. Technological convergence, R&D, trade and productivity growth. European Economic Review 49-3, 775–809

Campa, J.M., 2004. Exchange rates and trade: how important is hysteresis in trade? European Economic Review 48; 527–548

Campa, J. M., Shaver, J. M., 2002. Exporting and capital investment: on the strategic behavior of exporters. Discussion Paper No. 469. IESE Business School, University of Navarra

Cannolly, R.A., Hirschey, M., 2005. Firm size and the effect of R&D on Tobin's Q. R&D Management 35, 217-223

Cardamone, P., 2012. A micro-econometric analysis of the role of R&D spillovers using a nonlinear translog specification. Journal of Productivity Analysis 37, 41–58

Carlton, D. W., 1992. The rigidity of prices. In Mankiw, N.G., Romer, D., (eds.), New Keynesian economics. Vol. 1. MIT Press. Cambridge, MA.

Carpenter, R., Petersen, B., 2002. Is the growth of small firms constrained by internal finance? Review of Economics and Statistics 84, 298-309

Cassiman, B., Golovko, E., Martinez-Ros, E., 2010. Innovation, exports and productivity. International Journal of Industrial Organization. Elsevier 28-4, 372-376

Cassiman, B., Martinez-Ros, E., 2004. Innovation and exports: evidence from Spanish manufacturing. Working Paper. Accessed: 01/03/2016. Available at: http://web.econ.ku.dk/CIE/Seminars/pdf%20%20seminar/Innovation%20and%20Exports%20julio-04CPH.pdf

Castellacci, F., Zheng, J., 2010. Technological regimes, Schumpeterian patterns of innovation and firm-level productivity growth. Industrial and Corporate Change 19-6, 1829-1865

Chaney, T., 2005. Liquidity constrained exporters. Mimeograph, Massachusetts Institute of Technology

Chen, M., Guariglia, A., 2009. Do financial factors affect firms employment? Evidence from Chinese manufacturing firms. School of Economics, University of Nottingham. Mimeograph

Chen, M., Guariglia, A., 2013. Internal financial constraints and firm productivity in China: Do liquidity and export behaviour make a difference? Journal of Comparative Economics 41-4, 1123-1140

Chen, M., Miller, D., 1994. Competitive attack, retaliation and performance: an expectancy-valence framework. Strategic Management Journal 15, 85-102

Chesbrough, H., 2003. Open innovation: the new imperative for creating and profiting from technology. Harvard Business School Press

Chiru, R., 2007. 'Innovativeness and export orientation among establishments in knowledge intensive business services. Statistics Canada, Cat. No. 88F0006XIE, No. 001.

Chyi, Y.-L., Lai, Y.-M., Liu, W.-H., 2012. Knowledge spillovers and firm performance in the high-technology industrial cluster. Research Policy 41, 556-564

Cincera M., 2005. Firms' productivity growth and R&D spillovers: an analysis of alternative technological proximity measures. Economics of Innovation and New Technology. 14-7, 657-682

Cincera, M., Kempen, L., van Pottelsberghe de la Potterie, B., Veugelers, R., Villegas Sanchez, C., 2003. Productivity growth, R&D and the role of international collaborative agreements: some evidence for Belgian manufacturing companies. In Brussels Economic Review, Special Issue: The Economics of Knowledge Spillovers 46 - n°3

Cincera, M., Ravet, J., 2011. Globalisation, industrial diversification and productivity growth in large European R&D companies. IPTS Working Paper on Corporate R&D and Innovation No. 01/2011

Cincera, M., Ravet, L., Veugelers, R., 2015. The sensitivity of R&D investments to cash flows: comparing young and old EU and US leading innovators. Economics of Innovation and new technology 25/3, 304-320

Cleary, S., Povel, P., Raith, M., 2004. The U-shaped investment curve: theory and evidence. Centre for Economic Policy Research, Discussion Paper No. 4206

Clerides, S. K., Lach, S., Tybout, J. R., 1998. Is learning-by-exporting important? Micro-dynamic evidence from Colombia, Mexico and Morocco. Quarterly Journal of Economics 113, 903-947

Coad, A., Rao, R., 2008. Innovation and firm growth in high-tech sectors: a quantile regression approach. Research Policy 37, 633-648

Coe, D.T., Helpman, E., 1995. International R&D spillovers. European Economic Review 39, 859–887

Coe, D.T., Helpman, E., Hoffmaister, A., 1997. North-South spillovers. Economic Journal 107-440, 134-149

Cohen, W.M., Klepper, S., 1996. A reprise of size and R&D. Economic Journal 106, 925–951

Cohen, W. M., Levin, R. C., 1989. Empirical studies of innovation and market structure. In: Schmalensee R. and Willig, R. D., Handbook of Industrial Organization.Vol. II. Ch.18 (eds.). Elsevier Science Publishers B.V.

Cohen, W. M., Levin, R. C., Mowery, D. C., 1987. Firm size and R&D intensity: a re-examination. Journal of Industrial Economics 35, 543-563

Cohen, W. M., Levinthal, D., 1989. Innovation and learning: two faces of R&D. Economic Journal 99, 569–596

Cohen, W.M., Levinthal, D., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35, 128-152

Comanor, W. S., 1967. Market structure, product differentiation, and industrial research. Quarterly Journal of Economics 81-4, 639-57

Conti, G., 2005. Training, productivity and wages in Italy. Labour Economics 12-4, 557-576

Constantini, J., Melitz, M., 2007. The dynamics of firm-level adjustment to trade liberalization. In E Helpman, Marin, D, and Verdier, T., The organization of firms in a global economy. Cambridge: Harvard University Press

Corrado, C., Hulten, C., Sichel, D., 2007. Intangible capital and economic growth. Research Technology Management, January, 2007. Also available as National Bureau of Economic Research working paper 11948, January 2006.

Crepon. B., Duguet, E., Mairesse, J., 1998. Research, innovation and productivity: an econometric analysis at the firm level. Economics of Innovation and New Technology 7-2, 115-58

Criscuolo, C., Haskel, E.J., 2003. Innovations and productivity growth in the UK: evidence from CIS2 and CIS3. SeRiBa Discussion paper, available at www.ceriba.org.uk.

Cuneo, P., Mairesse, J., 1984. Productivity and R&D at the firm level in French manufacturing. In Griliches, Z., R&D, patents, and productivity, (eds.). University of Chicago Press, Chicago, IL 393-416

Damijan, J. P., Kostevc, C., Polanec, S., 2010. From innovation to exporting or vice versa? World Economy 33, 374-98

Damijan, J.P., Kostevc, C., Rojec, M., 2008. Innovation and firms productivity growth in Slovenia: sensitivity of results to sectoral heterogeneity and to estimation method. Licos'. Discussion paper No. 203/2008

Damijan, J.P., Kostevc, C., Rojec, M., 2012. Does innovation help the good or the poor performing firms? Economocs Letters 115, 190-195

Davidson, C., Matusz, S., Shevchenko, A., 2005. Globalization and firm-level adjustment with imperfect labor markets. Mimeograph, Michigan State University

Davidsson, P., Lindmark, L., Olofsson, C., 1994. New firm formation and regional development in Sweden. Regional Studies 28, 395-410

Davidsson, P.B., Kirchhoff, A., Hatemi, J., Gustavsson, H., 2002. Empirical analysis of business growth factors using Swedish data. Journal of Small Business Management 40, 332-349

Dearden, L., Reed, H., Van Reenen, J., 2006. The impact of training on productivity and wages: evidence from British panel data. Oxford Bulletin of Economics and Statistics 68-4, 397-421

De Bondt, R., 1996. Spillovers and innovative activities. International Journal of Industrial Organization 10, 35-54

De Loecker, J., 2007. Do exports generate higher productivity? Evidence from Slovenia. Journal of International Economics 73-1, 69-98.

de Jong, P., 2007. The relationship between capital investment and R&D spending: a panel cointegration analysis. Applied Financial Economics 17, 871-880

Del Monte, A., Papagni, E., 2003. R&D and the growth of firms: empirical analysis of a panel of Italian firms. Research Policy. Elsevier, 32-6, 1003-1014

Dhanaraj, C., Beamish, P. W., 2003. A resource-based approach to the study of export performance. Journal of Small Business Management 41, 242-61

Ding, Y., Stolowy, H., Tenenhaus, M., 2007. R&D productivity: an exploratory international study. Review of Accounting and Finance 6, 86-101

Doraszelski, U., Jaumandreu, J., 2008. 'R&D and productivity: estimating production functions when productivity is endogenous. CEPR Discussion Papers 6636, CEPR Discussion Papers

Dorfman, N., 1987. Innovation and market structure: lessons from the computer and semi-conductor industries. Ballinger, Cambridge, MA

Dosi, G., 1988. Sources, procedures and microeconomic effects of innovation. Journal of Economic Literature 25, 1120-1171

Dosi, G., Llerena, P., Labini, M.S., 2006. The relationships between science, technologies and their industrial exploitation: an illustration through the myths and realities of the so-called 'European Paradox'. Research Polic 35, 1450–1464

Dosi, G., Pavitt, K., Soete, L., 1990. The economics of technical change and international trade. Harvester Wheatsheaf, New York

Drucker, P.F., 1995. Managing in a time of great change. Truman Talley Books. USA

Drukker, D., 2014. Some Stata commands for endogeneity in nonlinear panel-data models. German Stata Users Group meeting presentation. June 13, 2014

Dunne, T., Hughes, A. 1994. Age, size growth and survival: UK companies in the 1980s. Journal of Industrial Economics 42,115-140

Dunne, T., Roberts, M.J., Samuelson, L. 1989. The growth and failure of U.S. manufacturing plants. Quarterly Journal of Economics 104, 671-698

Duso, T., Röller, Lars-Hendrik, Seldeslachts, J., 2010. Collusion through joint R&D: an empirical assessment. Tinbergen Institute Discussion Paper. TI 2010-112/1

Eaton, J., Kortum,S., 1999. International technology diffusion: theory and measurement. International Economic Review 40, 537-570

Edmond, C., 2001. Some panel cointegration models of international R&D spillovers. Journal of Macroeconomics 23-2, 241-260

Edquist, C., Mckelvey, M., 1998. The Swedish paradox: high R&D intensity without high-tech products. In Nielsen, K., Johnson, B., Evolution of Institutions, Organizations and Technology (eds.). Aldershot, 131–149

Ejermo, O., Kander, A., 2009. The Swedish paradox revisited. In Karlsson, C., Johansson, B., Stough, R., Entrepreneurship and innovation in functional regions, (eds.). Edward Elgar, Cheltenham, 49–76

Ejermo, O., Kander, A., Henning, M.S., 2011. The R&D-growth paradox arises in fast-growing sectors. Research Policy 40, 664-672

Engelbrecht, H.-J., 1997. International R&D spillovers, human capital and productivity in OECD economies: an empirical investigation. European Economic Review 41-8, 1479-1488

Ericson, R., Pakes, A., 1995. Markov-perfect industry dynamics: a framework for empirical work. Review of Economic Studies 62-1, 53-82

Evans, D.S., 1987a. The relationship between firm growth, size and age: estimates for 100 manufacturing industries. Journal of Industrial Economics 35, 567-581

Evans, D.S., 1987b. Tests of alternative theories of firm growth, Journal of Political Economy 95, 657-674

Evenson, R. E., 1968. The contribution of agricultural research and extension to agricultural production. PhD Diss. University of Chicago

Eurostat, 2012. Second task force on the capitalisation of R&D in national accounts - final report: Eurostat. Publications Office of the European Union

Eurostat, 2014. Manual on measuring R&D in ESA 2010. (eds.). Publications Office of the European Union.

Fagerberg, J., 1988. International competitiveness. The Economic Journal 98, 355-374

Falk, M., 2012. Quantile estimates of the impact of R&D intensity on firm performance. Small Business Economics 39-1, 19-37

Fernandes, A.M., & Isgut, A. E., 2005. Learning-by-doing, learning-by-exporting, and productivity: evidence from Colombia. Policy Research Working Paper Series 3544, The World Bank

Frantzen, D., 2000. R&D, human capital and international technology spillovers: a cross-country analysis. Scandinavian Journal of Economics 102, 57-75Fraser, I. 2002. The Cobb-Douglas production function: an antipodean defence? Economic Issues 7-1

Freeman, C., Lourca, F., 2001. As time goes by: from the industrial revolutions to the information revolution. Oxford University Press, New York

Galbraith J. K., 1952. American capitalism: the concept of countervailing power. Houghton Mifflin Company, Boston

Ganotakis, P., Love, J.H., 2011. R&D, innovation and exporting: evidence from UK new technology based firms. Oxford Economic Papers 63-2, 279-306

Gatti, R., Love, I., 2008. Does access to credit improve productivity? Evidence from Bulgaria. Economics of Transition 16-3, 445-65

Geishecker, I, Gorg, H., Taglioni, D. 2009. Characterising euro area multinationals. World Economy 32-1, 49-76

George, G., Zahra, S. A., Wheatley, K. K., Khan, R., 2001. The effects of alliance portfolio characteristics and absorptive capacity on performance: a study of biotechnology firms. Journal of High Technology Management Research 12, 205-226

Geroski, P.A., 1991. Market dynamics and entry. Basil Blackwell. Oxford

Geroski, P. A., Machin, S., Van Reenen, J., 1993. The profitability of innovating firms. RAND, Journal of Econometrics 24, 198-211

Geroski, P.A., Pomroy, R., 1990. Innovation and the evolution of market structure. The Journal of Industrial Economics 38-3, 219-314

Girma, S., Görg, H., Hanley. A., 2008. R&D and exporting: a comparison of British and Irish firms. Review of World Economics / Weltwirtschaftliches Archiv 144-4, 750-773

Girma, S., Greenaway, D., Kneller, R., 2004. 'Does exporting increase productivity? A microeconometric analysis of matched firms. Review of International Economics 12-5, 855-866

Glancey, K., 1998. Determinants of growth and profitability in small entrepreneurial firms. International Journal of Entrepreneurial Behavior and Research 4,18-27

Goto, A., Suzuki, K., 1989. R&D capital rate of return on R&D investment and spillover of R&D in Japanese manufacturing industries. Review of Economics and Statistics 71-4, 555–64

Gou, B., Wang, Q., Shou, Y., 2004. Firm size, R&D, and performance: an empirical analysis on software industry in China. International Engineering Management Conference. IEEE, Singapore

Gourlay, A., Seaton, J., Suppakitjarak, J., 2005. The determinants of export behaviour in UK service firms. Service Industries Journal 25, 879-889

Grabowski, H. G., 1968. The determinants of industrial R&D: a study of the chemicals, drug, and petroleum industries. Journal of Political Economy 76, 292-306

Greenaway, D., Kneller, R., 2004. Exporting and productivity in the United Kingdom. Oxford Review of Economic Policy 20, 358–371

Greenaway, D., Guariglia, A., Kneller, R., 2007. Financial factors and exporting decisions. Journal of International Economics 73, 377–395

Greenaway, D., Kneller, R., 2007. Firm heterogeneity, exporting and foreign direct investment. Economic Journal 117, F134–F161

Greenaway, D., Yu, Z., 2004. Firm level interactions between exporting and productivity: industry-specific evidence. Review of World Economics 140, 376-392

Greenhalgh, C., Rogers, M., 2006. The value of innovation: the interaction of competition, R&D and IP. Research Policy 35-4, 562-580

Greenhalgh, C., Taylor, P., 1994. Innovation and export volumes and prices-a disaggregated study. Oxford Economic Papers 46-1, 102-124

Griffith, R., Huergo, E., Mairesse, J., 2006. Innovation and productivity across four European countries. Oxford Review of Economic Policy 22-4, 483-498

Griffith, R., Redding, S., Simpson, H., 2004a. Foreign ownership and productivity: new evidence from the service sector and the R&D lab. Oxford Review of Economic Policy 20-3, 440-456

Griffith, R., Redding, S., Van Reenen, J., 2004b. Mapping the two faces of R&D: productivity growth in a panel of OECD industries. The Review of Economics and Statistics 86-4, 883–895

Griliches, Z., 1957. Hybrid corn: an exploration in the economics of technological change. Econometrica 24-4, 501-522

Griliches, Z., 1958. Research cost and social returns: hybrid corn and related innovations. Journal of Political Economy 66-5, 419-431

Griliches, Z., 1964. Research expenditures, education, and the aggregate agricultural production function. American Economic Review 54-6, 961-974

Griliches, Z., 1967. Distributed lags: a survey. Econometrica 35,16-49

Griliches, Z., 1973. Research expenditures and growth accounting. In B. R. Williams, Science and technology in economic growth, (eds.). London, MacMillan, 1973, 59-95

Griliches, Z., 1979. Issues in assessing the contribution of R&D to productivity growth. Bell Journal of Economics 10-1, 92-116

Griliches, Z., 1980. 'Returns to R&D expenditures in the private sector. In Kendrick, J. W. and Vaccara, B., New developments in productivity measurement, (eds.). NBER Studies in income and wealth.Vol. 44. University of Chicago Press. Chicago 419-454

Griliches, Z., 1984. R&D, patents and productivity. Z. Griliches, (eds.) Chicago, University of Chicago Press 1984

Griliches, Z., 1990 Patent statistics as economic indicators: a survey. Journal of Economic Literature 28, 1661-1707

Griliches, Z., 1992 The search for R&D spillovers. Scandanvian Journal of Economics 94, 29-47

Griliches Z., 1995. R&D and productivity: econometric results and measurement issues. In Stoneman, P., Handbook of the economics of innovation and technological change, (eds.). Blackwell, Oxford, 52-89

Griliches, Z., 1996. R&D and productivity: The econometric evidence. Chicago University Press, Chicago.

Griliches, Z., Mairesse, J., 1983. Comparing productivity growth: an exploration of French and U.S. industrial and firm data. European Economic Review 21/1-2, 89-119

Griliches, Z., Mairesse, J., 1984. Productivity and R&D at the firm level. In Griliches, Z., R&D, patents, and productivity, (eds.). 339–374

Griliches, Z., Mairesse, J., 1990. R&D and productivity growth: comparing Japanese and U.S. manufacturing firms, in productivity growth in Japan and the U.S. Hulten, C., (eds), University of Chicago Press. Chicago, 317-340

Griliches, Z., Mairesse, J., 1998. Production functions: the search for identification. In Econometrics and economic theory in the twentieth century: The Ragnar Frisch Centennial Symposium, 169-203. Cambridge University Press, New York

Gross Domestic Expenditure on Research and Development, Office for National Statistics, webarchive http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/rdit1/gross-domestic-expenditure-on-research-and-development/index.html

Grossman, G., Helpman, E., 1990. Trade, innovation, and growth. The American Economic Review 80-2, 86-91

Grossman, G.M., Helpman, E., 1991a Trade, knowledge spillovers, and growth. European Economic Review 35, 517-526

Grossman, G.M., Helpman, E., 1991b Innovation and growth in the world economy Cambridge, MA: MIT PressGrossman, G.M., Helpman, E., 1994. Endogenous innovation in the theory of growth. Journal of Economic Perspectives 8-1, 23

Guariglia, A., Mateut, S., 2010. Inventory investment, global engagement, and financial constraints in the UK: evidence from micro data. Journal of Macroeconomic32-1, 239-50

Guellec, D., Van Pottelsberghe de la Potterie, B., 2001. The internationalisation of technology analysed with patent data. Research Policy 30, 1253-1266

Guellec, D., Van Pottelsberghe de la Potterie, B., 2004. From R&D to productivity growth: do the institutional settings and the source of funds of R&D matter. Oxford Bulletin of Economics and Statistics 66, 353–378

Guillen, M.F., 2001. The limits of convergence: globalisation and organisational change in Argentina, South Korea, and Spain. Princeton and Oxford: Princeton University Press

Gupta, A.K., Raj, S.P., Wilemon, D., 1985. The R&D - marketing interface in high-technology firms. Journal of Product Innovation Management 2-1,12–24

Hall, B.H., 2002. The financing of R&D. Oxford Review of Economic Papers 18, 35–51

Hall, B. H., 2007. Measuring the returns to R&D: The depreciation problem. Annales d'Economie Et De Statistique 79-80, 341 - 381

Hall, B.H., 2011. Innovation and productivity. NBER Working Paper No. 17178

Hall, B.H., Griliches Z., Hausman, J.A., 1986. Patents and R&D: is there a lag? International Economic Review 27-2, 265-284

Hall, B.H., Lotti, F., Mairesse, J., 2008. R&D, innovation and productivity: new evidence from Italian manufacturing microdata. Industrial and Corporate Change 17, 813-839

Hall, B.H., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs: empirical evidence for Italy. Small Business Economics. Springer, 33-1,13-33

Hall, B.H., Mairesse, J., 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of Econometrics 65-1, 263–293

Hall, B. H., Mairesse, J., Mohnen, P., 2010. Measuring the returns to R&D. In B.H. Hall and N. Rosenberg, Handbook of the Economics of Innovation, (eds.). V. 2, Chapter 22. Elsevier, 1033-1082

Hall, R.E., Jones, C.I., 1999. Why do some countries produce so much more output per worker than others? Quarterly Journal of Economics 114-1,83−116

Hallward-Driemeier, M., Iarossi, G., Sokoloff, K.L., 2002. Exports and manufacturing productivity in East Asia: a comparative analysis with firm-level data. http://search.epnet.com/login.aspx?direct=true&db=ecn&an=0715248

Hamberg, D., 1964. Size of firm, oligopoly and research: the evidence. Canadian Economics Association, 30-1

Hamilton, J., Monteagudo, J., 1998. The augmented Solow model and the productivity slowdown. Journal of Monetary Economics 42-3, 495-509

Hansen, L. P., 1982. Large sample properties of generalized method of moments estimators. Econometrica 50, 1029-1054

Harhoff, D., 2000. R&D spillovers, technological proximity, and productivity growth - evidence from German panel data. Schmalenbach Business Review 52, 238-260

Harris, R., Li, Q., 2005. Establishment level empirical study of links between exporting, innovation and productivity. Report submitted to UKTI, December 2005 http://www.gla.ac.uk/economics/harris/FRIONS.pdf

Harris, R., Li, Q., 2009. Exporting, R&D, and absorptive capacity in UK establishments. Oxford Economic Papers 61-1, 74-103

Harris, R., Li, Q., 2010. Study of the relationship between innovation, exporting and the use of e-commerce. http://www.ukti.gov.uk/uktihome/aboutukti/ourperformance/research/benefitsofinternationalisation.html.

Harris, R., Moffat, J., 2012. R&D, innovation and exporting in Britain: an empirical analysis. Centre for Public Policy for Regions (CPPR). Working Paper 28. http://www.gla.ac.uk/media/media_232346_en.pdf

Hejazi, W., Safarian, E., 1996. 'Trade, investment and United States R&D spillovers. Canadian Institute for Advanced Research. Working Paper ECWP-56

Heckman, J.J., 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In: Annals of Economic and Social Measurement, Volume 5, number 4. NBER, pp. 475-492.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica: Journal of the econometric society, 153-161

Helpman, E., Melitz, M.J., Rubinstein, Y., 2004a. Trading partners and trading volumes. Working Paper Harvard - Tel Aviv https://www.nottingham.ac.uk/gep/documents/conferences/2005/june2005conf/melitz-june05.pdf

Helpman, E., Melitz, M.J., Rubinstein, Y., 2008. Estimating trade flows: trading partners and trading volumes. Quarterly Journal of Economics 123, 441-487

Helpman, E., Melitz, M.J., Yeaple, S.R., 2004b. Export versus FDI with heterogeneous firms. American Economic Review 94, 300-316

Henderson, R., 1993. Under-investment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry. RAND Journal of Economics 24, 248 - 270

Hiep, N., Nishijima, S., 2009. Export intensity and impacts from firm characteristics, domestic competition and domestic constraints in Vietnam: a micro-data analysis. Paper presented at the RIEB Seminar on March 19, 2009 http://www.apeaweb.org/confer/cruz09/papers/hiep-nishijima.pdf

Hirsch, S., 1974. Hypotheses regarding trade between developing and industrial countries. In Giersch, H., The international division of labor, (eds.) Tubinger: Mohr

Hirsch, S., Bijaoui, I., 1985. R&D intensity and export performance: a micro view. Weltwirtschaftliches Archiv 121-2, 238-251

Hobday, M., 1995. East Asian latecomer firms: learning the technology of electronics. World Development 23-7, 1171-1193

Horowitz, I., 1962. Firm size and research activity. Southern Economic Journal 28, 298-301

Hu, G.A., 2001. Ownership, government R&D, private R&D, and productivity in Chinese industry. Journal of Comparative Economics 29-1, 136–157

Huang, C.J., Liu, C.J., 2005. Exploration for the relationship between innovation, IT and performance. Journal of Intellectual Capital 6, 237-252

Huang, N., Diewert, E., 2007. Estimation of R&D depreciation rates for the US manufacturing and four knowledge intensive industries. Working Paper for the Sixth Annual Ottawa Productivity Workshop, Bank of Canada, May 14-15.

Hubbard, G. 1998. 'Capital market imperfections and investment. Journal of Economic Literature 35, 193-225

Hufbauer, G. C., 1966. Synthetic materials and the theory of the international trade. Duckworth, London

Huggins, R., Izushi, H., Clifton, N.,Jenkins, S.,Prokop, D.,Whitfield, C. , 2010. Sourcing knowledge for innovation. The international dimension. NESTA SKFI/44

Hulten, C. R., 2001. Total factor productivity: a short biography. In Studies in income and wealth. Vol. 65. New developments in productivity analysis. The University of Chicago Press. Chicago.

International Accounting Standards Board, 2008. Business combinations. International Financial Reporting Standards (IFRS) No.3

International Accounting Standards Board, 2008. IAS 38 Intangible assets (revised)

Islam, N., 1995. Growth empirics: a panel data approach. Quarterly Journal of Economics 110-4, 1127-1170

Ito, K., Pucik, V., 1993. R&D spending, domestic competition, and export performance of Japanese manufacutring firms. Strategic Management Journal 14-1, 61-75

Iyer, K., 2010. The determinants of firm-level export intensity in New Zealand agriculture and forestry. Economic Analysis & Policy, 40-1

Jackson, S., 2007. Market share is not enough: why strategic market positioning works. Journal of Business Strategy 28-1, 18–25

Jaffe, A. B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. American Economic Review 75-6, 984-1002

Jaffe, A. B., 1988. Demand and supply influences in R&D intensity and productivity growth. Review of Economics and Statistics 70-3, 431–437

Jaffe, A. B., Trajtenberg, M. and Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108, 557-98

Jefferson, G., Huamao, B., Xiaojing, G. and Xiaoyun ,Y., 2006. R&D performance in Chinese industry. Economics of Innovation and New Technology 15, 345-366

Jones, C.I., 1995. R&D-based models of economic growth. Journal of Political Economy103, 759–784

Jones, C.I., 2002. Sources of U.S. economic growth in a World of ideas. American Economic Review 92, 220–239

Jones, C.I., 2005. The shape of production functions and the direction of technical change. The Quarterly Journal of Economics MIT Press 120-2, 517-549

Jones, R., 2016. Innovation, research and the UK's productivity crisis. SPERI Paper No. 28. The University of Sheffield

Jovanovic, B., 1982. Selection and the evolution of industry. Econometrica 50, 649-670

Kaen, F., & Baumann, H., 2003. Firm size, employees and profitability in US manufacturing industries. (January 13, 2003). Available at: SSRN http://ssrn.com/abstract=382402

Kafouros., M. I., Buckley, P. J., 2008. Under what conditions do firms benefit from the research efforts of other organizations? Research Policy 37-2, 225-239

Kaiser, U., 2002a. Measuring knowledge spillovers in manufacturing and services: an empirical assessment of alternative approaches. Research Policy 31, 25–144

Kaiser, U., 2002b. Testing the quality of knowledge spillovers using innovation survey data. Research Policy 31-3, 125-144

Kamien, M. I., Schwartz, N. L., 1982. Market structure and innovation. Cambridge University PressKamien, M. I., Schwartz, N. L., 1982. Market structure and innovation. Cambridge University Press

Kanwar, S., Hall, B.H., 2015. The market value of R&D in weak innovation regimes: evidence from India. NBER Working Papers, N: 21196

Kao, C., Chiang, M.H., Chen, B., 1999. International R&D spillovers: an application of estimation and inference in panel cointegration. Oxford Bulletin of Economics and Statistics 61-S1, 691-709

Katayama, H., Lu, S., Tybout, J. R., 2005. Firm-level productivity studies: illusions and a solution. NBER Working Paper 9617

Katsikeas, Constantine S., Leonidas C., Leonidou, N., Morgan, A., 2000. Firm-level export performance assessment: review, evaluation, and development. Journal of the Academy of Marketing Science 28-4, 493-511

Keller, W., 1998. Are international R&D spillovers trade-related? Analyzing spillovers among randomly matched trade partners. European Economic Review 42, 1469–1481

Keller, W., 2000. Do trade patterns and technology flows affect productivity growth? World Bank Economic Review 14-1,17-47

Keller, W., 2001. International technology diffusion. NBER Working Paper 8573

Keller, W., 2002. Geographic localization of international technology diffusion. American Economic Review 92, 120–142

Keller, W., Yeaple, S., 2003. Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States. NBER Working Paper

Kim, L., 1997. From imitation to innovation: the dynamics of Korea's technological learning. Cambridge MA, Harvard Buisness School Press

Kim, J., Lee, S.J., Marschke, G., 2009. Relation of firm size to R&D productivity. International Journal of Business and Economics 8, 7–19.

Klette, T.J., Griliches, Z., 2000. Empirical patterns of firm growth and R&D investment: a quality ladder model interpretation. Economic Journal 110, 363–387

Klette, T.J., F. Johansen 1998. Accumulation of R&D capital and dynamic firm performance: a not so fixed effects model. Annales d'Économie et de Statistique 49-50, 389-419

Kobrin, S. J., 1991. An empirical analysis of the determinants of global integration. Strategic Management Journal 12, 17-37

Kodama, F., 1995. Emerging patterns of innovation: sources of Japan's technological edge. MA, Havard Business School Press, Boston

Kraay, A., 1999. Exports and economic performance: evidence from a panel of Chinese enterprises. Revue d'Economie du Developpement 1-2, 183-207

Kraft, K., 1989. Market structure, firm characteristics and innovative activity. Journal of Industrial Economics 37, 327-336

Krueger, A.O., 1978. Foreign trade regimes and economic development: liberalisation attempts and consequences. Ballinger: Cambridge, MA

Krugman, P., 1979. A model of innovation, technology transfer and the world distribution of income. Journal of Political Economy 87-2, 253- 266

Krugman, P., 1986. A 'Technology Gap" model of international trade. In K.Jungenfelt, K and Hauge, D., Structural adjustment in advanced economies, (eds.). NewYork: Macmillan, 35–49.

Krugman, P., 1991. History versus expectations. The Quarterly Journal of Economics 106-2, 651-667

Krugman, P., 1994. The age of diminished expectations. Cambridge: MIT Press

Kumar, N., Siddharthan, N.S., 1994. Technology, frm size and export behaviour in developing countries. Journal of Development Studies 32, 288–309

Kumbhakar, S. C., Ortega-Argilés, R., Potters, L., Vivarelli, M., Voigt, P., 2010. How corporate R&D affects firms' productivity: empirical evidence and toehold for targeted policy measures. CONCORD 2010 Conference, Seville. 01/2010

Kumbhakar, S. C., Ortega-Argilés, R., Potters, L., Vivarelli, M., Voigt, P., 2012. Corporate R&D and firm efficiency: evidence from Europe's top R&D investors. Journal of Productivity Analysis 37, 125-140

Lachenmaier, S., Wössman, N, L., 2006. Does innovation cause exports? Evidence from exogenous innovation impulses and obstacles using German micro data. Oxford Economic Papers 58-2, 317-350

Lawless M., Whelan, K., 2008. Where do firms export, how much, and why? Working Papers 200821. School of Economics, University College Dublin

Lee, C. A., 2005. New perspective on industry R&D and market structure. The Journal of Industrial Economics 53, 299-299

Lee, C. A., Sung, T., 2005. Schumpeter's legacy: a new perspective on the relationship between firm size and R&D. Research Policy 34, 914-931

Lefebvre, E., Lefebvre, L.A., Bourgault, M., 1998. R&D-related capabilities as determinants of export performance. Small Business Economics 10-4, 365-377

Levin, R. C., Klevorick, A.K., Nelson, R.R., Winter, S.G., 1987. Appropriating the returns from industrial R&D. Brookings Papers on Economics Activity 3, 783-820

Levin, R. C., Reiss P. C., 1984. Tests of a Schumpeterian model of R&D and market structure. In: Griliches, Z., R&D, patents, and productivity, (eds.), 175–208, Chicago

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70, 317-342

Li, C.Y.W., Hall, B.H., 2016. Depreciation of business R&D capital. NBER Working Paper No. 22473.

Liao, H., Liu, X., Holmes, M., Weyman-Jones, T., 2009. The impact of foreign R&D on total factor productivity in the East Asian manufactoring industry. The Manchester School. 77-2, 1463–6786, 244–270

Lileeva, A., Trefler, D., 2010. Improved access to foreign markets raises plant-level productivity... for some plants. The Quarterly Journal of Economics MIT Press,125-3, 1051-1099

Lin, B., Chen, J., 2005. Corporate technology portfolios and R&D performance measures: a study of technology intensive firms. R&D Management 35, 157-170

Link, A.N., 1980. Firm size and efficient entrepreneurial activity: a reformulation of the Schumpeter hypothesis. Journal of Political Economy 88, 771-782

Link, A.N., 1981. Research and Development in US manufacturing. Praeger, New York

List J. A., Zhou H., 2007. 'Internal increasing returns to scale and economic growth. NBER. Technical Working Papers 0336. National Bureau of Economic Research, Inc.

Loderer, C. F., Waelchli, U., 2010. Firm age and performance. SSRN:http://ssrn.com/abstract=1342248 or http://dx.doi.org/10.2139/ssrn.1342248

Loeb, P.D., 1983. Further evidence of the determinants of industrial Research and Development using single and simultaneous equation models. Empirical Economics 8, 203-214

Lokshin, B., Belderbos, R., Carree, M., 2008. The productivity effects of internal and external R&D: evidence from a dynamic panel data model. Oxford Bulletin of Economics and Statistics 70, 399-413

Long, W. F., Ravenscraft, D.J., 1993. LBOs, debt and R&D intensity. Strategic Management Journal 14, 119–135

Los, B., Verspagen, B., 2000. R&D spillovers and productivity: evidence from US manufacturing microdata. Emp Econ 25, Empirical Economics Letters, 127–148

Love, J. H., Mansury, M. A., 2007. Exporting and productivity in business services: evidence from the United States. Working Paper. Aston University, Birmingham

Love, J. H., Roper, S., Hewitt-Dundas, N., 2010. Service innovation, embeddedness and business performance: evidence from Northern Ireland. Regional Studies 44-8, 983-1004

Lucas, R., 1988. On the mechanics of economic development. Journal of Monetary Economics 22-1, 3-42

Luintel, K. B., Khan, M., 2004. Are international R&D spillovers costly for the US?. Review of Economics and Statistics 86-4, 896-910

Lumenga-Neso, O., Olarreaga, M., Schiff, M., 2001. On 'indirect' trade-related R&D spillovers. World Bank Policy Research Working Paper No. 258023/01/2010. http://www.worldbank.org/research/trade

Lumenga-Neso, O., Olarreaga, M., Schiff, M., 2005. On indirect trade-related R&D spillovers. European Economic Review 49, 1785–1798

Lynskey, M. J., 2004. Determinants of innovative activity in Japanese technology-based start-up firms. International Small Business Journal 22,159–196

Maeshiro, A., 1996. Teaching regressions with a lagged dependent variable and autocorrelated disturbances. Journal of Economic Education 27, 72-84

Maeshiro, A., 1999. A lagged dependent variable, autocorrelated disturbances, and unit root tests - peculiar OLS bias properties - a pedagogical note. Applied Economics 31, 381-396

Magnier, A., Toujas-Bernate, J., 1994. Technology and trade: empirical evidence for the major five industrialized countries. Weltwirtshaftliches Archiv.131, 494-520

Maidique, M.A., Hayes, R.H., 1984. The art of high-technology management. Sloan Management Review 25-2,17–31

Mairesse, J., 1995. R&D productivity: a survey of the econometric literature. Paper presented at the CEPR Workshop on R&D Spillovers, Lausanne

Mairesse, J., Cuneo, P., 1985. Recherche-developpement et performances des entreprises. Revue Economique 36-5, 1001-41

Mairesse, J., Hall, B.H., 1996. Estimating the productivity of Research and Development in French and US manufacturing firms: an exploration of simultaneity issues with GMM methods. In Wagner, K. and B. Van Ark, International productivity differences and their explanations, (eds.). Elsevier Science, 285-315

Mairesse, J., Mohnen, P. 2005. The importance of R&D for innovation: A reassessment using French survey data. The Journal of Technology Transfer 30-2, 183-197.

Mairesse, J., Mohnen, P., Zhao, Y., Zhen, F., 2012. Globalization, innovation, and productivity in manufacturing firms: a study of four sectors of China. ERIA Discussion Paper 2012-10. Jakarta, Indonesia, ERIA

Mairesse, J., Sassenou, M., 1991. R&D and productivity: a survey of econometric studies at the firm level. Science-Technology-Industry Review 8. (OECD, Paris) 3, 17-348

Malerba, F., 1985. The semiconductor business: the economics of rapid growth and decline. Pinter, F., London

Malerba, F., 2002. Sectoral systems of innovation and production. Research Policy 31, 247-264

Malerba, F., 2005. Sectoral systems: how and why innovation differs across sectors. In Fagerberg, David and Nelson, The Oxford handbook of innovation, (eds.). New York, Oxford University Press, 380-406

Manova, K., Shang-Jin Wei., Zhang, Z., 2011. Firm exports and multinational activity under credit constraints. National Bureau of Economic Research. Inc. NBER Working Papers 16905

Mansfield, E., 1961. Technical change and the rate of imitation. Econometrica 29-4, 741-766

Mansfield, E., 1964. Industrial Research and Development expenditures: determinants, prospects, and relation to size of firm and inventive output. The Journal of Political Economy 703 72-4, 319–340

Mansfield, E., 1965. Rates of return from industrial Research and Development. The American Economic Review 55-2, 310-322

Mansfield E., 1996. The contribution of new technology to the economy. Washington, DC. The Brookings Institution

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., Beardsley, G., 1977. Social and private rates of return from industrial innovations. Quarterly Journal of Economics 91-2, 221–240

Mansfield, E., Romeo, A., Wagner, S., 1979. Foreign trade and US Research and Development. Review of Economics and Statistics 61,49-57

Maryouma, E., Sazelli, A. G., Zulkifley, M., 2011. Multicollinearity problem in Cobb-Douglas production function. Journal of Applied Sciences 11, 3015-3021

Mazzucato, M., 2000. Firm size, innovation and market structure: the evolution of industry concentration and stability. Edward Elgar Publishing, Cheltenham

McGahan A.M., Silverman B.S., 2006. Profiting from technological innovation by others: the effect of competitor patenting on firm value. Research Policy 35, 1222-1242

McVicar, D., 2002. Spillovers and foreign direct investment in UK manufacturing. Applied Economics Letters 9, 297–300

Mead, C., 2007. R&D depreciation rates in the 2007 R&D satellite account. Bureau of

Economic Analysis/National Science Foundation: 2007 R&D Satellite Account Background Paper

Meisel, J. B., Lin, S.A.Y., 1983. The impact of market structure on the firm's allocation of resources to Research and Development. Quarterly Review of Economics and Busines 23, 28-43

Melitz, M.J., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71-6, 1695-1725

Mincer, J., 1974. Schooling, experience and earnings. Columbia University Press, New York

Mohnen, P., 1991. Survol de la littérature sur les externalités technologiques. Volume L'evalution economique de la recherce et du changement technique. CNRS

Mohnen P., 1996. R&D externalities and productivity growth. STI Review 18. OECD, 39-66

Mohnen, P., 2001. International R&D spillovers and economic growth. In Pohjola, M., Information technology, productivity, and economic growth: international evidence, (eds.). UNU/WIDER and Sitra, Oxford: Oxford University Press

Mohnen, P., Bronwyn H., 2013. Innovation and productivity: an update. UNU-MERIT Working Paper Series 021. United Nations University. Maastricht Economic and social Research and training centre on Innovation and Technology

Montresor, S., Vezzani, A., 2015. The production function of top R&D investors: accounting for size and sector heterogeneity with quantile estimations. Research Policy 44, 381-393

Moreno-Badia, M., Slootmaekers, V., 2009. The missing link between financial constraints and productivity. IMF Working Paper 09/72

Myers, S. C., Rajan, R. G., 1998. The paradox of liquidity. Quarterly Journal of Economics 113-3, 733-71.

Nadiri, I., 1993. Innovations and technological spillovers. NBER Working Paper No. 4423. Boston: National Bureau of Economic Research

Neary, J.P., Leahy, D., 1999. R&D spillovers and the case for industrial policy in an open economy. Oxford Economic Papers 51-1, 40-59

Nelson, R. R., 1959. The simple economics of basic research. Journal of Political Economy 67, 297-306

Nucci, F., Pozzolo, A. F., Schivardi, F,. 2005. Is firm's productivity related to its financial structure? Evidence from microeconomic data'. Rivista di Politica Economica I-II, 177-98

Obstfeld, M., Rogoff, K., 1996. Foundations of international macroeconomics. MIT Press: Cambridge, MA

Odagiri, H., Iwata, H., 1986.The impact of R&D on productivity increases in Japanese manufacturing companies. Research Policy 15, 13-19

OECD 1993 The measurement of scientific and technological activities: standard practice for surveys of research and experimental development – Frascati Manual. Paris

OECD 2005. Main Science and Technology Indicators. OECD, Paris

OECD 2012. The OECD analytical BERD (ANBERD) database

OECD 2013. Main Science and technology indicators. Vol. 2013/1. Paris

Office for National Statistics 2014. UK Gross domestic expenditure on research and development. Statistical bulletin. http://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/bulletins/ukgrossdomesticexpenditureonresearchanddevelopment/2014

Office for National Statistics 2014. UK Trade March, 2016. Statistical bulletin. https://www.ons.gov.uk/economy/nationalaccounts/balanceofpayments/bulletins/uktrade/mar2016

Olley, S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263-97

Oliveira, F. H. P., Jayme, F. G. Jr., Lemos, M. B., 2006. Increasing returns to scale and international diffusion of technology: an empirical study for Brazil (1976–2000). World Development 34-1, 75-88

O' Mahony, M., de Boer, W., 2002. Britain's relative productivity performance: updates to 1999.London, National Institute of Economic and Social Research, 179

Onodera, O., 2008. Trade and investment project: a synthesis paper. OECD Trade Policy Working Papers No. 72, OECD, Paris

Ortega-Argiles, R., Brandsma, A., 2010. EU-US differences in the size of R&D intensive firms: Do they explain the overall R&D intensity gap? Science and Public Policy 37-6, 429-441

Ortega-Argiles, R., Vivarelli, M., Voigt, P., 2009. R&D in SMEs: A paradox?. Small Business Economics 33, 3-11

Oster, S., 1982. The diffusion of innovation among steel firms: the basic oxygen furnace. Bell Journal of Economics 13, 45-56

Pagano, P., Schivardi, F., 2003. Firm size distribution and growth. Scandinavian Journal of Economics 105, 255-274

Pakes, A., Schankerman, M., 1984. The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources. In Griliches, Z., R&D, patents andpProductivity, (eds.). University of Chicago Press. Chicago

Palangkaraya, A., Stierwald, A., Yong, J., 2009. Is firm productivity related to size and age? The case of large Australian firms. Journal of Industry, Competition and Trade 9-2-2, 167-95

Parisi, L. M., Schiantarelli, F., Sembenelli, A., 2006. Productivity, innovation and R&D: micro evidence for Italy. European Economic Review 50-8, 2037-2061

Pavitt, K., 1983. Some characteristics of innovation activities in BritishiIndustry. Omega 11-2, 113-130

Pavitt, K., 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Research Policy 13, 343–373

Pavitt, K., Robson, M., Townsend, J., 1987. The size distribution of innovating firms in the UK:1945-1983. Journal of Industrial Economics 35, 297-316

Penrose, E. T., 1959. The theory of the growth of the firm. Oxford University Press, Oxford

Perks, H., Kahn, K., Zhang, C., 2009. An empirical evaluation of R&D - marketing NPD integration in Chinese firms: The Guanxi effect. Journal of Product Innovation Management 26, 640–651

Petrin, A., Poi, B. P., Levinsohn, J., 2004. Production function estimation in Stata using input to control for unobservales. The Stata Journal 4-2, 113-23

Phillips, A., 1966. Patents, potential competition, and technical progress. American Economic Review 56, 301-310

Phillips, A., 1971). Technology and market structure. Lexington. Mass: D.C. Heath

Pla-Barber, J., Alegre J., 2007. Analysing the link between export intensity, innovation and frm size in a science-based industry. International Business Review 16, 275–293

Porter, M. E., 1980. Competitive strategy. New York: Free Press

Posner, M., 1961. International trade and technical change. Oxford Economic Papers 13, 323-341

Quintana-Garcia C. and Benavides-Velasco, C. A., 2004. Cooperation, competition, and innovation capability: a panel data of European dedicated biotechnology firms. Technovation 24, 927-938

Rabe-Hesketh, A. S. S., Pickles, A., 2004. Generalized multilevel structural equation modeling. Psychometrika 69, 167-90

Rammer, C., Czarnitizki, D., Spielkamp, A., 2009. Innovation success of non-R&D-performers: substituting technology by management in SMEs. Small Business

Economics 33, 35-58

Raymond, W., Mairesse, J., Mohnen, P., Palm, F., 2013. Dynamic models of R&D, innovation and productivity: panel data evidence for Dutch and French manufacturing. NBER Working Papers 19074, National Bureau of Economic Research, Inc.

Redding, S.J., 1996. The low-skill, low-quality trap: strategic complementarities between human capital and R&D. Economic Journal 106, 458-470

Redding, S.J., 2011. Theories of heterogeneous firms and trade. Annual Review of Economics 3, 77-105

Rein, G.J., 2004. From experience: creating synergy between marketing and R&D. Journal of Product Innovation Management 21, 33-43

Revilla, A.J., Fernandez, F., 2012. The relation between firm size and R&D productivity in different technological regimes. Technovation 32, 609–623

Riahi-Belkaoui, A., 1999. Value-added reporting and research: state of the art. Westport, CT: Quorum Books

Ribeiro, S.P., Menghinello, S., De Backer, K., 2010. The OECD ORBIS database: responding to the need for firm-level micro-data in the OECD. OECD Working Paper STD/DOC

Rindova, V., 2008. Editor's comments. Publishing Theory when you are new to the game. Academy of Management Review 33-2, 300–303

Rivera-Batiz, L.A., Romer, P. M., 1990. Economic integration and endogenous growth. NBER Working Papers 3528. National Bureau of Economic Research, Inc.

Rivera-Baits, L.A., Romer, P.M., 1991a. Economic integration and endogenous growth. Quarterly Journal of Economics 106-2, 531-555

Rivera-Baits, L.A., Romer, P.M., 1991b. International trade with endogenous technological change. European Economic Review 35-4, 971-1001

Roberts, M., Tybout, J., 1997. The decision to export in Colombia: an empirical model of entry with sunk costs. American Economic Review 87-4, 545–64

Romer, P. M., 1986. Increasing returns and long-run growth. Journal of Political Economy. University of Chicago Press 94-5, 1002-37

Romer, P. M., 1990. Endogenous technological change. The journal of Political Economy 98-5. Part 2. S71- 102

Romer, P. M., 1994. New goods, old theory, and the welfare costs of trade restrictions. Journal of Development Economics. Elsevier 43-1, 5-38

Roodman, D., (2006/Revised 2008). How to do xtabond2: an introduction to 'Difference' and 'System' GMM in Stata. Working Paper #103. The Center for Global Development

Roodman, D., 2008. How to do xtabond2: an introduction to 'Difference' and 'System' GMM in Stata. Working Paper #103. The Center for Global Development

Roodman, D., 2009. A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics 1-71, 135-158

Roodman, D., 2011. Fitting fully observed recursive mixed-process models with cmp. Stata Journal 11, 159–206

Roper, S., Love, J.H., 2002. Innovation and export performance: evidence from the UK and German manufacturing plants. Research Policy 31-7, 1087-1102

Rosenberg, N., 1982. Inside the black box: technology and economics. Cambridge University Press, Cambridge

Rothaermel, F. T., Deeds, D. L., 2004. Exploration and exploitation alliances in biotechnology: a system of new product development. Strategic Management Journal, 25-3, 201 - 221

Ruane, F., Sutherland, J., 2005. Export performance and destination characteristics of Irish manufacturing industry. Review of World Economics/Weltwirtschaftliches Archiv 141-3, 442-59

Salomon, R.M., Shaver, J.M., 2005. Learning by exporting: new insights from examining firm innovation. Journal of Economics and Management Strategy 14-2, 431-460

Samuelson, P. P. 1979. Douglas's measurement of production functions and marginal productivities. Journal of Political Economy 923-39

Scarpetta, S., Tressel, T., 2002. Productivity and convergence in a panel of OECD industries: Do regulations and institutions matter? OECD Economics Department Working Papers No. 342, Paris

Schankerman, M., 1981. The effects of double-counting and expensing on the measured return to R&D. The Review of Economic and Statistics 63, 454–458

Scherer, F.M., 1965a. Firm size, market structure, opportunity, and the output of patented inventions. American Economic Review 55, 1097-1125

Scherer, F. M., 1965b. Size of firm oligopoly, and research: a comment. Canadian Journal of Economics and Political Science 31, 256-266

Scherer, F. M., 1965c. Corporate inventive outputs, profits and growth. Journal of Political Economy 73, 290-297

Scherer, F.M., 1980. Industrial market structure and economic performance. Houghton Mifflin Company, Second Edition. Rand-McNally. Chicago

Scherer, F.M., 1982. Inter-industry technology flows and productivity growth. Review of Economics and Statistics 64-4, 627-634

Scherer, F.M., 1984. Using linked patent and R&D data to measure interindustry technology flows. In Z. Griliches, R&D, patents and productivity, (eds.). 417-64. Chicago: University of Chicago Press

Scherer, F.M., Ross, D., 1990. Industrial market structure and economic performance. Houghton and Mifflin Company. Boston

Schumpeter, J. A., 1942. Capitalism, socialism, and democracy. New York:Harper and Brothers Publishers

Scott, J. T, 1984. Firm versus industry variability in R&D intensity. NBER Chapters. In: R & D, patents, and productivity, 233-248. National Bureau of Economic Research, Inc.

Scott, J.T., Pascoe, G., 1987. Purposive diversification of R&D in manufacturing. Journal of Industrial Economics 36-2, 193-205

Segerstrom, P.S., 1991. Innovation, imitation, and economic growth. Journal of Political Economy 99, 807–827

Shan, W., Walker, G., Kogut, B.,1994. Inter-firm cooperation and startup innovation in the biotechnology industry. Strategic Management Journal 15, 387-394

Shy, O., 1995. Industrial organization: theory and applications. The MIT Press

Simonetti, R., Archibugi, D., Evangelista, E., 1995. Product and process innovations: how are they defined? How are they quantified? Scientometrics 32-1, 77-89

Solomon, E. M., Ugur, M., Guidi, F., Trushin, E., 2015 Variations in the effect of R&D investment on firm productivity: UK evidence. Greenwhich Political Economy Research Centre, Working Paper N 30

Solow, R. M., 1957. Technical change and the aggregate production function. Review of Economics and Statistics. The MIT Press 39, 312-320

Spaliara Marina-Eliza, 2008. Do financial factors affect the capital-labour ratio: evidence from UK firm-level data. Working Paper: WP 2008-02. ISSN 1750-4171 Dept. Economics. Loughborough University

Spence, A. M., 1984. Cost reduction, competition and industry performance. Econometrica 52-1, 101-121

Srinivasan, R., Lilien, G., Sridhar, S., 2010. Should firms spend more on R&D and advertising during recessions? ISBM Report 04-2010. Institute for the Study of Business Markets.The Pennsylvania State University

StataCorp. 2015. STATA Structural equation modelling reference manual. Release 14. Stata: Statistical Software. College Station, TX: StataCorp LP

Sterlacchini, A., 1989. R&D innovations, and total factor productivity growth in British manufacturing. Applied Economics 21, 1549-62

Sterlacchini, A., 1999. Do innovative activities matter to small firms in non-R&D-intensive industries? An application to export performance. Research Policy 28, 819–832

Stoedinova, S., 2011. The relationship between R&D expenditure and the firm's market share in the UK highly innovative industries. MSc Thesis. Economics and Strategy Group. Aston University

Sveikauskas, L., 2007. R&D and productivity growth: a review of the literature. Government of the United States of America - Division of Productivity Research. Bureau of Labor Statistics, Working Paper 408

Symeonidis, G., 1996. Innovation, firm size and market structure: Schumpeterian hypotheses and some new themes. OECD Economics Department Working Papers 161. OECD. Economics Department

Tang, J., 2006. Competition and innovation behaviour. Research Policy 35-1, 68–82

Terleckyj, N. E., 1974. Effects of R&D on the productivity growth of industries: an exploratory study. National Planning Association. Washington DC

Terleckyj, N. E., 1980. Direct and indirect effects of industrial R&D on the productivity growth of industries. In J. W. Kendrick and B. Vaccara, New Developments in Productivity Measurement, (eds.). National Bureau of Economic Research, New York

Thatcher, M., Pingry, D., 2009. Optimal policy for software patents: model and comparative implications. Journal of Management Information Systems 26, 103-134

The 2013 EU Industrial R&D Investment Scoreboard, 2013. EU R&D Scoreboard. Luxembourg: Publications Office of the European Union

Tsai, K-H., Wang, J-C., 2005. Does R&D performance declines with firm size? – A re-examination in terms of elasticity. Research Policy 34, 966-976

Tybout, J., 2000. Manufacturing firms in developing countries: How well do they do, and why? Journal of Economic Literature 38-1, 11-44

UK Value Aded Scoreboards. http://webarchive.nationalarchives.gov.uk/20100908131539/http://innovation.gov.uk/value_added/default.asp?page=60

UK Research & Development Scoreboards. http://webarchive.nationalarchives.gov.uk/20101208170217/http://www.innovation.gov.uk/rd_scoreboard/?p=31

UK Government Expenditure on Science, Engineering and Technology. Statistical bulletins, Office for National Statistics.

http://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/bulletins/ukgovernmentexpenditureonscienceengineeringandtechnology/previousReleases

United Nations Educational, Scientific and Cultural Organization (UNESCO), Institute for Statistics, Science and Technology. Table 25: Gross domestic expenditures on R&D, 2013. http://www.uis.unesco.org/ScienceTechnology/Pages/default.aspx.

Van Beveren, I., Vandenbussche, H., 2010. Product and process innovation and firms. Decision to export. Journal of Economic Policy Reform 13-1, 3–24

Van Biesebroeck, J., 2006. Exporting raises productivity in Sub-Saharan African manufacturing firms. Journal of International Economics (forthcoming)

Van Dijk, B., Hertog, R.D., Menkveld, B., Thurik, R., 1997. Some new evidence on the determinants of large- and small-firm innovation. Small Business Economics 9, 335-343

Van Pottelsberghe de la Potterie, B., 1997. Issues in assessing the effect of inter-industry R&D spillovers. Economic Systems Research 9, 331-356

Van Pottelsberghe de la Potterie, B., Lichtenberg, B., 2001. Does foreign direct investment transfer technology across borders? Review of Economics and Statistics 83-3, 490-497

Van Reenen, J., 1997. Why has Britain had slower R&D growth. Research Policy 26, 493-507

Vandenbussche, J., Aghion, P., Meghir, C., 2004. Growth, distance to frontier and composition of human capital. The Institute for Fiscal Studies Working Paper WP04/31

Vernon, R., 1966. International investment and international trade in the product life cycle. Quarterly Journal of Economics 80, 190-207. Reprinted in Buckley, P. J. and Pervez N. G (1999). The internationalization of the firm: a reader. (2nd eds.), 14-26. International Thomson Business Press. London

Verspagen, B., 1995. R&D and productivity: a broad cross-section cross-country look. Journal of Productivity Analisys 6, 117–135

Verspagen, B., 1997. Measuring intersectoral technology spillovers: estimates from the European and US patent office databases. Economic Systems Research 9-1, 47-65

Veugelers, R., Cassiman, B., 1999. Make and buy in innovation strategies: evidence from Belgian manufacturing firms. Research Policy 28, 63-80

Vivero, R., 2002. The impact of process innovations on firms productivity growth: the case of Spain. Applied Economics 34,1007-1016

Von Tunzelmann, N., Malerba, F., Nightingale, P., Metcalfe, S., 2007. Technological paradigms: past, present and future. Industrial and Corporate Change 17-3, 467-484

Wagner, J., 1995. Exports, firm size, and frm dynamics. Small Business Economics 7, 29–39Wagner, J., 2002. The causal effects of exports on firm size and labor productivity: first evidence from a matching approach. Economics Letters 77, 287–292

Wagner, J. 2007. Exports and productivity: a survey of the evidence from firm-level data. World Economy 30, 60-82

Wagner, J., 2012. Exports, R&D and productivity: a test of the Bustos-model with German enterprise data. Economics Bulletin 32-3, 1942-1948

Wagner, L.U., 1968. Problems in estimating R&D investment and stock. In: Proceedings of the business and economic statistics section, 189-98. D.: American Statistical Association. Washington

Wakelin, K., 1998a. Innovation and export behaviour at the firm level, Research Policy26, 829–841

Wakelin, K., 1998b. The role of innovation in bilateral OECD trade performance. Applied Economics 30-10, 1335–1346

Wakelin, K., 2001. Productivity growth and R&D expenditure in UK manufacturing firms. Research Policy 30, 1079–1090

Walker, W. B., 1979. Industrial innovation and international trading performance. Greenwich, Connecticut, JAI Press Inc.

Wang, Jiann-Chyuan, Tsai, Kuen-Hung, 2004. Productivity growth and R&D expenditure in Taiwan's manufacturing firms. In Growth and productivity in East Asia. NBER-East Asia Seminar on Economics,13. University of Chicago Press

Warusawitharana, M., 2010. The return to R&D. Federal Reserve Board Working Paper, December, 2010.

Wei, Y., Liu, X., 2006. Productivity spillovers from R&D, exports and FDI in China's manufacturing sector. Journal of International Business Studies 37, 544–557

Wijewardena, H., Tibbits,G.E, 1999. Factors contributing to the growth of small manufacturing firms: data from Australia. Journal of Small Business Management 37-2, 88-95

Willis, R., 1999. Wage determinants: a survey and reinterpretation of human capital earnings functions. In Ashenfelter and Card, Handbook of Labor Economics, (eds.). Volume 1, Ch10. Elsevier, Amsterdam

Willmore, L., 1992. Transnationals and foreign trade: evidence from Brazil. Journal of Development Studies 28-2, 314-335

Wooldridge, J., 2013. Introductory econometrics: a modern approach. 5th Edition. Michigan State University

Yeaple S.R., 2005. A simple model of firm heterogeneity, international trade and wages. Journal of International Economics 65-1,1-20

Young, A., 1991. Learning by doing and dynamic effects of international trade. Quarterly Journal of Economics 106-2, 369-405

Zadeh, F. O., & Eskandari, A., 2012. Firm size as company's characteristic and level of risk disclosure: review on theories and literatures. International Journal of Business and Social Science 3, 17

Zhao, H., Li, H., 1997. R&D and export: an empirical analysis of Chinese manufacturing firms. Journal of High Technology Management Research 8-1, 89-105

Zou, S., Stan, S., 1998. The determinants of export performance: a review of the empirical literature between 1987 and 1997. International Marketing Review 15-5, 333 – 356

Appendices:

Appendix 1: R&D Deflators

This study utilises the R&D deflators, newly developed by the *ONS,* to deflate the R&D expenditure instead of the GDP deflators, thus capturing R&D-cost idiosyncrasies that differ across industries.

According to Ker (2014), it is a standard in the national accounting to separate the fluctuations in the total value of output into fluctuations in the price of that output and fluctuations in the quantity of the output produced. The issue is that the sales of R&D are not observed directly; hence, developing a price index for R&D is complex. Additionally, by description, deflators measure the price fluctuations of relatively homogeneous products. Controversially, every individual R&D output is unique by description; hence there is an argument that creating a R&D deflator is not theoretically sound. However, in practice, we need to measure the fluctuations in the costs of R&D to avoid the general rises in the costs of conducting R&D to be taken as an additional output. In these terms, the EU Second European Task-Force on R&D Capitalisation advocates that the 'input approach' should be employed. That is, the applicable price indices for the various costs of R&D should be weighted jointly on the grounds of their share of total costs. Hence, the published *ONS* UK R&D deflators are computed by weighting the whole UK economy materials and services input (producer) price indices jointly with unique R&D labour cost deflators (Ker 2014). This labour cost index is estimated using data on the labour employed in conducting R&D (available from the *BERD Survey*[39]), combined with gross hourly wage estimates for associated professions (available from the *Annual Survey of Hours and Earnings*) to compute a Laspeyre's fixed weight wage index. However, the *ONS* R&D deflator does not have an embedded adjusted labour cost index for fluctuations in productivity (Ker 2014).

[39] The Business Enterprise Research and Development Survey (*BERD*) is a statutory annual survey which provides information on Science and Technological Activities, by UK firms. The data enables the estimation of the resources allocated to R&D in the UK and allows for international comparisons.

Appendix 2: R&D stock of knowledge: depreciation rates

Historically, most studies (Griliches & Mairesse 1984, Hall & Mairesse 1995, Los & Verspagen 2000, Branstetter 2001) employ a single depreciation rate to construct the R&D stock of knowledge capital, produced by R&D investments for all firms and industries (usually of 15%). This is because determining this rate is almost impossible as the applicable depreciation rate is endogenous to both firm's own conduct and that of its rivals. Determining the R&D depreciation rates is particularly difficult because both the price and output of R&D stock of knowledge are, generally, unobservable (Griliches 1996). It also depends on the development of public research and science. This means that it is not constant over time or across firms and industries, though, it usually varies sluggishly from year to year. However, some studies (e.g. Bernstein & Mamuneas 2006, Corrado *et al*. 2007, Hall 2007, Huang & Diewert 2007, Warusawitharana 2010) suggest that the depreciation rates for business R&D are likely to vary significantly across industries, because of the diverse rivalry environments.

Trying to determine the appropriate depreciation rate, many studies (Hall *et al*. 1986, Bernstein & Mamuneas 2006, Hall 2007) use variations of the production function, market value equations and patent production models, however, reporting different results, which cannot easily be reconciled (Li & Hall 2016). The above methodologies experience the issue of insufficient data, thus, cannot independently determine the R&D depreciation rates without imposing tough identifying assumptions which in most cases are unverifiable (Mead 2007, Li & Hall 2016). For example, regarding patent renewal data, the issue is that this approach covers only knowledge, that can be patented and it does not account for the fact that the knowledge may continue to be beneficial even when patent protection is not needed (Li & Hall 2016). In contrast to the tangible capital which depreciates because of the physical 'decay' or 'wear and tear', business R&D stock of knowledge depreciates as its contribution to a firm's profit decreases over time (Li & Hall 2016). Therefore, it is difficult to independently estimate the depreciation rate of R&D capital stock (Corrado *et al*. 2007).

Other studies (e.g. Griliches & Mairesse 1984, Mairesse & Cunéo 1985, Bernstein 1988, Bernstein & Nadiri 1989, Hall & Mairesse 1995), instead of trying to independently calculate the depreciation rate, simply experiment with different rates in calculating the R&D stock of knowledge. They report trivial differences, if any, at all, in the estimated R&D effects when the depreciation rate fluctuates from about 8% to 25%.

Presently, there is no consensus on which method can offer the best results (Li & Hall 2016).

Appendix 3: R&D stock of knowledge descriptive statistics for each industry and year

Desriptive statistics: R&D stock of knowledge for each industry and year

Industry		**2003/4**	**2004/5**	**2005/6**	**2006/7**	**2007/8**	**2008/9**	**2009/10**	**2010/11**	**2011/12**	**2012/13**	**2013/14**
A&D	*Obs.*	*27*	*35*	*35*	*39*	*42*	*44*	*49*	*49*	*49*	*49*	*49*
	Mean	*163248.3*	*171087.3*	*173000.1*	*158965.1*	*150524.9*	*145679.9*	*147324.9*	*152002*	*155327.2*	*155866.7*	*153958.8*
	S.D.	*381319.3*	*407609.9*	*407458.7*	*388603.1*	*376378*	*368924.8*	*356790.9*	*357975.9*	*358670.2*	*357933.7*	*356270*
	p50	*33500*	*24937.5*	*30913.97*	*23649.99*	*24150.59*	*21963.29*	*21193.99*	*21995.89*	*23428.05*	*22335.46*	*23056.14*
	Min.	*687.5*	*369.004*	*387.454*	*400.595*	*559.284*	*159.067*	*167.020*	*171.534*	*155.189*	*176.265*	*199.826*
	Max.	*1466236*	*1466432*	*1466432*	*1466234*	*1466453*	*1466765*	*1466876*	*1466654*	*1466543*	*1466223*	*1466223*
P&B	*Obs.*	*71*	*99*	*119*	*128*	*132*	*169*	*186*	*186*	*186*	*186*	*186*
	Mean	*123282.9*	*86856.33*	*75667.35*	*76328.36*	*89072.55*	*79630.49*	*77047.2*	*80117.12*	*81859.86*	*81516.72*	*80942.66*
	S.D.	*250233.9*	*176026.2*	*160492.4*	*163173.2*	*204744.5*	*191048.8*	*190236.9*	*197652*	*201187.7*	*203755*	*208632.3*
	p50	*22500*	*20278.13*	*18997.29*	*18960.57*	*20486.1*	*20565.42*	*20569.02*	*21639.24*	*21630.25*	*21382.11*	*19806.87*
	Min.	*312.5*	*184.502*	*118.765*	*124.703*	*393.954*	*369.536*	*158.395*	*166.315*	*176.821*	*201.709*	*230.453*
	Max.	*1462211*	*1050000*	*896587.1*	*973274.8*	*1461122*	*1462211*	*1461122*	*1462211*	*1462212*	*1462155*	*1462211*
S&CS	*Obs.*	*92*	*124*	*146*	*155*	*187*	*253*	*263*	*264*	*264*	*264*	*264*
	Mean	*52961.82*	*48552.02*	*44329.42*	*44279.5*	*43578.18*	*35645.22*	*35867.78*	*37498.43*	*37571.05*	*36699.05*	*34826.89*
	S.D.	*133216.8*	*127751.7*	*121645*	*120084.2*	*114634.9*	*102360.9*	*103622.4*	*108041.6*	*106729.1*	*104891.3*	*98928.56*
	p50	*10843.75*	*9534.421*	*9110.173*	*9491.051*	*9644.087*	*7953.34*	*8629.374*	*9275.628*	*9418.384*	*9242.946*	*9000.969*
	Min.	*562.5*	*246.003*	*258.303*	*268.251*	*111.857*	*10.604*	*11.135*	*10.520*	*9.985*	*10.503*	*10.928*
	Max.	*1031250*	*1082813*	*1072912*	*1042617*	*988405.6*	*952001.5*	*930092.1*	*927853.9*	*788675.8*	*808667.3*	*831967.2*
T&HE	*Obs.*	*52*	*65*	*73*	*74*	*100*	*173*	*186*	*186*	*186*	*186*	*185*
	Mean	*66495.19*	*59862.96*	*56914.67*	*59422.84*	*49589.49*	*37774.13*	*44808.85*	*45835.58*	*45715.38*	*52432.78*	*44591.72*
	S.D.	*96906.85*	*94313.17*	*93677.34*	*97192.43*	*89918.38*	*84980.62*	*134896.6*	*136070.4*	*135242*	*171222.8*	*138021.1*
	p50	*27468.75*	*26250*	*24850.87*	*23183.35*	*15274.3*	*6892.895*	*6631.519*	*7204.901*	*8087.772*	*7640.999*	*7713.883*
	Min.	*187.5*	*196.875*	*220.234*	*347.532*	*11.186*	*11.745*	*5*	*5*	*60.670*	*64.674*	*65.973*
	Max.	*447500*	*469875*	*484264.6*	*504261.5*	*526440.9*	*535394.2*	*1466098*	*1464355*	*1461237*	*1466434*	*1462322*

Industry		2003/4	2004/5	2005/6	2006/7	2007/8	2008/9	2009/10	2010/11	2011/12	2012/13	2013/14
A&P	Obs.	24	27	30	30	33	62	69	69	69	69	69
	Mean	272022.9	264323.2	243590.7	245703.6	235975.9	135047.3	123547.8	126954.5	127944.3	129169.6	126138
	S.D.	497682	473419.4	456877.2	456368.4	435674.5	334632.2	319440.4	323979	325855.6	325554.9	312711.1
	p50	36000	37800	38765.92	40041.29	45994.45	11252.15	12590.85	13585.17	12654.49	12171.01	12471.3
	Min.	3812.5	4003.125	261.283	274.347	100.671	5.302	5.567	5.788	21.604	20.380	19.323
	Max.	1466566	1466544	1466333	1466232	1466322	1466543	1466321	1466234	1466222	1466540	1466323
PG	Obs.	2	2	2	3	4	5	9	15	16	17	18
	Mean	36823.1	36688.59	2783.109	5193.414	3846.665	4354.534	3390.317	4603.373	4586.939	4510.096	4522.971
	S.D.	18952.64	20288.07	3562.571	4738.374	4733.957	4447.354	3495.102	6876.489	7009.155	7121.31	7638.312
	p50	36823.1	36688.59	2783.109	5694.542	2525.777	4114.306	2148.891	2256.336	1976.019	1678.586	1512.137
	Min.	23421.56	22342.76	263.992	224.393	190.734	162.124	152.587	171.938	235.613	200.271	263.23
	Max.	50224.64	51034.43	5302.227	9661.309	9661.309	10529.88	10598.33	27090.72	28445.26	29411.33	32333.63
BP	Obs.	2	2	2	2	2	2	4	5	7	7	8
	Mean	43789.17	43675.77	45173.87	45729.16	46423.18	45763.52	26337.1	21770.63	57254.42	59795.29	56551.23
	S.D.	58815	58975.38	61494.99	62409.93	64028.8	62754.79	45717.14	40640.24	100875	105889.7	104079.6
	p50	43789.17	43675.77	45173.87	45729.16	46423.18	45763.52	5338.614	3269.03	8806.315	8063.997	11237.15
	Min.	2200.69	1973.88	1690.34	1598.67	1147.98	1389.184	26.399	27.719	171.632	285.00	400.250
	Max.	85377.66	85377.66	88657.39	89859.64	91698.38	90137.86	94644.75	94175.6	272177.4	285786.3	298918.3
FP	Obs.	3	3	5	7	7	11	45	57	68	70	74
	Mean	76988.21	81770.41	89254.16	67123.49	58682.16	40953.03	14452.18	16524.02	14173.97	14071.69	13362.73
	S.D.	131064.5	139154.8	172715.5	154881.5	131045	112071.8	50032.5	51389.66	45524.41	44245.12	42049.81
	p50	1488.89	1520.54	13064.13	9352.731	12083	2439.024	2154.171	2261.88	2294.742	2583.01	2617.564
	Min.	1147.438	1338.243	1811.164	183.697	192.882	187.439	31.679	33.263	15.121	15.877	5
	Max.	228328.3	242452.4	397862.2	417755.3	355092	377890.9	321207.2	273026.2	277877.7	294447.1	298260
O&GP	Obs.	2	2	2	2	2	2	4	7	9	10	12
	Mean	21212.67	21250.99	21826.74	23079.45	25568.74	26207.7	85716.33	56994.24	56344.01	57841.05	58264.06
	S.D.	26554.81	27049.09	27917.92	29085.6	32543.15	33989.26	135229.4	108627.6	98607.61	99364.46	107939.5
	p50	21212.67	21250.99	21826.74	23079.45	25568.74	26207.7	28109	15641.29	16423.36	18302.62	17057.23
	Min.	2435.586	2124.396	2085.793	2512.829	2557.26	2173.671	1536.431	1570.477	1334.906	1134.67	133.796
	Max.	39989.76	40377.59	41567.7	43646.08	48580.22	50241.74	285110.9	299366.4	304513.6	323352.7	380849.8

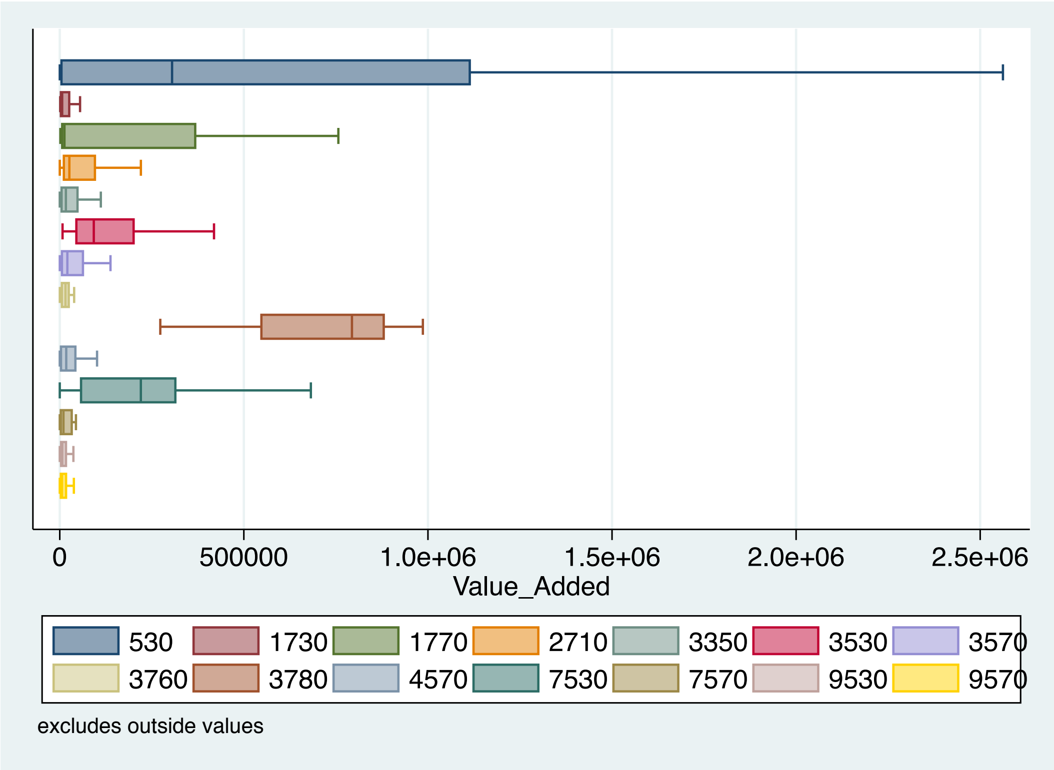
Industry		2003/4	2004/5	2005/6	2006/7	2007/8	2008/9	2009/10	2010/11	2011/12	2012/13	2013/14
F&P	Obs.	1	1	1	1	1	1	10	21	24	25	26
	Mean	247.64	280.84	321.45	360.23	334.78	375.65	957.761	26506.74	24418.07	24434.84	23653.19
	S.D.							1007.168	67514.21	66746.23	68502.32	68685.93
	p50							498.944	1548.488	858.3044	749.7844	746.034
	Min.							15.840	16.631	20.393	23.383	19.875
	Max.							2639.915	251585	264164.2	278427.7	293774.5
M	Obs.	2	2	2	2	2	2	7	9	9	9	10
	Mean	65645.68	75513.3	68803.44	72243.62	75330.72	75330.72	24814.5	19987.91	20103.62	20343.9	20933.28
	S.D.	78149.75	90675.7	95849.92	100642.4	104823	105510.9	57286.73	50165.31	48911.98	49442.47	55329.82
	p50	65645.68	75513.3	68803.44	72243.62	75330.72	75916.46	1752.904	2752.867	2919.003	2917.62	2982.977
	Min.	10385.46	11395.89	1027.316	1078.682	1209.646	1308.96	15.83949	16.63147	19.35051	21.48826	20.26502
	Max.	120905.9	139630.7	136579.6	143408.5	149451.8	150524	154456.5	153463.3	150256.1	151911.3	178124.6
T	Obs.	1	1	1	1	1	2	2	2	3	3	3
	Mean	165322.3	172201.7	180811.8	188131.8	201243.9	175855.7	189244	199928.2	151469.8	159663.3	172047.1
	S.D.						61235.48	70796.36	81083.97	120589.4	142684.3	169078.1
	p50						175855.7	189244	199928.2	143102	125669	116818.6
	Min.						139183.5	142593.2	142593.2	35282.26	37046.37	37489.42
	Max.						219155.7	239304.6	257263.2	276025.1	316274.6	361833.4
E	Obs.	3	3	3	3	3	3	5	19	19	22	23
	Mean	31162.89	30766.11	28947.06	27844.11	28843.07	30103.74	25640.28	19719.07	20097.1	18152.23	17597.23
	S.D.	33703.24	33131.1	31708.92	30936.8	31508.83	32761.69	34001.74	25209.17	24955.73	25562.74	25931.59
	p50	25254.78	25254.78	22983.53	21542.56	23275	24457	1583.95	7820.61	8211.68	5946.77	4186.66
	Min.	804.345	736.286	643.32	543.231	489.45	532.45	105.597	10.876	121.36	5	5.25
	Max.	67429.54	66307.27	63214.33	61446.54	62764.77	65321.77	63357.9	73106.9	78824.9	82122.1	86562.9
GW&M	Obs.	3	3	7	8	9	9	13	25	26	28	28
	Mean	2770.143	2747.028	14215.46	13076.88	14619	14739.97	10739.51	8723.357	8793.147	8241.61	9580.44
	S.D.	2693.486	2607.317	19169.91	19350.58	18334.01	20022.07	17845.37	15488.6	16307.03	16399.87	18940.65
	p50	2351.524	2337.023	5811.808	4268.26	6140.878	5219.746	2639.915	2606.882	2546.675	2183.38	1990.524
	Min.	310.476	369.004	387.454	281.286	295.350	421.875	405.254	408.95	466.791	5	5.25

Max.	*5648.428*	*5535.056*	*53444.18*	*56116.39*	*54587.56*	*60940.82*	*62404.15*	*73106.88*	*78824.9*	*82122.13*	*84803.81*

Note: R&D stock of knowledge measured in thousands. Data is presented in levels. The abbreviations used are as follows: A&D - Aerospace & Defence, P&B - Pharmaceutical & Biotechnology, S&CS - Software & Computer Services, T&HE - Technology & Hardware Equipment, A&P - Automobile & Parts, PG - Personal Goods, BP - Beverage Producers, FP - Food Producers, O&GP - Oil & Gas Producers, F&P - Forestry & Paper, M - Mining, T - Tobacco, E – Electricity, GW&M – Gas, Water & Multiutilities, Obs. - the number of observations, S.D. - Standard Deviation, p50 - Median, Min. - minimum value, Max. - maximum value.

Appendix 4: Firms' heterogeneity per industry group: firm value-added and exports

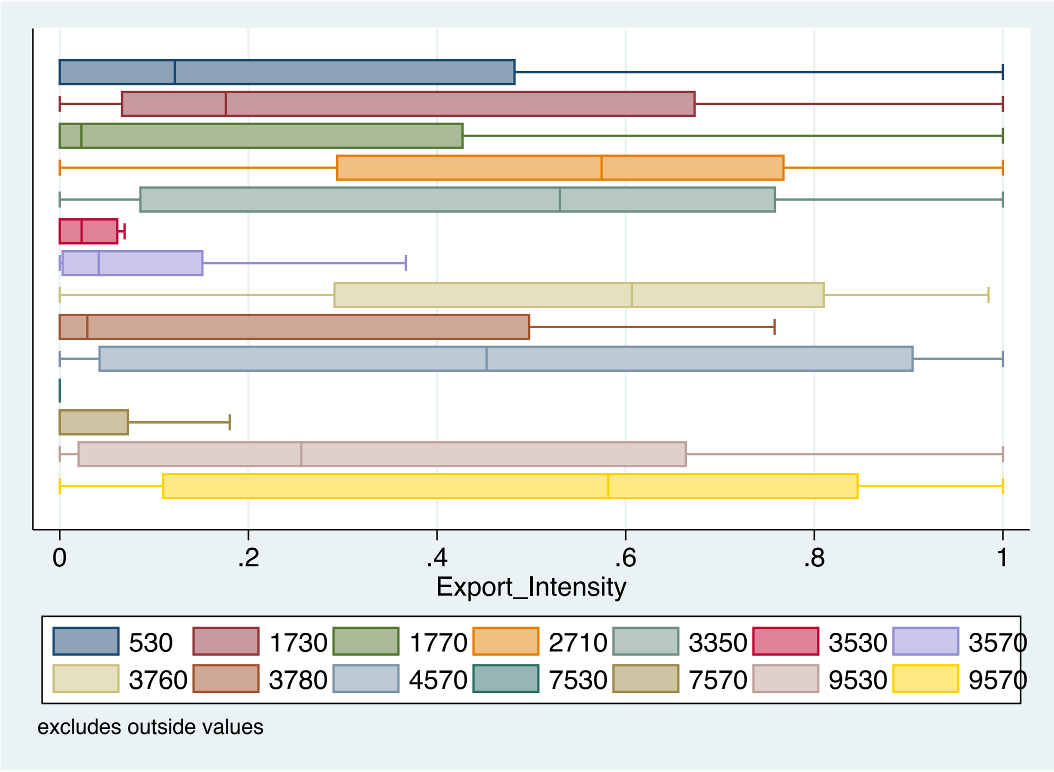
Appendix 4.1 Firms' heterogeneity per industry group: firm value-added[40] (ICB categories codes as per Table 1, Chapter 2)



[40] Note: the line within the boxes shows the 'median' (the midpoint of the data after it has been ranked) while the line of the box, on the right hand side of the median (upper hinge) shows the 75th percentile and the line of the box, on the left hand side of the median (lower hinge) shows the 25th percentile. The lines outside the box show the upper adjacent (right) and lower adjacent (left) values of the data.

Ind. Group	***Sector Description***
2710	*Aerospace & Defence*
4570	*Pharmaceuticals & Biotechnology*
9530	*Software & Computer Services*
9570	*Technology Hardware & Equipment*
3350	*Automobiles & Parts*
3760	*Personal Goods*
3530	*Beverages*
3570	*Food Producers*
0530	*Oil & Gas Producers*
1730	*Forestry & Paper*
1770	*Mining*
3780	*Tobacco*
7530	*Electricity*
7570	*Gas, Water & Multi-utilities*

Appendix 4.2: Firms' heterogeneity per industry group: firm export intensity



Appendix 5: Correlation matrix and VIF tests, Chapter 3

Historically, it is well documented in the literature that, in general, the conventional variables (capital, labour, materials) involved in the Cobb-Douglas production function are closely interrelated - multicollinear (Samuelson 1979, Fraser 2002, Ackerberg *et al.* 2006, Maryouma *et al.* 2011).

There are many methods employed to detect multicollinearity. The most used one is the correlation matrix, reported in Appendix 5.1. In our case, both cost of sales and labour variables are correlated with each other and with the dependent variable, value-added. However, there is no perfect collinearity in any of the cases. Multicollinearity effects are about collinearity between the explanatory variables; multicollinearity between independent and dependent variables does not matter (Allison 1998, Wooldridge 2013). Furthermore, multicollinearity is only an issue for the variables that are collinear (Wooldridge 2013).

The correlation matrix method has a drawback: it cannot produce a clear estimation of the rate (degree) of multicollinearity (Maryouma *et al.* 2011). Therefore, we also use the Variance Inflation Factor (VIF) approach for testing multicollinearity. Generally, when VIF > 10, (or a tolerance level is less than 0.1), it is assumed that strong multicollinearity exists between the tested variables (Adnan *et al.* 2006). However, there are cases, where even a high VIF is not an issue and can be safely ignored (Allison 1998, Wooldridge 2013). For example, when the variables with high VIFs are employed as control variables, and the variables of interest do not have high VIFs (Allison 1998, Wooldridge 2013). In our case, labour is a size control variable while the cost of sales is not a variable of interest in our study. Both variables are not collinear with any of our variables of interest. According to Wooldridge (2013), multicollinearity increases the standard errors of the coefficients associated with the collinear variables and makes those coefficients unstable. If collinear variables are employed as control variables, and they are not collinear with any variables of interest, there are no intolerable multicollinearity issues (Wooldridge 2013). It is not necessary to delete/transform one or the other of the two controls as the estimates of the variables of interest are not disturbed, and the performance of the control variables as controls also is not compromised (Allison 1998, Wooldridge 2013). Even if the individual coefficients of the control variables have large standard errors, together, they still exercise the same control function (Wooldridge 2013). In our case, we find that all the variables have VIF values less than 10.

Appendix 5.1: Correlation matrix

Correlation matrix, Chapter 3: 'All-Firms'

Variable	*Value Added*	*Capital Stock*	*Labour*	*Cost of Sales*	*Human Capital*	*Export Int.*	*Int. A. Int.*	*Age*	*R&D Stock*	*Intra-ind. Sp.*	*Inter-ind. Sp.*	*Global Sp.*
Value Added	*1*											
Capital Stock	*0.32*	*1*										
Labour	*0.83*	*0.15*	*1*									
Cost of Sales	*0.77*	*0.22*	*0.83*	*1*								
Human capital	*0.06*	*0.14*	*-0.20*	*-0.11*	*1*							
Export Intensity	*-0.01*	*0.06*	*-0.01*	*-0.05*	*0.12*	*1*						
Int. Assets Int.	*-0.01*	*0.29*	*-0.04*	*-0.15*	*0.1*	*0.12*	*1*					
Age	*0.33*	*0.05*	*0.36*	*0.39*	*-0.09*	*-0.11*	*-0.22*	*1*				
R&D Stock	*0.55*	*0.26*	*0.48*	*0.34*	*0.33*	*0.21*	*0.09*	*0.06*	*1*			
Intra-ind.Sp.	*-0.09*	*-0.04*	*-0.16*	*-0.20*	*0.22*	*0.21*	*0.19*	*-0.27*	*0.26*	*1*		
Inter-ind.Sp.	*-0.03*	*-0.16*	*0.07*	*0.04*	*-0.15*	*-0.12*	*-0.09*	*0.13*	*-0.26*	*-0.58*	*1*	
Global Sp.	*0.01*	*0.20*	*0.01*	*0.05*	*-0.04*	*-0.07*	*-0.10*	*0.04*	*-0.07*	*-0.05*	*0.22*	*1*

Appendix 5.1: VIF tests

Variable	***VIF***	***Tolerance***
Labour	*5.12*	*0.20*
Cost of Sales	*3.99*	*0.25*
R&D Stock	*2.24*	*0.45*
Intra-ind.Sp.	*1.93*	*0.52*
Inter-ind.Sp.	*1.81*	*0.55*
Capital Stock	*1.52*	*0.66*
Human capital	*1.46*	*0.69*
Int. Assets Int.	*1.34*	*0.74*
Age	*1.28*	*0.78*
Global Sp.	*1.21*	*0.83*
Export Intensity	*1.10*	*0.91*
Mean VIF	***2.09***	

Appendix 6: Heckman's 'sample selection bias' two-step procedure

In order to check for 'sample selection bias', we perform Heckman's (1976, 1979) two-step procedure which controls for firms' decisions to engage in R&D expenditure. We check for 'sample selection bias' in both 'All-Firms' and 'Innovators' datasets, using a number of specifications, based on the above procedure. For simplicity, here we report only the special application of Heckman's 'sample selection' model, where the second stage equation is also a Probit technique. The first stage involves determining the firm probability of investing in R&D, employing a Probit model. From the first stage, we obtain the 'inverse Mill's ratio' which we incorporate in the equation from the first stage as a proxy variable, accounting for the omitted effect of the R&D investment decision (the second stage). The estimations are based on the following first-stage models Eq. (H1) and Eq. (H2):

$$\begin{aligned} DRD_{i,t} = {} & a_0 + a_1 lnEI_{i,t} + a_2 lnC_{i,t} + a_3 lnL_{i,t} + a_4 lnE_{i,t} + a_5 lnQ_{i,t} + a_6 lnA_{i,t} \\ & + a_7 lnK_{t,1} + a_8 lnK_{t,2} + a_9 lnK_{t,f} + Ind.D. + TimeD. + \omega_i + \varepsilon_{it} \end{aligned} \qquad \text{Eq.(H1)}$$

$$\begin{aligned} DRD_{i,t} = {} & \beta_0 + \beta_1 lnLP_{i,t} + \beta_2 lnEI_{i,t} + \beta_3 lnC_{i,t} + \beta_4 lnL_{i,t} + \beta_5 lnCOL_{i,t} + \beta_6 lnMS_{i,t} \\ & + \beta_7 lnE_{i,t} + \beta_8 lnQ_{i,t} + \beta_9 lnLqR_{i,t} + \beta_{10} lnA_{i,t} + \beta_{11} lnROCE_{i,t} \\ & + \beta_{12} lnK_{t,1} + \beta_{13} lnK_{t,2} + \beta_{14} lnK_{t,f} + Ind.D. + TimeD. + u_i + v_{it} \end{aligned} \qquad \text{Eq.(H2)}$$

The subscripts *i* and *t* denote firms and time respectively.

In both equations, $DRD_{i,t}$ is a dummy variable equal to 1 if a firm *i* invest in R&D in year *t*, and 0 if not.

In the first equation, included are firm export intensity - ($EI_{i,t}$), measured by the ratio of exports to total sales, capital - ($C_{i,t}$), measured by the physical capital stock, labour - ($L_{i,t}$), measured by the number of employees, human capital - ($E_{i,t}$), measured as a firm's remuneration per employee relative to its industry's remuneration per employee, age - ($Q_{i,t}$), measured by current year minus the year of establishment and intangible assets intensity - ($A_{i,t}$), measured by the ratio between intangible assets and total assets. In addition, included are the intra-industry spillovers - $K_{t,1}$, the inter-industry spillovers - $K_{t,2}$, and the global spillovers - $K_{t,f}$ (the measurement of which is discussed in Chapter 3, Section 3.5.1.2).

In the second equation, the new variables are labour productivity - $LP_{i,t}$, (proxied by the firm value-added divided by the number of employees), the return on capital employed - $ROCE_{i,t}$, measuring firm profitability and also, competitive pressure and market share - $MS_{i,t}$, (included to account for the firm's competitive environment and also, as a size variable). The financial variables, measuring firm financial health are collateral - ($COL_{i,t}$) and liquidity ratio - ($LiqR_{i,t}$).

The a_s and β_s are the models' parameters. The error terms of Eq.(H1) and Eq.(H2) contain two components: the firm-specific component - ω_i and u_i, respectively, and the idiosyncratic *i.i.d.* elements - $\varepsilon_{i,t}$ and $v_{i,t}$, respectively.

The inclusion of industry dummies accounts for industry-specific effects (Wakelin 2001, Odagiri & Iwata 1986). In line with Mairesse & Cuneo (1985) and Mairesse & Sassenou (1991), in our both models, technological opportunities are proxied by intra- and inter-industry spillovers as well as global spillovers. Time dummies are included to capture business-cycle effects. The variables included as well as the justification for their inclusion are based on the literature review (Chapter 3 to Chapter 5).

Using Eq.(H1) and Eq.(H2) we compute the 'Inverse Mill's Ratio' for each observation. In the second-stage, we incorporate the 'Inverse Mill's Ratio' into Eq.(H1) and Eq.(H2) and estimate the Probit models following Cincera *et al*. (2003). For simplicity, the final models are not presented). Appendix 6.1 reports the results from the first-stage (Models 1 and 3) and from the second-stage (Models 2 and 4) in regard to Eq.(H1), with 'Inverse Mill's Ratio' included in Models 2 and 4. Appendix 6.2 presents the outcomes in regard to Eq.(H2), where the results from the first-stage are reported in Model 5 and Model 7, while the results from the second-stage are shown in Model 6 and Model 8.

Appendix 6.1: Heckman's 'sample selection bias' two-step procedure, Chapter 3

Results: Heckman's two-step procedure

Model	***(1) 'All-Firms' Probit***	***(2) 'All-Firms' Probit***	***(3) 'Inno-vators' Probit***	***(4) 'Inno-vators Probit***
Constant	*-1482.02**** *(141.2)*	*-1545.62**** *(359.73)*	*-1554.78**** *(341.17)*	*-1582.41**** *(446.86)*
ln(Labour)	*.819** *(.460)*	*1.128**** *(.396)*	*.979*** *(.432)*	*1.234*** *(.539)*
ln (Capital)	*.684** *(.453)*	*.429** *(.238)*	*.334* *(.264)*	*.303* *(.307)*
ln (Human Capital)	*.922* *(.843)*	*1.165** *(.627)*	*1.315*** *(.673)*	*1.273** *(.783)*
ln (Intangible Assets Intensity)	*.618**** *(.200)*	*.457**** *(.174)*	*.342** *(.195)*	*.406** *(.218)*
ln (Export Intensity)	*.595*** *(.283)*	*.566**** *(.217)*	*.817**** *(.239)*	*.975**** *(.361)*
ln (Age)	*-2.105**** *(.696)*	*-1.747**** *(.521)*	*-.966*** *(.482)*	*-1.083** *(.638)*
ln (Intra-Ind./Sales Spill.)	*.168* *(1.3)*	*-.461* *(1.344)*	*2.727* *(1.907)*	*3.192** *(2.082)*
ln (Inter Ind./Labour Spill.)	*-46.177**** *(16.085)*	*-49.989*** *(22.381)*	*-38.992* *(37.556)*	*-34.78* *(38.193)*
ln (Global Spillovers)	*86.996**** *(7.110)*	*90.878**** *(18.154)*	*89.243**** *(15.244)*	*89.223**** *(21.19)*
Lambda		***.316*** ***(.240)***		***.341*** ***(.427)***
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
LR	*268.27****	*265.86****	*192.07****	*185.36****
Rho	*.982*	*.977*	*.979*	*.976*
Sigma	*7.284*	*6.589*	*6.783*	*6.357*
Observations	*2215*	*2172*	*1336*	*1333*

Notes: The reported Z-statistics (in parentheses) are based on robust standard errors, corrected for clustering. LR is a test of independence of equations (Rho=0)
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 6.2: Heckman's 'sample selection bias' two-step procedure (Extended)

Heckman's two-step procedure (Extended)				
Model	***(5) 'All-Firms' Probit***	***(6) 'All-Firms' Probit***	***(7) 'Innovators' Probit***	***(8) 'Innovators' Probit***
Constant	*-1508.03**** *(225.35)*	*-1587.82**** *(469.62)*	*-606.21* *(679.47)*	*-506.16* *(740.45)*
ln(Labour)	*1.384* *(1.817)*	*1.165* *(1.629)*	*1.021* *(1.934)*	*1.194* *(2.037)*
ln (Capital)	*-546* *(.533)*	*-.585* *(.553)*	*-.213* *(.567)*	*-.273* *(.602)*
ln (Human Capital)	*.012* *(1.143)*	*-.166* *(1.317)*	*.152* *(1.157)*	*.079* *(1.225)*
ln (Intangible Assets Intensity)	*.834**** *(.340)*	*.879** *(.499)*	*.771*** *(.395)*	*.812* *(.614)*
ln (Export Intensity)	*.985**** *(.383)*	*1.053*** *(.422)*	*1.405**** *(.484)*	*1.205*** *(.538)*
ln (Age)	*-1.387** *(.934)*	*-1.521* *(1.16)*	*-.464* *(.926)*	*-.317* *(.953)*
ln (Intra-Ind./Sales Spill.)	*-.568* *(1.939)*	*-.409* *(1.827)*	*2.697**** *(3.877)*	*2.419* *(3.841)*
ln (Inter-Ind./Labour Spill.)	*-74.132**** *(23.233)*	*-83.988**** *(33.543)*	*-238.983** *(130.965)*	*-221.664** *(136.822)*
ln (Global Spillovers)	*99.109**** *(14.550)*	*105.645**** *(31.395)*	*109.027**** *(28.728)*	*98.207**** *(34.453)*
ln (Labour Productivity)	*.692* *(1.199)*	*.650* *(1.236)*	*.293* *(1.302)*	*.548* *(1.45)*
ln (Collateral)	*.736** *(.483)*	*.759* *(.629)*	*-.176* *(.551)*	*-.117* *(.534)*
ln (Liquidity Ratio)	*.329* *(.454)*	*.293* *(.675)*	*.895* *(.790)*	*.846* *(.826)*
ln (Market Share)	*1.013* *(1.330)*	*1.280* *(1.482)*	*1.315* *(1.543)*	*.977* *(1.658)*
ln (ROCE)	*-.081* *(.415)*	*-.101* *(.456)*	*-.075* *(.492)*	*-.027* *(.429)*
Lambda		***.508*** ***(.396)***		***-.195*** ***(.558)***
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
LR	*111.81****	*103.53****	*67.26****	*66.48****
Rho	*.980*	*.976*	*.977*	*.973*
Sigma	*7.009*	*6.405*	*6.498*	*6.020*
Observations	*1031*	*994*	*621*	*621*

Notes: The reported Z-statistics (in parentheses) are based on robust standard errors, corrected for clustering. LR is a test of independence of equations (Rho=0)
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 7: Firm size and R&D stock of knowledge: the logarithmic transformation applied only on continuous variables

Appendix 7.1: Firm absolute size: 'All-Firms' analysis

Firm absolute size and R&D stock of knowledge: 'All-Firms' analysis				
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***
Constant	1.642 (2.479)	-.983 (3.149)	Omitted	Omitted
ln (Value Added $_{t-1}$)	.739*** (.038)	.166*** (.048)	.588*** (.089)	
ln (Total Sales $_{t-1}$)				.273*** (.103)
ln (R&D Stock of Knowledge)	.003 (.010)	-.077* (.046)	-.029 (.059)	-.027 (.070)
Intangible Assets Intensity	.051 (.060)	-.238* (.128)	-.081 (.283)	-.445* (.308)
Human Capital	.003*** (.001)	.008*** (.002)	.007 (.005)	.002 (.005)
Export Intensity	.062 (.043)	.385*** (.139)	.427** (.186)	.362** (.187)
ln (Age)	-.023 (.018)	Omitted	.020 (.036)	.058* (.038)
ln (Physical Capital Stock)	.035** (.014)	.0200 (.057)	.032 (.074)	.033 (.071)
ln (Labour)	.160*** (.035)	.569*** (.092)	.259** (.100)	.394*** (.126)
ln (Cost of Sales)	.043** (.016)	.113*** (.043)	.078 (.061)	.278*** (.083)
Intra-Ind./Sales Spillovers	-.629 (.671)	.019 (.747)	-1.207* (.768)	.102 (.681)
Inter-Ind./Labour Spillovers.	-.001 (.001)	.0001 (.001)	-.002* (.001)	-.0002 (.001)
ln (Global Spillovers)	-.016 (.136)	.221 (.181)	.132*** (.047)	.142*** (.042)
Ind. & Year Dummies	Yes	Yes	Yes	Yes
AR(1) Test			0.016	0.013
AR(2) Test			0.224	0.308
Hansen's J test			0.222	0.284
Observations(groups)	1678	1678 (390)	1678 (390)	1732(397)
Instruments (lags)			137, (3 3)	137,(3 3)
R^2	0.929	0.382		
F	F(29,389)= 770.34***	F(17,389)= 33.34***	F(37, 389)= 13102.00 ***	F(37,396)= 13659.42***

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 7.2: Firm absolute size: 'Innovators' analysis

Firm absolute size and R&D stock of knowledge: 'Innovators' analysis				
Model/Dependent Variable	***1.Pooled OLS (lnVA)***	***2. Fixed Effects (lnVA)***	***3. GMM (lnVA)***	***4. GMM (lnTotal Sales)***
Constant	*1.460*	*.273*	*Omitted*	*Omitted*
	(2.681)	*(3.155)*		
ln (Value Added $_{t-1}$)	*.760****	*.190****	*.607****	
	(.034)	*(.049)*	*(.086)*	
ln (Total Sales $_{t-1}$)				*.267****
				(.102)
ln (R&D Stock of Knowledge)	*.005*	*-.079**	*-.037*	*-.026*
	(.011)	*(.045)*	*(.061)*	*(.071)*
Intangible Assets Intensity	*.033*	*-.262***	*-.072*	*-.454*
	(.061)	*(.128)*	*(.300)*	*(.324)*
Human Capital	*.003****	*.008****	*.005*	*.002*
	(.001)	*(.002)*	*(.005)*	*(.006)*
Export Intensity	*.050*	*.345***	*.442***	*.371***
	(.041)	*(.135)*	*(.190)*	*(.189)*
ln (Age)	*-.027**	*Omitted*	*.026*	*.064**
	(.019)		*(.037)*	*(.041)*
ln (Physical Capital Stock)	*.028**	*.041*	*.030*	*.045*
	(.015)	*(.053)*	*(.075)*	*(.073)*
ln (Labour)	*.149****	*.530****	*.226***	*.372****
	(.032)	*(.084)*	*(.089)*	*(.126)*
ln (Cost of Sales)	*.042***	*.113****	*.088**	*.288****
	(.016)	*(.043)*	*(.060)*	*(.083)*
Intra-Ind./Sales Spillovers	*-.659*	*-.028*	*-1.337**	*.011*
	(.707)	*(.780)*	*(.814)*	*(.720)*
Inter-Ind./Labour Spillovers.	*-.001*	*.00003*	*-.002***	*-.0003*
	(.001)	*(.001)*	*(.001)*	*(.001)*
ln (Global Spillovers)	*-.007*	*.155*	*.126****	*.117****
	(.147)	*(.184)*	*(.044)*	*(.038)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.017*	*0.014*
AR(2) Test			*0.224*	*0.334*
Hansen's J test			*0.121*	*0.386*
Observations(groups)	*1538*	*1538 (347)*	*1538 (347)*	*1592(354)*
Instruments (lags)			*131, (3 3)*	*131,(3 3)*
R^2	*0.929*	*0.382*		
F	*F(23,346)= 821.92****	*F(17,346)= 35.64****	*F(29, 346)= 13115.42 ****	*F(29,353)= 13967.28****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 7.3: Firm market share: 'All-Firms' analysis

Firm market share and R&D stock of knowledge: 'All-Firms' analysis				
Model/Dependent Variable	***1.Pooled OLS (VA/Ind.)***	***2. Fixed Effects (VA/Ind.)***	***3. GMM (VA/Ind.)***	***4. GMM (Total Sales/Ind.)***
Constant	*.210*** (.064)*	*.036 (.049)*	*Omitted*	*Omitted*
Value Added/Ind. $_{(t-1)}$	*.684*** (.180)*	*-.179*** (.044)*	*.698*** (.089)*	
Total Sales/Ind. $_{(t-1)}$				*.359** (.154)*
ln (R&D Stock of Knowledge)	*.0004** (.0002)*	*-7.15e-06 (.0005)*	*.001* (.001)*	*.001*** (.0003)*
Intangible Assets Intensity/Ind.	*.0003* (.0002)*	*.0003* (.0002)*	*.0004 (.001)*	*.0002 (.0002)*
Human Capital/Ind.	*.001 (.001)*	*.001 (.001)*	*.002 (.003)*	*.001* (.001)*
Export Intensity/Ind.	*-.0001 (.0002)*	*-.0004 (.0003)*	*-.0003 (.001)*	*-.001*** (.0004)*
ln (Age)	*.001* (.001)*	*Omitted*	*.001 (.001)*	*.00003 (.0002)*
Physical Capital Stock/Ind.	*.018 (.113)*	*-.185 (.139)*	*.074 (.122)*	*.041 (.045)*
Labour/Ind.	*.077 (.109)*	*.225 (.240)*	*.017 (.109)*	*.046 (.034)*
Cost of Sales/Ind.	*.198** (.096)*	*.539* (.354)*	*.200* (.133)*	*.203*** (.055)*
Intra-Ind./Sales Spillovers	*.088*** (.018)*	*.059*** (.016)*	*.078*** (.029)*	*.036*** (.010)*
Inter-Ind./Labour Spillovers.	*.0001*** (.00001)*	*.0001*** (.00001)*	*.0001*** (.00002)*	*.00003*** (7.60e-06)*
ln (Global Spillovers)	*-.014*** (.004)*	*-.004 (.003)*	*-.003*** (.001)*	*-.002*** (.0004)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.233*	*0.093*
AR(2) Test			*0.290*	*0.366*
Hansen's J test			*0.000*	*0.005*
Observations(groups)	*1642*	*1642 (385)*	*1642 (385)*	*1697(392)*
Instruments (lags)			*235, (3 5)*	*235, (3 5)*
R^2	*0.788*	*0.189*		
F	*F(29,384)= 128.53****	*F(17,384)= 9.51****	*F(37, 384)= 233.59 ****	*F(37,391)= 69.60****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 7.4: Firm market share: 'Innovators' analysis

Firm market share and R&D stock of knowledge: 'Innovators' analysis				
Model/Dependent Variable	***1.Pooled OLS (VA/Ind.)***	***2. Fixed Effects (VA/Ind.)***	***3. GMM (VA/Ind.)***	***4. GMM (Total Sales/Ind.)***
Constant	*.228*** (.059)*	*.032 (.040)*	*Omitted*	*Omitted*
Value Added/Ind. $_{(t-1)}$	*.909*** (.029)*	*-.086 (.117)*	*.878*** (.040)*	
Total Sales/Ind. $_{(t-1)}$				*.328** (.153)*
ln (R&D Stock of Knowledge)	*.0004* (.0002)*	*-.0003 (.0003)*	*.001 (.0005)*	*.001*** (.0004)*
Intangible Assets Intensity/Ind.	*.0001 (.0001)*	*.0001 (.0001)*	*-.0002 (.0004)*	*.0002 (.0002)*
Human Capital/Ind.	*1.14e-06 (.001)*	*.0003 (.001)*	*.005 (.005)*	*.001 (.001)*
Export Intensity/Ind.	*-.0001 (.0001)*	*-.0002 (.0003)*	*-.001 (.001)*	*-.001*** (.0004)*
ln (Age)	*.0003 (.0003)*	*Omitted*	*-.0002 (.001)*	*.0001 (.0002)*
Physical Capital Stock/Ind.	*.067 (.069)*	*-.131 (.108)*	*.152 (.132)*	*.035 (.063)*
Labour/Ind.	*.021 (.097)*	*.500*** (.080)*	*.087 (.074)*	*.047 (.034)*
Cost of Sales/Ind.	*-.003 (.046)*	*.087* (.053)*	*-.020 (.080)*	*.184*** (.053)*
Intra-Ind./Sales Spillovers	*.086*** (.016)*	*.060*** (.011)*	*.062*** (.021)*	*.040*** (.011)*
Inter-Ind./Labour Spillovers.	*.0001*** (.00001)*	*.0001*** (.00001)*	*.00005*** (.00002)*	*.00003*** (8.40e-06)*
ln (Global Spillovers)	*-.014*** (.003)*	*-.004* (.002)*	*-.003*** (.001)*	*-.002*** (.0004)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.239*	*0.099*
AR(2) Test			*0.167*	*0.324*
Hansen's J test			*0.001*	*0.003*
Observations(groups)	*1533*	*1533 (347)*	*1533 (347)*	*1588(354)*
Instruments (lags)			*229, (3 5)*	*229, (3 5)*
R^2	*0.869*	*0.223*		
F	*F(23,346)= 391.93****	*F(17,346)= 10.07****	*F(29, 346)= 526.45****	*F(29,353)= 57.92****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 8: Correlation matrix, Chapter 4

Correlation matrix, Chapter 4: 'All-Firms'

Variable	*Export Int.*	*Capital Stock*	*Human Capital*	*Labour Prod.*	*Labour*	*Market Share*	*Coll.*	*Liq. Ratio*	*Int. A.Int.*	*Age*	*R&D Stock*	*Intra-ind. Sp.*	*Inter-ind. Sp.*	*Global Sp.*
Export Intensity	*1*													
Capital Stock	*0.09*	*1*												
Human Capital	*0.10*	*0.19*	*1*											
Labour Prod.	*0.01*	*0.38*	*0.33*	*1*										
Labour	*-0.02*	*0.13*	*-0.06*	*-0.11*	*1*									
Market Share	*-0.01*	*0.33*	*0.18*	*0.37*	*0.81*	*1*								
Collateral	*-0.04*	*0.02*	*-0.14*	*-0.25*	*0.45*	*0.32*	*1*							
Liquidity Ratio	*-0.01*	*-0.26*	*-0.04*	*0.05*	*-0.18*	*-0.15*	*-0.11*	*1*						
Int. Assets Int.	*0.15*	*0.30*	*-0.05*	*0.11*	*-0.06*	*-0.04*	*-0.24*	*-0.28*	*1*					
Age	*-0.14*	*0.07*	*0.08*	*0.04*	*0.36*	*0.40*	*0.25*	*-0.05*	*-0.25*	*1*				
R&D Stock	*0.22*	*0.28*	*0.19*	*0.24*	*0.47*	*0.44*	*0.07*	*-0.05*	*0.11*	*0.05*	*1*			
Intra-ind.Sp.	*0.18*	*-0.03*	*-0.19*	*0.08*	*-0.15*	*-0.28*	*-0.23*	*0.09*	*0.22*	*-0.27*	*0.26*	*1*		
Inter-ind.Sp.	*-0.11*	*-0.17*	*0.12*	*-0.17*	*0.07*	*0.09*	*0.04*	*-0.10*	*-0.13*	*0.13*	*-0.26*	*-0.59*	*1*	
Global Sp.	*-0.07*	*0.20*	*0.07*	*0.02*	*-0.01*	*0.07*	*-0.02*	*0.03*	*-0.10*	*0.03*	*-0.08*	*-0.06*	*0.22*	*1*

Note: In our case, labour and market share are correlated with each other, however, there is no perfect multicollinearity. Using the VIF method, we find that all the variables have VIF values less than 10. Both variables are size control variables. In this situation, even a high VIF is not an issue and can be safely ignored (Allison 1998, Wooldridge 2013), as per our discussion in Appendix 5.

Appendix 9: Firm exports and R&D stock of knowledge: the logarithmic transformation applied only on continuous variables

Appendix 9.1: Firm exports and R&D stock of knowledge: 'All-Firms' analysis

'All-Firms' analysis			
Model/Dependent Variable	***1. Pooled OLS/(Exp. Int.)***	***2. FE (Exp.Int.)***	***3. GMM/ (Exp. Int.)***
Constant	*1.160*	*-3.826**	*Omitted*
	(.968)	*(2.246)*	
Export Intensity $_{(t-1)}$	*.899****	*.177***	*.773****
	(.019)	*(.072)*	*(.058)*
ln (Age $_{t-1}$)	*-.016****	*Omitted*	*-.028***
	(.006)		*(.011)*
ln (Physical Capital	*.0001*	*-.015*	*-.010*
Stock $_{t-1}$)	*(.004)*	*(.026)*	*(.014)*
Labour Prod. $_{(t-1)}$	*.00002*	*.00003*	*-.00004*
	(.00005)	*(.0001)*	*(.0001)*
ln (Labour $_{t-1}$)	*-.002*	*.022*	*.016*
	(.007)	*(.028)*	*(.020)*
Human Capital$_{(t-1)}$	*.007*	*.005*	*.077***
	(.014)	*(.041)*	*(.035)*
Collateral $_{(t-1)}$	*-.025*	*-.098*	*.112*
	(.034)	*(.103)*	*(.113)*
Intangible Assets	*.018*	*.031*	*.116**
Intensity $_{(t-1)}$	*(.024)*	*(.066)*	*(.073)*
Liquidity Ratio $_{(t-1)}$	*-.040**	*.042*	*.083*
	(.023)	*(.055)*	*(.074)*
Market Share $_{(t-1)}$	*-.261*	*.381*	*-.668*
	(.638)	*(1.384)*	*(1.379)*
ln (R&D Stock of	*.006**	*.009*	*.023***
Knowledge $_{t-1}$)	*(.004)*	*(.013)*	*(.012)*
Intra-Ind./Sales	*-.230*	*-.247*	*-.382*
Spillovers$_{(t-1)}$	*(.350)*	*(.436)*	*(.530)*
Inter-Ind./Labour	*.00003*	*.0002*	*.00002*
Spillovers$_{(t-1)}$	*(.0003)*	*(.0003)*	*(.0004)*
ln (Global	*-.054*	*.199**	*-.002*
Spillovers $_{t-1}$)	*(.050)*	*(.122)*	*(.019)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.001*
AR(2) Test			*0.388*
Hansen's J test			*0.000*
Obs. (groups)	*1104*	*1104(328)*	*1104(328)*
Instruments (lags)			*323, (2 5)*
R^2	*0.852*	*0.085*	
F	*F(29,327)= 612.78****	*F(18,327)= 3.09****	*F(39, 327)= 368.64 ****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 9.2: Firm exports and R&D stock of knowledge: 'Innovators' analysis

	'Innovators' analysis		
Model/Dependent Variable	***1. Pooled OLS(Exp. Int.)***	***2. FE (Exp. Int.)***	***3. GMM/ (Exp. Int.)***
Constant	*1.278*	*-3.814**	*Omitted*
	(1.033)	*(2.294)*	
Export Intensity $_{(t-1)}$	*.897****	*.175***	*.778****
	(.020)	*(.073)*	*(.060)*
ln (Age $_{t-1}$)	*-.017****	*Omitted*	*-.029****
	(.006)		*(.011)*
ln (Physical Capital	*.001*	*-.015*	*-.006*
Stock $_{t-1}$)	*(.004)*	*(.026)*	*(.013)*
Labour Prod. $_{(t-1)}$	*.00002*	*.00002*	*-.00005*
	(.0001)	*(.0001)*	*(.0001)*
ln (Labour $_{t-1}$)	*-.003*	*.017*	*.010*
	(.007)	*(.029)*	*(.019)*
Human Capital$_{(t-1)}$	*.007*	*.008*	*.078***
	(.015)	*(.042)*	*(.035)*
Collateral $_{(t-1)}$	*-.029*	*-.093*	*.086*
	(.038)	*(.108)*	*(.110)*
Intangible Assets	*.013*	*.028*	*.084*
Intensity $_{(t-1)}$	*(.025)*	*(.066)*	*(.067)*
Liquidity Ratio $_{(t-1)}$	*-.044**	*.036*	*.067*
	(.024)	*(.056)*	*(.069)*
Market Share $_{(t-1)}$	*-.100*	*.601*	*.246*
	(.920)	*(1.429)*	*(1.445)*
ln (R&D Stock of	*.006**	*.010*	*.017**
Knowledge $_{t-1}$)	*(.004)*	*(.013)*	*(.011)*
Intra-Ind./Sales	*-.197*	*-.243*	*-.334*
Spillovers$_{(t-1)}$	*(.364)*	*(.448)*	*(.568)*
Inter-Ind./Labour	*.0001*	*.0002*	*.0001*
Spillovers$_{(t-1)}$	*(.0003)*	*(.0004)*	*(.0004)*
ln (Global	*-.060*	*.200**	*-.003*
Spillovers $_{t-1}$)	*(.055)*	*(.125)*	*(.021)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.001*
AR(2) Test			*0.413*
Hansen's J test			*0.790*
Obs. (groups)	*1027*	*1027(300)*	*1027(300)*
Instruments (lags)			*318, (2 5)*
R^2	*0.838*	*0.085*	
F	*F(24,299)= 365.21****	*F(18,299)= 2.92****	*F(31, 299)= 465.33 ****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen test reported are the p-values.
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 10: Levinsohn & Petrin's (2003) procedure for estimating firm-level TFP

The explanation is based on Levinsohn & Petrin's (2003) study and Petrin's *et al.* (2004) research. Levinsohn & Petrin (2003) construct productivity by accounting for unobservables. Considering Equation (A1) in logarithmic form and only three inputs, we have:

$$y_t = \beta_0 + \beta_C c_t + \beta_L l_t + \beta_M m_t + \omega_t + \varepsilon_t$$

Eq. (A1)

where the subscript t represents time. We denote with y_t, c_t , l_t, and m_t, firm value-added, physical capital stock, labour and intermediate inputs (e.g. materials, energy), respectively. The unobserved productivity term - ω_t, is estimated by assuming that ω_t is a state variable transmitted element in the firm's decision-making rules influencing the firm's decision-making process, while *i.i.d.* element - ε_t, does not influence firms' decisions, and it represents unexpected deviations from the mean due to measurement error, non-predictable productivity shock or other external to the firm factors (Olley & Pakes 1996). Using intermediate inputs as a proxy for unobserved productivity implies that intermediate inputs are expressed as a function of capital and productivity. The m_t demand function, in this case, is: $m_t = m_t(\omega_t, c_t)$, which has to be monotonic in m_t for all related c_t to be regarded as valid determinants of ω_t. The other condition that has to be met is that the intermediate inputs should be increasing in ω_t .

Eq. A1 does not account for selection biases and endogeneity. The issue of endogeneity arises from the correlation between unobservable productivity shocks, included in the error term and firm inputs, which makes OLS estimation biased and inconsistent. The endogeneity is present when some of the TFP is undetected by the econometrician but detected by a firm at an early time, allowing it to alter its factor inputs. In the case of positive productivity shock profit-maximizing firms increase their output, which involves extra inputs while in the case of negative productivity shocks, the opposite behaviour is envisaged. The Olley & Pakes' (1996) remedy of the endogeneity employs capital investment as a proxy for such unobservable shocks but as this requires firms to make positive investments yearly, it causes issues in regard to observations where investment is reported as zero, omitting them from the dataset.

Levinsohn & Petrin's (2003) estimator employs intermediate inputs as proxies as they are usually different from zero and expected to react more smoothly to productivity shocks, therefore, the strict monotonicity assumption is likely to hold. However, there is some criticism of this approach. Ackerberg *et al.* (2005) argue that the assumption that labour is perfectly flexible in Levinsohn & Petrin's (2003) approach is unrealistic. Although there are some consequent improvements of this technique made by Ackerberg *et al.* (2005) and Wooldridge (2005), the approach is still widely used in the literature as the improvements are yet to be proven beneficial (Smarzinska Javorcik 2004, Griffith *et al*. 2006). Wooldrige (2009) discusses the differences between Olley & Pakes' (1996), Levinsohn & Petrin's (2003) and Ackerberg's *et al.* (2005) approaches to estimating TFP. De Loecker (2011) provides an extension to the above procedures.

Under the monotonicity assumption, we invert the input demand function letting us to re-write unobserved productivity as a function of observables, to receive:
$\omega_t = \phi_t(m_{t,} c_t)$, where $\phi_t(.) = m_t^{-1}(.)$ and modify Eq. (A1), as:

$$y_t = \beta_L l_t + \phi_t(m_{t,}c_t) + \varepsilon_t$$

Eq. (A2)

where:

$$\phi_t(m_{t,}c_t) = \beta_0 + \beta_C c_t + \beta_M m_t + \omega_t(m_{t,}c_t)$$

We could receive consistent non-parametric coefficients of the parameters in equation Eq. (A1) by taking the expectation of the equation Eq. (A2), conditional on m_t and c_t. As ε_t is *i.i.d.* and independent from m_t and c_t and as:

$$E[\phi_t(m_{t,}c_t)|m_{t,}c_t] = \phi_t(m_{t,}c_t)$$

we obtain:

$$E\,[y_t|m_t, c_t] = \beta_L E[l_t|m_t, c_t] + \phi_t(m_{t,}c_t)$$

Eq. (A3)

Subtracting equation Eq. (A3) from Eq. (A2) we receive:

$$y_t - E\,[y_t|m_t, c_t] = \beta_L(l_t - E[l_t|m_t, c_t]) + \varepsilon_t$$

Eq. (A4)

As ε_t is *i.i.d.* and independent of l_t, OLS (limiting the intercept to be 0) will provide a consistent estimate of β_L.

Making further assumptions that ω_i follows a first-order Markov process and that physical capital stock does not immediately respond to the productivity innovation shock ξ_t, where:

$$\xi_t = \omega_t - E[\omega_t|\omega_{t(t-1)}]$$

we can receive a consistent estimator of β_C. Let's denote y_t^* as firm output net of labour input, e.g.:

$$y_t^* = y_t - \beta_L l_t = \beta_0 + \beta_C c_t + \beta_M m_t + E[\omega_t|\omega_{t(t-1)}] + \varepsilon_t^*$$

Eq. (A5)

where:

$$\varepsilon_t^* = \xi_t + \varepsilon_t$$

The assumption made that:

$$E[c_t, \varepsilon_t^*] = 0$$

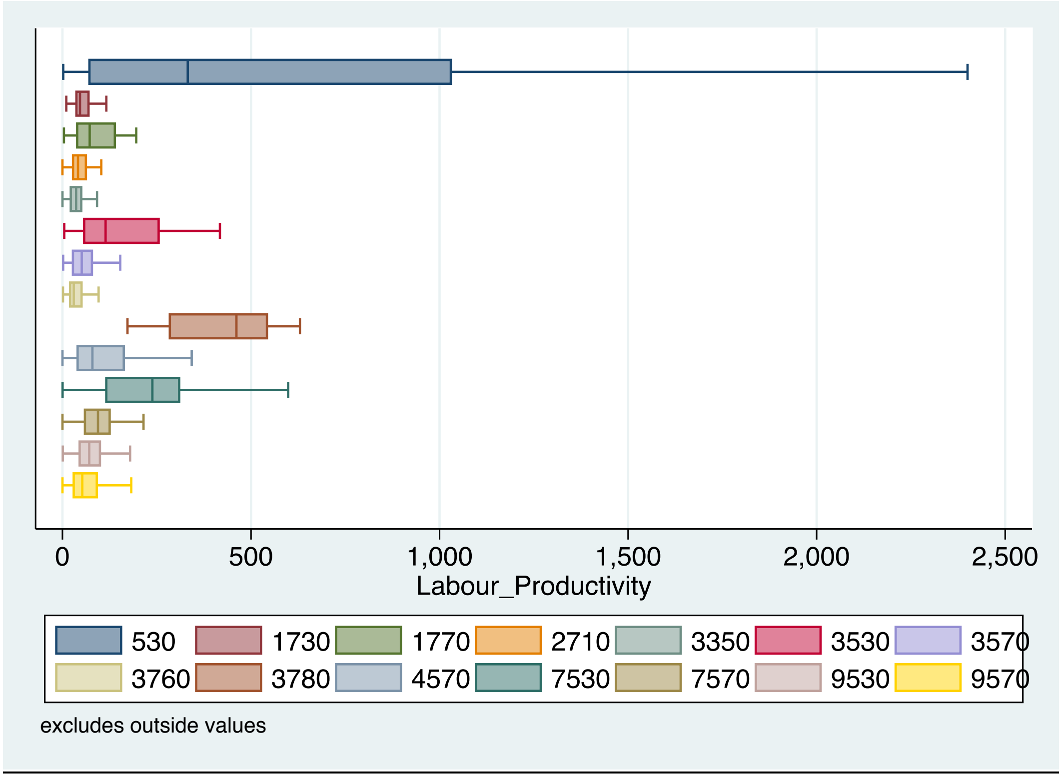
holds, as both ξ_t and ε_t are not correlated with c_t. If we assume that:

$$E[m_{t(t-1)}, \varepsilon_t^*] = 0$$

then we can obtain consistent estimates of β_C and $E[\omega_t|\omega_{t(t-1)}]$

A consistent estimate of firm-level TFP can also be computed as the difference between actual and estimated output. There is a STATA programme (levpet) for implementing Levinsohn & Petrin's (2003) procedure, developed by Petrin, Levinsohn and Poi (2004), used in this research.

Appendix 11: Firms' heterogeneity per industry group: firm labour productivity



Appendix 12: Correlation matrix, Chapter 5

Correlation matrix, Chapter 5: 'All-Firms'

Variable	*LP.*	*Exp. Int.*	*Capital Stock*	*R&D Stock*	*Labour*	*COL.*	*Market Share*	*Human Capital*	*Age*	*Liq. Ratio*	*Int. A. Int.*	*ROCE*	*Intra-ind. Sp.*	*Inter-ind. Sp.*	*Global Sp.*
Labour Prod.	*1*														
Export Intensity	*0.05*	*1*													
Capital Stock	*0.37*	*0.12*	*1*												
R&D Stock	*0.23*	*0.24*	*0.27*	*1*											
Labour	*-0.31*	*0.05*	*0.12*	*0.49*	*1*										
Collateral	*-0.33*	*-0.03*	*0.06*	*0.02*	*0.42*	*1*									
Market Share	*0.18*	*0.09*	*0.33*	*0.49*	*0.79*	*0.30*	*1*								
Human Capital	*0.41*	*0.06*	*0.16*	*0.18*	*-0.05*	*-0.13*	*0.24*	*1*							
Age	*-0.07*	*-0.13*	*0.03*	*0.03*	*0.30*	*0.23*	*0.32*	*0.10*	*1*						
Liquidity Ratio	*0.14*	*-0.04*	*-0.24*	*-0.07*	*-0.18*	*-0.11*	*-0.11*	*-0.04*	*0.01*	*1*					
Int. Assets Int.	*0.08*	*0.19*	*0.22*	*0.16*	*-0.04*	*-0.23*	*-0.05*	*-0.05*	*-0.28*	*-0.27*	*1*				
ROCE	*0.17*	*-0.09*	*-0.23*	*0.03*	*0.02*	*0.02*	*0.10*	*0.03*	*0.09*	*0.14*	*-0.23*	*1*			
Intra-ind.Sp.	*0.09*	*0.17*	*-0.05*	*0.25*	*-0.15*	*-0.24*	*-0.30*	*-0.23*	*-0.25*	*0.07*	*0.23*	*-0.04*	*1*		
Inter-ind.Sp.	*-0.26*	*-0.07*	*-0.16*	*-0.23*	*0.01*	*-0.01*	*-0.01*	*0.20*	*0.06*	*-0.08*	*-0.11*	*-0.01*	*-0.58*	*1*	
Global Sp.	*0.01*	*-0.10*	*0.23*	*-0.10*	*-0.05*	*-0.04*	*0.01*	*0.07*	*-0.01*	*0.06*	*-0.09*	*-0.01*	*-0.06*	*0.21*	*1*

Note: In our case, labour and market share are correlated with each other, however, there is no perfect multicollinearity. Using the VIF method, we find that all the variables have VIF values less than 10. Both variables are size control variables. In this situation, even a high VIF is not an issue and can be safely ignored (Allison 1998, Wooldridge 2013), as per our discussion in Appendix 5.

Appendix 13: Firm productivity and R&D stock of knowledge: the logarithmic transformation applied only on continuous variables

Appendix 13.1: Firm productivity: 'All-Firms' analysis

Firm productivity: 'All-Firms' analysis				
Model/Dependent Variable	***1.Pooled OLS (LP)***	***2. Fixed Effects(LP)***	***3. GMM (LP)***	***4. GMM (lnTFP)***
Constant	*3.498*	*387.927*	*Omitted*	*Omitted*
	(180.924)	*(324.144)*		
Labour Prod. $_{(t-1)}$	*.904****	*.340***	*.799****	
	(.037)	*(.169)*	*(.158)*	
ln (TFP $_{t-1}$*)*				*.579****
				(.038)
Export Intensity	*6.204**	*30.653**	*8.093*	*2.667**
	(3.600)	*(19.417)*	*(12.507)*	*(1.772)*
ln (Age)	*.293*	*Omitted*	*.451*	*.022*
	(1.685)		*(2.999)*	*(.435)*
ln (Capital Stock)	*5.820****	*11.387**	*14.775***	
	(1.681)	*(7.172)*	*(6.908)*	
ln (Labour)	*-10.688****	*-26.255***	*-17.388***	*-.826*
	(2.151)	*(10.798)*	*(8.476)*	*(.659)*
Human Capital	*15.239***	*67.111****	*21.673**	*4.373****
	(5.898)	*(13.962)*	*(13.524)*	*(1.635)*
Collateral	*-18.801***	*-66.219**	*-3.086*	*5.102*
	(9.610)	*(41.554)*	*(37.052)*	*(4.770)*
Intang. Assets Int.	*-11.967*	*-40.654*	*-16.689*	*2.634*
	(9.848)	*(28.601)*	*(31.278)*	*(2.976)*
Liquidity Ratio	*-2.343***	*5.351*	*.491*	*6.063**
	(8.133)	*(24.856)*	*(33.247)*	*(3.193)*
Market Share	*75.093*	*1518.56****	*-470.032*	*36.481*
	(164.376)	*(478.105)*	*(598.678)*	*(39.772)*
ln (R&D Stock of Knowledge)	*.380*	*-1.567*	*-.137*	*.319*
	(.768)	*(3.581)*	*(2.654)*	*(.417)*
ROCE	*.272****	*.356****	*.404*	*.157****
	(.079)	*(.130)*	*(.377)*	*(.036)*
Intra-Ind./Sales Spill.	*-59.142*	*-112.236*	*-59.055*	*-27.790***
	(74.961)	*(88.240)*	*(67.544)*	*(13.498)*
Inter-Ind./Labour Spill.	*.032*	*.040*	*.033*	*-.013*
	(.101)	*(.113)*	*(.083)*	*(.013)*
ln (Global Spill.)	*-3.576*	*-19.225*	*-3.475*	*.681*
	(11.838)	*(18.926)*	*(4.171)*	*(.506)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.026*	*0.000*
AR(2) Test			*0.839*	*0.507*
Hansen's J test			*0.290*	*0.407*
Obs.(groups)	*974*	*974 (286)*	*974 (286)*	*1061(301)*
Instruments (lags)			*190, (2 2)*	*212,(2 2)*
R^2	*0.915*	*0.349*		
F	*F(31,285)= 84.66****	*F(20,285)= 7.59****	*F(40, 285)= 291.92 ****	*F(39,300)= 518.85****

Notes: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values. In Models 1 to 3, the interpretation of the estimates of ln(Labour) is (a_5 -1) as the dependent variable is stated in 'per employee' terms (VA/L)
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*

Appendix 13.2: Firm productivity: 'Innovators' analysis

	Firm productivity: 'Innovators' analysis			
Model/Dependent Variable	***1.Pooled OLS (LP)***	***2. Fixed Effects(LP)***	***3. GMM (LP)***	***4. GMM (lnTFP)***
Constant	*100.776*	*392.312*	*Omitted*	*Omitted*
	(191.445)	*(334.571)*		
Labour Prod. $_{(t-1)}$	*.838****	*.340***	*.812****	
	(.039)	*(.174)*	*(.051)*	
ln (TFP_{t-1})				*.567****
				(.040)
Export Intensity	*5.269*	*30.116**	*7.753*	*3.080**
	(3.866)	*(19.620)*	*(12.740)*	*(1.785)*
ln (Age)	*-.435*	*Omitted*	*-.587*	*-.147*
	(1.961)		*(2.889)*	*(.466)*
ln (Capital Stock)	*7.239****	*12.302**	*19.126***	
	(1.848)	*(7.333)*	*(7.861)*	
ln (Labour)	*-13.500****	*-26.183***	*-20.710***	*-.528*
	(2.339)	*(11.171)*	*(8.058)*	*(.647)*
Human Capital	*19.843****	*71.106****	*15.074**	*5.410****
	(6.563)	*(14.649)*	*(9.867)*	*(1.583)*
Collateral	*-20.421**	*-62.792**	*-14.242*	*4.560*
	(11.592)	*(43.002)*	*(36.829)*	*(4.898)*
Intang. Assets Int.	*-14.041*	*-43.976**	*-11.072*	*1.955*
	(10.667)	*(28.861)*	*(25.178)*	*(3.140)*
Liquidity Ratio	*.522*	*5.589*	*27.153*	*6.755***
	(9.050)	*(25.279)*	*(34.147)*	*(3.292)*
Market Share	*418.216**	*1570.119****	*148.517*	*43.430*
	(252.732)	*(513.934)*	*(713.506)*	*(48.235)*
ln (R&D Stock of	*.351*	*-1.599*	*-1.783*	*.132*
Knowledge)	*(.865)*	*(3.590)*	*(2.905)*	*(.410)*
ROCE	*.324****	*.345***	*.617****	*.161****
	(.086)	*(.135)*	*(.232)*	*(.036)*
Intra-Ind./Sales	*-58.780*	*-129.412*	*30.331*	*-24.435**
Spill.	*(79.445)*	*(91.503)*	*(98.468)*	*(14.231)*
Inter-Ind./Labour. Spill.	*.039*	*.028*	*.115*	*-.009*
	(.103)	*(.112)*	*(.121)*	*(.013)*
ln (Global Spill.)	*-7.250*	*-19.444*	*-10.239*	*.273*
	(12.288)	*(19.381)*	*(7.106)*	*(.577)*
Ind. & Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
AR(1) Test			*0.035*	*0.001*
AR(2) Test			*0.817*	*0.489*
Hansen's J test			*0.294*	*0.438*
Obs.(groups)	*886*	*886 (254)*	*886 (254)*	*968(270)*
Instruments (lags)			*185, (2 2)*	*207,(2 2)*
R^2	*0.866*	*0.352*		
F	*F(26,253)=*	*F(20,253)=*	*F(32, 253)=*	*F(31,269)=*
	*100.96****	*7.16****	*282.78 ****	*288.04****

Note: Robust standard errors are reported in parentheses. In pooled OLS & FE, robust standard errors clustered by ID are shown. For AR(1), AR(2) and Hansen tests reported are the p-values. In Models 1 to 3, the interpretation of the estimates of ln(Labour) is $(a_5 - 1)$ *as the dependent variable is stated in 'per employee' terms (VA/L).*
, **, * indicate significance at 10%, 5%, and 1% level, respectively.*