PRICE DYNAMICS, PROFIT POTENTIAL, AND CANNIBALISATION EFFECT OF REMANUFACTURED SMARTPHONES: EMPIRICAL STUDY USING EBAY DATA

by

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Abstract

Despite proven benefits of remanufacturing, original equipment manufacturers have yet to fully engage with such an activity due to increased complexities and fears of lost sales. This thesis aims to shed light on the viability of smartphone remanufacturing by empirically investigating live-listing prices of new and remanufactured smartphones on eBay. Using Functional Data Analysis, it uncovers the price dynamics at each life cycle stage, and reveals notable similarities amongst smartphones, regardless of the differences in generations, models, and conditions. This study then explores the relationship between price and volume, and finds that remanufactured smartphones have high profit potential in online secondary markets. By examining the price-volume relationship across multiple product generations, it shows that remanufactured smartphones cannibalise the profit potential of their new counterparts only when the smartphones are mature. These results challenge the belief that remanufactured smartphones are a threat to new smartphones, and signify a future business avenue that is profitable, yet, environmentally-friendly.

List of Publications

The following work was published / submitted for publication as a result of the investigations performed in the course of this thesis:

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Chapter 1

Introduction

"It's not what you look at that matters, it's what you see"

Henry David Thoreau

1.1 Background and Motivation[1]

In the past decade, rapid advancements in innovation and technology have significantly accelerated improvements of consumer electronics products (e.g. smartphones, tablets, PCs, laptops, e-readers, and many more). Driven by innovation, a vast amount of consumer electronics products are being traded globally, with the smartphone industry being one of the fastest growing segments – where 1.5 billion units were sold in 2019 alone (Gartner, 2019a). Despite the general trend of increased durability of such items, the end-of-use cycle of

[1] The text in this section (Section 1.1) appeared in part in a joint paper published in the International Journal of Production Economics on pages 78-94. This paper can be found at: https://www.sciencedirect.com/science/article/pii/S0925527318300999.

smartphones has shortened considerably due to software obsolescence and the desire of consumers to upgrade their handsets to the newest generation; as a result, the replacement cycle of smartphones is approximately two years, regardless of their durability (Entner, 2015). Considerably shorter life cycles, combined with high turnover rates and an expansive amount of consumer electronics products circulating within the market, pose detrimental threats to the environment, especially when these products reach the end of their life cycles.

According to the EU WEEE (Waste of Electrical and Electronic Equipment) regulations, producers are responsible for the collection of end-of-use/end-of-life EEE items (Tsai and Hung, 2009). In the subsequent stage of EEE acquisition, original equipment manufacturers (OEMs) have various options to manage collected smartphones including reuse, remanufacture, recycle, scrap, and salvage (Blackburn *et al.*, 2004). One of the most common practices is remanufacturing, which can be defined as "returning a used product to at least its original performance with a warranty that is equivalent to or better than that of the newly manufactured product" (British Standards Institution, 2009).

The potential benefits of remanufacturing have been widely recognised; for example, it extends the useful life of a product, thus reducing the demand for new products and environmental burden (United States Environmental Protection Agency, 1997; 1998; 2011). Remanufacturing is also an economically viable process, as the production of remanufactured products costs 40-65 per cent less than new products (Webster and Mitra, 2007) because it requires less raw material and consumes less energy (United States Environmental Protection Agency, 1997). In the United States (US), sales of remanufactured products are in excess of 40 billion dollars annually, and more than 26,000 firms in the US are engaged in remanufacturing in some way

(U.S. International Trade Commission, 2012). As for smartphones, profits can be generated by the reselling of remanufactured versions – especially in online secondary markets – with great prospects, as the global remanufactured smartphone market grew 13 per cent in 2017, accounting for nearly 10 per cent of the total global smartphone market (Counterpoint, 2018). It is also expected that, by 2022, the market will have a total value of 52.7 billion dollars (International Data Corporation, 2018).

Despite remanufacturing being a multibillion-dollar industry, the current body of literature appears to have only just begun to investigate market-related issues on the subject. In the literature of closed-loop supply chains (CLSCs) and reverse logistics (RLs) (more specifically, in relation to remanufacturing), the majority of research relies on quantitative modelling perspectives (see Govindan, Soleimani and Kannan (2015) for a review) or theoretical frameworks (see for example, Subramoniam, Huisingh and Chinnam (2010), Subramoniam *et al.* (2013), and Agrawal, Atasu and van Ittersum (2015)). Such prescriptive and normative studies do not simulate exact market conditions (Souza, 2013) as they rely on selected influencing factors whose importance is not yet established in a generalised business environment (Prahinski and Kocabasoglu, 2006). In addition, the assumptions made in the analytical models must be tested in order to establish their validity, and only through empirical research can this be done (Gupta, Verna and Victorino , 2006). Furthermore, Guide and Van Wassenhove (2009) note that empirical findings can potentially allow for the development of more sophisticated analytical models. There is also a chance that empirical research can guide management practitioners, since they are currently operating under techniques and know-how from their own experiences rather than empirically tested strategies (Guide and Van Wassenhove, 2009). Therefore, the necessity to conduct further empirical research has become apparent. The reviews of Guide and Van Wassenhove (2006; 2009) and Atasu, Sarvary and Van Wassenhove (2008) also strongly emphasise the need for empirical market-oriented studies in CLSCs and RLs. As suggested by Souza (2013), using actual sales data (see e.g. the works of Guide and Li (2010) and Subramanian and Subramanyam (2012)) can substantially contribute to the existing CLSCs and RLs literature.

The significant growth of online secondary marketplaces provides new research avenues, one of which is how prices of coexisting new and remanufactured products behave and interact. This is yet to be uncovered, as e-commerce studies that utilise product price data have only paid attention to new products that are offered through e-auctions (see for example, Lucking-Reiley *et al.*, 2007; Fuchs, Eybl and Höpken, 2011; Einav *et al.*, 2015; Dinerstein *et al.*, 2018). In doing so, they overlook an equally important side of the market – buy-it-now (BIN) – that constitutes 90 per cent of the gross merchandise volume (GMV) of marketplaces such as eBay (eBay Inc., 2019a). This oversight of a major part of the online market must be addressed if sellers are to take advantage of its unique market intelligence that can facilitate better pricing decisions.

Additionally, recent empirical studies on price in CLSCs and RLs are not only scarce, but the ones that exist focus almost exclusively on customer's willingness to pay (WTP). For instance, Guide and Li (2010) study the WTP of new and remanufactured consumer and commercial goods; Pang *et al.* (2015) empirically analyse determinants of price differentials for new and remanufactured electronics products in the UK; Quariguasi-Frota-Neto, Bloemhof and Corbett (2016) investigate how customers' perception of remanufactured products, relative to used and new consumer electronics products, affect their prices. Other studies in CLSCs and RLs literature that take pricing decisions into account are mainly quantitative in nature, and they fail to account for online marketplaces where new and remanufactured products with different product generations (and same generation yet various models) coexist (see for example, the works of Majumder and Groenevelt (2001) and Ferrer and Swaminathan (2006)). Moreover, this stream of literature focuses on how OEMs maximise economic benefits from both producing new products and remanufacturing used counterparts. Due to the coexistence of new and remanufactured products, the existing literature emphasises the increasing price competition between OEMs and their competitors (i.e. independent remanufacturers); however, there is a lack of research focusing on the fierce price competition amongst independent remanufacturers based in online market platforms across the world (see for instance, Jung and Hwang (2011); Wu (2012)). Understanding this would help alleviate the challenge of marketing and pricing of remanufactured products while capitalising on their potential profitability.

This study aims to fill these literature gaps by empirically investigating price dynamics of coexisting new and remanufactured smartphones listed as BIN (i.e. live-listing); different smartphone brands, models, and generations are selected in order to obtain comprehensive views of the price behaviours over entire product life cycles. This study also takes into account fierce competition amongst sellers from different geographical locations by exploring product prices across two major e-commerce platforms, eBay US and eBay UK. An additional aspect of competition that this thesis focuses on is the cannibalisation effect amongst smartphone brands and conditions. It does this by way of a proxy that can reflect changes in customer demand from one product to another, which is a phenomenon that characterises product cannibalisation (Albuquerque and Bronnenberg, 2009). Unlike other studies, this research utilises a novel statistical method, coupled with econometrics methods, to not only capture temporal characteristics embedded in actual prices but also comprehend the microstructure of online markets. This serves as a more widely applicable alternative to developing a predictive model with strict assumptions that are unattainable under real market conditions.

The reason behind narrowing the focus to the BIN setting, specifically, is as follows. BIN sellers benefit from a different type of information than auction sellers, since the latter inherently rely on customers' WTP (Chan, Kadiyali and Park, 2007); this limits the potential value of the products by attributing market power to the buyers. BIN sellers, on the other hand, potentially have more market power than their auction equivalents as they are able to set their own prices rather than being entirely dictated to by buyers' WTP. They also have access to a pool of competitors' prices through either the use of historical database or price scraping websites. By analysing these prices over time, BIN sellers can obtain a clearer picture of both historical and current product valuation within the market – in other words, the prices other BIN sellers set at different times in hopes of successful transactions. One might argue that, in competitive markets, new product prices inevitably decrease over time (Bayus, 1992) and sellers that offer the lowest price win sales, thus they should only focus on offering the best price for the day. However, the presence of remanufactured products further complicates this, since buyers now have access to cheaper alternatives. By analysing actual pricing data and deriving meaningful patterns that are beneficial to sellers, it is possible for them to develop a strategy beyond cost advantage.

The rationale behind studying online price dynamics of new and remanufactured smartphones are as follows. Firstly, the rise of e-commerce enables information transparency, which paves the way for an analysis of a large pool of previously unexplored market dimensions. With the abundance of data including prices, volume, and product details, sellers can derive, and take advantage of, essential market intelligence that can help them make strategically important decisions more effectively. Secondly, while an understanding of the drivers of WTP and localised competition is beneficial to price adjustment and profit assessment, a knowledge of patterns and behaviours of prices over time is equally important to OEMs and independent sellers alike, especially when the market is further complicated by the presence of remanufactured products. This allows sellers to improve their trading strategies in terms of when and how to adjust price levels in order to maximise profit at different points in the product life cycle. Thirdly, despite the expansive growth of e-commerce and the tremendous revenue generated via online platforms, the understanding of the mechanism behind these markets is still limited. Insights into the structure of online markets are imperative, as they would enable sellers to determine the predictability of prices, which in turn would allow them to adjust their price levels more efficiently. Furthermore, the understanding of the interplay between factors such as price, volume, and product condition would facilitate the sellers in gauging profit potential within the market of interest before investing and tapping into such a market.

In a dynamic environment like an online marketplace, prices fluctuate more frequently; thus, sellers are required to be responsive and adjust their prices promptly regardless of their incumbency period. Therefore, it is crucial for sellers to develop a new approach to price setting instead of waiting to adjust prices in preparation for important events such as holidays and product launch dates. One aspect that has been largely overlooked is the evolution of prices in online marketplaces, with the exception of a few literature on auction (see for example, Shmueli and Jank (2006) and Reddy and Dass (2006)). Currently, when sellers first enter the secondary market, they might choose to either observe the general primary market prices of the product they are about to sell, or observe other sellers within the same secondary market and set a price to match – or slightly lower. This method may prove effective at first, but the task might become cumbersome if said product is being listed for a longer period of time, as the sellers have to continually review their prices throughout. Therefore, rather than focusing purely on a static outcome such as listing prices on a particular day, sellers can benefit from a knowledge of the price formation processes of their products over time. This gives them a better understanding of the price dynamics in terms of speed and changes in speed, which can help sellers answer questions such as: How fast does price change at different stages of the product life cycle? How fast does price move towards the final price? Which dynamics are common, and which are different across various product generations?

To determine the best price possible, sellers must understand demand, and how it reacts to price changes. This is a difficult task, as some observable demand signals can be misleading; for instance, a surge in demand due to promotional efforts may lead retailers to increase prices, but this observed signal does not imply that high prices will always be accompanied by high demand (Johnson and Myatt, 2006). Sellers selling a range of similar products have to take the price levels of all products in the range into account, as well as the price levels of their competitors selling the same range, as these factors further complicate the relationship between demand and price. Since existing mathematical models developed to determine prices are overly reliant on assumptions regarding demand and supply functions and behaviours of players in the market which may not hold in reality, sellers should consider a different factor that is more tangible and universally applicable – volume – as a potential predictor of prices.

The study of the relationship between price changes and trading volume in different markets is well established in the finance literature (see, for instance, the works of Brida, Matesanz and

Seijas (2016), Alizadeh and Tamvakis (2016), and Magkonis and Tsouknidis (2017)). The comprehension of such a relationship provides useful insights into the market structure and helps traders determine the optimal time to deliver stocks and futures contracts (Karpoff, 1987). Likewise, the unravelling of the link between price and volume is important for producers and sellers operating in online markets, as it provides a first glance as to how prices react to changes in volumes, and vice versa, under heightened competition. In fact, the sign and magnitude of the elasticity of prices to volume are what determine the sensitivity of revenues – and, consequently, the profit potential of a given market. For instance, a market with the most profit potential would be a market in which prices increase following an increase in the volume offered; conversely, a market with less profit potential would be a market in which prices fall following an increase in volume.

Understanding the link between prices and volume is also of paramount importance for primary markets, which constitute by far the largest portion of trading volume. The term 'primary market' characterises a marketplace where a customer purchases a product directly from the source, such as high street shops, without any reselling; this is in contrast with secondary markets, where consumers make a purchase through a third-party reseller. However, the estimation of the price-volume relationship in primary markets is problematic, as prices are set by the producers and they do not change frequently over time as a result of the interaction between demand and supply. This means that it is difficult for OEMs to estimate product demand and observe customer preferences for a particular product. On the other hand, online secondary markets such as eBay are an ideal setting to investigate such a link for a number of reasons. Firstly, in e-trading platforms, the prices fluctuate on an intraday basis as a result of the interaction between market forces, delivering long time series of prices and volume which can be studied empirically. Secondly, such platforms host markets for a large variety of new and remanufactured products, making it possible to investigate the influence of competing items on the price-volume relationship of a given product. Finally, the same platforms host exchanges for new items – therefore, the price-volume series originated by such platforms can be taken as a good proxy to shed light on the pricing mechanism of new items in primary markets. It is also an indication of products with the most profit potential that OEMs can concentrate their resources on. This is particularly important, as major companies such as smartphone manufacturers Apple and Samsung, are taking initiative to sell remanufactured versions of their own products via official channels in the US. Furthermore, they are aiming to strengthen their market presence in emerging remanufactured smartphone markets like India, which has seen a growth of 8.8 per cent in 2019 (Counterpoint, 2019).

With recent market developments, firms in many industries face important strategic decisions regarding pricing – even more so for those dealing with technologically advanced products. In managing technology, change is inevitable, as any given product generation is practically guaranteed to be succeeded by a newer generation at a fast pace. For instance, televisions advance from CRT, to LCD, to OLED; audio formats progress from vinyl, to cassette tape, to CD, and so forth. The smartphone market is one of the most heavily segmented into generations of technology. Since the introduction of iPhone in 2007, new smartphone iterations have been introduced on an almost yearly cycle with varying degrees of technological advancements. When multiple product generations compete in the same market, cannibalisation can occur. Such a scenario may lead to unexpected profit loss, as less profitable older product generations partition the company's market share originally expected to be monopolised by the latest generation with the highest profit margin (Lin and Kremer, 2014). Organisations are required to carefully plan and differentiate amongst product generations to prevent the profit loss caused by cannibalisation. The presence of remanufactured products may exacerbate this as they are considered a viable, but significantly cheaper, alternative to new products. Such a possibility is one of the main deterrences from remanufacturing for OEMs (Ferguson and Toktay, 2006; Guide and Li, 2010; Sun *et al.*, 2019).

Considering the impact caused by multiple product generations together with potential complications attributable to remanufactured products, it is reasonable for this thesis to examine the concern regarding product cannibalisation. This is done by investigating the relationship between price and volume across different product generations since it is reflective of the market structure, along with factors such as the behaviours of key players in the market. By comparing amongst the resulting profit potential of different smartphones, it is possible to determine if product cannibalisation occurs. For instance, if one product has higher profit potential than the other, it can be said that the former cannibalises the profit potential of the latter. On the other hand, if two products share the same profit potential, then they do not actively compete with each other, and can coexist within the same market. This concept is based on the definition given by Albuquerque and Bronnenberg (2009), which describes cannibalisation as the fraction of demand lost from customers switching from other product iterations to the new product marketed by the same manufacturer. Since customer demand governs the profitability of a product, the change in profit potential of a given product is a good proxy for the shift in customer demand.

In addition to exploring these themes, this research has implications for gaining a deeper understanding of price dynamics which are greatly consequential to the wider picture of data analytics. Data analytics is here defined as the process of examining raw data in order to draw conclusions about the information they contain, a definition shared by Akturk, Ketzenberg, and Heim (2018). As such, this study uses a combination of analytical tools such as functional data analysis (FDA) and econometrics models to uncover the required insights from price data. These methods are, in a way, novel in their nature since no-one has yet applied them in the same setting and on the same – or even similar – datasets. As such, the extent to which application of FDA and econometrics models in this study is successful in revealing hidden information regarding price behaviours will attest to their potential in analysing more complex data. In other words, it is possible that FDA and econometrics models may be included in the toolset for more advanced data analytics.

Data analytics will continue to grow in importance as more and more companies turn their attention inwards to the tremendous amount of data they are creating to make better use of their assets. According to Manyika *et al.* (2011), organisations capture trillions of bytes of transactional data that include information on their respective supply chains, and pioneering companies that process these data can create great value that many desire. Data analytics plays an important role in supporting strategic decision makers in various organisations. It helps companies explore the data surrounding them to uncover hidden patterns, correlations, trends, and insights at faster speed – thus, helping them stay agile. Business and market intelligence gathered through data analytics allows firms to identify new revenue opportunities, optimise their operations, market their products more efficiently, offer better customer service, and ultimately, gain advantage over their competitors. It was predicted that by 2020, 80 per cent of organisations would purposefully plan for competency development in information literacy, which could alleviate their extreme deficiency (Gartner, 2019b).

By paving the way for organisational decision-makers to make strategically well-informed decisions in a timely manner, data analytics has already proven itself to be both powerful and valuable (Tsai *et al.*, 2015). This thesis harnesses the potential of data analytics by examining untapped data in CLSCs and e-commerce and deriving a widely applicable method to help sellers make better pricing decisions. According to Baker, Kiewell and Winkler (2014), approximately 30 per cent of the numerous pricing decisions companies make annually fail to deliver the best price. This is translated into a considerable amount of lost revenue, since a 1 per cent price increase equates to an increase of 8.7 per cent in operating profits (Baker, Kiewell and Winkler, 2014). These statistics on suboptimal pricing are surprising considering the availability of pricing data, together with the existence of price comparison websites that firms can use to improve their decision-making process. The increased price transparency, which is greatly advantageous to customers, promotes fierce rivalry amongst online sellers and necessitates constant monitoring and swift responses to the competition (Angwin and Mattioli, 2012). To cope with this new challenge, many online sellers relentlessly observe their competitors' prices and use them as benchmarks for their own (Fisher, Gallino and Li, 2017). Typically, they may decide to charge a certain percentage higher or lower than their target competitor, but with such rudimentary heuristics, sellers inevitably miss several profit opportunities – it is such opportunities that this thesis aims to bring to light.

The motivation for this thesis is based on an effort to extend existing research and present applications of data analytics. Undoubtedly, data analytics are highly beneficial to organisations, but current practices have yet to reach their full potential as they predominantly focus on developing algorithms and analytical software and hardware in hopes of dealing with complex data structures (Watson and Wixom, 2007; Turban *et al.*, 2008; Chaudhuri, Dayal and

Narasayya, 2011). With the rise of e-platforms, more and more studies explore data sources online, but they focus almost entirely on user-generated content and its effect on product sales (for instance, Archak, Ghose and Ipeirotis (2011), Liu and Toubia (2018), Netzer *et al.* (2012), and Wedel and Kannan (2016)). The insights derived from a sole emphasis on product sales, though advantageous, can limit the improvement of firms' pricing decisions as they overly rely on customers' WTP, disregarding the effect of competition caused by price transparency on the internet. In order to find new ways to use data analytics to help firms cope with increasingly complex business environments, this thesis takes into account shortened product life cycles and the growing number of remanufactured products – two factors that can exacerbate pricing decisions. The BIN setting chosen in this study seems a promising source of empirical data to determine the usefulness of data analytics in analysing price data of new and remanufactured products, and whether it can facilitate OEMs, sellers, and remanufacturers in making more informed pricing decisions.

1.2 Research Questions

The goal of this thesis is to contribute to the CLSCs and RLs literature by applying data analytics to an empirical investigation of the price dynamics of new and remanufactured smartphones in two different online market platforms, eBay US and eBay UK. In order to achieve this goal, various generations and models of smartphones are selected in order to obtain comprehensive views of their price behaviours over their entire product life cycles. Different analytical tools are chosen and applied to process the data and derive meaningful insights with respect to three overarching research questions:

(1) How do online prices of new and remanufactured smartphones behave over time?

(2) Can volume be used to predict prices in online secondary markets?

(3) Do remanufactured smartphones cannibalise the profit potential of their new counterparts?

1.3 Contributions

This study contributes to the literature in CLSCs and RLs in three ways:

Firstly, this study employs FDA to acquire information embedded in the eBay price data to shed light on the price formation processes of new and remanufactured smartphones (see Chapter 4). The application of FDA within the context of online marketplaces is limited to auctions in the extant literature, with a sole focus on new products (see for example, the works of Reddy and Dass (2006), Bapna, Jank and Shmueli (2008), and Wang, Jank and Shmueli (2008)). No-one has yet applied FDA within the context of CLSCs and RLs. To the best of the researcher's knowledge, this study is the first to investigate the price dynamics of new and remanufactured smartphones in terms of speed and acceleration. The understanding of this mechanism provides OEMs and remanufacturers with the magnitude and timing of price changes, which allows them to make more informed pricing decisions. Furthermore, this research aims to verify the generalisability of price formation processes obtained across multiple product brands, generations, and conditions; this is to aid sellers in developing more effective trading strategies for all products in their range.

Secondly, this study investigates the relationship between price changes and volume of new and remanufactured smartphones in online marketplaces (see Chapter 5). The unravelling of such a link provides both OEMs and remanufacturers with a clear picture of the profit potential of a given market, which has not been done outside economics and finance literature. Furthermore, since the dataset used in this study is a good proxy for new items in primary markets, the insights are transferrable; this is highly beneficial to OEMs and sellers, as the same analysis is not possible due to the static nature of prices in these markets.

Thirdly, this research examines the effects of competition caused by the rapid succession of new smartphone models in recent years and their increasingly common remanufactured counterparts (see Chapter 6). By revisiting the price-volume relationship and applying the analysis in a multi-generation setting, the study determines the change in profit potential of each smartphone generation. Such insights shed light on cannibalisation effects of remanufactured smartphones, which can help guide OEMs in determining the viability of remanufacturing activities.

1.4 Outline

The structure of this thesis can be summarised as follows. Chapter 2 locates the questions raised in this chapter within the extant literature through a review of several streams of relevant research and generates a series of research objectives. Chapter 3 describes the methodology designed to address the research objectives in this thesis. Chapter 4 studies the price dynamics of new and remanufactured smartphones. Chapter 5 investigates the relationship between price changes and volume of new and remanufactured smartphones. Chapter 6 examines the cannibalisation effects of remanufactured smartphones. Chapter 7 concludes with summaries of the empirical findings, draws out key theoretical and methodological insights, and identifies future research directions.

Chapter 2

Literature Review

"The alchemists in their search for gold discovered many other things of greater value."

Arthur Schopenhauer

2.1 Introduction

This chapter integrates literature in closed-loop supply chains (CLSCs) and reverse logistics (RLs) to create a theoretical platform for this research. The central question posed at the beginning of this research concerns the online price dynamics of new and remanufactured smartphones. The notion of price dynamics in this study is considered in terms of its mechanics – the rate of change – over time, and the extent to which the dynamic behaviours of prices are influenced by external variables; as such, this chapter examines current literature with such a query in mind.

The review procedure employed in this chapter is as follows: it begins with focusing on peer-reviewed journals with rankings of ABS3 or higher to ensure quality and robustness of methods employed. The keywords such as price dynamics, price-volume, price erosion, price evolution, remanufactured products, remanufactured smartphones, phones, and consumer electronics are used to find the papers addressing the areas that were relevant to this research. The abstract and conclusion sections of such papers are briefly examined to determine their relevancy. Afterwards, the remaining papers are categorised into different themes according to the findings and / or implications proposed. Based on the resulting compilation, a conclusion is reached on whether they help answer the research questions. Subsequently, gaps in the literature can be established.

The outline of this chapter is as follows. Section 2.2 examines the literature on one of the fastest growing market segments in consumer electronics, smartphones, which has significant potential for sales of remanufactured products. Section 2.3 provides a brief summary of economic theories that shape and explain pricing behaviours in a wider context. Section 2.4 reviews the literature on price dynamics in an e-commerce setting to examine how prices of products in online marketplaces behave over time. Section 2.5 explores empirical studies on the pricing of remanufactured products, which is informative of how prices are determined in the CLSCs and RLs context. Section 2.6 gives an overview of studies that focus on the management of coexisting new and remanufactured products, shedding light on the role of competition within the market. Section 2.7 provides a discussion on the cannibalisation effects of remanufactured products to evaluate the strength of such a concern. Finally, Section 2.8 concludes with a summary of the gaps in the literature and defines research objectives of this study.

2.2 Research on Smartphones in the Remanufacturing Industry

This section justifies the empirical focal point of this thesis – remanufactured smartphones – and provides an overview of the literature addressing operational concerns that OEMs and remanufacturers of smartphones and mobile phones may have. It also examines current research, establishing how their findings help OEMs of such products overcome difficulties in implementing their respective remanufacturing activities.

Due to technological advancements, product life cycles in the electronics industry are significantly shorter than before (Hsueh, 2011). This poses threats to the environment and sustainability, which has induced stringent legislation such as the Waste of Electrical and Electronics Equipment (WEEE) that came into effect in 2014. Such legislation incentivises companies, producing electrical and electronics goods, to pay more attention to the proper management of WEEE in European Union countries; this presents great opportunity for remanufacturing as part of the fulfilment of the extended producers' responsibility. One of the fastest growing categories in consumer electronics is smartphones, with a global sale of 1.5 billion units in 2019, according to Gartner (2019a). The replacement cycle of these products is also short[2] – only slightly over two years (Gartner, 2019c) – due to the desire of customers to upgrade their handset to newer or most recent models. This provides an expansive volume of used smartphones potentially available for remanufacturing, as the majority of disposed smartphones tend to be in good working condition (Alqahtani, Joshi and Gupta, 2019). As a result, substantial value could be added through remanufacturing, and profits can then be

[2] Though it is not the intention of this thesis to define a "normal" product life cycle length, this observation is made by comparing the length of smartphone's product life cycle (2 years) against the life cycles of other products provided in a paper by Bilir (2014).

captured from resale; this promotes the prosperity of secondary markets, as attested by a report from Deloitte (2018) stating that the used and refurbished smartphones market accounts for approximately 15 per cent of the smartphones base in the UK in 2018 – a two percentage point increase compared to the year prior. Both the thriving remanufacturing industry and the potential environmental benefits in this product category make smartphones an ideal focal point of this thesis.

Despite the environmental benefits and the economic value recovery potential of smartphones remanufacturing, such an activity poses challenges of its own. In order to explore the difficulties in implementing and operationalising remanufacturing, this section refers to the literature in CLSCs and RLs. In the CLSCs and RLs literature, a variety of consumer electronics such as computers (Quariguasi-Frota-Neto and bloemhof (2011); Cho, Jun and Kiritsis (2017); Jakowczyk *et al.* (2017)), laptops (Jiménez-Parra, Rubio and Vicente-Molina (2014); Abbey *et al.* (2015b); de Vicente Bittar (2018)), and Apple iPods (Agrawal, Atasu and van Ittersum (2015); Quariguasi-Frota-Neto, Bloemhof and Corbett (2016)) have been studied. Nevertheless, the studies that focus specifically on smartphones are relatively scarce, which can limit the depth of insights that can be gathered from existing research. Therefore, this section covers not only research that focuses on smartphones, but also those that take into account mobile phones. The inclusion of mobile phones is due to the two products being highly similar, both in terms of their functionality and manufacturing processes (Ellen MacArthur Foundation, 2012). The similarity in the value of embedded raw materials also contributes to the comparability of economic value drawn from the remanufacturing of both products (Ellen MacArthur Foundation, 2012). Therefore, it is reasonable to expect that the insights gathered from different studies on both mobile phones and smartphones are interchangeable.

Having established the scope of the literature, it is appropriate to proceed to discuss the factors encumbering the implementation of remanufacturing activity. Based on the literature on smartphones and mobile phones, the potential obstacles mostly consist of economic factors, but there are also a few legislative concerns. For instance, Quariguasi-Frota-Neto and Bloemhof (2011) and Esenduran, Kemahlıoğlu-Ziya and Swaminathan (2017) state that government should not impose legislation that specifies minimum take-back targets, as it can be detrimental towards remanufacturing activities for several reasons. Firstly, higher collection targets may encourage OEMs to reduce their obligation to remanufacture, leading to lower remanufacturing even when remanufacturing costs are low. Secondly, remanufacturing can effectively reduce total energy consumption over the life cycle of mobile phones (and personal computers) only when their lifespan is significantly longer than their new counterparts. Thirdly, willingness to pay (WTP) for remanufactured units correlates to the prices of new products and the period between launch and remanufacturing. That is, when the initial unit price is high and the time elapsed between the launch of the products is short, the average price of remanufactured products will be high. Therefore, the choice of product and time to remanufacture is essential to maximise the efficiency of remanufacturing (Quariguasi-Frota-Neto and Bloemhof, 2011).

As for economic concerns, there exist two main aspects that can significantly impact the profitability of remanufacturing – product acquisition (Guide, Teunter and Van Wassenhove, 2003; Galbreth and Blackburn, 2006, 2010) and customer demand (Rathore, Kota and Chakrabarti, 2011; van Weelden, Mugge and Bakker, 2016). Certainly, for OEMs to be able to remanufacture, they must ensure their ability to gather enough remanufacturing cores in the first place, which is why product acquisition management plays such an important role. However, this is a challenge in itself, as suggested by Sabbaghi, Behdad and Zhuang (2016).

The authors consider the cases of mobile phones and smartphones, and identify customers' behaviour as an issue confronting the profitability of product acquisition systems. Since users have a tendency to keep their end-of-use/end-of-life products in storage instead of returning them to the OEMs, the expected profit of recovered cores will be suboptimal. This is because the delay in remanufacturing time directly impacts the potential profit of remanufacturing activities. Therefore, OEMs are encouraged to offer monetary and convenience incentives to the consumer to promote shorter product return times.

Some OEMs circumvent the shortage of remanufacturing cores by working with third-party suppliers, but in spite of that, another complication arises. This is because remanufacturing cores offered by these providers can vary greatly in quality (Guide, Teunter and Van Wassenhove, 2003; Galbreth and Blackburn, 2006, 2010; Van Wassenhove and Zikopoulos, 2010). Guide, Teunter and Van Wassenhove (2003), who study the remanufacturing of cellular phones, highlight the importance of acquiring the best quality remanufacturing cores, as it can ease the remanufacturing process. In order to do so, Van Wassenhove and Zikopoulos (2010) recommend in a case study on remanufactured mobile phones that OEMs can impose penalties upon their suppliers. This is done by lowering acquisition prices in cases of classification inaccuracy – where supplied cores are of lower quality than promised – in order to reduce the impact of misspecification on profits. Alternatively, Robotis, Bhattacharya and Van Wassenhove (2005) indicate that it is possible for mobile phone remanufacturers to adjust their acquisition strategies, depending on their remanufacturing capacity. If remanufacturing of the cores is possible, then remanufacturers can acquire a low number of used items regardless of their condition, as they can be worked on to improve quality. However, if it is not possible to upgrade the cores, then remanufacturers should procure a large amount of them so that low quality cores can be discarded later. This sentiment is shared by Galbreth and Blackburn (2006, 2010), who study cell phones remanufacturing, as they emphasise the need for remanufacturers to employ a sorting policy that identifies which products should be remanufactured and which should be scrapped.

Another factor, customer demand, governs economic viability of remanufacturing, as OEMs rely on purchases of remanufactured products to generate profits. Most, if not all, of the research indicates that increasing the awareness of customers can help maximise economic benefits of remanufacturing. This is partly because, in certain countries, remanufactured products are perceived negatively. For instance, Rathore, Kota and Chakrabarti (2011) conduct a case study of remanufactured mobile handsets in India. They report that formally establishing a used mobile phones market is important, and that more support is needed from the government to raise the stakeholders' awareness and to promote adoption of remanufacturing activity; this is because the lack of support from government, together with negative perception of remanufactured products, significantly impacts the effectiveness of remanufacturing in India (Rathore, Kota and Chakrabarti, 2011). In the same vein, van Weelden, Mugge and Bakker (2016) conduct interviews with consumers in the Netherlands to explore factors influencing their acceptance of remanufactured mobile phones. The results show that both the lack of awareness and the lack of understanding of what a remanufactured product is can deter customers from considering remanufactured mobile phones. A study by Mugge, Jockin and Bocken (2017) confirms that increased awareness of environmental benefits of remanufactured smartphones, as well as incentives such as quality assurance and improved battery life, can improve customers' purchase intentions.

Based on the overview of the studies focusing on mobile phones, cellular phones, and smartphones above, it appears that researchers in CLSCs and RLs acknowledge the challenges in implementing remanufacturing activities in relation to strict legislation, insufficient remanufacturing cores, and lack of customers' awareness. In order to help alleviate such difficulties, existing research encourages better acquisition management, cooperation amongst players within a supply chain, together with the collaboration between OEMs (and remanufacturers) and their respective governments in order to maximise profits from remanufacturing. The abundant volume and high turnover rates, coupled with potential benefits from remanufacturing, should make smartphones highly appealing to remanufacturers – but in reality, not all OEMs are fully taking advantage of remanufacturing activities. Many are concerned with its repercussions, such as segmentation and increased competition, which can potentially deter them from remanufacturing at a capacity beyond minimum compliance. To shed more light on this issue, this chapter considers three main challenges surrounding the implementation of remanufacturing activities, namely pricing decisions (Chen and Chang, 2013; Abbey, Blackburn and Guide, 2015), competition between new and remanufactured products (Wu, 2012; Huang *et al.*, 2019), and product cannibalisation (Guide and Li, 2010; Atasu, Sarvary and van Wassenhove, 2008). In order to better understand the aforementioned challenges, especially pricing decisions, the next section first examines the general concept of price by referring to important economic theories.

2.3 The Economic Theories behind Prices

Before considering the operational challenges of remanufacturing activities further, this section investigates current economic theories that are fundamental to pricing decisions in different settings. This is to better comprehend the ways in which markets are expected to function – and how prices are meant to be formed – and establish a theoretical foundation behind the behaviours of different market participants.

The first economic theory that this section covers is closely linked to prices – the law of supply and demand – which explains the interaction between the sellers and buyers of a specific good or service. It defines the effect of the relationship between the availability of a product and the demand for it on the price of that product; typically, low supply and high demand increase the price, while high supply and low demand decrease the price (Mankiw, 2018). Considering a situation in which all other factors remain equal, the law of demand states that the higher the price of a good, the less the demand for that good. On the other hand, the law of supply indicates that the higher the price for a good, the higher the quantity supplied. Thus, an equilibrium price, or market-clearing price, exists at the point where the supplier can sell all the goods they want to sell and the buyer can buy all the goods they want to buy (Mankiw, 2018). Nevertheless, the way in which supply or demand react to price change differs between products, with some products' demand being less sensitive to prices than others. Such a sensitivity is referred to as price elasticity. If the demand of a product changes substantially in response to its price changes, that particular product is elastic. In contrast, if the change in price causes minimal change in demand, the product is considered inelastic. The price elasticity of a product is affected by its degree of substitutability; that is, the more easily substituted a product is, the more elastic it becomes (Mankiw, 2018).

Although the law of supply and demand is regarded as a fundamental guide to pricing, in reality, the prices are not always determined by the two factors because of the imperfect competition within the market. Theoretically, in a market with perfect competition, available resources would be divided amongst companies fairly and equally, and no monopoly would exist; all companies would possess the same level of industry knowledge while selling identical products (Hutchinson, 2017). However, none of them would be able to control the market prices of their products, as prices are governed by customer demand (Hutchinson, 2017). There would also be information transparency between buyers and sellers, and the market share would be equal between companies. This also means that there would be little or no barriers to entry or exit (Mankiw, 2018). If one of the aforementioned conditions are not met, imperfect competition occurs. The market with imperfect competition exists in every industry, especially those with the following types of market structures: monopoly, oligopoly, monopolistic competition, monopsony, and oligopsony.

In a monopolistic setting, barriers to market entry are very high, which means there is only one dominant seller who offers a product that has no substitute within the market (Hutchinson, 2017). Since there is no competition, this single seller is able to control the price regardless of supply and demand. The company can also change the price at any given point in time without consulting the consumers (Mankiw, 2018). As for an oligopolistic setting, the barriers to entry are also high, which means that the number of buyers far exceeds the number of sellers (Hutchinson, 2017). Consequently, the market is controlled by a few sellers and there is a risk that the prices for products are set through tacit collusion (Hutchinson, 2017). A monopolistic competition occurs in a market with many sellers who offer products that are similar, but not perfect substitutes (Hutchinson, 2017). Barriers to entry and exit in the overall market are relatively low (Mankiw, 2018), but sellers are able to operate in niche market segments and the overall business decisions of any one seller do not directly affect those of others in the market. In the reverse scenario, where the market comprises of many sellers but few buyers, monopsony and oligopsony can occur. The difference between the two is the number of buyers that the sellers attempt to offer their products to, with monopsony being only one (Mankiw, 2018) and oligopsony being a selected few (Jones and Robinson, 2019). In these types of market structure, the buyers have control over market prices by increasing competition between selling firms.

Considering the structure of online marketplaces such as eBay, some researchers regard them as being nearly a perfect market due to the richness of information that can be obtained easily and instantaneously (see for example, Kuttner, 1998; Srinivasan, Anderson and Ponnavolu, 2002; Hsieh, Chiu and Chiang, 2005). This means that buyers can evaluate prices globally to find and purchase at the lowest price possible, instead of buying from sellers at an unreasonably high price mark up. As a result, sellers in electronic markets face intense price competition where profit margin decreases (Peterson, 1997). Additional characteristics of eBay markets include low entry and exit barriers, facilitating to a large number of buyers and sellers, low search cost, and product homogeneity – all of which are key conditions of a near perfect market as previously described. Nevertheless, online prices are not always lower than offline (Degeratu, Rangaswamy and Wu, 2000; Lynch and Ariely, 2000; Suri, Long and Monroe, 2003), indicating that the marketplace is not as perfect as it seems. In other words, the online market may be more transparent, and thus, more competitive than traditional market – but it is not, by definition, less profitable.

The assumption of information transparency associated with the perfect competition model underpins another theory that is, perhaps, the most dominant economic theory since the early 1960s to date – the efficient market hypothesis (EMH) – which was developed by Fama (1965). According to the EMH, a market is considered efficient when all available information is reflected in the prices without delay – thus, rendering it impossible for traders to outperform the market by predicting future prices based on past prices (i.e. technical analysis), or identifying undervalued products based on company earnings and asset values (i.e. fundamental analysis). In other words, it should not be possible for traders to purchase undervalued products, or sell products for inflated prices. Essentially, this hypothesis is closely associated with the concept of a random walk – where future price movements are thought to be independent of past price movements. This is because all information is supposedly immediately reflected in prices, so price changes the next day will reflect only new information, and since news is unpredictable, resulting price changes must also be unpredictable and random.

By considering the types of information reflected in the prices, it is possible to distinguish between three levels of market efficiency: weak, semi-strong, and strong (Nan and Kaizoji, 2019). The weak form of EMH suggests that prices capture all publicly available market information – but not new, private information – and that future prices are independent of past information regarding price, volume, and returns (Malkiel and Fama, 1970). This implies that traders cannot use technical analysis to consistently generate economic profits beyond average returns, but can possibly use a superior fundamental analysis to do so. The semi-strong form of EMH incorporates the assumptions of the weak form, and further assumes that prices adjust quickly to any newly available public information (Malkiel and Fama, 1970). Accordingly, fundamental analysis is now incapable of predicting future price movements. The strong form of EMH states that prices always reflect the entirety of not only public, but also private information. This means that even traders with insider knowledge are not able to consistently generate excess returns and outperform the overall market.

Since its advent, the EMH has been widely accepted by economists and statisticians alike. Many researchers consistently supported such a hypothesis, as attested by a survey article by Fama (1970), indicating that markets are commonly believed to be incredibly efficient in reflecting information about individual products and the market as a whole. Nevertheless, towards the end of the twentieth century, the idea that prices are predictable based on past price patterns emerged (Malkiel, 2003) – thus, signalling that markets may not, in fact, be efficient. Consequently, the EMH, especially in its weakest form, has been extensively tested and debated over the years; though, reported evidence can neither support nor reject the EMH completely. These debates have inspired several new theories to challenge the EMH – one of which is the mixture of distribution hypothesis (MDH).

The MDH is a popular paradigm that has been used widely to describe how prices and volume evolve over time (see, among others, Karpoff (1987)). It hinges on the idea that prices and volume are jointly determined by the preferences of market participants, which can change as a result of the arrival of specific types of information over time; these include, for example, past price levels and volume for the focus and substitute items. Since information dissemination within the EMH is completely efficient, any long-run relationship between price and volume series as proposed by the MDH violates such an assumption. This is because price-volume correlation indicates that volume has explanatory power in predicting prices – and therefore, contains further information that is not reflected in the prices immediately[3].

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[3] The text in this paragraph appeared in part in a joint paper published in the International Journal of Production Economics on pages 78-94. This paper can be found at: https://www.sciencedirect.com/science/article/pii/S0925527318300999.

It is important to note that the theories included in this section are specifically chosen as they are fundamental to this thesis. Specifically, since the law of supply and demand governs prices, it helps establish an understanding of how prices are expected to behave. Considering that actual markets are imperfect, information on different market structures sheds light on unexpected price behaviours. Since this thesis utilises datasets gathered from eBay, the literature on how prices behave in online marketplaces is considered. This stream of literature is related to the efficient market hypothesis, as the latter defines levels of information transparency that characterise online platforms. Finally, the mixture of distribution hypothesis is selected as it allows for the testing of market efficiency and linkage between price and volume. Though other theories such as the adaptive market hypothesis and noisy market hypothesis exist, they are not applicable to this thesis.

Having explored important economic theories that help understand prices and markets in general, it is apparent that price is dependent upon factors such as demand and supply and information availability, but the degree of dependency differs according to the structure of the market. Since the market structure of online platforms is still in question, it is imperative to understand the actual behaviours of online prices in order to see how these compare with views about how such prices are meant to be formed. As such, the next section of this chapter proceeds to investigate the literature on price dynamics in e-commerce.

2.4 The Price Dynamics in E-Commerce

In this section, literature on price dynamics in an e-commerce setting is investigated to comprehend how prices behave in online platforms beyond observable trends and levels. This facilitates a better understanding of the characteristics of online price adjustments, and how different market forces, such as supply and demand, impact such price movements in this particular environment.

A number of studies have been done on price dynamics in the economics and finance literatures, but, to the best of the researcher's knowledge, the measure of "dynamics" in those studies is different than that used in this thesis. In most economic and finance research, the price dynamics are considered in terms of standard deviation (see for example, Chernov *et al.* (2003), Benz and Trück (2009)) or estimated response from econometrics models (e.g. the works of Caglayan and Filiztekin (2015), Elberg and Hagspiel (2015)). However, the dynamics that this study focuses on are in terms of the speed of price fluctuation and the rate at which this speed changes. This sheds light on the price formation processes on online marketplaces despite the unobserved factors such as the true pricing strategies of online sellers, and how those strategies change notwithstanding the competition. Although these behavioural aspects of the online transaction process remain unobserved, the resulting changes in price dynamics are documented; this can potentially reveal drivers of online pricing processes. As such, the ability to measure and model price dynamics can be considered an important component in the understanding of online transactions.

The concept of price dynamics adopted in this thesis is shared by very few studies in e-commerce research. One of them is a seminal paper by Shmueli and Jank (2006), who study the dynamics of auctions for a variety of auction items on eBay including children's items, sporting event tickets, fashion accessories, and electronics. The authors find that the dynamics of the price formation processes vary, even when the same items are being considered. The results indicate that the opening bid positively affects the bid values especially at the start of the auction, whereas the effect dissipates towards the end. Additionally, the opening bid has growing adverse effects on the velocity of price increase over the entire auction length. Interestingly, the acceleration is positively influenced by the opening bid in the first half of the auction, while the reverse is true for the second half. In the same year, Reddy and Dass (2006) study online price dynamics using modern Indian art auction data. The empirical results support the findings reported by Shmueli and Jank (2006) in relation to the opening bid. The authors extend the former work by including product-related variables such as the lot position, artist reputation, and size; they find that only the artist reputation positively affects the rate of change in prices, whereas both the lot position and the size of the paintings contribute to slower increase in prices.

Hyde, Jank and Shmueli (2006) study simultaneous auction price processes of palm pilots and find that, although online auctions tend to resemble the stock market in that most auctions typically close around their market value, they still contain variability that allows bidders to purchase products at significantly lower than market value. Additionally, it is reported that median closing prices vary at different times of the day, meaning a bidder could potentially gain advantage by taking part in auctions at times where fewer bidders are taking part. A work by Bapna, Jank and Shmueli (2008) uncovers that, even though the price formation process appears to increase gradually at the beginning with the sharpest increase towards the end, the actual dynamics are different. The authors find that after the first initial bid, the price increase slows down significantly before gaining momentum towards the end of the auction due to an increase in the number of bids. These findings are supported by Wang, Jank and Shmueli (2008), who investigate the auction price dynamics of Xbox gaming system and Harry Potter books. The authors further extend previous research by developing a dynamic forecasting model that takes into account features typically found in auctions, such as the unequal spacing of bids and the changing dynamics of price and bidding throughout the auction period. Their results indicate that the forecasting model benefits from both static and time-varying information, thereby outperforming traditional forecasting models.

Wang *et al.* (2008) examine the price process of eBay auctions, both low- and high-valued items, in terms of item, auction, bidder, and seller characteristics; they do so by proposing a family of differential equation models that captures online auction dynamics well. The authors further introduce a multiple-comparisons test for comparing dynamic models of a range of auctions grouped by characteristics of the auction, item, seller, and bidders. They find that price dynamics differ throughout the auction and are mainly influenced by factors that affect the level of outcome uncertainty (e.g. seller rating, item condition) and the degree of competitiveness (e.g. early bidding, number of bids).

Similarly, Jank and Shmueli (2009) study price formation processes in online auctions of palm PDAs along with their dynamics; they report that the price process in an online auction can be diverse, even when both the items in question and their surrounding settings are virtually indistinguishable. Based on a functional representation of the price evolution, the authors find and characterise three "types" of auctions that exhibit different price dynamics: steady, low energy, and bazaar. These differences stem not only from the difference in auction settings such as seller ratings, closing days, and opening prices, but also from the diverse dynamics that occur throughout the auction. Therefore, both static and dynamic sources of information should be considered together in order to better understand the mechanics of online auctions and prevent potential loss of valuable information.

Based on the above research, it seems that the concept of price dynamics is relatively well-developed for auctions. The common findings indicate that the price formation processes vary greatly even for auctions of the same items. Additionally, the auction dynamics can be illuminating since they reveal valuable patterns that are often hidden under price levels. In terms of the rate of change in prices, it appears that the price increment slows down during the auction period, then gains significant speed towards the end. The consensus is that the incoming of bids towards the end of an auction plays an important role.

Many studies have been conducted to uncover how auction-related variables affect the auction dynamics by including a variation of factors in the regression model. Importantly, the results show that common variables, such as opening bids and seller ratings, have a similar influence on the dynamics regardless of the items being considered. Nevertheless, it is clear that no attention has been paid to the BIN side where the price formation processes are likely to be affected by a different set of parameters. This provides an invaluable opportunity to investigate the price dynamics of different BIN, or live-listing, products to better understand how their prices behave in the long run. Such knowledge is important, especially in the scenario where new and remanufactured products coexist. To help form a more comprehensive view on how the formation of prices of remanufactured products are currently understood, the next section investigates empirical research on prices within the CLSCs and RLs literature.

2.5 Empirical Research on Pricing of Remanufactured Products[4]

This section examines existing empirical research in CLSCs and RLs literature in order to establish current knowledge on the pricing of remanufactured products. In the extant literature, the benefits of remanufacturing have been widely established, but the degree of acceptance of customers towards remanufactured products is still in question. This can constrain the price levels, and hence can discourage OEMs and remanufacturers from engaging in remanufacturing activities. Therefore, a better understanding of how prices of remanufactured items are currently determined can potentially help both parties in making more informed decisions. In the extant literature, researchers suggest that the price of remanufactured products is governed by the customers' WTP, which is thought to be influenced by several factors, including behavioural, market-related, and brand preferences. To comprehend how they affect the levels of WTP, the studies that address each of the aforementioned factors are summarised below.

First, the studies that determine the effect of behavioural factors on the customers' WTP. According to Jiménez-Parra, Rubio and Vicente-Molina (2014), there exists a "green" consumer segment where the perception of remanufactured products is positive. A number of studies suggests that the rationale for consumers to purchase such items is influenced by peers (Jiménez-Parra, Rubio and Vicente-Molina, 2014), functionality of the products (Mugge, Jockin and Bocken, 2017), perceived environmental benefits (Hazen, Mollenkopf and Wang., 2016; Khor and Hazen, 2017; Mugge, Jockin and Bocken, 2017), and how up-to-date the

[4] The text in this section (Section 2.5) appeared in part in a joint paper published in the International Journal of Production Economics on pages 78-94. This paper can be found at: https://www.sciencedirect.com/science/article/pii/S0925527318300999.

products are (Quariguasi-Frota-Neto and Bloemhof, 2011; Jakowczyk *et al.*, 2017). However, consumers perceive remanufactured products as economic substitutes for the corresponding new products. They are often willing to purchase remanufactured products only when the price is less than the price of their new counterparts. This claim is empirically evaluated by Guide and Li (2010), who find a clear difference in consumer's WTP between new and remanufactured products for consumer and commercial goods such as jigsaws and security devices.

Other researchers attempt to discover the reasons behind this lower WTP for remanufactured products, showing that scepticism regarding the product's functionality due to its remanufactured parts (Guide and Li, 2010; Hamzaoui Essoussi and Linton, 2010), less robust remanufacturers' reputation (Subramanian and Subramanyam, 2012), consumers' low tolerance of ambiguity in terms of perceived quality (Hazen *et al.*, 2012; Hamzaoui Essoussi and Linton, 2014), and disgust caused by the products' contact with previous owners (Abbey *et al.*, 2015a), are among the determinants of the above price gap.

Abbey *et al.* (2017) investigate the effect of risk aversion behaviour of consumers on their WTP for remanufactured products. Their results indicate that the discount factor, which is the fraction of the consumers' WTP for new products, varies significantly across customers due to different degrees of risk aversion behaviour. This means that optimal prices that are derived from linear demand functions by assuming constant discount factor can yield significantly lower profits. In their later work, Abbey *et al.* (2019) explore factors influencing risk preferences such as risk aversion, loss aversion, and ambiguity aversion in order to derive WTP distributions. The authors find that ambiguity and loss aversion only have a minor effect on WTP, whereas risk aversion has a major impact. Consequently, firms should provide information on the performance of remanufactured products compared to their new counterparts to reduce perceived risk, rather than solely focusing on educating customers about remanufacturing processes to resolve ambiguity.

Second, the studies that investigate the effects of market-related factors on the levels of WTP. Pang *et al.* (2015) empirically analyse determinants of price differentials for new and remanufactured electronics products in the UK. The authors find that price differentials are determined by market-related factors – such as seller reputation, length of warranties, proxies for demand and supply of remanufactured products, duration, and end day of product listings, together with the availability of return policies. Their results are mainly driven by transactions offered by non-manufacturer-approved vendors, and their study concludes that seller identity plays an important part in the pricing mechanism; this finding is further supported by Xu, Zeng and He (2017).

Quariguasi-Frota-Neto, Bloemhof and Corbett (2016) investigate how customers perceive remanufactured products relative to used and new consumer electronics products. By gathering a sample of used, remanufactured, and new Apple iPods, these authors show that remanufactured products are offered at a discount compared to new products. They also find that customers are willing to pay a premium for remanufactured products in comparison with used items; this is because the aesthetics and functionalities of remanufactured products can be brought up to the standards of their new counterparts (Quariguasi-Frota-Neto, Bloemhof and Corbett, 2016). However, mixed results regarding the use of positive descriptions of product across different generations are reported. Customers need more reassurance for used iPods through positive product descriptions in two out of three selected iPod models; this is reflected in an increase in price for used products in relation to their remanufactured counterparts. Similarly, Xu, Zeng and He (2017) explore the differences in WTP for new, manufacturer-refurbished, seller-refurbished, and used Apple iPad 2 in both auctions and fixed price transactions on eBay US. The authors find that buyers tend to pay a premium for seller-refurbished iPads compared to used ones, and that such premia are even higher for new and manufacturer-refurbished iPads.

Third, the studies that address how brand preferences affect the customer's WTP. The study of Guide and Li (2010) finds that customers are willing to pay for a remanufactured version of branded products instead of new counterparts from low-priced competition. Other researchers indicate that brand names help alleviate the perception of risk in terms of quality (Hamzaoui Essoussi and Linton, 2014; van Weelden, Mugge and Bakker, 2016). Nevertheless, there are conflicting views regarding this matter. A study by Abbey *et al.* (2015a) suggests that brand does not always lead to higher WTP, and argues that brand names do not compensate for ambiguity regarding quality for product categories such as cameras, printers, and tyres. They state that the presence of remanufactured versions of the brands in a high technology category can lead to a negative perception of the brand as a whole. This is in agreement with the results provided by Agrawal, Atasu and van Ittersum (2015), who investigate whether the perceived value of new products is influenced by the presence of remanufactured products and seller identity. The authors find that there is a negative perception of value for new products if their remanufactured counterparts are available through OEMs. However, this negative effect differs across brands and product categories.

The above studies are all based on datasets in a cross-sectional format, where only the prices at which transactions occur are observed and then matched with a number of market, seller and item features existing at the same time as the transactions. In this sense, such studies lack the time dimension – as they neglect to analyse the time-series properties of prices – which could uncover meaningful trends, patterns, and behaviours that can provide support in the decision-making process in relation to price setting. In doing so, they inherently make assumptions regarding the market of interest, as the use of historical data (i.e. sales data) implies that future market behaviours can be predicted using past demands. This thesis takes a different approach, focusing on the link between the time dynamics of prices and volume, in order to shed light on important features of the markets under scrutiny.

In addition to the lack of a time dimension, existing studies are mainly focused on customers' WTP, which sheds light on customers' perspectives from the demand side, but does not provide guidance to the sellers in making more informed pricing decisions. This is a crucial matter, as the introduction of remanufactured products – products with an equal functionality but at a discount – can lead to increased competition, which can hinder the profit potential of OEMs and independent sellers alike. To explore this insight further, a stream of research focusing on the coexistence of new and remanufactured products is introduced in the following section.

2.6 Managing Coexisting New and Remanufactured Products

Having discussed current knowledge on pricing of remanufactured products in Section 2.5, this section outlines available research that emphasises the competition between new and remanufactured products, and the resulting roles of OEMs and remanufacturers. It is especially relevant today that OEMs and remanufacturers are made aware of the heightened competition between new and remanufactured products caused by the growth of online platforms; this is because the presence of remanufactured variants exacerbates the existing price competition amongst new products engendered by the internet. As such, the knowledge of how both types of competition (i.e. amongst sellers and between new and remanufactured products) affects price is crucial for sellers to decide on the best price possible. To help alleviate the challenges created by the competition between new and remanufactured products, studies in the CLSCs and RLs literature propose different practices that OEMs can follow. These include optimisation of strategies, competition strategies between OEMs and remanufacturers, cooperation strategies, and self-remanufacturing strategies – all of which will be addressed below.

First, the studies that propose different optimisation strategies. These researchers realise that the coexistence of new and remanufactured products within the same market poses a challenge for both OEMs and their competitors due to an interrelationship between the two products. On the one hand, when a remanufactured product is introduced into the market, competition between such a product and its new counterparts occurs. On the other hand, the supply of remanufactured products themselves depends on the availability of end-of-use new items. A strategically important decision for OEMs to make is, therefore, to decide whether to price their products higher in order to deter remanufacturers as the number of remanufacturing cores decreases, or lower the price to attract sales. With this in mind, researchers study the relationship between coexisting new and remanufactured products in attempts to find optimal operating strategies such as network configurations, inventory policies, and market segmentations (e.g. Purohit (1992), Purohit and Staelin (1994), Debo, Toktay and Van Wassenhove (2005), Francas and Minner (2009), and Aras, Güllü and Yürülmez (2011)).

Other studies develop models to determine optimal selling prices of both new and remanufactured products. For instance, Majumder and Groenevelt (2001) study price competition between an OEM and a local independent remanufacturer using a two-period model. The authors assign cost structures for both the OEM (which considers both manufacturing and remanufacturing costs) and the local independent remanufacturer (which only considers the remanufacturing cost), and explore subsequent decisions based on a cost function. Their results provide insights into the behaviours of an OEM and their competitors; in such a competition, the OEM tends to increase remanufacturing cost for local independent remanufacturers. The OEM's competitors, on the other hand, aim to do the opposite. Consequently, the OEM produces more new products in the first period which, in turn, increases the number of cores available in the subsequent period.

Ferrer and Swaminathan (2006) extend the study of Majumder and Groenevelt (2001) by considering multi-period and infinite time horizons. They propose that if the savings from remanufacturing are high, an OEM should lower the price of new products and sell additional units. This enables the OEM to increase the available number of cores in the next period where all available cores will be utilised, and remanufactured products can be offered at a lower price. Abbey, Blackburn and Guide (2015) use a model of consumer preferences to examine the optimal pricing of new and remanufactured products. By setting up experiments, the authors uncover two distinct customer segments based on their attitude towards remanufactured products and their sensitivity to price discounts. The results from the pricing analysis indicate that when remanufactured products enter the market, the optimal price of new products should increase in order to mitigate the effects of cannibalisation and increase profitability.

Second, the studies that investigate the competition between OEMs and independent remanufacturers. Jung and Hwang (2011) study the competition and cooperation between an OEM and a remanufacturer using a repeated game model and search procedure. The authors find that the return rate of used products increases when both parties compete against each other, while the sum of their net profits increases when the OEM and the remanufacturer cooperate. This gives an incentive to governments to support and encourage independent remanufacturers in order to promote collective efforts in reducing waste.

In the same vein, Wu (2012) formulates a two-period model to examine an OEM’s design strategy and an independent remanufacturer’s pricing strategy in a setting in which the latter is encouraged to intensify price competition. The author suggests that, to maximise their profits, the independent remanufacturer should adopt a low pricing strategy when cost savings are low due to inconvenience in product disassembly designed by the OEM, and compete in the same market as the OEM rather than targeting a ‘green’ market segment. In their later work, Wu (2015) focuses on price and incentive competition between OEMs and remanufacturers. The reported results suggest that OEMs should collect end-of-use products as much as they can to limit the remanufacturing capacity of their competitors. As for remanufacturers, they can focus on achieving economics of scale and sell remanufactured products at lower price points, which softens the incentive competition but strengthens the price competition.

Zheng *et al.* (2019) consider two cases where, in one, an OEM works together with an independent remanufacturer and, in another, both parties actively compete using a theoretical model. Surprisingly, their results indicate that the OEM is less willing to engage in remanufacturing activities in the former setting, even if production and remanufacturing costs are reduced. On the other hand, competition attracts an independent remanufacturer, which subsequently diminishes the OEM's market share.

Third, researchers that present a different view on the competition between OEMs and remanufacturers by focusing on potential cooperation strategies. For instance, Wu and Zhou (2016) investigate whether the presence of independent remanufacturers can somehow benefit OEMs by taking into account two customer groups: newness-conscious and functionality-oriented. The authors find that when OEMs do not have the capacity to remanufacture, the entry of independent remanufacturers can raise the profit of each OEM. In contrast to common beliefs held by competing OEMs, the entry of more than one independent remanufacturer causes less profit reduction than a single entry; this means that OEMs should not always deter remanufacturers and sometimes should even facilitate more new entrants. This finding is supported by the work of Jin *et al.* (2017), who extend the perspective by considering a case where an OEM purchases components from one main supplier but also remanufactures. Additionally, the authors find that the detrimental effect of an independent remanufacturer is less than that of the OEM's in-house remanufacturing system, which is driven by the degree of cooperation between the supplier and the OEM without remanufacturing capacity.

Liu *et al.* (2018) develop competition models between an OEM and a third-party remanufacturer, examining the effect of an authorisation strategy; in this strategy, the OEM chooses to provide refurbishing authorisation to an independent remanufacturer at a fee. The authors suggest that the OEM should not charge an excessively high authorisation fee, as that would promote competition rather than cooperation. Additionally, when the customers' preference for remanufactured products is low, the OEM should authorise the third-party remanufacturer, since the degree of sales cannibalisation is limited. When an independent remanufacturer is authorised by the OEM, their products will be more recognised in the market, which increases their WTP for the authorisation fee. Huang *et al.* (2019) study the incentives of cost information sharing between an OEM and a third-party remanufacturer. They find that if the optimal new product quantity is higher than the optimal remanufactured product quantity, the independent remanufacturer should always share their cost information with the OEM to avoid suboptimal production quantity. On the other hand, if the cost of the new product production is higher such that the quantity is constrained, the third-party remanufacturer should not share cost information since the OEM can reduce the new product quantity, which limits remanufacturing capacity.

Fourth, the studies that consider a different scenario, where an OEM launches remanufactured products in the same market as their new counterparts. Debo, Toktay and Van Wassenhove (2005) develop a joint pricing and production technology selection decision model for an OEM. The authors find that key drivers of technology include high manufacturing cost of a single-use product, low remanufacturing cost, and low incremental costs in making a single-use product remanufacturable. Customer profile also plays an important role; if the customers value remanufactured products less, the price decreases and fixed costs increase. This reduces the profitability of remanufacturing; therefore, it is crucial to investigate the market before launching remanufactured products (Debo, Toktay and Van Wassenhove, 2005).

In a similar context, Vorasayan and Ryan (2006) study a scenario where an OEM sells both new and remanufactured products using a queuing network model to solve optimal prices and determine the quantity to be remanufactured. The authors find that when demand can be met by the OEM's manufacturing capacity, it is optimal either to not remanufacture any returns, or to remanufacture a significant portion of these returns. Additionally, the prices of remanufactured products must be set low enough to create a demand for them. To continue this line of enquiry, Ferguson and Toktay (2006) study a similar setting where an OEM offers both new and remanufactured products, yet with a threat from competitors. The authors find that remanufacturing can be used as a strategy for OEMs to deter entries of third-party remanufacturers. By collecting their own used products, OEMs can increase the cost of potential remanufacturing competitors and limit the opportunity for them to remanufacture profitably. Atasu, Sarvary and van Wassenhove (2008) consider a case where an OEM offers both new and remanufactured versions, but faces competition from a low-cost producer of new products. They find that if the competitor has no cost advantage, the OEM should continue to remanufacture as long as the remanufacturing cost is low.

The focus on the cases where an OEM offers both new and remanufactured products in the same market is still eminently relevant nowadays. The work of Bulmuş, Zhu and Teunter (2014) focuses on an OEM who operates a hybrid manufacturing and remanufacturing system. In this setting, the OEM decides on the acquisition prices based on quality levels of cores on offer, and on selling prices of both new and remanufactured products. The developed pricing procedure reveals that corresponding profit of new items depends only on manufacturing cost. As for remanufactured items, the profit is governed by the quality of acquired cores, so it is suboptimal for the OEM to set the same prices for all remanufactured items, especially when the quality of some core types is low. Liu, Chen and Diallo (2018) propose a two-period production and pricing model for an OEM who chooses to remanufacture. The authors take into account quality of cores, remanufacturing losses, and demand cannibalisation in order to determine whether the

OEM should produce only new, remanufactured, or both products at different times. Their results indicate that if the quality of returns is high and the remanufacturing cost is low, the OEM can obtain more profit by selling both new and remanufactured variants, as opposed to new products alone. Additionally, the OEM should not invest into improving customers' acceptance of remanufactured products if the level is sufficiently high, since overall profit may decrease (Liu, Chen and Diallo, 2018).

The life cycle perspective, as a tool in managing coexisting new and remanufactured products, is introduced by Debo, Toktay and Van Wassenhove (2006). They posit that new products follow a Bass-type diffusion model, which means that customers buy a product only once and use it for the entire life cycle. The authors extend the diffusion model by allowing price-dependent diffusion, and determine different diffusion patterns for different products under different market characteristics. Their extended model also allows for a diffusion of remanufactured products. As a result, joint diffusion paths for both new and remanufactured products are found, since the sales volume of new products and their prices constrain the diffusion of remanufactured products. This serves as a guideline for OEMs to decide whether and when to release remanufactured products in relation to the life cycle of their new product counterparts.

Similarly, Wang *et al.* (2017) examine the effect of product diffusion dynamics on the volume of remanufacturing cores in a single-generation life cycle of a product. The authors link the Bass diffusion model with economic benefit analysis of component reuse, in order to derive an optimal component reuse volume and corresponding acquisition costs. It is revealed that when there is a longer time delay in remanufacturing, the volume of reusable cores decreases significantly; this leads to reduced economic benefit. Although the proposed model can act as a guide for product designers and remanufacturers, it is based on assumptions such as equal WTP between new and remanufactured components, which may not be true in reality.

To rectify this, Ferrer and Swaminathan (2010) consider a case where new and remanufactured products coexist in the market but the remanufactured product is clearly distinguished from its new counterpart. Under two-period, multi-period, and infinite horizons settings, the authors identify thresholds for cost savings from remanufacturing which determine production and pricing strategies for the OEM. They suggest that OEMs should adopt a dynamic remanufacturing policy where different amounts of new and remanufactured products are produced in each period; said production quantity is driven by the need for used products in the subsequent period. For instance, if remanufacturing is profitable, OEMs should supply additional units of new products in the first planning period to increase the number of cores available for remanufacturing. Towards the end of the new product life cycles, where sales are becoming low, OEMs should refrain from remanufacturing in the interim periods; this preserves the cores for remanufacturing at the last stage of the life cycle (Ferrer and Swaminathan, 2010).

In the same vein, Chen and Chang (2013) develop a series of dynamic pricing models in a setting where an OEM sells new products in the first period, and then sells both new and differentiated remanufactured products in subsequent periods. Under assumptions of price-dependent and substitutable demand function, the authors find that pricing strategy is significantly influenced by product life cycle stages, cost-savings of remanufactured products, and degree of substitutability between new and remanufactured products. Additionally, the dynamic nature of the generated pricing strategy is proven to be more effective compared to those generated by a static model.

Despite the insights offered by the aforementioned studies, they suffer from two important limitations. First, they rely purely on mathematical modelling, and second, they only consider situations where an OEM competes locally. This means that the applicability of their insights can be limited, as the business environment today facilitates a situation where not all players are OEMs and the competition is borderless. Moreover, taking into account the nature of coexisting new and remanufactured products – along with the rise of online platforms – another issue arises; there is a lack of focus on the fierce competition amongst independent remanufacturers across different online market platforms, and how it affects the prices of all players involved. This necessitates a new perspective that provides empirical insights into the market platforms where new and remanufactured versions of different product generations (and same generation yet various models) coexist. A study in this context is beneficial to all competing parties, as a greater understanding of global pricing behaviours can shed light on the efficiency of their own pricing decisions; this will better equip them with a knowledge of the mechanism of ever-changing market conditions, which is especially relevant for the fast-paced and rapidly expanding industry of consumer electronics.

To fill this gap, the research in this thesis extends the application of the price-volume relationship analysis from a single product generation to multiple generations. Such an exercise facilitates both a better understanding of the market structure in the long run, and the complementary and substitution effects of the products under scrutiny based on the supply and demand theory. In the next section, a brief overview is given of studies that focus on the final issue relating to the implementation of remanufacturing activities – product cannibalisation – which can be considered a potential consequence of the competition between new and remanufactured products.

2.7 Cannibalisation Effect of Remanufactured Products

Having examined pricing and competition between new and remanufactured products in Section 2.5 and Section 2.6, this section investigates another potential barrier to remanufacturing, product cannibalisation, in more detail. This is in order to determine the strength of the claim that remanufactured products cannibalise the sales of their new counterparts. The section concludes by identifying measures that OEMs can take to alleviate the damage, should product cannibalisation occur.

Ever since the WEEE legislation has taken full effect, more and more OEMs have taken the initiative to incorporate the concept of Corporate Social Responsibility (CSR) in their business models. This means that they shift their focus from pure value creation to one that also includes environmentally-conscious practices (Guide and Van Wassenhove, 2009; Souza, 2013). In doing so, they engage in remanufacturing activities, which has engendered a competition between new and remanufactured products (Corbett and Savaskan, 2003; Savaskan, Bhattacharya and Van Wassenhove, 2004; De Giovanni and Zaccour, 2014). This is because customers are now able to choose from a pool of both product categories, especially in a setting where new and remanufactured versions coexist, which increases the risk of product cannibalisation. It is this very possibility that deters OEMs from remanufacturing at full capacity (Ferguson and Toktay, 2006; Guide and Li, 2010; Sun *et al.*, 2019).

According to Albuquerque and Bronnenberg (2009), cannibalisation is originally defined as the fraction of demand lost from customers switching from other product iterations to the new product marketed by the same manufacturer. It is possible to categorise cannibalisation effect into several types, namely cannibalisation within- and between-category, brand switching within- and between-category, and actual primary (new) demand (Van Heerde, Srinivasan and Dekimpe, 2010). The cannibalisation within- and between-category mirrors the internal cannibalisation within the CLSCs and RLs context (Atasu, Sarvary and van Wassenhove, 2008), where the OEMs manufacture and remanufacture in a monopolistic setting. Traditionally, this type of cannibalisation does not have any adverse effect on the firm's market potential as the number of units sold (and consequently, the market share) remains unchanged (De Giovanni and Ramani, 2018). Granted, once remanufactured products are taken into account, the profitability of the firm may be compromised.

Many studies have been conducted to determine the existence of internal cannibalisation, but the results are mixed. For instance, Ferguson and Toktay (2006) study a monopolistic case by modelling the competition between new and remanufactured products and find evidence of product cannibalisation. The authors indicate that when the remanufacturing cost is low enough, it is possible for the OEM to hedge the detrimental effect of cannibalisation. Research by Atasu, Sarvary and Van Wassenhove (2008) supports the OEMs' concern, but suggests that the negative impact of cannibalisation can be overcome using a smart pricing strategy. The authors also indicate that identifying the market segments correctly is crucial, since each segment's attitude towards new and remanufactured products can dictate product prices. Specifically, when there is a high ratio of customers who do not distinguish between new and remanufactured versions (or even value remanufactured products more as a result of their environmental benefits), the OEM can charge higher prices. Guide and Li (2010) use field auctions to uncover that the cannibalisation effect is minimal for consumer products, whereas the same effect is greater for commercial products. Ferrer and Swaminathan (2010) show that an excess supply of remanufactured products in a given period can partially cannibalise the sales of new products, which highlights the importance of dynamic optimal production policy. In other words, the production quantities of new and remanufactured products should change from period to period to mitigate such an effect.

Ovchinnikov (2011) examines pricing and remanufacturing strategy of an OEM who manufactures and remanufactures to determine the degree of demand cannibalisation. By incorporating a parameter that represents a fraction of consumers who switch from new to remanufactured products, the developed model allows OEMs to increase remanufacturing capacity and charge a much lower price compared to standard methodologies that rely only on WTP. This work is later extended by Ovchinnikov, Blass and Raz (2014), who consider multiple consumer segments across the firm's product lines. After performing a series of numerical simulations, the authors show that remanufacturing not only increases profit, but also decreases total environmental impact. The introduction of remanufactured products does not impact the prices of new counterparts in some product lines, while in other cases, the firm can increase profits by reducing the prices of new variants to achieve sustainable growth.

Yan *et al.* (2015) provide evidence for the cannibalisation effect of remanufactured products by modelling scenarios where an OEM offers remanufactured products through their own e-channel and through a third-party marketer. The results signify that low price is the main driver of product cannibalisation, and the more remanufactured products are available, the fiercer the competition between two versions. Therefore, it is advised that the OEM should market remanufactured products through a different channel than their new counterparts; this finding is supported by the work of Gan *et al.* (2017). Similarly, Mitra (2016) explores a setting where two OEMs compete in the primary market with one also selling remanufactured products in the secondary market. By developing single- and two-period economic models, the author reports that the sales of remanufactured products cannibalise the sales of new products offered by the OEM who chooses to remanufacture. However, the combined profitability and market share helps offset said cannibalisation effect.

On the other hand, Zhou *et al.* (2013) consider a case where an OEM can choose between centralised and decentralised control modes; they find that, in a decentralised control mode, remanufacturing is profitable but cannibalises the sales of higher-margin new products. Additionally, the authors suggest that, as long as remanufacturing is independently profitable, the OEM should simply carry out the exercise instead of considering the trade-off between the cost saving of remanufacturing and the cannibalisation effect of remanufactured products. This is in direct contrast to the implication reported in the work of Ferguson and Toktay (2006). In the same vein, Akan, Ata, and Savaşkan-Ebert (2013) find that the introduction of remanufactured products is accompanied by an increase in price of the new product. They suggest that it is optimal for the OEM to introduce the remanufactured version into the same market as the new product – if remanufacturing benefits are significant – so that the new product can phase out smoothly. Afterwards, the OEM can focus solely on selling remanufactured products at the end of the product life cycle.

Another type of cannibalisation effect, brand switching within- and between-category, relates to external cannibalisation that characterises a scenario in which independent remanufacturers are involved (Atasu, Sarvary and van Wassenhove, 2008). This type of product cannibalisation is much more challenging to companies, as customers change their brand preferences. OEMs, of course, do not intend to sell products to cannibalise their own products, but the existence of remanufactured counterparts can promote brand switching cannibalisation as consumers have a larger appetite for environmentally and socially responsible brands (Guide and Li, 2010). Yet, there exists an opportunity for OEMs to take advantage of green segment customers and create new primary demand (Guide and Van Wassenhove, 2003; Guide *et al.*, 2006; Geyer, Van Wassenhove and Atasu, 2007; Atasu, Sarvary and Van Wassenhove, 2008). These contradicting scenarios provide scholars with a research avenue that could unlock the full potential of an environmentally-friendly activity like remanufacturing, by promoting engagement from OEMs globally.

Some researchers who focus on external cannibalisation assume the presence of cannibalisation effect to model optimal scenarios or strategies, rather than determining whether said effect exists (see e.g. Wu (2013), Bulmuş, Zhu and Teunter (2014), and Zou *et al.* (2016)). Those that do attempt to validate the cannibalisation effect of remanufactured products express contradicting views. For instance, De Giovanni and Ramani (2018) study the partnership between Dell (OEM) and Goodwill (remanufacturer), where the OEM sells new products while the remanufacturer collects end-of-use products nationally before reworking and selling them in the same market as the OEM. Using a model of bilateral monopoly, the authors show that this partnership increases the degree of cannibalisation, which decreases the price charged by the OEM along with their profit. On the other hand, the price charged by the remanufacturer increases, leading to more profit on their end. It is found that the negative effect of product cannibalisation cannot be mitigated by price reduction, but can be partially overcome by means of a service strategy when the degree is low.

However, in their other work, Ramani and De Giovanni (2017) find that remanufactured products do not cannibalise the sales of new products by developing a two-period model of an atypical CLSC. In a framework by Atasu, Guide and Van Wassenhove (2010), evidences supporting cases where remanufactured products do not cannibalise, but benefit OEMs, are reported. They also suggest market segmentation and smart pricing strategy, which have previously been described in the work of Atasu, Sarvary and Van Wassenhove (2008). Ultimately, the authors make a compelling argument that, for an OEM, it is better to lose new market sales to their own remanufactured version than losing them to a third-party remanufacturer. Additionally, when the OEM does not have the majority of the market share, offering remanufactured products will cannibalise their competitor's market share faster than their own (Atasu, Guide and Van Wassenhove, 2010).

From the reported evidences in the literature, it is clear that there is a possibility that remanufactured products will cannibalise the sales of new products. However, it is crucial to also make a distinction that this is not always the case; remanufacturing does not always cannibalise new product sales, and when it does occur, it is rectifiable. There is significant evidence in the literature that, when the additional profits of remanufacturing outweigh cannibalisation costs, remanufacturing can be very attractive. Still, it is up to the OEM to make informed decisions by taking into account factors such as market segments, pricing strategies, and competitors, in order to minimise the effect of product cannibalisation. There exist also opportunities for OEMs to convert such threats into profit-making opportunities, or capitalise on remanufactured products by offering them in a different channel such as e-platforms.

Accordingly, a study that sheds light on the potential of remanufactured products in online secondary markets could unlock a new business practice that is both profitable and environmentally-friendly. For this very reason, this thesis uses data analytics to analyse prices of new and remanufactured smartphones in order to understand actual behaviours of each product throughout their life cycles. This can act as supplementary evidence that might attest to unexplored, yet valuable, opportunities in secondary markets for both OEMs and independent remanufacturers.

2.8 Research Objectives

The aim of this section is to develop the research objectives of this study in light of the gaps identified in the literature, in order to address the research questions posed in the introductory chapter. While previous research presents significant evidence that remanufacturing can be profitable, it appears that these studies do not provide guidelines for OEMs, and potentially online sellers, to make more informed decisions. Existing studies shed more light on customer perceptions, which leads to them advising remanufacturers to focus their efforts on influencing customers' purchase intentions, either by cooperating with governments to increase awareness or by eliminating risks (Rathore, Kota and Chakrabarti (2011); van Weelden, Mugge and Bakker (2016); Mugge, Jockin and Bocken (2017)). Nevertheless, not all players in the market have the capacity to influence customers in these ways, so it is imperative to shift the focus from the customers and shed light on the suppliers' side, in order to develop a more widely applicable strategy. All of the above research also overlooks the change in current business practice where more and more trades now occur online, which can be considered as an intensely active channel. Accordingly, a knowledge and understanding of the ever-changing nature of prices can greatly benefit online sellers during their decision-making process. This allows them to proactively adjust their price levels throughout their trading periods in expectancy of future changes instead of relying on a reactive approach, such as constant observation and revision of prices according to their competitors.

Based on the review of the studies on price dynamics in e-commerce setting (Section 2.4), it is apparent that this type of research is not only scarce, but also solely focuses on an auction setting. This signals a severe lack of understanding on the dynamic behaviours of price in a large portion of online marketplaces – BIN. BIN setting differs from auction in many ways, one of which is how the price is determined; with auctions, buyers bid for the prices they are willing to pay, whereas sellers take more control of the prices of live listings. This fundamental difference can greatly impact the price formation process, which means that the knowledge of the auction price dynamics may not be beneficial to BIN sellers. Additionally, upon reviewing empirical studies on pricing of remanufactured products in Section 2.5, it is clear that within the CLSCs and RLs literature itself, the understanding of the prices of remanufactured products is still limited. This is because researchers seem to have only considered prices from the customers' perspectives, thereby neglecting the needs of the suppliers for guidance in making appropriate decisions. Therefore, the research in this thesis takes into account the temporal nature of prices instead of focusing on cross-sectional data like most studies in the extant literature, and thereby aims to uncover insights that are incredibly beneficial to the decision-making process of sellers. Accordingly, the first research objective is formed as follows:

(1) To investigate price dynamics in terms of speed and timing of price changes at different product life cycle stages.

It is important for sellers in secondary markets, be it OEMs or independent remanufacturers, to gain a better understanding of the dynamic behaviours of their product prices in order to develop a proactive approach in price setting; this is so that they are well equipped to handle the temporal nature of the market they are trading in. As the price dynamics in this study represent the market valuation of the products from the buyers' perspective and the benefit potential from the suppliers' perspective, they can help shed light on the interrelationships between players in the markets. In CLSCs and RLs literature, there has not been any attempt to investigate the price dynamics of new and remanufactured products by deconstructing said dynamics down to speed and acceleration. This provides an unprecedented avenue to examine the price movements of such products to yield insights into the speed and magnitude of price fluctuations at different times in the product life cycle. Such insights can help improve the pricing decisions of sellers in the long run.

The second research objective is based on the review of the literature on competition between coexisting new and remanufactured products in Section 2.6. Such studies focus solely on OEMs who face local competition, which means that the insights may not be as useful for sellers who operate online. Therefore, this research aims to bring the literature up to date with modern practices by focusing on uncovering the trading mechanisms of online market platforms, specifically, eBay US and eBay UK. As such, the second research objective is as follows:

(2) To explore the relationship between price and volume of new and remanufactured smartphones across different online platforms.

The understanding of the price-volume relationship can provide useful insights into the market structure of both new and remanufactured smartphones. The information regarding the direction of the relationship allows both OEMs and remanufacturers to amend their trading strategies accordingly. Should the change in price explain the change in volume and vice versa, it will act as a signal indicating when the OEMs and remanufacturers should adjust the volume (or price). For instance, if a period with an upsurge in volume is typically followed by a period where the price decreases, OEMs and remanufacturers can reduce the volume in that particular period where the sales are not as profitable. Subsequently, both OEMs and remanufacturers can inject more volume at a later stage, where the price increases, to capture higher sales revenues.

Considering the reported findings in the literature, there is clear evidence that remanufactured products can be very profitable. This, coupled with the fact that the sales of smartphones will continue to grow in the near future, should make remanufacturing highly attractive to OEMs. However, it is surprising to observe that governments have to impose stringent regulations to ensure that OEMs participate in remanufacturing; this reluctance is due to uncertainty about potential risks posed to their existing sales model, in particular cannibalisation, even though the consensus seems to suggest that it is possible to overcome the initial threat (see Section 2.7). In order to assess the validity of the OEMs' concern regarding product cannibalisation and to examine if OEMs might be encouraged to willingly participate in environmentally-friendly practices, the third objective aims to determine the existence of product cannibalisation and investigate the long-term viability of remanufactured products. The objective is stated as follows:

(3) To examine the degree of product cannibalisation based on the evolution of the relationships between price and volume of new and remanufactured smartphones across product life cycles.

By taking into account multiple product generations, it is possible to establish a comprehensive view of their profit potential at different stages of the product life cycle, based on the nature of the price-volume relationship. Since such a relationship is influenced by the interaction between demand and supply, its direction may change across product life cycle stages, which, in turn, affects the profit potential of each product. The comparison between the profit potential of new and remanufactured smartphones reveals whether product cannibalisation exists, and thus, sheds light on the viability of remanufacturing activity. A better understanding of how price-volume relationship changes across product life cycles equips the OEMs and remanufacturers with the ability to adjust their trading strategies over time without relying on ad hoc practices. Additionally, both parties will be able to prepare for the upcoming changes invoked by the progression of product generations, along with the introduction of either complementary or substitute products.

Having discussed research objectives, the next chapter presents the methodological designs utilised in this thesis in order to gather relevant data and analyse them to fulfil the aforementioned research objectives.

Chapter 3

Methodology

> "I see the shape of the
> poem before I start
> writing, and the writing is
> just the process of
> arriving at the shape."
>
> ---
>
> Carol Ann Duffy

3.1 Introduction

This chapter discusses the research methodology adopted in this thesis to achieve the research objectives previously stated in Chapter 2. Section 3.2 outlines the philosophy that underpins the research approach taken by examining the positivist stance to research, and the consequent choice of a quantitative approach. Section 3.3 discusses the rationale for the research design and outlines the reasons for the adoption of the secondary data analysis method. Section 3.3 also provides an overview of the data collection method used for this thesis, as well as the means utilised to analyse the data. This chapter concludes with sections on the limitations of the research and ethical considerations.

3.2 Research Philosophy

This section examines the research philosophy that underpins the methodology in relation to its development, as specific philosophical stance guides the way in which data about a phenomenon should be gathered, analysed, and used (Saunders, Lewis and Thornhill, 2019). Various philosophies of research are encompassed by research paradigms – ontology, epistemology, and axiology – that can help researchers define their philosophical standpoint based on ideologies that govern their thinking and action. It is these differing views that generate four major philosophical positions: pragmatism, positivism, realism, and interpretivism. Each research philosophy has its own strengths and weaknesses and, therefore, is suitable for different types of research questions.

The research questions posed in Chapter 1 are descriptive in nature, as they concern the price dynamics of new and remanufactured smartphones, and how data analytics can be used to improve the decision-making process of sellers. As the questions themselves suggested, this research inevitably relies on a large dataset and its analysis, to generate sufficient insights to answer them – very much in line with positivists' approach to obtain knowledge. This thesis is, therefore, defined by a positivist ontology, whose central tenet is that reality exists externally, and that it is observable without interference from researchers; following this perspective, reality in this study is represented by actual price levels and volume, which have been observed and taken without the researcher's manipulation. Positivists are interested in the objective world, patterns, generalisation, and in finding causalities, which have all been reflected in the research objectives previously described in Chapter 2.

Epistemologically speaking, positivists focus on discovering observable and measurable facts or patterns, which constitute credible and meaningful data, before analysing them statistically to uncover regularities and generate law-like generalisations. Consequently, the corresponding research approach, or the way in which positivist researchers typically develop a theory, is deductive in nature; this involves the development of a number of propositions for testing based on existing theory, and subsequent empirical verification of such hypotheses. The results, be they confirmed or refuted, are then used to expand the theory further. However, when taking into account the research objectives outlined in Chapter 2, the research approach adopted in this thesis moves slightly away from the typical hypothetico-deductive approach, since the way in which the theory is developed – or used – in this thesis resonates more with an abductive reasoning. Such an inference concerns more with the development of the most likely theory that can explain emerging empirical observations than the testing of existing theory itself. Nevertheless, it does not infer theories directly from such observations, which corresponds with an inductive approach, but instead relies heavily on existing theories to derive appropriate theoretical explanations. Thus, it can be said that an abductive approach is more flexible compared to deductive and inductive reasoning, as it can move back and forth between data and theory (Dubois and Gadde, 2002; Saunders, Lewis and Thornhill, 2019). This approach fits better than deductive inference, since this research aims to generate new insights into price dynamics with guidance from relevant theories, rather than developing specific assumptions and/or hypotheses before testing them. Similarly, an abductive approach fits this research better than inductive inference, because it is unlikely that a comprehensive theory on price dynamics can be established based solely on the inferences made by analysing a subset of data.

Having established that the research reported in this thesis is characterised by a positivist philosophy, and recognised that an abductive approach to theory and evidence is the most suitable for this study, the next section will discuss the research design adopted in order to answer the research questions and achieve the proposed research objectives.

3.3 Research Design

Following the identification of the research philosophy and its corresponding research approach in Section 3.2, this section examines the research design, which acts as a plan or guideline for researchers to answer their research questions. It contains clear objectives based on posed research questions, specifies data sources, and considers data limitations and relevant ethical issues. The elements of the research design are summarised in Figure 3.1 below.

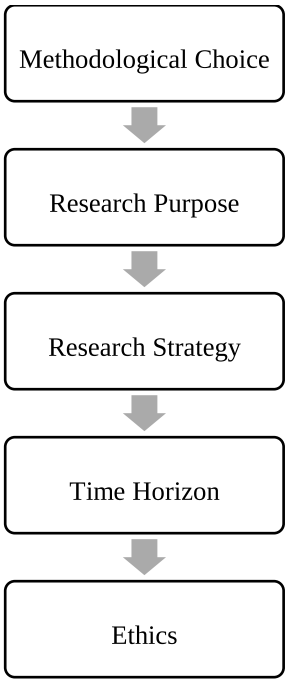

Figure 3.1: Elements of the research design

To design the research for the aim of obtaining evidence that addresses the research questions and objectives, researchers first decide on their methodological choice; be it quantitative, qualitative, or mixed-method. As this research focuses on price dynamics based on pricing data of new and remanufactured smartphones, the logical methodological choice that follows is quantitative method. Such a method examines relationships between variables, which are measured numerically and analysed either statistically or graphically – much like the aim to determine the relationship between price and time (see research objective one, Chapter 2), or to establish the relationship between price and volume in this study (see research objectives two and three, Chapter 2).

The next element of the research design that researchers should consider is the purpose of their study – exploratory, descriptive, or explanatory. This research is exploratory in nature as it is attempting to uncover new patterns and insights in order to improve the understanding of the price dynamics of new and remanufactured smartphones listed on major online platforms. As such, it differs from the interest in describing the situation or case at hand (which would be the focus of descriptive research design) or the emphasis on establishing causal relationships between variables (which would be more applicable to explanatory studies). The exploratory stance taken here emphasises openness and unobserved findings. It seeks to maximise the knowledge gained from the data, while adhering to the two principals of scepticism and openness (Hartwig and Dearing, 1979). By being open to unanticipated patterns in the data, one can obtain the most revealing outcome of the analysis, as opposed to taking a confirmatory viewpoint – which can sometimes conceal or misrepresent the most informative aspects of the data (Hartwig and Dearing, 1979).

Once the research purpose is determined, the next element of the research design, possible research strategies, can be considered. There exist a number of research strategies, with some relating more to a specific research approach (i.e. deductive, abductive, or inductive), but they are applicable to any of the research purposes (Yin, 2017). Researchers have to take into account their research questions and objectives, along with existing knowledge, time, and resources, before choosing the appropriate research strategy (Saunders, Lewis and Thornhill, 2019).

Considering the research questions and their corresponding research objectives in this study, it is clear that pricing data is essential for the subsequent analyses. Since the information regarding the prices of new and remanufactured products already exists on online platforms, this research employs a secondary data analysis strategy to achieve the research objectives previously set out in Chapter 2. Although secondary data are considered to be more economically viable and time-efficient to collect than primary data, they do present certain complications of their own. These problems include, but not limited to, the lack of availability and the usability of the data; therefore, it is imperative for researchers to determine the data relevancy, accuracy, currency, and objectiveness before using them (Kotler and Armstrong, 2010).

Ultimately, the processes involved in secondary data analysis, after the identification of research questions and objectives, are the identification of suitable datasets and the evaluation of such data (Johnston, 2017). For this thesis, there exists a unique aspect to the dataset employed; although the prices of new and remanufactured products are readily available on the respective eBay platforms (eBay US and eBay UK), the information required to fulfil the research objectives has not been collected before. Therefore, an original dataset needs to be constructed based on daily accumulation of published data. To determine the congruency and appropriateness of the dataset, the evaluation criteria proposed by Saunders, Lewis and Thornhill (2019) are followed; these include overall suitability, precise suitability, and costs and benefits.

The first criterion, overall suitability, comprises of measurement validity and coverage. Validity relates to whether the measure accurately reflects the concept it is intended to measure; for example, in this research, daily prices are required, so the secondary data containing monthly prices would not be valid. Coverage concerns the degree to which the data contains all the information needed to answer the research questions; for instance, the dataset utilised in this study should cover selected smartphone brands, span across the time period of interest, and include all relevant variables. Researchers must ensure that unwanted or irrelevant data are or can be excluded, and that the remaining data are sufficient for the subsequent analyses. In this case, neither of the criteria are of concern since, as previously mentioned, the dataset is created by the researcher, so it is possible to ensure that the measure is valid and that all required information is gathered.

The second criterion, precise suitability, encompasses reliability and validity and measurement bias. Researchers can assess both reliability and validity of the dataset by considering the source, as data from authoritative and reputable sources tend to have high credibility as a result of their rigorous data collection method. Since this study collects information directly from a database of raw, unprocessed data, both reliability and validity are ensured through the data collection method of the researcher, which will be discussed in Section 3.4.1. As for measurement bias, there are three reasons why it may occur: deliberate data distortion; changes in data collection method; and when the collected data misrepresent the topic of interest (Saunders, Lewis and Thornhill, 2019). Deliberate data distortion can be difficult to detect; however, in this research, it is possible to cross-reference the data gathered from the databases against the actual information published on the website to ensure their accuracy. Introducing changes in the collection method can lead to measurement bias, so it is important to be aware of any policy changes instigated by eBay while the data is being collected. In the case of this research, there were policy changes, but they are not relevant because the changes are applicable to those hosting an external search application that displays eBay content or personal information, such as a seller username – both of which are not disclosed within this study.

The final evaluative criteria are costs and benefits. According to Hair *et al.* (2010), researchers need to consider the trade-off between the costs of acquiring the data and the benefits they will bring. Costs apply to not only financial resources, but also time devoted to locate and obtain the data. This is potentially one of the most important aspects to consider in this research, since obtaining a full set of data from market research companies, should they exist, can incur substantial cost. On the other hand, a significant amount of time will have to be spent collecting data otherwise. Benefits of the data can be assessed based on the extent to which they can help researchers answer their research questions and fulfil their objectives. Considering that the data collected from eBay databases are tailored to fit with the purposes of this study, it is of utmost benefit to obtain them; consequently, the data collection method should be designed as efficiently as possible so as to minimise the time expended. This will be explained further in Section 3.4.1.

After determining an appropriate strategy that the research will apply, researchers then consider the time horizons; either cross-sectional or longitudinal. The strength of longitudinal research is that it facilitates the study of change and development (Saunders, Lewis and Thornhill, 2019), which is in line with the objectives in this research. Furthermore, this research aims to uncover the price dynamics of new and remanufactured smartphones over their respective product life cycles, which would not be possible with a cross-sectional dataset; rather, the longer the timespan of the data, the more insights this study can offer. The way in which the datasets are created to satisfy this criterion will be discussed in more detail in Section 3.4.1.

The final element of the research design that researchers take into account are any potential ethical issues. According to Saunders, Lewis and Thornhill (2019), the two ethical issues that researchers should acknowledge at the beginning of the design stage are sensitivity of information and consent. These factors will impact the research topic and how researchers proceed with the design, particularly with data collection. Since this study does not involve live participants, the ethical consideration lies in the use of secondary data and privacy issues themselves rather than sensitive information and consent. As such, privacy issues will be discussed further in Section 3.6.

To summarise, this section covers the research design elements of this study. It identifies quantitative method as the methodological choice, while the purpose is set to be exploratory. The secondary data analysis strategy is employed to fulfil research questions and objectives, whereby an original dataset is created in a longitudinal manner. The methods for data collection and subsequent statistical analyses will be defined in the next section.

3.4 Research Method

After discussing the elements making up the research design in Section 3.3, this section examines the research methods by which the data are collected and analysed, in order to achieve the research objectives previously set out in Chapter 2.

3.4.1 Data Collection Techniques

This section examines the data collection process in more detail. The central aim of this thesis is to investigate the price dynamics of new and remanufactured smartphones at different stages of their respective life cycles. Three aspects concerning price dynamics are considered; these include the impact of past prices and current volume on the behaviour of current prices, the impact of product generations on the price movements, and finally, the temporal characteristics of price changes. This thesis focuses on smartphones for two reasons; firstly, this particular consumer electronics category can be acquired in both new and remanufactured versions, which facilitates empirical comparisons between the two conditions. Secondly, they have thriving secondary markets (typically, online market platforms), which leads to the availability of sufficiently high volume of products on offer and the availability of price data for the analyses.

As mentioned in the research design (Section 3.3), it is imperative that the data collection process should be as efficient as possible, and that the dataset needs to be longitudinal; as such, the first solution that the researcher has recourse to is purchasing the required dataset. Upon exploring options for this purpose, it is found that acquiring datasets from market analytics companies is an unsuitable approach for two reasons. Firstly, the services provided were not sufficiently flexible because of the multiple dimensions required from the data. These include: product conditions (new, remanufactured), remanufacturer identities (manufacturer-approved remanufacturer, independent remanufacturer), and geographical locations of online markets (eBay US, eBay UK). Secondly, should the company be able to fulfil all of the requirements, the costs involved would not be affordable. Considering both the flexibility needed and the potential incurred costs, it appeared that the most suitable solution to data collection was to do so manually. This poses serious risk of delay, as a large amount of data needs to be collected. Consequently, the researcher decided to use another service that eBay provides, which is the application programming interface (API) that gives third party vendors access to market data and information. However, it is not possible to collect historical data from eBay's API due to its terms and conditions limiting the timeframe to only 30 days. Therefore, the data collection process needs to be repeated daily until the desired observation period is achieved, which is at least one year of each smartphone's lifespan; this is to ensure that each data series captures as much dynamic behaviour as possible. It is intended that the data collection should cover a wide selection of product generations (and models) to represent different stages in a life cycle of consumer electronics, and as new generations are being launched into the market, their price data will be collected as well.

The idea that each smartphone generation represents a different stage in their respective product life cycle is based on the definition given by Robert Buzzell in 1966. The author states that the product life cycle illustrates the unit sales curve for a certain product, extending from the time it is first introduced into the market until it is removed (Buzzell, 1966, p. 50). The yearly sales volume of different Apple iPhone models has been gathered from Apple's annual reports by Więcek-Janka *et al.* (2017). Based on its sales volume, launch date, and withdrawal date, the authors plot a graph spanning between 2006 – 2017, which clearly shows the shape of the product life cycle of each iPhone generation. Accordingly, this information helps confirm the initial stage of the product life cycle each smartphone model is thought to be in. Unfortunately, the same information on the product life cycle of Samsung Galaxy smartphones are not readily available. Nevertheless, based on the yearly release cycle comparable to that of Apple iPhones, it is reasonable to assume that each Samsung Galaxy generation will be in a similar stage to its iPhone counterpart. The detailed stage of the product life cycle that each smartphone is in will be explained further in the empirical result chapters (Chapters 4, 5, and 6).

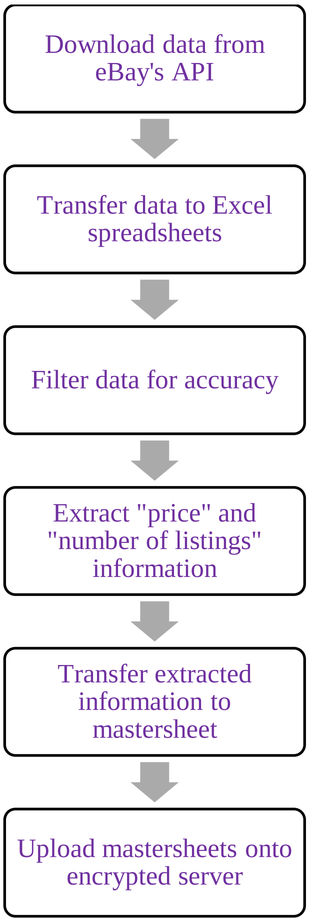

Figure 3.2: Data collection process

Figure 3.2 illustrates the data collection process. Given the time it would have taken to scour the websites for all of the relevant information, the process is optimised by writing a custom software script that retrieves active listing information from eBay online platforms. It is specified in the software that only active listings with "Buy it now" option should be collected to ensure that the prices are contingent upon the specified product conditions of smartphones. The downloaded data are saved in Excel spreadsheets, where they are sorted before relevant information can be exported. Subsequently, all the collected data are checked for accuracy; any eBay listings with ambiguous names (or product specifications), or those that use inaccurate tags (e.g. remanufactured, but they are used; or phones, but they are parts) are eliminated. After pre-processing, the "price" and "number of listings" information is gathered from the initial spreadsheets and transferred onto a master sheet containing daily observations. Finally, the master sheets are uploaded onto an encrypted server for safe keeping.

Coding preparation was completed on 28th January 2016, and the length of data series was deemed sufficient for analysis by 31st August 2017, thus the data collected spans between these two dates. The resulting dataset consists of daily listing prices and volume for new and remanufactured versions of selected Apple iPhone and Samsung Galaxy models. At the time of data collection, these were the two major competitors, taking a combined 28.2% of the market share for smartphones (Passport, 2016). In 2015, more than 71 million units of iPhone were sold globally, whereas at least 83 million units of Samsung smartphone were sold (Gartner, 2016). It is also noted that Apple and Samsung smartphones were most actively traded on eBay (US and UK), in comparison to other smartphone brands (e.g. HTC, LG) (eBay Inc., 2016). This observation presents a great opportunity to collect a large volume of smartphone listings for each selected model under both new and remanufactured conditions daily.

3.4.2 Data Analysis Techniques

This section outlines the analytical techniques employed in this study to achieve the research objectives previously set out in Chapter 2. Section 3.4.2.1 examines the functional data analysis (FDA) technique utilised to uncover the price dynamics of each smartphone over its respective product life cycle (research objective one; see Chapter 2, Section 2.8). Next, Section 3.4.2.2 describes the autoregressive moving average model (ARIMA) that is used as part of the investigation into the relationship between price and volume of new and remanufactured smartphones (research objectives two and three; see Chapter 2, Section 2.8).

3.4.2.1 FDA

This section describes the FDA method used in this study to investigate the price dynamics in terms of velocity and acceleration of prices of each series. It first outlines general concepts behind the method, then explains the steps involved in applying the technique.

FDA is a statistical method popularised by Ramsay and Silverman (2005). It has been applied successfully in many fields such as agricultural sciences (Xu, Li and Nettleton, 2018; French *et al.*, 2019; Wong, Li and Zhu, 2019), behavioural sciences (Haylen *et al.*, 2016; Slimen, Allio and Jacques, 2018; Cao *et al.*, 2020), and medical research (Backenroth *et al.*, 2018; Chen, Goldsmith and Ogden, 2018; Chen, Goldsmith and Ogden, 2019). FDA differs from traditional statistical method in that the input and/or output variables (i.e. x and / or y) can take the form of functional objects rather than data vectors, which means that it can handle data with more complex structures compared to its conventional counterpart. This is imperative, since a large amount of data that are being generated daily as a result of technological advancements in computing resemble the features of functional data (Ramsay and Silverman, 2005). These data possess intrinsic multidimensional characteristics, as they can vary not only in longitudinal aspect but also cross-sectional aspect. Consequently, they are rich in information and require a more advanced method to unveil them.

Although the object of interest in FDA is different from classical statistics, the subsequent analyses are based on a similar concept, as there have been generalisations of traditional statistical methods to the functional framework in recent years. These include, but not limited to, functional principal components analysis (James *et al.*, 2000), curve clustering (see for example, Abraham *et al.*, 2003; James and Sugar, 2003), functional ANOVA (Spitzner, Marron and Essick, 2003; Sung *et al.*, 2019), functional regression (Crainiceanu, Staicu and Di, 2009; Chen, Hall and Müller, 2011), and the functional generalised linear model (Li, Wang and Carroll, 2010; Dou, Pollard and Zhou, 2012).

Functional Data

Before describing the procedure involved in FDA, it is rational to explore some characteristics of functional data. Typically, functional data are observed discretely as *n* pairs (t_i, y_i), where y_i captures the behaviour of the function at time *t*. Although functional data are often recorded over time continuum, other scales such as spatial position, frequency, and weight are also possible.

The concept of FDA is based on two principal assumptions. Firstly, it is assumed that there exists a function *x* that generates the observed data. Secondly, the underlying function *x* is smooth. In other words, the values of a pair of adjacent observed data, y_i and y_{i+1}, are essentially linked to each other so that they are unlikely to be too different from each other.

Otherwise, these data observations can simply be treated as multivariate rather than functional (Ramsay and Silverman, 2005). This particular property allows the derivatives of the function (*Dx*) to be uncovered, which facilitates the study of its *dynamics*.

Regardless of the assumptions, the actual observed data may not be defined as smooth due to the presence of noise or measurement error. These inessential variables may be filtered out as efficiently as possible through one of the data smoothing techniques. To achieve smoothness, the three main techniques that can be employed include kernel smoothing (Troncoso, Arias and Riquelme, 2015; Cruz and Yu, 2017), smoothing splines (Ma, Huang and Zhang, 2015; Wood, Pya and Säfken, 2016), and wavelet smoothing (Michis, 2015; Marcjasz, Uniejewski and Weron, 2019). In this thesis, the smoothing splines technique is used exclusively and will be described in more detail in the following sections.

Functional Models

The process of analysing a set of data using FDA comprises of two main steps (Ramsay and Silverman, 2005). Firstly, the functional object is "recovered" from the data. This can be done through different methods, but the most common means is via smoothing technique (Bapna, Jank and Shmueli, 2008). Secondly, the recovered functional object is then used for data exploration and analysis in order to study the characteristics of the data. These exploratory data analyses include explanatory and predictive modelling and inference, akin to traditional statistics (Ramsay and Silverman, 2005). In the next sections, these steps will be described in more detail.

Step 1: Recovering Functional Objects

Basis Functions

The first step in any application of FDA is to recover the underlying functional object from the observed data at hand (Bapna, Jank and Shmueli, 2008). The functional object in this research is the price evolution of each specific smartphone. There exists a number of ways to do so, but the most common technique is to use basis functions. According to Ramsay and Silverman (2005), a basis function system is a linear combination of known functions φ_k that can approximate any given functional object. A function *x* (i.e. price function) can be defined as:

$$x(t) = \sum_{k=1}^{K} c_k \phi_k(t) \tag{3.13}$$

where $\phi_k(t)$ for (k = 1, …, K) is the k^{th} function in the expansion and c_k is its corresponding coefficient. The vector notation of function *x* is written as follows:

$$x = \boldsymbol{c}'\boldsymbol{\phi} \tag{3.14}$$

where **c** indicates the vector of length K of the coefficients c_k and $\boldsymbol{\phi}$ is the functional vector containing the basis functions ϕ_k.

Within the basis function framework, there are several notable bases that are widely used in practice. These include wavelet, Fourier, and polynomial bases and the choice depends on the nature of the data. Ideally, the features of the chosen bases should match those of the function being estimated. For instance, if the data exhibits a strong periodic property, then Fourier basis system is the most appropriate (Ramsay and Silverman, 2005). As for nonperiodic data such as the observed prices, the spline basis system is the most common, as it provides outstanding flexibility without exhausting the computing power or computation time.

To define a spline, the price function being approximated is first divided into *L* subintervals separated by *knots*. Within each interval, a spline is a polynomial of order *m*, which is one more than its highest power or *degree*. The number of knots impacts the flexibility of the spline, in that its flexibility increases with an increasing number of knots (Liu, Xiao and Chen, 2016). Therefore, more knots are generally placed over regions where the function exhibits the most complex variation, whereas only a few are needed over virtually linear regions. Unlike previous research where the knot vector *L* is chosen arbitrarily, this thesis employs the breakpoint analysis to determine the locations of the nodes where the 'break' or the change in dynamics happens, to eliminate the arbitrariness of the process. This is done using the Global Maximisation procedure proposed by Bai and Perron (1998), where the number of breaks, *l*, and their associated coefficients that minimise the sum of squares of the model are identified. The process begins by testing for a single structural break; if the hypothesis that there is no structural break is rejected, the sample is divided into two and the test procedure is reapplied to each subsample. This test sequence is repeated until each subsample test fails to reject the hypothesis of no structural break.

The most popular spline basis system in use is the *B-spline* basis system, which is developed by de Boor (2001). Other basis systems include truncated power functions, M-splines, and natural splines. According to the B-spline framework, a spline function *S(t)* can be expressed as:

$$S(t) = \sum_{k=1}^{m+L-1} c_k B_k(t, \tau) \quad (3.15)$$

where $B_k(t, \tau)$ indicates the value at t of the B-spline basis function defined by the knot sequence τ and *k* refers to the number of knots at value *t*.

One important variable to be decided is the amount of the basis expansion *K*. While larger *K* results in a better fit to the data, if *K* is too large, then the risk arises when noise or variation are also taken into account (Liu, Xiao and Chen, 2016). On the other hand, if *K* is too small, then certain important aspects of the smooth function *x* may be missed. In order to choose the appropriate *K*, a trade-off between *bias* and *variance* is considered (Ramsay and Silverman, 2005). The bias in estimating *x(t)* is:

$$bias[\hat{x}(t)] = x(t) - E[\hat{x}(t)] \quad (3.16)$$

For large values of *K* and *n*, the bias is small, whereas the bias will be zero if *K* = *n*. The variance of the estimate $\hat{x}(t)$ is defined as:

$$Var[\hat{x}(t)] = E[\{\hat{x}(t) - E[\hat{x}(t)]\}^2] \quad (3.17)$$

If *K* = *n*, then the value of the variance will be unacceptably high. It then follows organically that smaller *K* is preferred so as to reduce variance, but not too small so that the bias is unacceptable. If the data is noisy, then reducing variance takes priority.

An alternative way to express the goal of this trade-off is to minimise the *mean squared error (MSE)*:

$$MSE[\hat{x}(t)] = E[\{\hat{x}(t) - x(t)\}^2] \tag{3.18}$$

Substituting the expressions for bias and sampling variance, the MSE becomes:

$$MSE[\hat{x}(t)] = Bias^2[\hat{x}(t)] + Var[\hat{x}(t)] \tag{3.19}$$

A variety of algorithms exists as an aid to choose the most appropriate amount of basis functions (Ramsay and Silverman, 2005). For instance, the *stepwise variable selection* determines *K* by progressively adding basis function one after another until the added function does not improve the fit. On the other hand, the *variable pruning* method begins with a substantial amount of *K*, then gradually removes the basis function that seems to account for the least variation at each step. It is worth mentioning that there is no standardised method, since the choice is dependent upon the basis function and the smoothing process chosen.

Spline Smoothing

After the basis function is chosen, the data smoothing process can begin. The method of focus in this thesis is the *roughness penalty* or the *regularisation* approach, since it tends to produce better results – in particular, the estimations of derivatives (Ramsay and Silverman, 2005). The roughness penalty method relies on the optimisation of a fitting criterion that defines the smoothness that the data is trying to achieve. To illustrate how regularisation works with the spline basis function, first, the objectives of function estimation are visited.

The spline smoothing method estimates a curve x from price observations $y_i = x(t_j) + \epsilon_j$ by attempting to achieve two conflicting goals. First, the estimated curve should fit well with the data, for example, by minimising the residual sum of squares $\sum[y_i - x(t_j)]^2$. Nevertheless, the second objective is to ensure that the curve does not fit too well, which would result in the curve *x* being excessively varied locally. Recall from previous that:

$$\text{Mean squared error} = \text{bias}^2 + \text{sampling variance},$$

A perfect estimate of the function value $x(t_i)$ where the bias does not exist (i.e. bias = 0) is produced by fitting a curve exactly at every value of y_j. However, the resulting price curve will have high variance due to the rapid local variation of the curve in order to fit y_j seamlessly. Therefore, smoothness is imposed onto the estimated price curve at the cost of some increase in bias. This is where the roughness penalty comes into play, as it quantifies the sacrifice in bias to achieve the desired improvement in MSE.

Roughness Penalty

The concept behind the measurement of roughness is the *curvature* of a function (Ramsay and Silverman, 2005). This is defined as the square of the second derivative $[D^2x(t)]^2$ of a function at *t*. It follows that the second derivative of a straight line, which has no curvature, is zero. Consequently, the measure of the roughness of a function is defined as the integrated squared second derivative:

$$PEN_2(x) = \int [D^2x(s)]^2\, ds \tag{3.20}$$

It is expected that the larger the second derivative, the higher the values of $\text{PEN}_2(x)$, which means that highly variable functions will yield high values of $\text{PEN}_2(x)$ as their second derivatives are large over a particular range of interest. Since the function of interest may itself be derivatives, the notion of the roughness penalty is generalised to:

$$PEN_m(x) = \int [D^m x(s)]^2 \, ds \tag{3.21}$$

When fitting the model to the price data, the objective is to minimise the *sum of squared errors*, which is defined as:

$$SMSSE(\boldsymbol{y}|\boldsymbol{c}) = \sum_{j=1}^{n} [y_j - \sum_k^K c_k \phi_k(t_j)]^2 \tag{3.22}$$

Let $\boldsymbol{\Phi}$ represent the *n* by *K* matrix containing the values $\phi_k(t_j)$, the criterion can be expressed in matrix terms:

$$SMSSE(\boldsymbol{y}|\boldsymbol{c}) = (\boldsymbol{y} - \boldsymbol{\Phi c})'(\boldsymbol{y} - \boldsymbol{\Phi c}) \tag{3.23}$$

with the assumption that the residuals ϵ_j about the true curve are independently and identically distributed with mean zero and constant variance σ^2. However, in reality, the errors may suffer from nonstationarity and/or autocorrelation, so the differential weighting of residuals may prove useful (Ramsay and Silverman, 2005). Subsequently, the SMSSE is extended to:

$$SMSSE(\boldsymbol{y}|\boldsymbol{c}) = (\boldsymbol{y} - \boldsymbol{\Phi c})'\mathbf{W}(\boldsymbol{y} - \boldsymbol{\Phi c}) \tag{3.24}$$

where $\mathbf{W}$ is a symmetric positive definite matrix that allows for unequal weighting of squares and products of residuals. When evaluating function x at the vector $\mathbf{t}$ of argument values, the resulting vector is expressed as x($\mathbf{t}$). The trade-off between the data fit and the smoothness is defined as the *penalised residual sum of squares*:

$$PENSSE_{\lambda}(x|\boldsymbol{y}) = [\boldsymbol{y} - x(\mathbf{t})]'\mathbf{W}[\boldsymbol{y} - x(t)]^2 + \lambda \times PEN_2(x) \tag{3.25}$$

The estimated function is the function x that minimises $PENSSE_{\lambda}(x)$ for which $PEN_2(x)$ is defined. The variable λ is the *smoothing parameter* that mitigates the trade-off between the fit to the data, measured by the residual sum of squares in the first term, and the variability of the function x, quantified by $PEN_2(x)$ in the second term. As $\lambda \to \infty$, the function incurs larger and larger roughness penalty as $PENSSE_{\lambda}(x)$ emphasises more on the smoothness and less on the fit of the data. Ultimately, the resulting price curve x will approach the standard linear regression to the observed price data where $PEN_2(x) = 0$. On the contrary, as $\lambda \to 0$, there is less and less penalty imposed on the function, so the price curve tends to be more and more variable. Eventually, the price curve x will approach the interpolant of the data, which is the smoothest twice differentiable curve that fits exactly to the data. In other words, the curve x that satisfies $x(t_j) = y_j$ for all j.

According to de Boor (2002), the curve x that minimises $PENSSE_{\lambda}(x|y)$ is a cubic spline with knots at the data points t_j. Since the location of the knot can be decided arbitrarily, putting them at each data point helps alleviate this issue. Smoothing splines are also able to adapt to unequal spacing of data points by taking advantage of the regions with high data density and being especially smooth over regions with few observations. The most common technique in spline smoothing is, therefore, to use order four B-spline basis function with knots at the sampling points to minimise the $PENSSE_{\lambda}(x|y)$. However, with a very large amount of observed data, a lower dimensional B-spline basis defined by a limited knot sequence τ is preferable.

To choose the smoothing parameter λ, the *generalised cross-validation* or GCV method, developed by Craven and Wahba (1978), is used. This method is an extension, or rather, a generalisation, of the cross-validation or CV method. The CV method requires the sampling data to be divided into two sets, a *training* sample and a *validation* sample (Chen, Goldsmith and Ogden, 2019). The model is fit onto the training sample, then the estimated fit value is compared to the actual values of the validation sample. In extreme cases, only one observation is left in the validation sample, and the procedure is repeated with each observation in turn. The resulting error sum of squares across all values is called the *cross-validated* error sum of squares. By computing this criterion over a range of values of λ, the value that yields the minimum cross-validated error sum of squares is chosen. It follows that the CV method is computationally exhaustive for large sample sizes (Ramsay and Silverman, 2005). Additionally, minimising CV can lead to undersmoothing, as the method favours high frequency or noisy fitting of the data and therefore, always prioritises λ values that are too small. As for the GCV method, it simplifies the previous method by eliminating the need to re-smooth *n* times while being more reliable, as it is less likely to undersmooth. The criterion is expressed as:

$$GCV(\lambda) = \left(\frac{n}{n-df(\lambda)}\right)\left(\frac{SSE}{n-df(\lambda)}\right) \tag{3.26}$$

Similar to the CV method, this criterion is computed over a range of λ values from which the λ that minimises the generalised cross-validation statistic GCV is chosen.

Step 2: Taking Derivatives

After fitting the smoothing spline onto the data series, the resulting functional object, or price curve, can now be used for subsequent analyses. There exist a number of data exploration techniques that have been developed to handle functional objects, such as functional principle components analysis (fPCA) and functional linear models, but they are beyond the scope of this thesis. Since the aim of this research is to examine dynamic properties of the price series, in terms of how fast the prices are moving and the rate of change in such movements, only the derivatives of functional objects are taken into account. The velocity and acceleration of the price changes are represented by the first and second derivatives of the price function, respectively.

The above steps were carried out using MATLAB.

3.4.2.2 Econometrics Models

This section gives a brief overview of the regression models that are used to fulfil part of the aforementioned research objectives (see objectives two and three, Chapter 2). It first summarises important characteristics of the method, before defining each element in more detail in the subsequent sections.

To empirically investigate the price-volume relationship, the characteristics of the data are captured through the use of econometrics models. In this study, it is assumed that historical prices of the smartphones impact subsequent prices over time; in other words, current price of a particular series depends on its own previous prices. This is in line with the assumption of an ARIMA model, which states that the future value of a specific variable is a linear function of several past observations and random errors (Hamilton, 1989). As such, the underlying process that generates the time series can be represented as:

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (3.27)$$

where y_t is an actual data observation, which in this study is the listing prices, p_t; ε_t is a random error at time period *t*; φ_i (i = 1, 2, …, p) and θ_j (j = 0, 1, 2, …, q) are model parameters; *p* and *q* are integers and generally referred to as the orders of the model. An important assumption of an ARIMA model is that the random errors, ε_t, are independently and identically distributed with a mean of zero and a constant variance, σ^2.

From the general representation given in equation (3.27), several special cases of the ARIMA family of models exist. Considering an instance where *q* = 0, equation (3.27) then reduces to an autoregressive (AR) model of order *p*. Similarly, if *p* = 0, (3.27) becomes a moving average (MA) model of order *q*. Consequently, determining the appropriate model order (*p*, *q*) is the essential task when developing the ARIMA model. To determine the model order (*p*, *q*), the Box-Jenkins method is utilised. This is a three-step iterative approach that includes model identification, parameter estimation, and diagnostic checking. The principle behind model identification is the use of theoretical autocorrelation properties. By plotting autocorrelations of the series against time, an autocorrelation function (ACF) or correlogram is obtained. This can be matched against the theoretical patterns to identify one or more potential models for the time series. In addition, a partial autocorrelation function (PACF) is also used. This particular function eliminates indirect correlations that are present in all ACF of any AR process, to control for any underlying effects of unobservable parameters from other time periods. Both ACF and PACF are useful tools to identify the order (p, q) of the ARIMA model.

Stationarity is a necessary condition that has to be fulfilled so that a meaningful ARIMA model can be built (Zhang, 2003). This condition requires the time series to have constant mean and variance over time. However, this is rarely the case with time series obtained from the real world, as they tend to exhibit trends or heteroscedasticity (non-constant variance) (Brooks, 2014). Accordingly, data transformation methods such as differencing and power transformation are often applied to the data, to remove the presence of non-stationarity and stabilise the variance before fitting the time series with an ARIMA model. Therefore, the first step, model identification, begins by testing for unit roots and determining the order of integration.

Unit Root Testing

This method can be used to test for non-stationarity in time series. It is important to determine whether the series is stationary, since the behaviour and properties of the series depend on this characteristic. Also, non-stationarity may lead to 'spurious regressions', which is when a strong relationship is incorrectly identified between two unrelated variables. Further, statistical tests, such as t-statistics and F-tests, will not be valid asymptotically, as the frequency distribution of the data will not follow t-distribution and F-distribution respectively. As a result, it is more likely for both tests to reject the null hypothesis compared to when the data are stationary; therefore, the results obtained are unreliable. There exist two models that are frequently used to characterise non-stationarity: random walk model with drift, and trend-stationary process (Chaudhuri and Wu, 2003). The random walk model with drift takes the following form:

$$y_t = \mu + \varphi y_{t-1} + u_t \tag{3.28}$$

where μ is an intercept; φ is a model parameter of interest; φ < 1 indicates a stationary process while φ = 1 indicates otherwise; u_t is a white noise disturbance term. If non-stationarity exists, the model can be called 'stochastic non-stationarity', where a stochastic trend is present in the data. Such a trend can be eliminated by differencing the time series.

As for the trend-stationary process, the model can be represented by:

$$y_t = \alpha + \beta t + u_t \tag{3.29}$$

Where *t* is time; u_t is a white noise disturbance term. The trend-stationary process is also known as 'deterministic non-stationarity' as de-trending is required to induce stationarity. This can be carried out by regressing equation (3.29). The residuals obtained from this contain no trend and subsequent estimations can then be done on them. Since there is no stochastic component (i.e. no unit root) in deterministic trend series, unit root testing is unnecessary for this type of non-stationarity (Phillips and Perron, 1988).

To test for the presence of a unit root for stochastic non-stationarity models, the Dickey-Fuller (DF) test is introduced (Dickey and Fuller, 1979). The aim of this test is to test the null hypothesis that φ = 1 (i.e. the series has a unit root) against an alternative hypothesis that φ <

1 (i.e. the series does not have a unit root). If the null hypothesis can be rejected, the series is stationary. In practice, the following regression is employed rather than equation (3.28) for the ease of computation and interpretation:

$$\Delta y_t = \psi y_{t-1} + u_t \tag{3.30}$$

The test is consequently equivalent to the test of $\psi = 0$ since $\varphi - 1 = \psi$. Note that the DF test does not follow any standard distribution and the critical values are provided by Fuller (2009). An important assumption for this test is that u_t is a white noise process i.e. u_t is not autocorrelated. Otherwise, the null hypothesis would be incorrectly rejected, as the test is now biased due to autocorrelation (Brooks, 2014). Taking the possibility of autocorrelation into account, the test is 'augmented' by adding more lags to the dependent variable. The alternative model is given by:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \tag{3.31}$$

The additional lags for Δy_t ensure that there is no autocorrelation in u_t. This test is known as the augmented Dickey-Fuller (ADF) test (Said and Dickey, 1984). It still focuses on the value of ψ (i.e. whether $\psi = 0$) and uses the same critical values as the DF test. The determination of lags can be done using the frequency of the data, i.e. 12 lags are used for monthly data, 4 lags are used for quarterly data. However, if the frequency of the data is higher, e.g. hourly or daily, the choice of the number of lags will not be as clear (Brooks, 2014). To rectify this, information criteria can be utilised. Information criteria are used to indicate the goodness of fit of the model to the data, which in this case depends on the number of lags included in the model. The two most common selection criteria are the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) (Kirchgässner, Wolters and Hassler, 2013). It is best to choose the lag length with the smallest AIC and SBC, as both will approach -∞ as the fit of the model improves.

In cases where the hypothesis $H_0: \psi = 0$ is accepted, meaning that a unit root is present in the time series, a further test should be done to determine the order of integration (i.e. the repetition of the data differencing process). The principle is to first start with the highest plausible order of integration. For example, test the null hypothesis that the series is integrated of order two ($H_0: y_t \sim I(2)$) against the alternative hypothesis that the series is integrated of order one ($H_1: y_t \sim I(1)$). If I(2) is rejected, then test I(1) against I(0). Once the order of integration is determined, the series should be transformed accordingly. For example, if the series is found to be integrated of order one, the series needs to be differenced once (i.e. $\Delta X_t = X_t - X_{t-1}$); if it is integrated of order two, difference the series twice, and so on.

After specifying the prospective models, the estimation of the model parameters is done in the second step by following a nonlinear optimisation procedure. Different set of parameters estimated for different models are then compared, in order to find the most suitable model that minimises the overall measure of errors. Furthermore, model selection criteria can also be used. As previously mentioned, the goodness of fit of the model is demonstrated through information criteria. Similarly, the model that best captures the characteristics of the series is the one that minimises both AIC and SBC.

The last step of the Box-Jenkins method is the diagnosis of model adequacy. This is an essential step to check whether the model assumptions regarding the errors, ε_t, are satisfied. Diagnostic statistics and plots of residuals can be used to examine the appropriateness of the model. It is also possible to achieve this by overfitting the model; that is, to fit larger or higher order models to the data and run statistical analysis on the additional terms. If the coefficients of the added terms are not significant, then the original model was a good fit. Apart from the plots of residuals, residuals diagnostics, such as autocorrelation test, can be conducted to ensure that there is no evidence of linear dependence. If the chosen model is not adequate, a new tentative model should be identified and the steps discussed above are repeated.

Since one of the assumptions of the ARIMA-type models is constant variance and linear estimation of model parameters, they are not able to capture stochastic nature of the variance in the dataset. As a result, it is possible that the model specifications may not be optimal. Therefore, to explore potential volatility present in the data, an additional time series model called autoregressive conditional heteroscedasticity (ARCH) is adopted to complement the original ARIMA model.

ARCH-Type Model

This class of models is particularly useful to model a time series where the assumption of a constant variance (homoscedasticity) is inappropriate (Engle, 1982). It is able to capture the volatility in the variance of the data and therefore, is mostly used in situations where there may be periods of increased or decreased variance (Bera and Higgins, 1993). The ARCH(p) model or "variance model" is given by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{3.32}$$

where ω and α_i (i = 1, 2, …, p) are model parameters, and both must be more than or equal to 0 ($\omega \geq 0$, $\alpha_i \geq 0$), since the value of σ_t^2 must be strictly positive.

In order to test for the presence of ARCH effects, the following steps, based on the work of Brooks (2014), can be followed:

1. Regress *y* on *x* by any means of linear regression and obtain the residuals, $\hat{\varepsilon}_t$

2. Square the residuals and regress them on p own lags to test for ARCH of order p, i.e. run the regression:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^2 + \gamma_2 \hat{\varepsilon}_{t-2}^2 + \cdots + \gamma_p \hat{\varepsilon}_{t-p}^2 + v_t \tag{3.33}$$

   where γ_i (i = 1, 2, …, p) is the model parameter; v_t is an error term.
   Obtain R^2 from this regression.

3. The test statistic is defined as TR^2 (the number of observations multiplied by the coefficient of determination) from the previous step, and is distributed as $\chi^2(p)$.

4. Test the joint significance of $\hat{\gamma}_1$, …, $\hat{\gamma}_p$.

   The null and alternative hypotheses are

$$H_0: \gamma_1 = 0 \text{ and } \gamma_2 = 0 \text{ and } \gamma_3 = 0 \text{ and } \dots \text{ and } \gamma_p = 0$$

$$H_1: \gamma_1 \neq 0 \text{ or } \gamma_2 \neq 0 \text{ or } \gamma_3 \neq 0 \text{ or } \dots \text{ or } \gamma_p \neq 0$$

Under the null hypothesis, it is assumed that there is an absence of ARCH components while the alternative hypothesis states that, in the presence of ARCH components, at least one of the estimated γ_i coefficients must be significant.

The generalised version of ARCH model, called GARCH, takes into account the previous lags of the conditional variance, which is more applicable to ARIMA models. It can be written as:

$$\sigma^2 = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (3.34)$$

This allows researchers to interpret the current fitted variance as a weighted function of a long-term average value (depending on ω), information on the volatility of the previous period ($\alpha_j \varepsilon_{t-j}^2$), and the fitted variance from the model from the previous period ($\beta_j \sigma_{t-j}^2$).

An estimation of ARCH and GARCH models can be done using a technique called maximum likelihood (ML). Under ML method, a set of parameters is found based on the observed dataset; to be more specific, the method estimates the values of the parameters that are most likely to have produced the given data. This is achievable by first forming a likelihood function (LF) which will be a multiplicative function of the actual data. Nevertheless, the chosen function will be difficult to maximise with respect to the parameters, due to its multiplicative property. Thus, its logarithm is taken so that the function is transformed into an additive function of the sample data. This new function is then called log-likelihood function (LLF). Essentially, the method iteratively searches through the parameter-space until all the values of the parameters that maximise the log-likelihood function are found.

After deciding upon the appropriate model specifications that best capture the characteristics of the price series, the estimation of the finalised model is carried out through the use of ordinary least squares (OLS) estimator.

There exist two types of relationships between price and volume that can be examined: contemporaneous and lead-lag relationships. For contemporaneous relationship, the variables of focus are the price and the change in volume. Here, ARIMA model is applied in combination with ARCH model. As for lead-lag relationship, the focus is on price and volume per se, so a different type of model, called a vector autoregressive (VAR) model, is used.

VAR Models

Unlike the models described above, the VAR class of models is suitable for multivariate time series. It is particularly useful for capturing the dynamics in the behaviour of time series in economics and finance (Kirchgässner, Wolters and Hassler, 2013). VAR models are adopted in this research in order to investigate causal relationships among price series. There exist two different forms of VAR processes that can be utilised in practice, depending on the analysis to be done on the time series of interest, both of which are described below:

The Reduced Form

It is assumed that a set of K time series variables can be separated into deterministic and stochastic components:

$$y_t = \mu_t + x_t \tag{3.35}$$

where y_t is a vector of observed variables (i.e. the listing prices); μ_t is the deterministic term; x_t is a purely stochastic process with zero mean. The deterministic term, μ_t, can be assumed to be zero ($\mu_t = 0$), a constant ($\mu_t = \mu_0$), or a linear trend ($\mu_t = \mu_0 + \mu_1 t$). Usually, the stochastic part, x_t, is unobservable and contains stochastic trends and cointegration relations. Apart from the zero-mean assumption, x_t is also assumed to have a VAR representation. The VAR(p) representation for x_t is:

$$x_t = A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t \tag{3.36}$$

where A_i ($i = 1,\ldots, p$) are ($K \times K$) parameter matrices; the error process $u_t = (u_{1t}, \ldots, u_{Kt})'$ is a K-dimensional zero mean white noise process.

The VAR(p) model can be written as:

$$y_t = \mu_t + A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t \tag{3.37}$$

The Structural Form

In cases where the contemporaneous relations between the observable variables are of interest, they can be modelled using the structural form models, allowing for contemporaneous variables to appear as explanatory variables in some equations. A structural form of a VAR(p) model may be of the form:

$$Ay_t = \mu_t^* + A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + v_t \qquad (3.38)$$

where A = ($K \times K$) matrix reflects the instantaneous relations between the parameters; A_j^* = AA_j (j = 1, …, p); v_t is the structural form error term.

In order to construct a VAR model, the central decision to make is to determine the lag length, which is essentially the time taken for the changes in the variables to work through the system. This can be done using either cross-equation restrictions or information criteria. The principle behind the cross-equation restrictions is to simultaneously test the coefficients on a set of lags on all variables for all equations in the VAR. The hypothesis to be tested is the assumption that a particular number of lags is sufficient for the model, and that the coefficients of all other lags beyond that point is jointly zero. It is assumed that the test statistic is asymptotically distributed as χ^2 variate with degrees of freedom equal to the number of total restrictions. In general, for a VAR with g equations, imposing that the last q lags have zero coefficients, the total number of restrictions can be obtained by g^2q.

The cross-equation restrictions test described above has a major drawback, since it assumes that the errors from each equation are normally distributed (Brooks, 2014); otherwise, the χ^2 will not be valid asymptotically. In order to mitigate this, an alternative approach – information criteria – can be used. Again, the appropriate lag length will minimise the values of information criteria. After deciding on the suitable lag length, a VAR model is then estimated by means of OLS.

Causality Testing

In order to test for causality, the block significance and causality tests can be used. As the name implies, this method allows the researcher to determine the sets of variables that have significant effects on each dependent variable. In this case, the impact of listing volume on listing prices, and vice versa. This can be done by restricting all the lags of one particular variable in a VAR model to be equal to zero, then testing the joint hypotheses that all the coefficients of the variable of interest, say y_1 (i.e. listing volume), will not be significantly different from zero. This is done under an F-tests framework. If the lags of y_1 are significant in the equation for y_2 (i.e. listing price) then it is concluded that y_1 causes y_2. The causality would be classified as 'Granger-causality' if the causality is unidirectional – that is, y_1 causes y_2, but not vice versa. Else, if both sets of lags are significant, it would imply that there is a 'bi-directional causality' between the two. If none of the lags are significant, it is said that the two variables are independent.

The above models and tests were implemented using EViews.

3.5 Limitations of this Research

This section discusses the limitations of this research, based on the previously outlined elements of the research design. It begins by exploring potential weaknesses in the methodological choice, followed by scrutinising the adoption of secondary data. Afterwards, this section acknowledges the flaws in the analytical techniques applied.

Although this study chooses quantitative research approach for its objective and methodical nature, together with the fact that its purpose corresponds to the aims of this thesis, the approach is not without limitations. Since quantitative method requires collection of data that satisfy certain criteria and produce exact numerical results, it can only reflect what is happening, but not why it may be happening. In other words, the data used in quantitative methods do not reveal causation. For this study, the observable prices delineate how they change over time, and – with help from FDA – potential changes in such dynamics; nevertheless, the prices do not reveal underlying causal mechanisms, or indicate why fluctuations occur. The understanding of price movements and what they represent in this research is, therefore, guided by available economics theory such as the supply and demand model and the efficient market hypothesis (EMH).

For instance, when the relationship between price and volume is under scrutiny, the interpretation of the results is guided by the supply and demand model. On the other hand, EMH will guide the researcher in providing insights into the market structure of both eBay US and eBay UK platforms. It is also logical to acknowledge that not all behaviours can be explained and generalised in a wider context. This is why larger sample sizes are preferred, in order to increase the degree of generalisability, along with the representativeness of the population (i.e. new and remanufactured smartphones in general). Furthermore, it is important to avoid ungrounded inferences, especially with non-randomised design since specific smartphone models are selected based on certain criteria, without further experimentation to verify such claims.

With regards to the use of secondary data, one major concern commonly involved with such a data type is that the original dataset was collected for a different purpose than the secondary analysis. Nevertheless, as previously discussed, this is not the case for this thesis, as an original dataset is created based on available data. By such a method, it is possible to ascertain that the dataset provides all the necessary information, and that the unit of measurement is accurate. Having alleviated the drawback of the data type, the attention is then paid to the methodology itself. Since the aim of this thesis is to examine the price dynamics of new and remanufactured smartphones using statistical analyses, it is important that the data points related to each selected brand are sufficiently large in volume, in order to ensure the asymptotic properties of the methods employed. This is done before the data collection process begins by determining the most popular smartphone brands, and examining the number of listings available on each eBay website. It is found that Apple iPhone and Samsung Galaxy smartphones are highly sought after on eBay (eBay Inc., 2019b), which means that the daily number of listings is sufficiently high in all models of interest. Therefore, the asymptotic properties of the statistical methods are valid.

Another limitation concerns the lack of access to historical sales data because there is no centralised database, and the market analytics services are either not flexible enough, or too expensive. Consequently, the data collection procedure is performed by the researcher, which is a major challenge in itself. Even though it is preferable to extend the data collection period in order to cover an entire life cycle of a particular smartphone, it is not feasible, since enough time should be reserved for subsequent analyses. This is because, on average, the life cycle of smartphones spans over two years (Gartner, 2019c); which means that at least three years of the PhD programme will have to be spent collecting the data, as opposed to one and a half years.

However, Box and Jenkins (1970) and Glass, Wilson and Gottman (2009) suggested that in order to utilise the Box and Jenkins method (refer to Section 3.4.2 for more details) effectively, there must be at least 50 observations and preferably more than 150 observations. The datasets used in this research are at least 280 observations long; hence, despite not being able to cover the entire life cycle of each smartphones, the data series are of sufficient length to facilitate meaningful analyses.

Taking into account econometrics methods applied in this study, it is appropriate to recognise that they involve strict assumptions that may not be attainable in reality. These assumptions include, but are not limited to, stationarity of the series, homoscedasticity, and no autocorrelation. The researcher has taken measures to ensure that each data series satisfy such assumptions, either by testing for stationarity or by differencing them, but this act in itself may take away potential insights that can be gained by fully encompassing the stochastic nature of prices. However, the usage of FDA, whose only assumption is the smoothness of the input, should help alleviate this matter.

3.6 Research Ethics

Having discussed the limitations in this research in Section 3.5, this section takes into account ethical considerations involved in conducting research in order to ensure that the researcher's behaviour is appropriate when the rights of research subjects or those affected by the study are concerned. According to Bell, Bryman and Harley (2018), the ethical issues that researchers should reflect upon when conducting research in the social science context consist of voluntary participation, informed consent, risk of harm, confidentiality, and anonymity. It is also appropriate to consult the code of ethics published by the affiliated university (Saunders, Lewis and Thornhill, 2019).

The researcher follows the code of ethics provided by the University of Birmingham, and takes measures to ascertain that this research is conducted in an ethical manner. This included the completion and submission of an ethical review application to the research ethics committee. Since this study does not involve live participants or animals, and does not cause any harm to persons or the environment, no further ethical review was required. Upon submission of the ethical review application, the Humanities and Social Sciences Ethical Review Committee of the University of Birmingham granted full ethical approval to this study.

Considering other ethical issues that may pertain to the use of secondary data, the researcher conforms to the license agreement published on eBay's website (eBay Inc., 2019c) in that no retrieved data is made public, and that no buyer or seller information can be displayed. Even though the thesis analyses pricing data, it is not the intention of the researcher to derive any site-wide statistics, performance indicators, or gross merchandise sold. The dataset is stored in an encrypted database, where no person other than the researcher has access; it is intended that the dataset will be destroyed within ten years of the completion of this research.

3.7 Summary

This chapter examines the research methodology used in this thesis. The first section of this chapter concerns the research philosophy that encompasses this research. The positivist stance is chosen for its objective nature, but also for its suitability in analysing observable data in order to fulfil the research objectives. The corresponding abductive approach to theory and empirical evidence is then discussed and identified as the most suitable form of inference in this research. The second section of this chapter outlines the research design that is shaped by quantitative method and exploratory purpose of the study. Given that the prices of new and remanufactured smartphones can be obtained from a publicised platform, and that a large amount of data is needed to ensure the generalisability of the results, the justification is made for this research to utilise secondary data analysis strategy. Within the same section, issues surrounding the use of secondary data, together with the rectification made in this thesis, are considered. It is also decided that this research is set to be longitudinal in nature, in order to fully capture the temporal characteristics of the price dynamics.

Following on from the first two sections, this chapter delineates the research method in the third section. It includes a data collection procedure, which entails the use of eBay's API, before exploring the analytical techniques employed to analyse the dataset to achieve corresponding research objectives. Several potential model specifications are defined, with further analysis steps to identify the most suitable model for each series and its consequent estimators.

This chapter concludes with sections on limitations of this research and ethical issues that researchers need to consider. This first limitation stems from the quantitative research method itself, with its aim to quantify and generalise findings, which may not be achievable in practice. This study attempts to navigate this matter by incorporating as large a dataset as possible, while also strategically choosing the samples that represent the population best in place of randomised sampling. The next limitation relates to the use of econometrics models and their assumptions, since strict assumptions may restrict the applicability of the inferences, whereas the data transformation process may hinder deeper understanding of the price dynamics. It is indicated that the use of FDA should offset the limitation to a certain extent. Regarding the ethical consideration, the final section summarises the steps followed to obtain ethical approval, in line with the ethical review committee of the University of Birmingham, and to ensure that the research conforms to the license agreement set out by eBay.

Having explained the methodological design in full detail, this thesis proceeds to perform the empirical analyses outlined in this chapter. The results and analyses of findings in relation to each of the research objective (see Chapter 2, Section 2.8) will be presented in the next three chapters.

Chapter 4

The Price Dynamics of New and Remanufactured Smartphones: An FDA Approach

"Never doubt that a small group of thoughtful, committed citizens can change the world; indeed, it's the only thing that ever has."

Margaret Mead

4.1 Introduction

This chapter is the first of the three empirical results chapters in this thesis. It fulfils the first research objective of this study (see Chapter 2, Section 2.8 for more details), which is to investigate price dynamics in terms of speed and timing of price changes at different product life cycle stages. The FDA approach is applied here with the purpose to not only deconstruct price dynamics into velocity and acceleration, but also to identify the time where significant changes in such patterns occur. Section 4.2 describes the dataset used in this analysis. Section 4.3 presents the results obtained from the data smoothing procedure. Section 4.4 exemplifies the price dynamics revealed through the use of FDA method. Section 4.5 discusses the insights. Section 4.6 concludes the chapter with a summary of the findings, then identifies research limitations and future research avenues.

4.2 Data Description

This dataset consists of daily live listing prices of iPhone SE (64GB and 16GB), 6s (64GB and 16GB), and 6 (64GB and 16GB), as well as Samsung Galaxy S7 Edge (32GB), S7 (32GB), S6 Edge (32GB), S6 (32GB), and S5 (16GB). Each smartphone model has three conditions: new (N), manufacturer-refurbished (MR) and seller-refurbished (SR). The two remanufactured conditions (MR and SR) are the products that have been professionally restored to their full functionality by two types of vendors; the MR products are processed by OEM-approved sellers, while the SR products are handled by third parties that are not approved by OEMs. According to eBay, all listed remanufactured items – regardless of the seller identity – have gone through rigorous inspection processes where they are cleaned, repaired to full working order, and ensured that they are in excellent condition. The sampling period spans from 28th January 2016 to 31st August 2017, for a total of 582 observations. On average, 2845 and 1340 daily live listings were retrieved for the iPhone models listed on eBay US and UK, respectively. As for Samsung models, 5337 and 2492 daily live listings were retrieved from eBay US and UK, respectively.

The aforementioned smartphone models are incorporated in the dataset used to achieve the first objective in this thesis – which is to investigate price dynamics in terms of speed and timing of price erosion at different product life cycle stages – for four reasons. Firstly, these products are amongst the best-selling smartphones on eBay (eBay Inc., 2019b), which means they can be taken as accurate representations of the products with the highest demand in OEMs' and independent sellers' profiles. As such, the uncovered dynamics based on such products are likely to be more beneficial than those obtained from less popular items. Secondly, at the time of data analysis, the number of daily listings for each model is sufficiently large in each product condition; this ensures that the patterns revealed through the use of FDA method resemble actual behaviours of the eBay market price rather than outliers. Thirdly, each smartphone model delineates a specific product life cycle stage at the time of data collection based on the information provided in a paper by Więcek-Janka *et al.* (2017) (see Section 3.4.1 for more detail). For example, iPhone SE and Samsung Galaxy S7 Edge (and S7) were released in 2016, which means that the data collection period covers their introduction into the market. In other words, both products characterise an introductory phase of their respective product life cycles. This allows the researcher to explore the price movements at different stages of the product life cycle, along with the change in such dynamic behaviours in terms of velocity and acceleration as the smartphones age.

The reason iPhone 5s and Samsung Galaxy S4 are not included in this chapter is because they represent the decline stage of the product life cycle, which implies that the dynamics that both series exhibit may not be as strong as those captured by newer, more recent series. Finally, by incorporating comparable models across two product brands, it is possible to compare the price dynamics and determine whether they are affected by brand name.

4.2.1 Data Construction Process

Before data analysis begins, it is worth acknowledging that one of the challenges in fulfilling the current research objective is the lack of a centralised database where historical pricing data can be obtained. This is because, in order to provide a comprehensive view of the changes in price dynamics at different stages, a longitudinal dataset that covers the entire product life cycle is preferred for the analysis. Although the data collection period spans 582 days, it is still not sufficient to facilitate analysis of the price dynamics over different smartphones' entire product life cycles, as the average life cycle of a smartphone is over two years (Gartner, 2019c). To overcome this challenge, existing data series are used to construct a longer dataset; this is done by connecting data series together based on the life cycle stages that each series represents. Figure 4.1 exemplifies this concept.

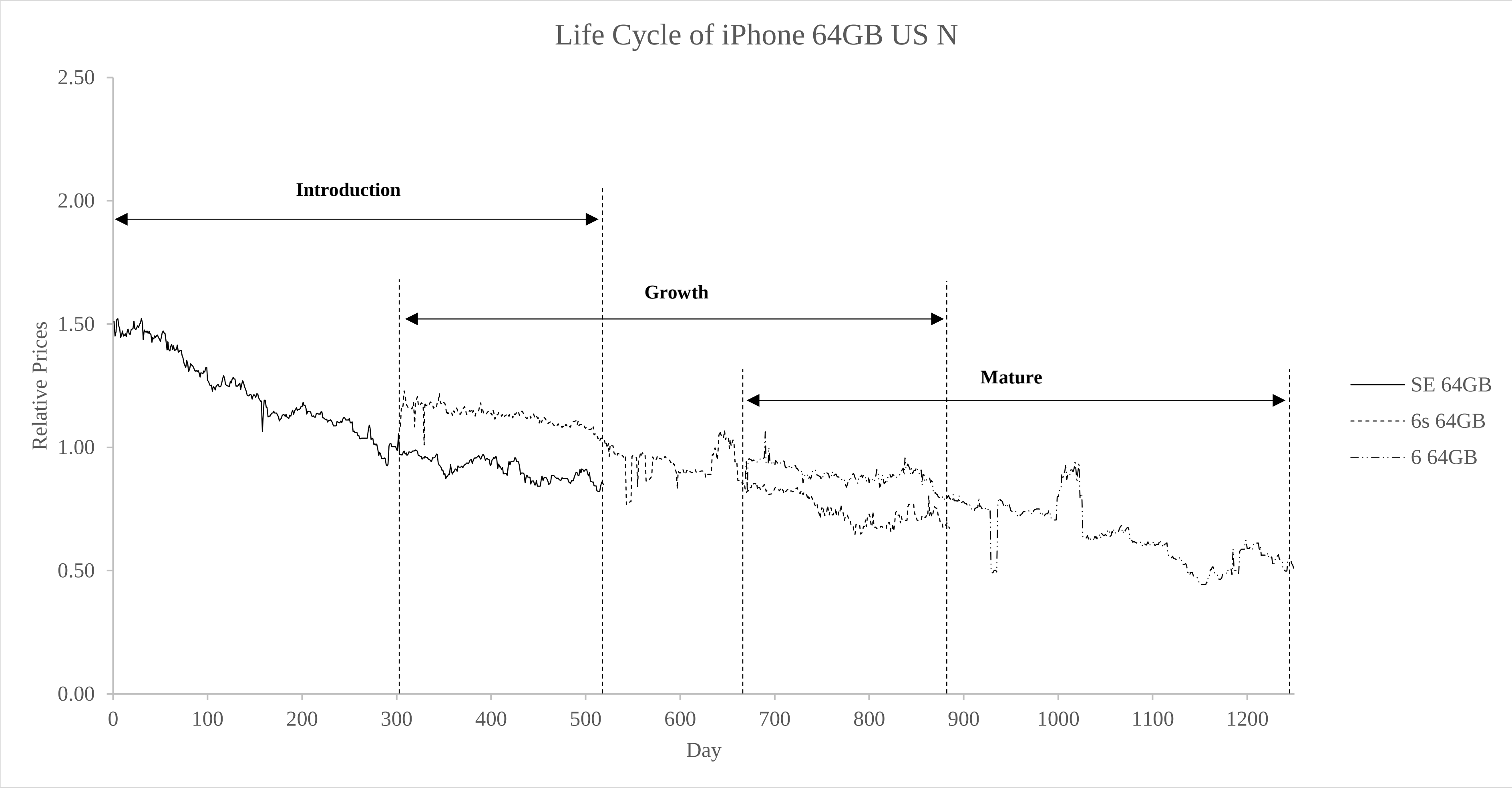

Figure 4.1: Constructing longer data series

Figure 4.1 shows the constructed life cycle of iPhone 64GB N in the US market, where its introductory phase is characterised by the prices of iPhone SE 64GB N in the same market. The growth and mature stages of the depicted life cycle are represented by the prices of iPhone 6s 64GB N and iPhone 6 64GB N, respectively. Although the data collection for all products began at the same time, not all products were released on the same day; for instance, iPhone SE was released on 31 March 2016, whereas other generations were released in September 2014 and 2015. Ultimately, there is an overlapping period of approximately 200 days where two consecutive product generations coexist within the same market.

In order to establish whether it is possible to construct longer data series, as illustrated in Figure 4.1, statistical methods are used to determine if average prices of the two series within the same overlapping period are sufficiently similar. To achieve this, relative prices for each product are first calculated by dividing retrieved prices by their corresponding prices at the time of product launch. After obtaining relative prices, henceforth, referred to as prices, for every product, a Welch's t-test – which allows for unequal variances and unequal sample sizes – is used to determine whether these overlapping periods of consecutive generations have statistically equal means at standard significance levels. This is done using EViews.

Figure 4.2 illustrates this process, which begins by testing the overlap between the end of the iPhone SE series against the beginning of the iPhone 6s series. If Welch's t-test fails to reject the hypothesis of equal means, the average values between the prices of SE and 6s are computed; these values will replace the original values during the overlap.

The procedure continues with the testing of the overlap between the end of iPhone 6s series and the beginning of iPhone 6 series, as shown in Figure 4.3. Again, if the means of this overlapping period are not statistically different from each other, the consecutive series are joined by taking average values between the two. Figure 4.4 depicts the resulting iPhone 64GB US N series, as it is the most representative of both the procedure and the end results. The series comprises of sections containing values from the original SE, the average between SE and 6s, the original 6s, the average between 6s and 6, and finally, the original 6. The results indicate that, for all data series, the means of each overlapping period are not statistically different from each other at 95% confidence level. This means that it is possible to join consecutive generations of each smartphone brand from both the US and UK markets to create longer series, all of which are summarised in Table 4.1.

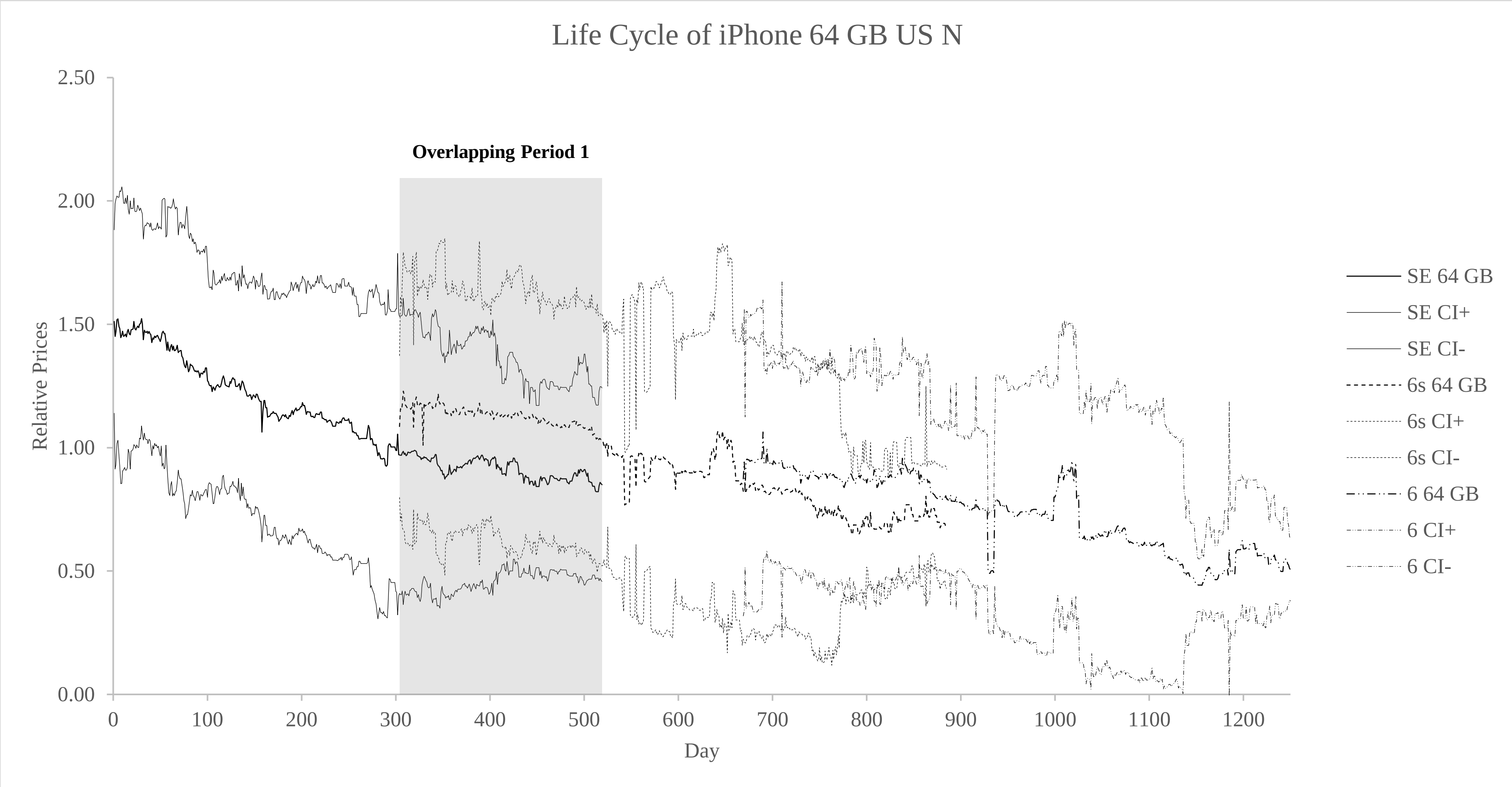

Figure 4.2: The construction process – Overlapping period 1

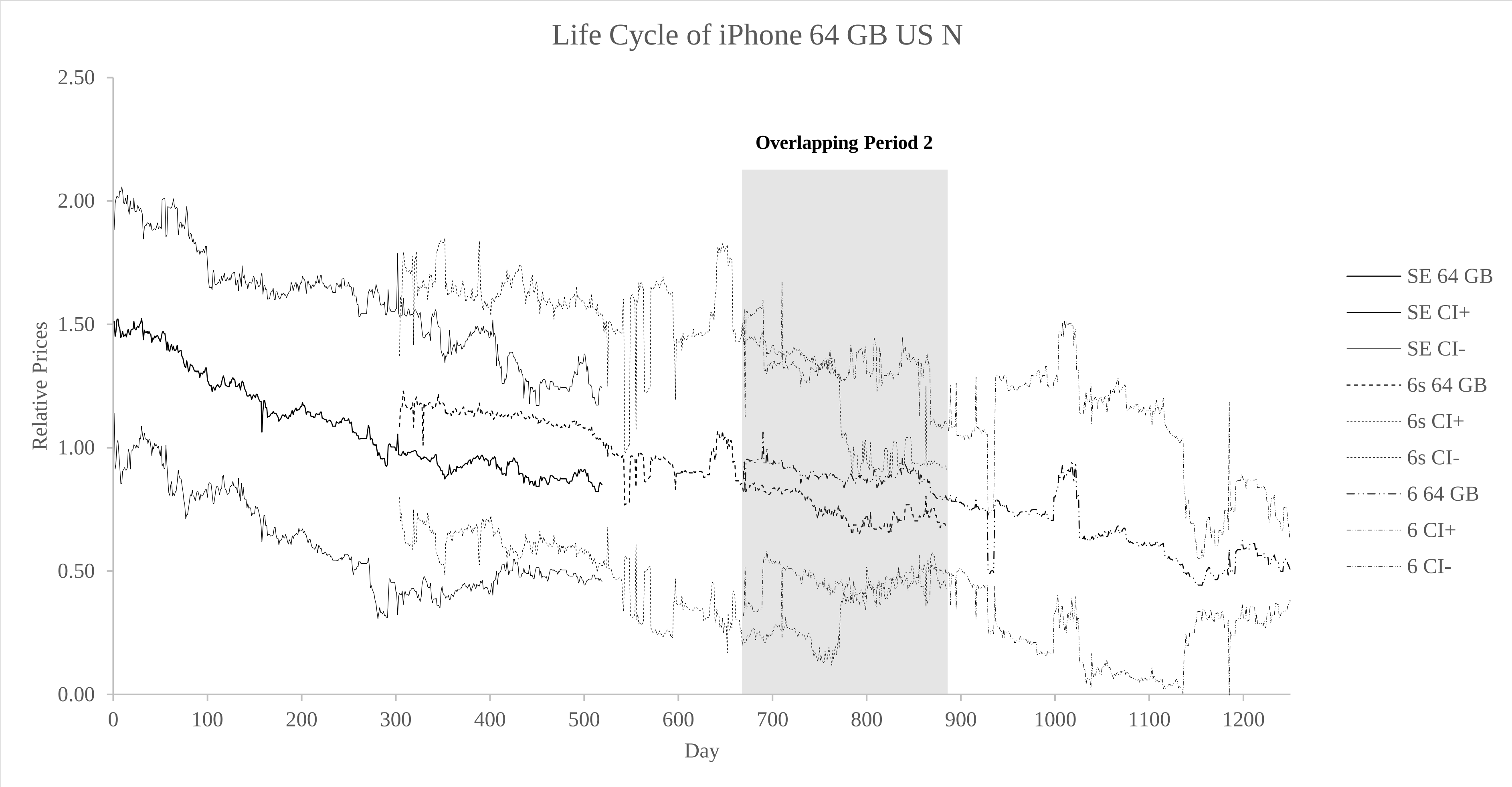

Figure 4.3: The construction process – Overlapping period 2

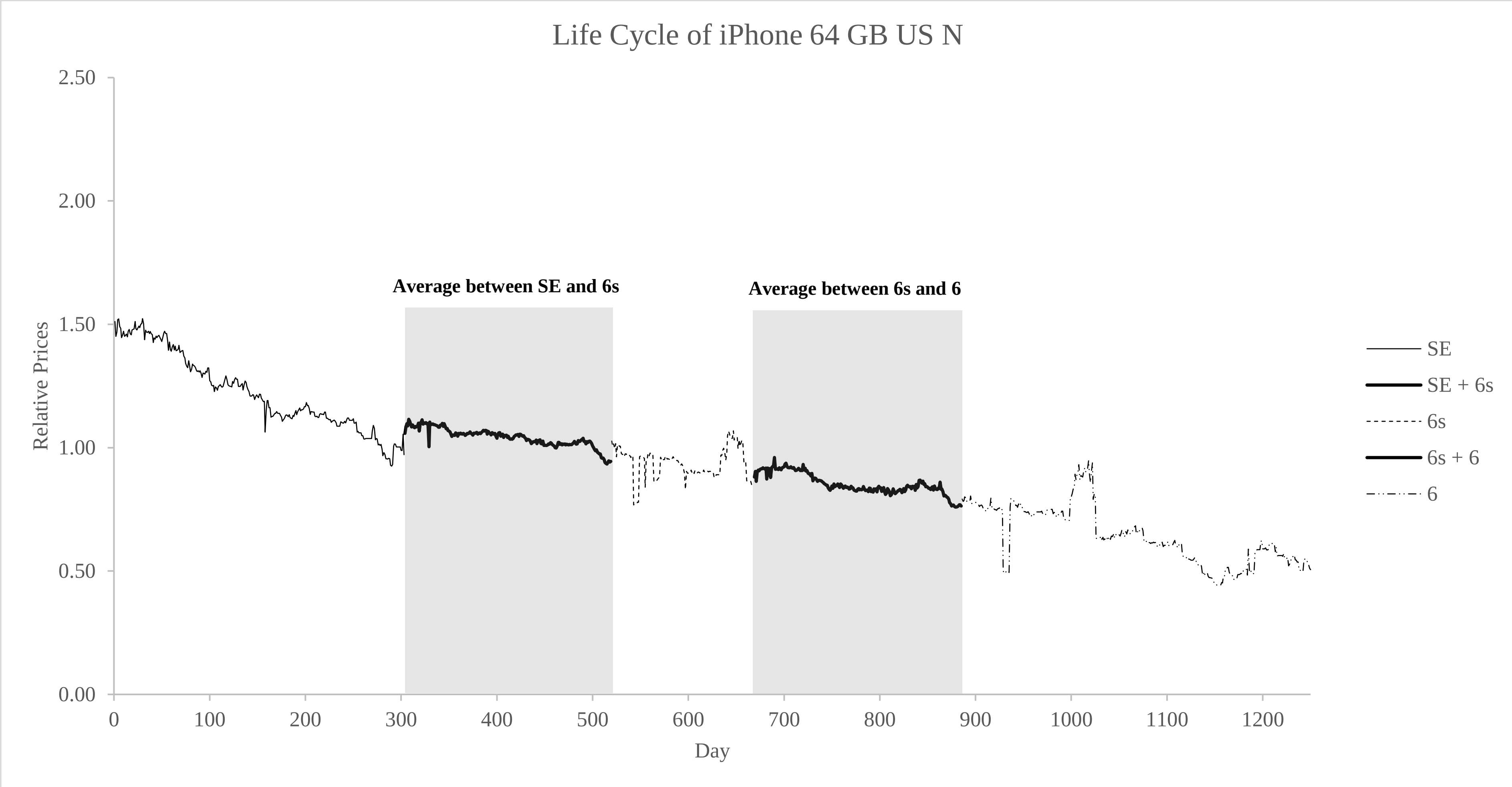

Figure 4.4: The construction process – Resulting series

Taking into account the length of the original data series, coupled with the overlapping periods, each resulting series is 1250 observations long; this spans just over three years, which means that each series is now able to capture the entire life cycle of the smartphones.

Table 4.1: The constructed data series

Brand	Original Models	Capacity	Origin	Condition	Result
iPhone	SE, 6s, 6	64GB	US	N	iPhone 64GB US N
				MR	iPhone 64GB US MR
				SR	iPhone 64GB US SR
			UK	N	iPhone 64GB UK N
				MR	iPhone 64GB UK MR
				SR	iPhone 64GB UK SR
		16GB	US	N	iPhone 16GB US N
				MR	iPhone 16GB US MR
				SR	iPhone 16GB US SR
			UK	N	iPhone 16GB UK N
				MR	iPhone 16GB UK MR
				SR	iPhone 16GB UK SR
Samsung	Galaxy S7, Galaxy S6, Galaxy S5	32GB / 16GB	US	N	Samsung US N
				MR	Samsung US MR
				SR	Samsung US SR
			UK	N	Samsung UK N
				MR	Samsung UK MR
				SR	Samsung UK SR

4.3 Empirical Results

4.3.1 Smoothed Data

In this section, the polynomial smoothing splines are fit onto the price series previously set out in Table 4.1. Ramsay and Silverman (2005) suggest that the order of the spline depends on the order of the derivatives required from the spline function. Typically, a cubic spline of order 4 is used in most computational exercises because the resulting spline function appears to be perfectly smooth. The first derivative of an order 4 spline will show noticeable changes at breakpoints, while its second derivative will be a polygonal line (Ramsay, 2005). If smoother derivatives are required, then splines of order 6 should be used; this will result in a second derivative that is as smooth as a cubic spline. Since this study focuses on the velocity and acceleration of different price formation processes, which are respectively characterised by the first and second derivatives, the researcher considers amongst the splines of order 4, 5, and 6.

After an initial test, it is found that the order 4 splines produce the least Root-Mean-Square (RMS) errors, compared to the splines of orders 5 and 6. Additionally, when observing the resulting derivatives, it is concluded that the appearance of the first and second derivatives produced by the splines of orders 4 are the most informative; this is because the focal point of this exercise is to identify the exact points at which the changes in dynamics occur. As such, the polygonal nature of the second derivative produced by the order 4 splines is more advantageous than the smooth derivatives produced by the splines of higher orders. Consequently, the splines of order 4 are chosen for the analysis.

The smoothing parameter λ is determined using the GCV method for each price series (see Section 3.4.2.2). It is found that the value of GCV remains at similar values for a wide range of smoothing parameters before decreasing to a minimum when $\lambda = 0.1$ for all series in this study. Figures 4.5 and 4.6 illustrate the fit of the polynomial smoothing spline on the series in the US and the UK, respectively. The grey circles denote the price values, while the continuous curves show smoothing splines of order 4 using a smoothing parameter $\lambda = 0.1$. These recovered curves represent the price evolution, which is used in the subsequent analyses. It can be seen that, overall, the prices are decreasing, with slight fluctuations in certain periods.

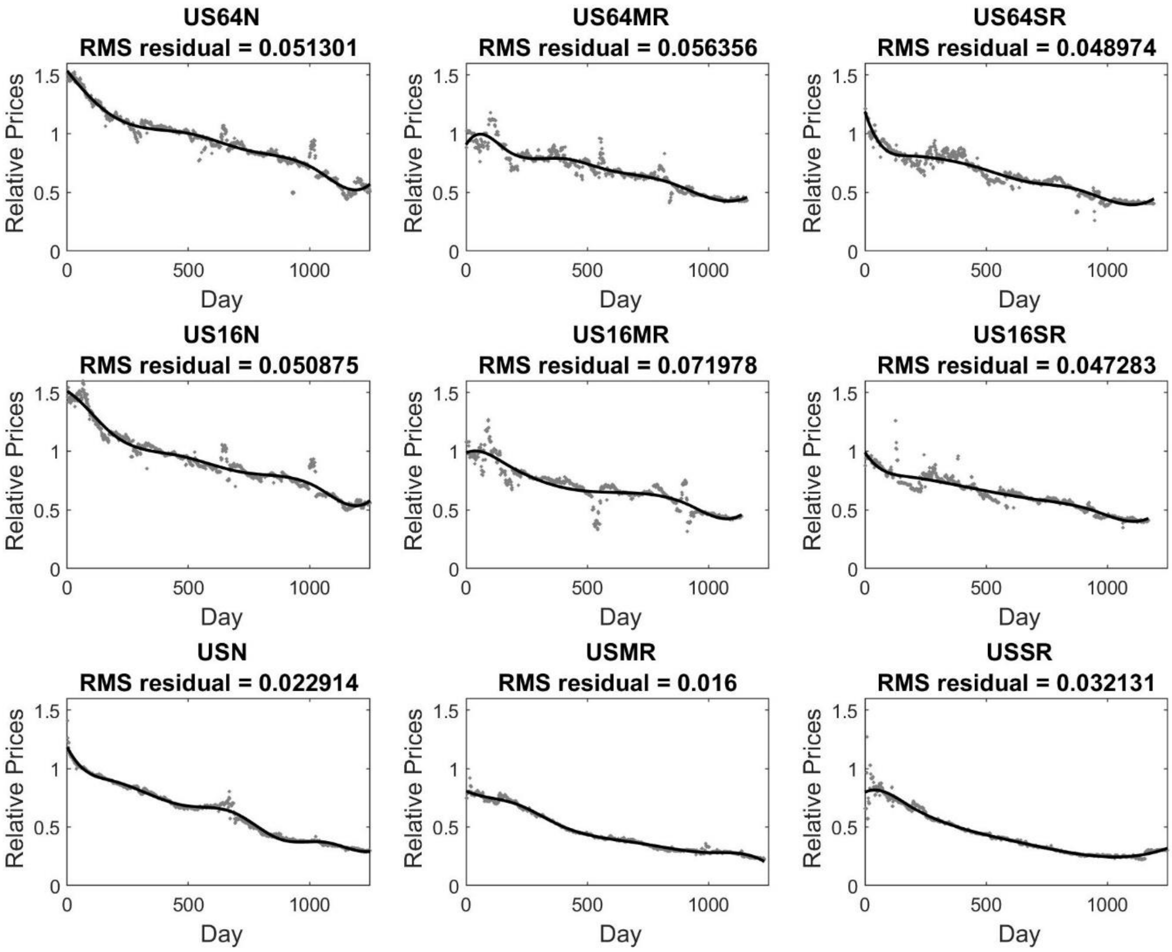

Figure 4.5: The fitted curve on the current price of the series in the US

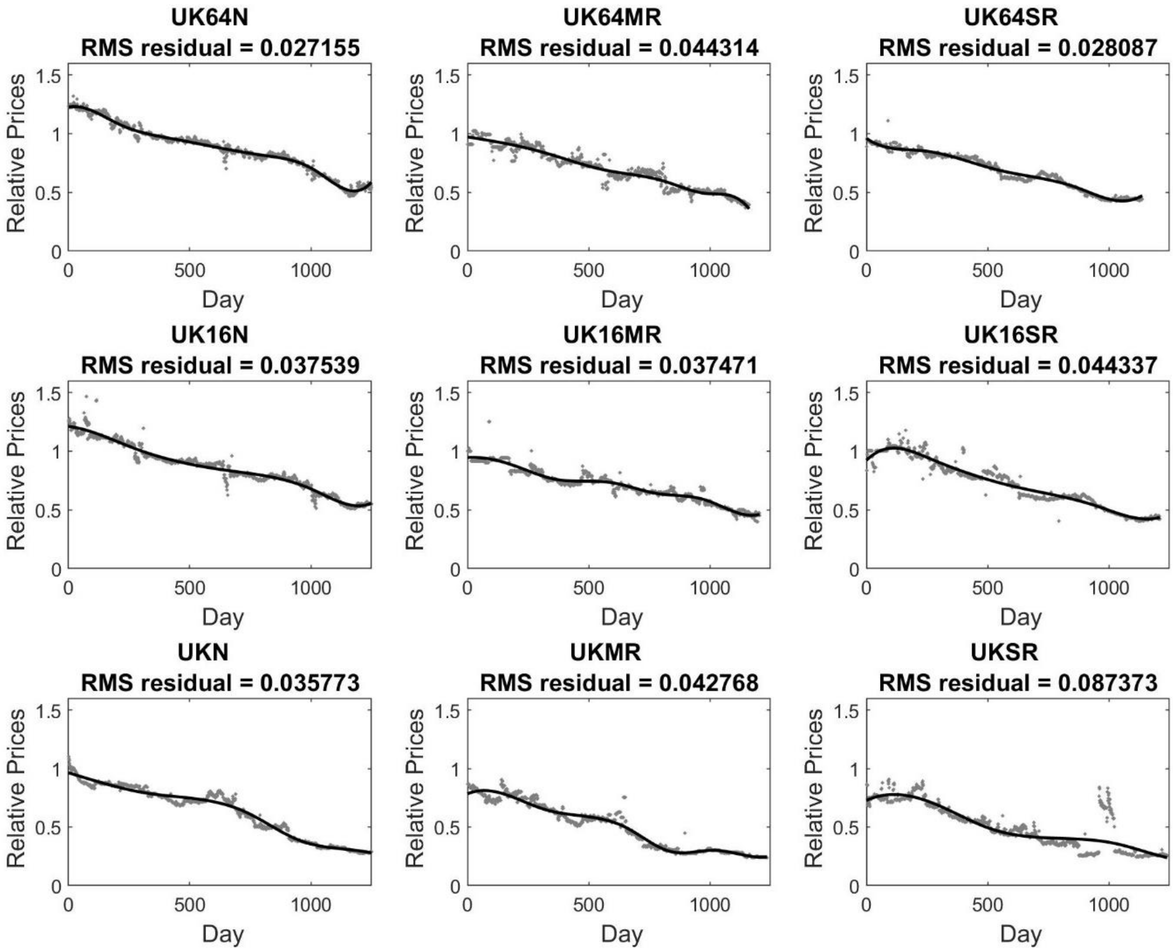

Figure 4.6: The fitted curve on the current price of the series in the UK

4.3.2 The Derivatives

After obtaining the smoothing spline, *f(t),* in Section 4.3.1, the next step is to examine the first (*f'(t)*) and second (*f''(t)*) derivatives of the curve, which respectively represent the velocity and acceleration of the price formation processes. Since there are several dimensions of interest, namely the product conditions, market locations, brands, and specifications, the results are reported as follows. First, the results focus on the velocity and acceleration amongst the three product conditions: N, MR, and SR (see Figure 4.7). This is followed by the results on the price dynamics across market locations: US and UK (see Figure 4.8). Next, the results focus on the dynamics of velocity and acceleration of iPhone and Samsung Galaxy smartphones (see Figure 4.9). Finally, the results conclude with the focus on the price dynamics between the two iPhone specifications: 64GB and 16GB (see Figure 4.10).

As previously described, the first dimension of interest is the price dynamics of the three product conditions. Figure 4.7 depicts the dynamics of the prices of N, MR, and SR iPhone 64GB in the US. The top panel shows the velocity of the price formation processes, while the acceleration is displayed in the bottom panel. The negative values of velocity indicate that the prices are decreasing, whereas the positive values suggest that the prices are increasing. The nature of the acceleration in relation to the velocity designates how the speed changes. In other words, if the acceleration has the same sign as the velocity, the price formation process is gaining speed. On the other hand, if the acceleration has a different sign from the velocity, the process is losing speed.

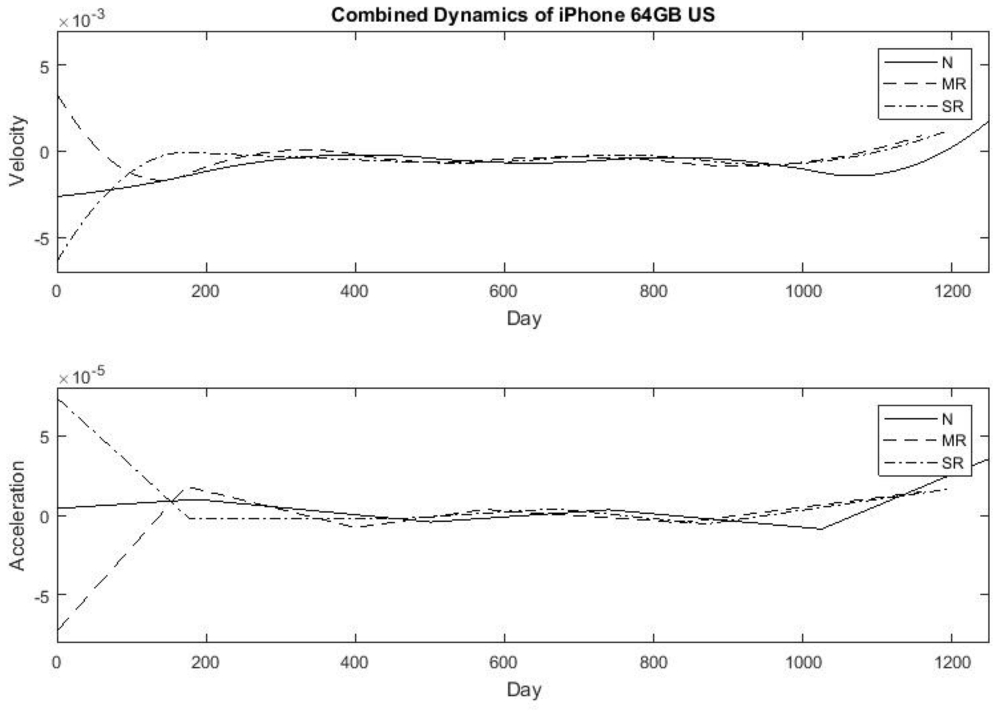

Figure 4.7: The dynamics of new and remanufactured iPhone 64GB in the US

Figure 4.7 reveals some similarities in dynamics amongst the three conditions of iPhone 64GB US, where the price formation processes experience the most change in the beginning and towards the end of the observation period. To be more specific, for the first 200 days from the launch of the product (i.e. the introduction stage of the product life cycle; see Figure 4.1 for more details), the velocity decreases continuously based on the observation that both the velocity and acceleration graphs move in opposite directions. Additionally, the acceleration graph reveals that the reduction in speed does not occur at the same rate, as the slope of iPhone 64GB US SR is the steepest, followed by the MR, and the N, respectively. This means that the new iPhone 64GB US loses speed the slowest, whereas the SR variant loses its speed the fastest.

After the aforementioned change in dynamics, it can be seen that between 200 – 1000 days after the initial launch (i.e. the growth life cycle stage as depicted in Figure 4.1), the velocity enters a plateau period where the speed remains relatively constant. The fact that the slopes of both the velocity and acceleration graphs of N, MR, and SR iPhone 64GB US remain virtually flat suggest that the prices decrease steadily for a considerable amount of time – approximately for 800 days. The prices then increase towards the last 250 days (i.e. the mature stage of the product life cycle; refer to Figure 4.1) since the velocity graphs of all smartphone conditions move in the same direction as their corresponding acceleration graphs. The sharp slope of the acceleration graph of the new iPhone 64GB US indicates that its price increases the fastest compared to the MR and SR counterparts, whose prices increase at comparable velocity.

Having discussed the overall dynamics across the three product conditions, the results now focus on the magnitude of the velocity at each stage of the product life cycle. Starting with the magnitude of the velocity at the beginning of the introduction stage of iPhone 64GB US life cycle, the N condition appears to have the lowest velocity (0.0026), while the SR condition has the highest velocity (0.0063). In other words, the SR condition loses 0.63 per cent of its starting price of 1.2124, compared to the value loss of 0.26 per cent for its new counterpart, whose starting price is 1.5111. This is interesting, since the N condition has the highest starting price yet the value decreases slower, or less dramatically, than that of the SR version. Concerning the MR variant, it is the only condition experiencing a positive velocity of 0.0033, indicating that the MR condition gains 0.33 per cent of its starting price of 0.8817.

Next, the results report the magnitude of the velocity at the beginning of the growth stage of iPhone 64GB US life cycle (i.e. at day 200). The new iPhone 64GB US has the highest magnitude of velocity of 0.0012, followed by the MR and SR of 0.0009 and 0.0001, respectively. In other words, the new variant of iPhone 64GB US loses value the most, at 0.12 per cent of its starting price of 1.5111, compared to 0.09 per cent for MR, whose price at the start is 0.8817, and only 0.01 per cent of the price of 1.2124 for the SR condition.

Lastly, the results look into the magnitude of the velocity at the beginning of the mature stage of iPhone 64GB US life cycle (i.e. at day 1000). The magnitude of the N variant is the highest at 0.0010, compared to the rest of the conditions at 0.0006 for MR and 0.0007 for SR. That is, the prices of the new iPhone 64GB US lose 0.10 per cent of its starting price of 1.5111, whereas the MR and SR lose 0.06 and 0.07 per cent of their initial prices of 0.8817 and 1.2124, respectively. The ending velocity of all three conditions are positive, with the new condition having the most velocity, while the MR has the least. The corresponding magnitude shows that the prices of the new variant increase by 0.18 per cent, while the prices of the MR and SR increase by 0.09 and 0.12 per cent.

Based on the magnitude of the velocity reported above, it is possible to calculate the slope of each section, which represents the rate of price change over each life cycle stage. Starting with the introduction stage of the product life cycle, the prices of the SR iPhone 64GB US change the most at 0.0031 per cent each day, but the prices of its new counterpart change the least at 0.0007 per cent per day. On the other hand, the rate of change of the prices of the MR variant is 0.0021 per cent daily. During the next stage of the product life cycle, growth, the rate of price changes becomes significantly smaller, with the SR condition having the most at 0.0001 per cent. The rate of change in prices of the N and MR variants are virtually negligible – at -7.12E-05 and 3.36E-05 per cent, respectively. Finally, at the mature stage of the product life cycle, the rate of price changes of the N iPhone 64GB US is the most at 0.0011 per cent each day, while the prices of both the MR and SR conditions change at similar rates of 0.0006 per cent and 0.0008, respectively.

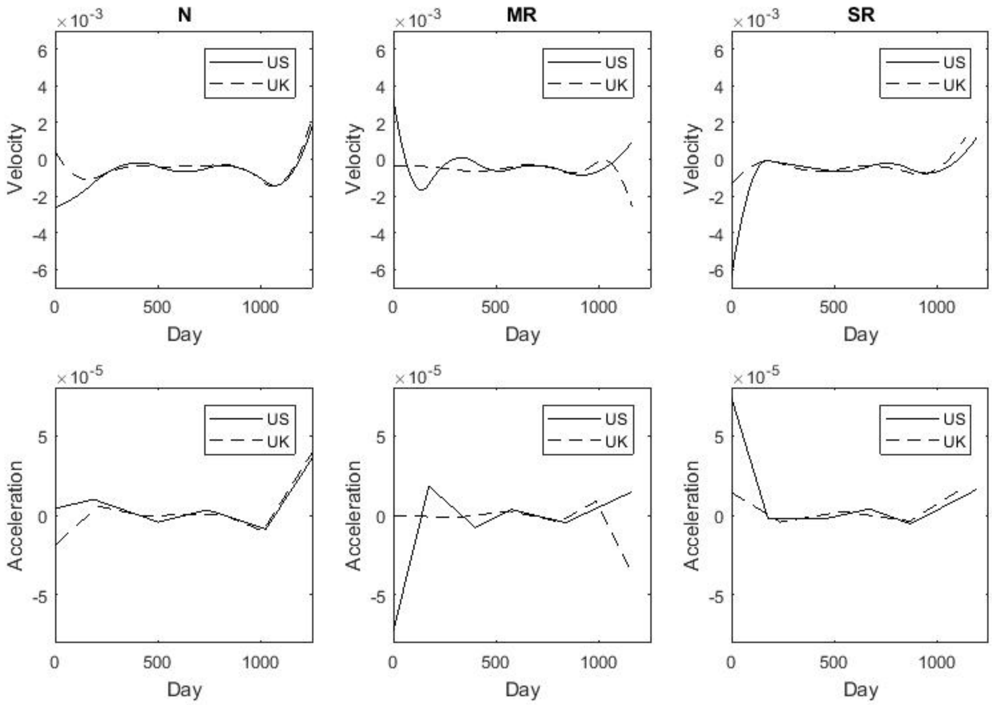

Figure 4.8: The comparison between the dynamics of new and remanufactured iPhone 64GB in the US and the UK

The next element that the results focus on is the velocity and acceleration of each product condition in the US and the UK markets. Figure 4.8 compares the dynamics of new and remanufactured iPhone 64GB in the US and the UK. It shows similarities in the behaviours of the price formation processes spanning across both platforms, where the change in dynamics occurs the most in the beginning and towards the end of the observation period. However, it can be seen that the dynamics in the US fluctuate more than its UK counterpart – especially for the remanufactured conditions – based on the irregularities displayed by the curves. Focusing on the introduction stage of the product life cycle (i.e. the first 200 days; see Figure 4.1), the velocity of both the iPhone 64GB US and iPhone 64GB UK decreases continuously, as the acceleration curves move in the opposite direction to the velocity curves. Additionally, the velocity of iPhone 64GB US typically decreases significantly faster than its UK counterpart, as the slope of the acceleration curves in the US is much steeper. Concerning the growth stage of the product life cycle (i.e. between day 200 – 1000; refer to Figure 4.1 for more details), the velocity of the iPhone 64GB US experiences more changes than the iPhone 64GB UK throughout. Nevertheless, such variations are on a lower magnitude than those exhibited during the introduction stage of the product life cycle, suggesting that the prices change much slower during the growth stage. Then, at the start of the mature stage of the product life cycle (i.e. the last 250 days depicted in Figure 4.1), the price formation processes in both the US and the UK gain speed at very similar rates in general, as the velocity curves – which move in the same direction as the acceleration curves – almost overlap with each other.

After obtaining a general overview of the dynamics across the two platforms, the results then explore the differences in magnitude of the velocity at each stage of the product life cycle. Starting with the beginning of the introduction stage of iPhone 64GB UK life cycle, the MR condition has the lowest velocity of 0.0003, which translates into the loss of 0.03 per cent of its starting price of 0.9089. On the other hand, the SR variant has the highest velocity of 0.0014, meaning that the iPhone 64GB SR loses 0.14 per cent of its starting price of 0.8884. The N condition is the only variant having a positive velocity of 0.0004, meaning that it gains 0.04 per cent of its price of 1.2366. Overall, the patterns in magnitude between the iPhone 64GB US and the iPhone 64GB UK are relatively similar – with the SR having the highest velocity, while the N and the MR variants have a much lower velocity. Additionally, the magnitude of the velocity of the iPhone 64GB US is significantly larger than its UK counterparts in every condition. This indicates that the products in the US lose (or, in some cases, gain) speed much faster than the smartphones in the UK, which may stem from the fact that they have lower starting prices (e.g. starting prices of iPhone 64GB N = 1.5111 (US) vs 1.2366 (UK)).

Concerning the magnitude of the velocity at the beginning of the growth stage of iPhone 64GB UK life cycle (i.e. at day 200), the N condition has the highest magnitude of velocity (0.0010), followed by the MR (0.0004), and the SR (0.0001) variants. This means that the N condition of iPhone 64GB UK loses 0.10 per cent of its starting price of 1.2366, while the MR condition, whose starting price is 0.9089, loses 0.04 per cent. The SR variant of the iPhone 64GB UK loses the least value of all – only 0.01 per cent of its starting price of 0.8884. Comparing these dynamics to the previously reported patterns of the iPhone 64GB US, it can be seen that they are identical, as the N condition loses the most of its starting price and the SR variant loses the least. In addition to the similarities in the dynamics, the magnitude of the velocity itself is also incredibly similar; this is unexpected considering the stark differences in velocity in the introduction stage of the product life cycle.

As for the magnitude of the velocity at the beginning of the mature stage of iPhone 64GB UK life cycle (i.e. at day 1000), the N condition has the highest velocity of 0.0011, compared to the MR and SR at 0.0001 and 0.0005, respectively. In other words, the price of the new iPhone 64GB UK loses 0.11 per cent of its starting price of 1.2366, whereas the SR loses 0.05 per cent of its initial price of 0.8884. The MR variant loses the least of its starting price of 0.9089 – at 0.01 per cent. At this point in time, the observable dynamics of iPhone 64GB UK are similar to those of its US counterpart in terms of both the overall patterns and the magnitude of the velocity. With regards to the ending velocity of all three conditions of the iPhone 64GB UK, both the N and SR variants have positive values, but the velocity of the MR variant is negative. The magnitude of the velocity of each condition indicates that the prices of the N and SR conditions increase by 0.23 per cent and 0.12 per cent, respectively, while the prices of the MR condition decrease the most by 0.26 per cent. In general, the ending velocity of the iPhone 64GB UK is higher than the iPhone 64GB US, which means that the prices increase faster.

Having reported the magnitude of the velocity, the results examine the slope of each section in more detail. First, the introduction stage of iPhone 64GB UK life cycle. It is observed that the rate of change in prices of its N variant is the most at 0.0007 per cent each day, whereas the MR variant exhibits the least change at 0.0001 per cent daily. The prices of the SR condition change at a rate comparable to its N counterpart – at 0.0006 per cent per day. Next, the growth stage of the product life cycle. The results indicate that the rate of change in prices of all three conditions are significantly smaller, with the prices of the SR condition exhibiting the most change, but still only at 5.00E-05 per cent daily. On the other hand, the rate of change in prices of the N variant drops significantly to 1.43E-05 per cent per day, which is the lowest amongst the three conditions. The MR condition has a similar rate of change in prices to the SR variant, which is 4.21E-05 per cent each day.

Last, the rate of change in prices during the mature stage of the product life cycle. The prices of the N condition exhibit the most change at 0.0014 per cent per day, while the SR condition exhibits the least change at 0.0007 per cent daily. The rate of change in prices of the MR variant is 0.0010, which is the highest across all of its life cycle stages. Overall, the rate of change in prices of the iPhone 64GB UK is lower than its US counterpart, except for when the products are in the mature stage of the product life cycle. This reiterates that the prices of mature iPhone 64GB UK increase faster than the iPhone 64GB US not only at the end, but throughout the life cycle stage as well.

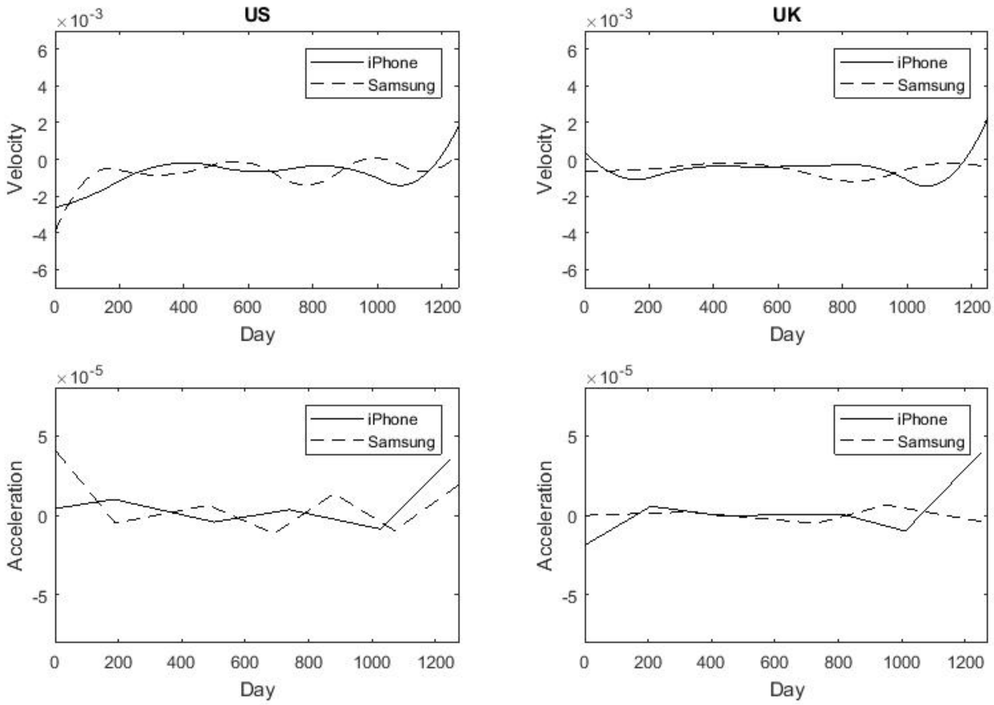

Figure 4.9: The comparison between new iPhone 64GB and Samsung in both markets

The results now focus on the dynamics of velocity and acceleration between the two product brands – iPhone and Samsung. Figure 4.9 depicts the price dynamics of new iPhone 64GB and Samsung in the US and the UK markets. Similar patterns can be observed between the two brands in that the price formation processes have the most dramatic changes in the beginning and towards the end of the observation period. Particularly, during the introduction stage of the product life cycle (i.e. the first 200 days, according to Figure 4.1), the velocity of both iPhone and Samsung products decreases, as the velocity curves move in the opposite direction to the acceleration curves. The steepness of the acceleration curves in the US indicates that the prices of Samsung products decrease significantly faster than its iPhone counterpart, whereas in the UK, iPhone products lose value significantly faster than Samsung products.

Considering the growth stage of the product life cycle (i.e. between 200 – 1000 days after the initial launch, see Figure 4.1 for more details), the velocity of iPhone products in both platforms enters a plateau period where the changes in dynamics are small. In contrast, the velocity of Samsung products, especially those in the US market, exhibits more changes throughout. This suggests that the prices of Samsung products fluctuate more dramatically than its iPhone counterparts. When the products reach the mature stage of their respective life cycles (i.e. the last 250 days, as shown in Figure 4.1), the velocity increases considerably since both velocity and acceleration curves move in the same direction. The acceleration curves of both the US and UK platforms further indicate that the prices of iPhone products increase faster than the prices of Samsung smartphones, based on the sharpness of the slope.

Following the general view on the price dynamics of iPhone and Samsung products, the results then discuss the magnitude of their corresponding velocity at each stage of the respective product life cycles. The first point of interest is at the beginning of the introduction stage. In the US, Samsung products have a velocity of 0.0039, meaning that they lose 0.39 per cent of the initial price of 1.2907. This is faster than the velocity of iPhone 64GB US (0.0026), even though the price of the latter is higher – at 1.5111. As for the UK, the velocity of the prices of Samsung products is 0.0006, which translates into the loss of 0.06 per cent of the initial price of 1.1026. Again, this is higher than the velocity of iPhone 64GB UK (0.0004), whose initial price is also higher (1.2366).

Proceeding to the beginning of the growth stage of the product life cycle (i.e. day 200), the magnitude of the velocity of Samsung products in the US is 0.0006, while the magnitude of the velocity of its UK counterparts is 0.0005. In other words, Samsung US loses 0.06 per cent of its starting price of 1.2907, as opposed to 0.05 per cent for Samsung UK, whose initial price is 1.1026. These aforementioned values indicate that the prices of Samsung products in both markets decrease slower than those of their respective iPhone 64GB counterparts, whose prices decrease at 0.12 (US) and 0.10 (UK) per cent.

With regards to the magnitude of the velocity at the beginning of the mature stage of the product life cycle (i.e. day 1000), the magnitude of the velocity of Samsung US products, although positive, is considerably low – only 5.7799E-05. This means that the prices of Samsung US products increase by 0.006 per cent, compared to an increase of 0.03 per cent of iPhone 64GB US. The prices of Samsung UK products lose 0.05 per cent of their starting price, which is also lower than the loss of 0.11 per cent experienced by its iPhone 64GB UK counterpart. The ending velocity of Samsung US products remains positive, while the ending velocity of Samsung UK products remains negative. The corresponding magnitude shows that Samsung US gains 0.06 per cent of its initial price of 1.2907, while Samsung UK, whose starting price is 1.1026, loses 0.05 per cent. Again, these aforementioned values are lower than those previously reported for iPhone 64GB products, suggesting that the ending dynamics of Samsung products are less dramatic than those of iPhone.

The results now investigate the rate of price change at each stage of Samsung product life cycle in comparison to the previously reported rates for iPhone products. During the introduction stage of the product life cycle, the prices of Samsung US change at the rate of 0.0017 per cent per day, which is significantly higher than the rate of price change of iPhone 64GB US (0.0008). The prices of Samsung UK change at a considerably lower the rate than its US counterpart – only 0.0001 per cent daily; such a rate is also lower than the rate of price change obtained for iPhone 64GB UK (0.0007). When the smartphones enter the growth stage of the product life cycle, the rates of price change plummet. Specifically, the prices of Samsung US change at the rate of 0.0001 per cent each day, while the prices of Samsung UK change at an incredibly low rate – at 9.79E-07 per cent per day. These negligible rates of price change are not unique to Samsung products, as their iPhone 64GB counterparts also exhibit considerably smaller changes at the growth stage of the product life cycle compared to the introduction stage.

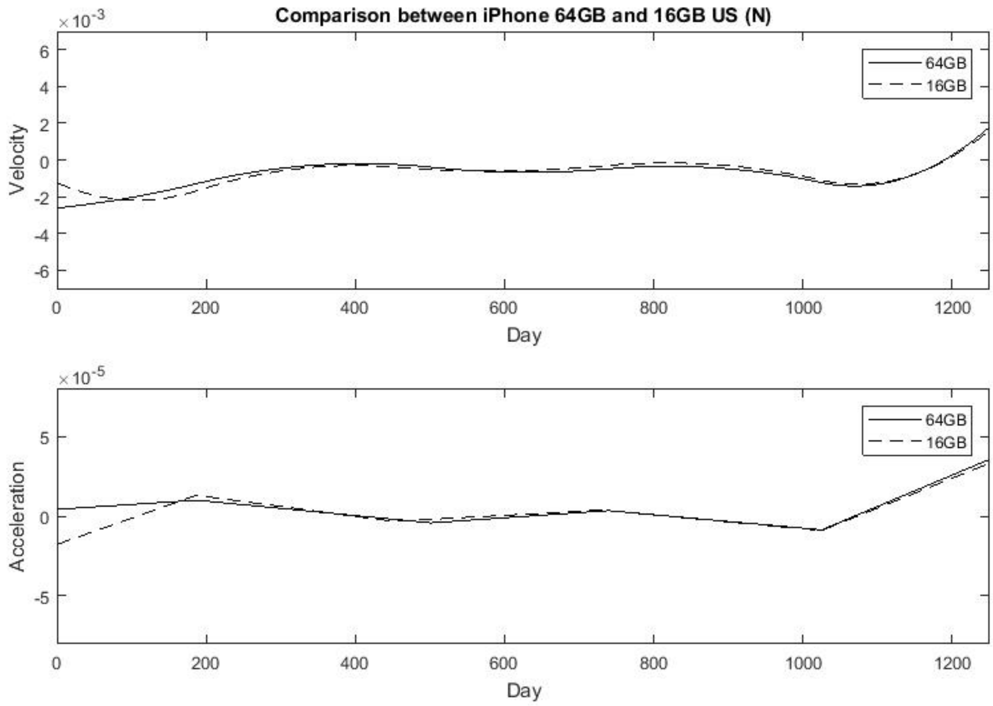

Figure 4.10: The comparison between new iPhone 64GB and 16GB US

The final aspect that the results focus on is the velocity and acceleration of the two iPhone specifications: 64GB and 16GB. Figure 4.10 exemplifies the price dynamics of new iPhone 64GB and 16GB in the US market. It can be seen that both the price velocity and price acceleration of both products are virtually identical, aside from the slight difference at the start. In particular, during the introduction stage of the product life cycle (i.e. the first 200 days from the product launch, see Figure 4.1), the velocity of both iPhone 64GB and 16GB decreases continuously. This is based on the observation that the velocity graph moves in the opposite direction to the acceleration graph.

The acceleration curve also indicates that the velocity of the 16GB decreases slower than its 64GB counterpart, as the slope of 64GB is steeper. During the next stage of the product life cycle, growth (i.e. between 200 – 1000 days after launch, as depicted in Figure 4.1), the relatively flat velocity and acceleration graphs of both iPhone specifications suggest that their speed remains virtually constant, and any changes in speed happen at very similar rates. When the products enter the mature stage of their respective life cycles (i.e. the last 250 days; refer to Figure 4.1 for more details), the speed increases sharply, as evident by the fact that both velocity and acceleration curves move in the same direction. At this point in time, the slopes of the acceleration graphs of both 64GB and 16GB are similar, suggesting that the prices are increasing at a comparable speed.

Having observed the price dynamics of the two iPhone specifications visually, the results proceed to explore the magnitude of velocity at each stage of the product life cycle. Starting with the beginning of the introduction stage of the product life cycle, the velocity of iPhone 16GB US is 0.0013, which means that it loses 0.13 per cent of the initial price of 1.2590. This is approximately half of the velocity of its 64GB counterpart (0.0026), whose starting price is slightly higher (1.5111). Next, at the beginning of the growth stage of the product life cycle (i.e. at day 200), the magnitude of the velocity of iPhone 16GB is slightly higher – at 0.0015, suggesting that it loses 0.15 per cent of the price at the start, which is 1.2590. Such a value is similar to the magnitude of the velocity iPhone 64GB reported earlier (0.0012). As for the magnitude of the velocity at the beginning of the mature stage of the product life cycle (i.e. at day 1000), the results indicate that iPhone 16GB loses 0.09 per cent of its starting price. This is, once again, comparable to the rate at which the 64GB variant loses its initial price (0.0010). The final velocity of iPhone 16GB is 0.0016, showing that its prices increase by 0.16 per cent – a rate that is similar to the iPhone 64GB (0.0018).

After obtaining an overview of the magnitude of the velocity at each stage of the product life cycle, it is possible to determine the slope of each section to reveal the rate of price change per day. To start with, the results look into the introduction stage of the product life cycle. The prices of iPhone 16GB US change at the rate of 0.0001 per cent daily, which is lower than the rate of price change of iPhone 64GB US (0.0007). During the growth stage of the product life cycle, the rate of price change of iPhone 16GB US remains stable at 0.0001 per cent each day. At this point in time, the rates of change in prices of both iPhone specifications are comparable. Moving on to the mature stage of the product life cycle, the prices of iPhone 16GB US now change at a significantly higher rate of 0.0010 per cent per day, which is, again, similar to the rate of price change of its 64GB counterpart.

In summary, the recovered functional objects suggest that all of the series under scrutiny in this study share similar dynamics, where the prices experience the most change at the introduction and mature stages of the product life cycles. On the other hand, the price dynamics during the growth stage of the product life cycles are virtually stagnant, as the rate of change in prices per day is incredibly low. The results further reveal that during the introduction stage of the product life cycles, the SR condition of the products exhibit the most change in dynamics, while the dynamics of the N variant change the least. Such patterns continue on to the growth stage of the product life cycles, with the dynamics of the SR condition being the most dramatic, compared to the negligible changes in the dynamics of its N counterpart. Once the products reach maturity, however, the prices of the N variant now experience the most changes, whereas the prices of the SR condition change the least. In general, the prices of the N and SR conditions decrease at the beginning of the introduction stage of the product life cycles, whereas the prices of the MR variant increase. At the beginning of the growth life cycle stage, the prices of all conditions decrease, albeit very slowly, before decreasing at slightly higher rates once the products reach maturity. The prices of all smartphone variants then increase towards the end of the observation period at rates comparable to those documented during the introductory stage.

In terms of the rate of price changes across different dimensions, it is observed that the price dynamics of the products in the US are significantly more dramatic than those of the products in the UK, particularly during the introduction stage of the product life cycles. This difference narrows once the products enter the growth stage of their respective product life cycles, before remaining relatively comparable when the products reach maturity. Concerning the dynamics between iPhone and Samsung products, the results indicate that the prices of Samsung smartphones, especially in the US, fluctuate more than the prices of iPhone throughout the introduction and growth stages of the product life cycle. Nevertheless, when both products reach maturity, the changes in price dynamics of iPhone products overtake those experienced by Samsung smartphones. As for the two iPhone specifications, the only difference in price dynamics is noticeable during the introduction stage of the product life cycle, where the prices of the 64GB variant change at approximately double the rate of its 16GB counterpart. However, such a difference dissipates from the growth stage of the product life cycle onwards, as the rate of change in prices of the two variants are relatively similar throughout.

4.4 Discussion and Managerial Implications

The reported empirical results highlight a number of managerial implications in relation to the price dynamics of different smartphone products over their life cycles. It is of paramount importance for both the manufacturers and the sellers to be able to properly understand how the prices of their products change over time – especially when both new and remanufactured variants coexist – as well as what influences those changes. The application of FDA on a novel dataset facilitates the uncovering of these complex relationships, together with the comprehension of the roles played by different dimensions surrounding the data.

Firstly, the results indicate that it is possible to refer to a single dynamics curve, representing the price velocity and price acceleration of the smartphones under investigation, to draw insights; this is based on the fact that, with exceptions to the differences in magnitude, all of the dynamics curves exhibit virtually indistinguishable behaviour. Such a finding directly contradicts the results reported by Shmueli and Jank (2006) and Reddy and Dass (2006). It is documented that the price evolutions experience the most changes immediately after the initial launch of the products (i.e. the introduction stage of the product life cycle), and towards the end of the observation period (i.e. the mature stage of the product life cycle). For the majority of the products under scrutiny, the initial price reductions happen at a high velocity at the beginning of the introductory stage, before slowing down around 200 days afterwards – which is at the beginning of the growth stage of the product life cycle. To make sense of this result, this section refers to the law of supply and demand previously explained in Section 2.3 (Chapter 2). At the product launch, the number of sellers is lower than towards the end, so it is likely that the markets are dominated by a small number of sellers. This resembles the monopolistic competition (see Chapter 2, Section 2.3), meaning that they are able to set prices at a high level without having to consider competitors. Additionally, the products are new to the market, which can translate into a high demand for such items; consequently, the sellers can take advantage of this and reap early profits. Unsurprisingly, the benefits are not long-lasting, as more sellers enter into the market together with competitors' products and lower customer demand; this is evident by the speedy decrease of the prices, conforming to the law of demand.

The prices continue to drop until the market saturates, which in this case is approximately 200 days after the first launch (i.e. during the growth stage of the product life cycle). From this point onwards, the prices change steadily, based on the long plateau period of around 800 days. During this period, some changes occur as new products are being introduced; however, the changes are incomparable to the changes at the beginning. It is possible that the dynamics are being sustained by both the increasing number of sellers and the leftover demand from the buyers. Perhaps at this point in time, the market reaches equilibrium (refer to Chapter 2, Section 2.3 for more details). The price evolution then experiences a significant change again after approximately 1000 days. This is translated into roughly 3 years after the initial launch, which is likely to coincide with the mature stage of the product life cycle. At this point in time, the sellers are aware of the fact that a new generation of the product, which is potentially far superior, is entering the market. As such, it is unlikely for them to sell declining products; they therefore decrease the prices in hopes of attracting more sales and emptying their inventories. Notably, it is observed that the prices increase sharply after the so-called ‘purge’. It is possible that the remaining sellers presume exclusivity – in other words, they perceive their now obsolete products as rarities and demand premium prices from potential buyers.

Secondly, the empirical results suggest that both the price velocity and acceleration of MR and SR products start off at higher levels, and experience more changes, than those of new products. This is noteworthy, since the prices of new products are the highest, but the dynamics change the slowest. Potentially, this is due to the nature of the products themselves; the new products are not only available through online channels, but also flagship stores, so the prices of these products are anchored in the primary market. This means that the sellers in the secondary markets are not able to set the prices freely, but rather have to follow the movements of prices set through official channels. Since these prices do not change frequently, the dynamics of new products on online platforms do not experience dramatic changes either. On the other hand, the prices of remanufactured products do not have the same price anchors, as most of them are sold through online channels. Additionally, they are not readily available after the initial launch – either because of the lack of remanufacturing cores (Guide, Teunter and Van Wassenhove, 2003; Sabbaghi, Behdad and Zhuang, 2016), or due to intentional delays to prevent cannibalisation (Sabbaghi, Behdad and Zhuang, 2016; Wang *et al.*, 2017). The sellers who enter the market first are able to set the prices at will, but soon face fierce competition as more sellers enter the market. They then experience further competition as official sellers start to release licensed remanufactured products. Since potential buyers of remanufactured products are price-sensitive, the dynamics of these products fluctuate throughout as sellers compete to attract sales.

The initial increase in the prices of MR products can be explained by considering both the number of sellers and the preference of the buyers towards this type of product over its SR counterparts. Since the number of sellers offering MR products is the lowest compared to the other two conditions, it is likely that they do not face as much competition (i.e. the market for MR products tends to resemble oligopolistic setting). This, coupled with the appearance of quality as certified remanufacturers, provide the sellers of these products slightly more freedom to set prices. However, this means that any changes in price, be it small or large, will have a stronger effect on the overall dynamics, as the market is not able to absorb the resulting shock. Consequently, the price dynamics of MR products are the most erratic.

Thirdly, it is revealed that the above interpretations are applicable to both the US and UK markets. The only difference lies in the magnitude of the change in dynamics at the initial launch of the products. The reported results show that the changes in velocity and acceleration of the smartphones in the US are considerably more dramatic than their UK counterparts. To explain this, the dataset is re-examined to uncover that the prices of the products in the UK market are more expensive than the US market, but the amount of the products present in the market is less. Therefore, it is likely that frequent changes in the US market, although small, contribute to a larger impact on the price dynamics than occasional changes of a higher magnitude. Although the homogeneity of the dynamics of price formation processes contradicts the findings reported in seminal papers by Shmueli and Jank (2006) and Reddy and Dass (2006), the observation that small, but regular, changes can overcome the impact of larger, irregular, changes is in agreement with their results.

Fourthly, by comparing the dynamics of Apple and Samsung, it is found that the changes in dynamics of Samsung are more severe than the patterns found for iPhone. This may be attributable to the number of sellers in the market, since the amount of Samsung sellers is significantly more than iPhone sellers. Accordingly, Samsung sellers not only compete against iPhone sellers, but also fellow Samsung sellers; even though the Samsung market is thicker than the iPhone market, it is not able to dissipate the resulting shock. This suggests that, with enough force, the changes can overcome the ability of the market to absorb them. Such a finding is supported by the works of Shmueli and Jank (2006) and Reddy and Dass (2006).

Finally, striking similarities between the dynamics of iPhone 64GB and 16GB are identified. On the one hand this is surprising, since iPhone 64GB and 16GB have distinct features in terms of specifications and prices, and sellers in the markets can differ significantly; therefore, the resulting pattern is indeed remarkable. On the other hand, it is to be expected, as the two variants are of the same brand, so the perceptions regarding them should not differ greatly from each other. Further evidence supporting this is found in the dataset, as the price series of iPhone 64GB and 16GB move closely with each other. In other words, although the listing prices are different, the price levels of the two products are comparable. This can happen if the sellers have a certain profit margin in mind, which means that they unknowingly set the prices of both models of iPhone close to each other. In addition, more sellers provide both variants in the market than only one type, so the perception that iPhone 64GB and 16GB are similar is inevitably strengthened.

After obtaining a comprehensive view of the price dynamics of new and remanufactured smartphones in this chapter, the next chapter proceeds to explore the competitive structure of the secondary markets that host a variety of smartphone products used in this study.

Chapter 5

The Price-Volume Relationship for New and Remanufactured Smartphones[5]

"Modern man has lost the sense of wonder about the unknown and he treats it as an enemy."

Laurens van der Post

5.1 Introduction

This chapter is the second of the three empirical results chapter in this thesis. It aims to fulfil the second research objective (see Chapter 2, Section 2.8 for more details) concerning the competitive structure and trading mechanisms of secondary market platforms by examining the relationship between price and volume of new and remanufactured smartphones. Section 5.2 describes the dataset used for the analysis. Section 5.3 outlines and presents the results from the

[5] The text in this chapter appeared in part in a joint paper published in the International Journal of Production Economics on pages 78-94. This paper can be found at: https://www.sciencedirect.com/science/article/pii/S0925527318300999.

preliminary data analysis in preparation for the estimation of the ARIMA model. Section 5.4 specifies the model used in the analysis. Section 5.5 exemplifies the empirical estimates of the model specified in Section 5.4. Section 5.6 discusses managerial insights. Section 5.7 concludes the chapter by summarising the findings and identifying research limitations and further research opportunities.

5.2 Data Description

The dataset consists of daily listing prices and volume for iPhone 5s (64GB, 32GB, and 16GB) and Samsung Galaxy S4 (16GB). Each specific smartphone model has three product conditions: N, MR, and SR. With the three product conditions (N, MR, SR) and two target locations of online platforms (eBay US and eBay UK), the dataset contains a total of 12 homogeneous items.

iPhone 5s and Samsung Galaxy S4 are selected for the fulfilment of the second objective for three reasons. Firstly, the volume of daily listings for these two smartphones is sufficiently large in each product condition. The abundance of daily listings ensures that the computed average price is a reliable representation of the eBay market price. Secondly, both iPhone 5s and Samsung Galaxy S4 were released in 2013, which makes them comparable in terms of their respective stages of the product life cycle. The life cycle stage is taken into account as it affects the price and demand of consumers which, in turn, influence the interaction between prices and volume. Therefore, the products at the same stage of life cycle are selected to control for this effect. Thirdly, their product specifications are similar in terms of storage, functionality, and performance. The inclusion of the 16GB model across two brands facilitates the analysis regarding the patterns for products with high specifications (iPhone 5s 64GB and 32GB) vs.

low specifications (iPhone 5s 16GB and Samsung Galaxy S4 16GB) and, of course, cross-brand comparisons between iPhone 5s 16GB and Samsung Galaxy S4 16GB.

The sampling period spans from 28th January 2016 to 3rd November 2016, for a total of 281 observations. On average, 1782 iPhone 5s listings from eBay US and 846 listings from eBay UK were retrieved daily. As for Samsung Galaxy S4, on average, 763 and 283 daily listings were retrieved from eBay US and eBay UK, respectively.

5.3 Preliminary Data Analysis

This section carries out preliminary data analysis for the dataset in order to ensure that the series are suitable for the empirical model. Figures 5.1 and 5.2 illustrate overall evolution of the prices and volume of the iPhone 5s (64GB, 32GB, and 16GB) and Samsung Galaxy S4. Overall, the price series show downward trends with a visible difference between the prices of new and remanufactured iPhone 5s listed on both eBay US and UK. Interestingly, the price difference between new and remanufactured products is less noticeable for the Samsung Galaxy S4 in both markets. The products retrieved from eBay UK were originally listed in British Pound Sterling (GBP) and have been converted into USD using the corresponding daily exchange rate series taken from the Bank of England (Bank of England, 2017).

The two figures also depict overall evolution of the listing volume for the four models under scrutiny. Both US and UK volume fluctuate over the entire period, with a significant decrease in all N and SR items around August 2016 for the UK markets. The volume then accumulates back afterward, and continues to grow towards the end of the sampling period – such a fall is not documented in the US. Overall, the listing volume of all MR products in the US is more erratic than its UK counterpart as it fluctuates throughout, whereas the latter gradually increases over the entire period. It appears that, like the UK, the behaviour of the listing volume of SR products mirror those of new items – except for Samsung Galaxy S4, where the listing volume of the former is closer to its MR counterpart. In terms of the number of listings per day, the listings for MR products are the lowest across all models under scrutiny, whereas the listings of SR items occasionally exceed those of N.

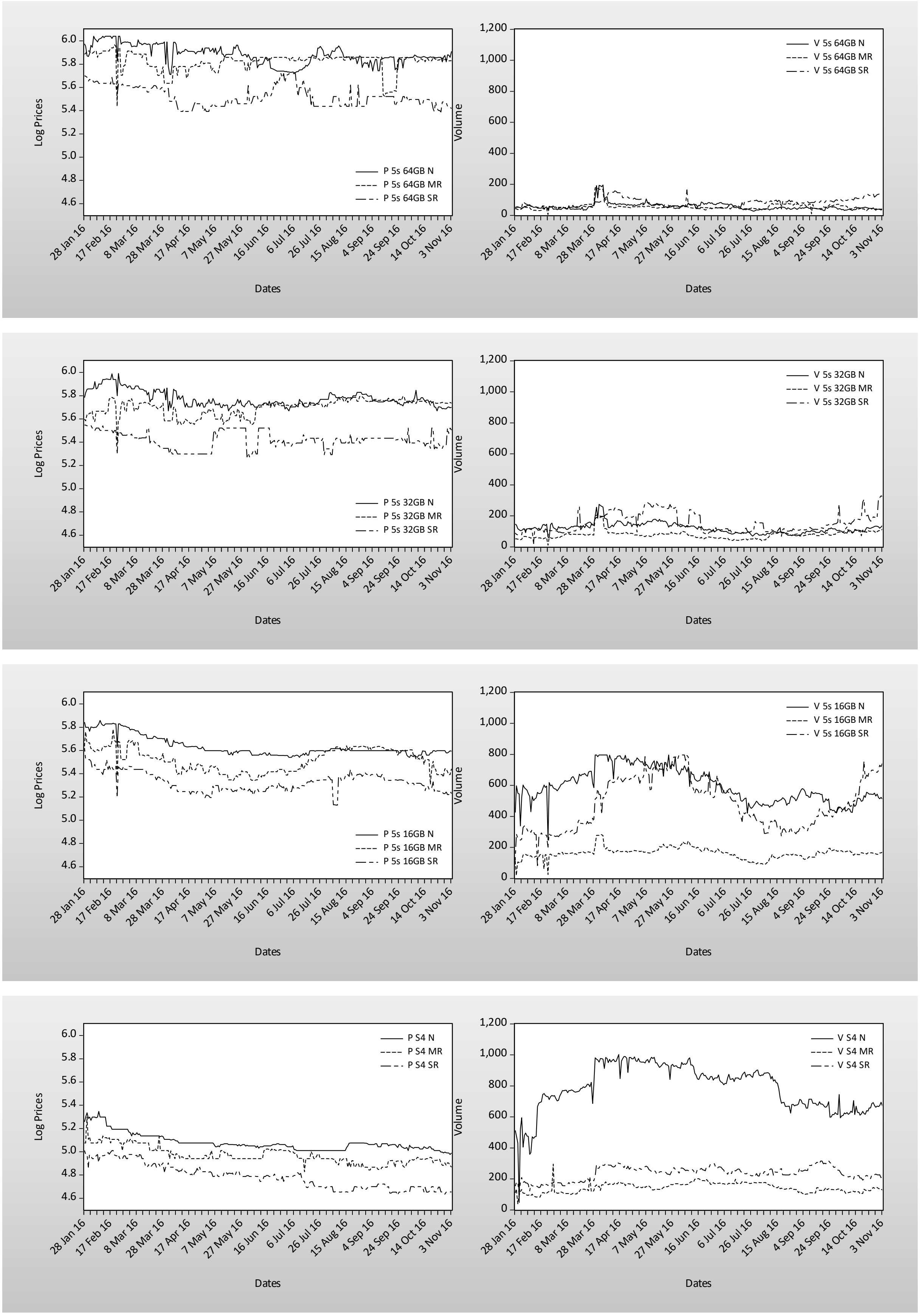

Figure 5.1: Price and volume of iPhone 5s and Samsung Galaxy S4 in the US markets

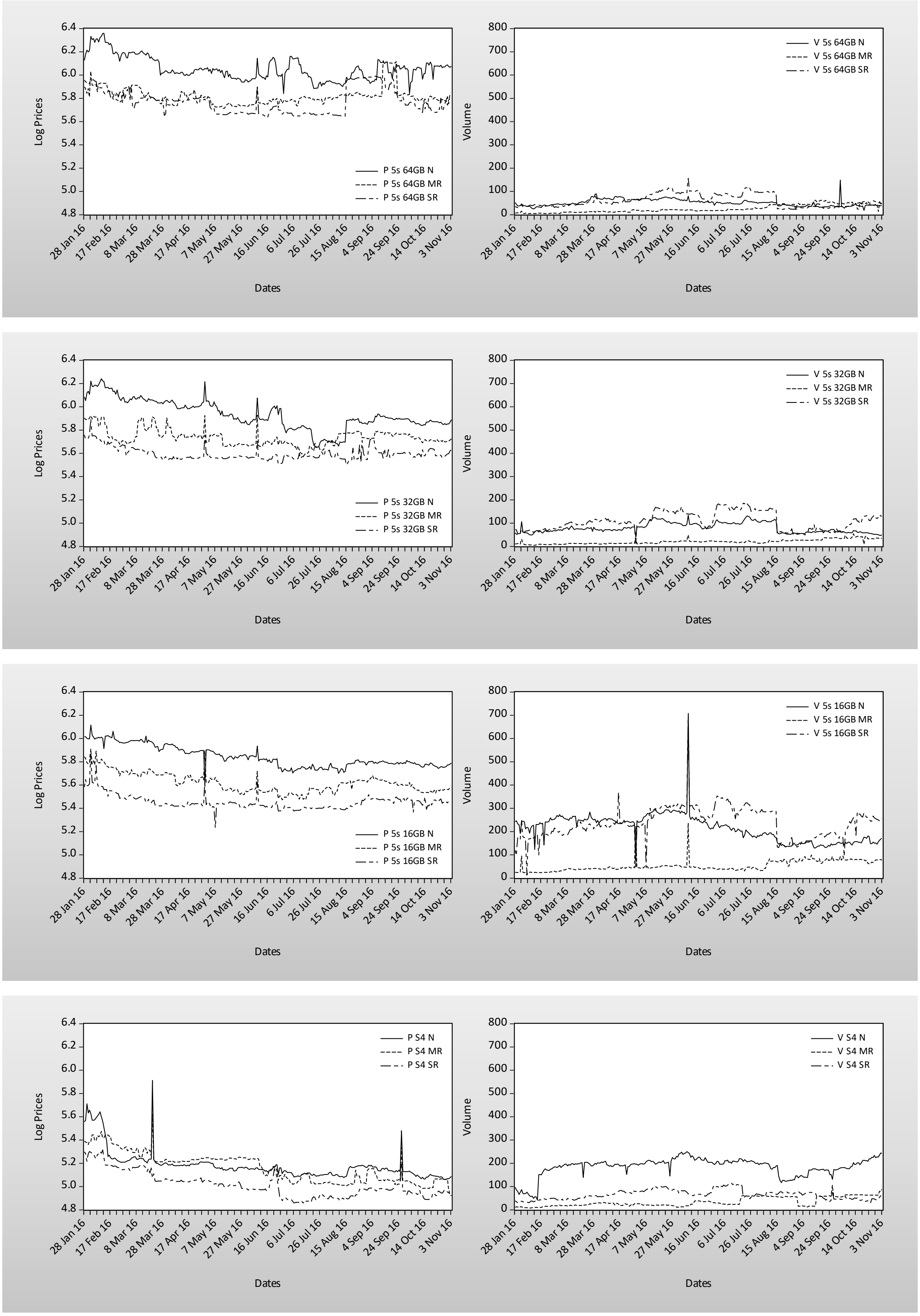

Figure 5.2: Price and volume of iPhone 5s and Samsung Galaxy S4 in the UK markets

Table 5.1 illustrates the average prices of iPhone 5s and Samsung Galaxy S4 on eBay US and UK. The mean prices of iPhone items are directly proportional to the capacity of the product model, regardless of the condition of the product. In other words, the prices of iPhone 5s 64GB are higher than those of iPhone 5s 32GB and 16GB, respectively, for every condition of the items in both the US and UK markets. Considering the prices of different conditions within a certain model, the new iPhone 5s have the highest price, while the MR phones are offered at the second highest and the SR conditions are offered at the lowest price. The patterns found for Samsung Galaxy S4 are similar to those for iPhone 5s 16GB. The same table also depicts the standard deviations of daily prices. The deviations in the price setting are the highest for the new version of iPhone 5s and Samsung Galaxy S4 across the US and UK markets. On the other hand, similar discrepancies in price are found for the two remanufactured versions in most models. In general, variations in the price setting of both iPhone 5s and Samsung Galaxy S4 are smaller in the US than the UK. Finally, the price settings of iPhone 5s 16GB are, overall, more volatile than those of Samsung Galaxy S4.

Table 5.1: Preliminary statistics of the dataset

Product Model				Statistics						
				Vol	**Mean**	**Median**	**SD**	**JB**	**Q(4)**	**Q^2(4)**
iPhone 5s	64GB	US	N	56.89	366.3	362.7	20.68	15.20 (0.000)	799.6 (0.000)	794.4 (0.000)
			MR	55.45	333.7	340.1	22.21	360.2 (0.000)	536.3 (0.000)	552.0 (0.000)
			SR	79.44	264.0	256.1	18.64	29.61 (0.000)	923.6 (0.000)	926.4 (0.000)
		UK	N	50.73	455.7	444.6	39.79	52.22 (0.000)	923.3 (0.000)	940.2 (0.000)
			MR	25.06	338.4	336.4	29.70	552.6 (0.000)	707.3 (0.000)	691.1 (0.000)
			SR	60.55	331.2	328.0	25.45	20.08 (0.000)	889.3 (0.000)	889.8 (0.000)
	32GB	US	N	120.1	328.2	322.2	18.36	71.07 (0.000)	938.8 (0.000)	934.6 (0.000)
			MR	77.80	291.5	291.4	12.80	6.556 (0.038)	806.4 (0.000)	813.8 (0.000)
			SR	153.3	234.2	233.7	15.11	1622 (0.000)	576.2 (0.000)	496.4 (0.000)
		UK	N	79.12	398.7	385.1	44.98	14.84 (0.001)	1016 (0.000)	1014 (0.000)
			MR	20.20	308.8	309.7	20.63	8.106 (0.017)	735.7 (0.000)	708.1 (0.000)
			SR	108.3	279.4	277.3	16.14	257.4 (0.000)	576.5 (0.000)	556.5 (0.000)

Product Model				Statistics						
				Vol	Mean	Median	SD	JB	Q(4)	$Q^2(4)$
	16GB	US	N	596.8	286.3	276.9	23.84	80.69 (0.000)	1012 (0.000)	1007 (0.000)
			MR	162.7	252.2	251.1	17.62	12.93 (0.002)	898.8 (0.000)	890.1 (0.000)
			SR	479.9	216.6	214.6	16.24	10.99 (0.004)	753.3 (0.000)	762.5 (0.000)
		UK	N	214.3	354.1	345.2	30.60	20.80 (0.000)	937.6 (0.000)	936.7 (0.000)
			MR	52.78	281.1	276.7	26.91	26.86 (0.000)	910.6 (0.000)	882.1 (0.000)
			SR	235.4	235.2	232.0	16.70	1879 (0.000)	625.6 (0.000)	586.9 (0.000)
Samsung Galaxy S4	16GB	US	N	786.0	159.9	153.9	17.79	826.0 (0.000)	939.5 (0.000)	916.6 (0.000)
			MR	142.4	152.4	149.5	11.40	65.98 (0.000)	929.6 (0.000)	909.7 (0.000)
			SR	235.6	133.4	131.0	10.50	28.60 (0.000)	1025 (0.000)	1025 (0.000)
		UK	N	184.4	191.7	184.4	33.15	1192 (0.000)	768.3 (0.000)	719.0 (0.000)
			MR	34.35	180.8	179.9	22.66	26.80 (0.000)	926.9 (0.000)	881.1 (0.000)
			SR	64.87	162.5	160.3	14.77	11.68 (0.003)	980.9 (0.000)	975.4 (0.000)

Notes: Sample period 28/01/16–03/11/16. Preliminary statistics for New (N), Manufacturer-refurbished (MR) and Seller-refurbished (SR) iPhone 5s 64GB, 32GB, and 16GB and Samsung Galaxy S4 16GB.
JB is Jarque-Bera statistics for the null of normality in distribution. P-Values in parentheses.
Q(4) and $Q^2(4)$ are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw series. P-Values in parentheses.

Table 5.1 also shows the average volume of iPhone 5s and Samsung Galaxy S4 in the US and UK markets. Overall, the mean total volume of iPhone 5s increases as the capacity specification of the model decreases, such that the iPhone 5s 64GB / 32GB have lower volume than the 16GB counterpart. This implies that the demand pattern of iPhone 5s in secondary markets mirrors the one in primary markets, as the new iPhone 5s 16GB was sold in larger volume than the iPhone 5s 64GB and 32GB. Interestingly, there are more iPhone 5s 16GB on offer than Samsung Galaxy S4 in both the US and the UK markets. All in all, iPhone 5s 16GB has the largest volume, while iPhone 5s 64GB has the smallest volume across all the segments under scrutiny.

5.3.1 Empirical Distributions of the Data

The analysis begins by taking the logarithmic transformation of the price series.[6] Both the Ng and Perron (2001) test for the null of integrated series and the KPSS (1992) test for the null of stationarity are applied to the log price series. The values of such statistics are reported in Tables 5.2 and 5.3.[7, 8] The top values are the statistics generated by taking both trend and intercept into account, whereas the values obtained by taking only the intercept are set out in parentheses. The empirical results suggest that most of the series are not stationary, as the unit-root tests consistently fail to reject the null of integrated series at standard significant levels. Similarly, the KPSS tests consistently reject the null of stationarity at standard significance levels. The

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[6] The logarithmic transformation makes it possible to reduce the level of heteroscedasticity in the series. The same transformation is not applied to the volume series, as these may drop to zero on specific days, which is undefined on a logarithmic scale.

[7] Such statistics are applied as they have better size and stronger power than other unit-root tests when the data generating process is characterised by heteroscedasticity and serial correlation (see Ng and Perron (2001)).

[8] Additional tests, such as the ADF and DF-GLS tests, are also applied, from which similar results as those set out in the two tables are obtained. Their results are not reported to save space.

non-stationary series are subsequently transformed by taking the first difference to achieve stationarity.

Table 5.2: Unit root tests results for iPhone 5s and Samsung Galaxy S4 in the US

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 5s	64GB	Price	N	2 (2)	−11.51 (−2.14)	−2.32 (−0.95)	0.20 (0.44)	8.31 (10.74)	0.26** (0.91)**
			MR	2 (2)	−26.80** (−22.84)**	−3.66** (−3.37)**	0.14** (0.15)**	3.41** (1.09)**	0.12 (0.12)
			SR	2 (2)	−6.43 (−0.36)	−1.79 (−0.20)	0.28 (0.57)	14.18 (21.39)	0.19* (0.76)**
		Volume	N	8 (8)	−17.09 (−8.10)	−2.08 (−1.92)	0.18 (0.24)	5.81 (3.44)	0.15* (0.49)*
			MR	10 (10)	−21.28* (−15.32)**	−3.26* (−2.76)**	0.15* (0.18)**	4.32* (1.64)**	0.10 (0.10)
			SR	2 (2)	−9.36 (−2.52)	−2.09 (−0.77)	0.22 (0.31)	10.07 (8.27)	0.15* (0.47)*
	32GB	Price	N	2 (2)	−5.79 (−1.32)	−1.70 (−0.65)	0.29 (0.49)	15.72 (14.28)	0.35** (0.71)*
			MR	5 (5)	−5.70 (−5.65)	−1.59 (−1.60)	0.28 (0.28)	15.81 (4.57)	0.22** (0.47)*
			SR	11 (11)	−3.39 (−0.73)	−1.27 (−0.47)	0.37 (0.65)	26.28 (23.23)	0.29** (0.35)*
		Volume	N	11 (11)	−7.28 (−3.51)	−1.82 (−1.32)	0.25 (0.38)	12.69 (6.97)	0.21* (0.90)**
			MR	8 (8)	−15.05 (−7.23)	−2.73 (−1.74)	0.18 (0.24)	6.15 (3.96)	0.18* (0.48)*

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
			SR	11 (2)	−3.04 (−4.76)	−1.03 (−1.14)	0.34 (0.24)	25.18 (5.98)	0.23** (0.52)*
	16GB	Price	N	4 (4)	−1.27 (0.61)	−0.63 (1.00)	0.49 (1.63)	50.02 (160.2)	0.42** (1.50)**
			MR	4 (4)	−2.42 (0.07)	−1.10 (0.05)	0.45 (0.73)	37.63 (33.90)	0.32** (0.54)*
			SR	8 (8)	−1.47 (0.19)	−0.80 (0.20)	0.54 (1.08)	55.96 (67.24)	0.37** (0.51)*
		Volume	N	4 (4)	−1.49 (−1.04)	−0.82 (−0.71)	0.55 (0.68)	56.60 (22.69)	0.30** (0.90)**
			MR	8 (6)	−6.06 (−4.47)	−1.74 (−1.43)	0.29 (0.32)	15.03 (5.60)	0.20* (0.54)*
			SR	8 (8)	−2.53 (0.41)	−1.12 (0.30)	0.44 (0.72)	35.61 (35.57)	0.29** (0.49)*
Samsung Galaxy S4	16GB	Price	N	11 (14)	−1.87 (0.06)	−0.90 (0.05)	0.48 (0.79)	44.21 (38.11)	0.36** (1.16)**
			MR	1 (1)	−16.29 (−1.27)	−2.85 (-0.54)	0.18 (0.43)	5.60 (12.64)	0.33** (1.39)**
			SR	4 (2)	−10.22 (0.70)	−2.23 (0.64)	0.22 (0.92)	9.06 (56.56)	0.35** (1.83)**
		Volume	N	11 (15)	−0.17 (0.01)	−0.29 (0.06)	1.70 (0.35)	52.68 (51.00)	0.23** (0.59)*
			MR	4 (4)	−6.08 (−3.76)	−1.70 (−1.36)	0.28 (0.36)	14.97 (6.52)	0.38** (0.39)*
			SR	7 (7)	−6.76 (−1.66)	−1.77 (−0.83)	0.26 (0.50)	13.54 (13.52)	0.26** (0.57)*

Notes: Sample period 28/01/16–03/11/16. Unit root tests are applied to series (log prices) in levels with constant and trend, and then with constant only (given in parentheses). * and ** denote statistical significance at 5% and 1% levels.

Ng-Perron test comprises of four test statistics, which are [a] MZa with critical values at 5% (1%) level equal to −17.30 (−23.80) for constant and trend (−8.10 (−13.80) for constant), [b] MZt with critical values at 5% (1%) level equal to −2.91 (−3.42) for constant and trend (−1.98 (−2.58) for constant), [c] MSB with critical values at 5% (1%) level equal to 0.17 (0.14) for constant and trend (0.23 (0.17) for constant), and [d] MPT with critical values at 5% (1%) level equal to 5.48 (4.03) for constant and trend (3.17 (1.78) for constant). [e] KPSS with critical values at 5% (1%) level equal to 0.15 (0.22) for constant and trend (0.46 (0.74) for constant). Tests computed using spectral GLS de-trended AR kernel based on Modified AIC.

Table 5.3: Unit root tests results for iPhone 5s and Samsung Galaxy S4 in the UK

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 5s	64GB	Price	N	1	−16.79	−2.21	0.18	5.39	0.26**
				(1)	(−5.12)	(−1.51)	(0.30)	(5.01)	(1.24)**
			MR	1	−18.99*	−3.08*	0.16*	4.81*	0.11
				(1)	(−11.02)*	(−2.31)*	(0.21)*	2.39*	(0.36)
			SR	1	−7.51	−1.90	0.25	12.22	0.25**
				(1)	(−2.85)	(−1.14)	(0.40)	(8.45)	(0.50)*
		Volume	N	6	−6.75	−1.82	0.27	13.51	0.35**
				(6)	(−5.94)	(−1.67)	(0.28)	(4.31)	(0.61)**
			MR	14	−5.61	−1.65	0.29	16.19	0.21*
				(15)	(1.11)	(0.90)	(0.81)	(49.46)	(1.72)**
			SR	1	−8.03	−1.98	0.25	11.43	0.36**
				(1)	(5.96)	(−1.72)	(0.29)	(4.12)	(0.46)*
	32GB	Price	N	1	−11.26	−2.34	0.21	8.24	0.27**
				(1)	(−0.99)	(−0.52)	(0.52)	(16.56)	1.45**
			MR	5	−6.29	−1.75	0.55	14.49	0.19*
				(3)	(−0.79)	(−0.44)	(0.33)	(18.59)	(0.91)**
			SR	5	−4.15	−1.36	0.33	21.19	0.41**
				(5)	(−1.10)	(−0.65)	(0.60)	(18.94)	(0.53)*
		Volume	N	2	−9.85	−2.15	0.22	9.55	0.35**
				(2)	(−7.42)	(−1.92)	(0.22)	(3.80)	(0.47)*
			MR	5	−11.47	−2.38	0.21	8.02	0.18*
				(5)	(−0.12)	(−0.06)	(0.51)	(19.21)	(1.65)**
			SR	1	−9.32	−2.16	0.23	9.77	0.27**
				(1)	(−4.65)	(−1.43)	(0.31)	(5.47)	(0.49)*

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
	16GB	Price	N	3	−6.10	−1.57	0.26	14.85	0.42**
				(3)	(−0.40)	(−0.30)	(0.76)	(31.89)	(1.51)**
			MR	9	−3.23	−1.18	0.37	26.36	0.26**
				(2)	(−0.28)	(−0.18)	(0.65)	(26.28)	(1.53)**
			SR	9	−2.50	−1.01	0.40	32.32	0.36**
				(9)	(−0.67)	(−0.48)	(0.73)	(28.07)	(0.59)*
		Volume	N	7	−5.73	−1.69	0.30	15.90	0.32**
				(6)	(−2.78)	(−1.08)	(0.39)	(8.52)	(1.29)**
			MR	15	−6.85	−1.85	0.27	13.31	0.15*
				(8)	(−1.26)	(−0.61)	(0.48)	(14.31)	(1.50)**
			SR	4	−6.80	−1.84	0.27	13.42	0.30**
				(4)	(−2.52)	(−1.02)	(0.41)	(9.25)	(0.36)*
Samsung Galaxy S4	16GB	Price	N	3	−3.84	−1.31	0.34	22.76	0.29**
				(2)	(−0.07)	(−0.05)	(0.81)	(23.14)	(1.20)**
			MR	4	−11.89	−2.43	0.20	7.71	0.18*
				(3)	(0.58)	(0.46)	(0.80)	(43.50)	(1.74)**
			SR	1	−9.66	−2.14	0.22	9.72	0.28**
				(1)	(−0.49)	(−0.31)	(0.63)	(23.71)	(1.42)**
		Volume	N	2	−4.82	−1.55	0.32	18.91	0.25**
				(2)	(−0.52)	(−0.28)	(0.54)	(19.08)	(0.51)*
			MR	15	−16.97	−2.01	0.18	5.49	0.20*
				(15)	(2.08)	(1.07)	(0.51)	(27.42)	(1.46)**
			SR	2	−6.72	−1.82	0.27	13.57	0.39**
				(2)	(−3.48)	(−1.26)	(0.36)	(7.03)	(0.41)*

Notes: Sample period 28/01/16–03/11/16. Unit root tests are applied to series (log prices) in levels with constant and trend, and then with constant only (given in parentheses). * and ** denote statistical significance at 5% and 1% levels.

Ng-Perron test comprises of four test statistics, which are [a] MZa with critical values at 5% (1%) level equal to −17.30 (−23.80) for constant and trend (−8.10 (−13.80) for constant), [b] MZt with critical values at 5% (1%) level equal to −2.91 (−3.42) for constant and trend (−1.98 (−2.58) for constant), [c] MSB with critical values at 5% (1%)

level equal to 0.17 (0.14) for constant and trend (0.23 (0.17) for constant), and [d] MPT with critical values at 5% (1%) level equal to 5.48 (4.03) for constant and trend (3.17 (1.78) for constant). [e] KPSS with critical values at 5% (1%) level equal to 0.15 (0.22) for constant and trend (0.46 (0.74) for constant). Tests computed using spectral GLS de-trended AR kernel based on Modified AIC.

The only series for which the evidence of stationarity in levels is obtained are the prices of MR iPhone 5s 64GB for the US and UK markets, where the Ng-Perron tests reject the null at 5% but not at 1% levels. The unit-root properties of such a series seem, therefore, to depart from the widespread evidence characterising the dataset. Given that the evidence provided by the above tests is not entirely conclusive only for these two series, two separate analyses are carried out by assuming that they are stationary in levels, and by assuming stationarity in first differences thereafter. The reliability of the estimates is then evaluated by means of bootstrap simulations.

After taking the first differences of the log price series, their empirical distributions are examined. The results suggest that they tend to resemble normal distributions; however, both the Jarque-Bera and Kolmogorov-Smirnov tests soundly reject the null of normality at standard significance levels for all the series under scrutiny. Therefore, the analysis is carried out using the log-transformed series, and by controlling for potential distortions generated from departures from normality of the above series using bootstrap analysis (see DiCiccio and Efron (1996)).

5.4 Model Specification

The section presents the model specification based on the preliminary statistics presented in Section 5.3. Since the preliminary analysis of the price and volume series has shown that such series are all integrated of order one (i.e. have a unit root), the empirical analysis which follows is carried out on the same series in first differences; this is because their stationarity is a necessary condition for the asymptotic properties of standard linear regression models to hold. The link between prices and volume is analysed by means of standard auto-regression models, which take the following specification[9]:

$$\Delta P_t = \alpha + \sum_{p=1}^{P} \beta_p \Delta P_{t-1} + \lambda \Delta V_t + \varepsilon_t \tag{5.1}$$

where ΔP_t and ΔV_t are the daily changes in price and volume at time *t*, and ε_t is a random disturbance term normally distributed with mean 0 and variance ${\sigma_\varepsilon}^2$. The above specification is estimated on daily series of 281 observations, where the most suitable lag length P is determined by applying both the AIC and SBC. The presence of heteroscedasticity and serial correlation in the residuals of the above models is then investigated by applying the Ljung-Box Q-stats, LM tests and ARCH-LM tests.

Given that the empirical estimates are carried out on daily series, the possibility that they present GARCH-type volatility is plausible. In this case, the volatility clusters in the disturbance terms should be modelled by supplementing eq. (4.1) with GARCH dynamics, and by estimating this particular model through ML. However, when it comes to the estimation of GARCH models, it is well documented that such models are affected by small sample bias when the sample size is smaller than 250 data points for ARCH, and 500 for GARCH specifications (see Hwang and Pereira (2006) for more details). Moreover, the reduced number of available data points makes it difficult to achieve a maximum in the LF, and ascertain that such maximum is global rather

[9] The Box-Jenkins method indicates that the most appropriate model specification does not include any MA terms.

than local – casting, therefore, doubts on the opportunity to adopt GARCH models. Consequently, GARCH dynamics are not modelled in this study and the estimation of eq. (5.1) is carried out by using OLS, which is less affected by small sample bias.

Any undesirable effect that departures from normality, heteroscedasticity, and serial correlation might have on the empirical estimates is controlled by carrying out WLS estimates, as well as bootstrap simulations of eq. (5.1). Given the limited number of observations available, bootstrap analysis is used to assess to what extent the finite sample properties of the estimators depart from their asymptotic properties, and to make any necessary correction through the bias-corrected (BC) confidence intervals (see DiCiccio and Efron (1996)).

Finally, eq. (5.1) is re-estimated using two-stage least squares (2SLS) methods to account for the possible endogeneity in the price-volume relationships. The two aggregates, in fact, might be jointly determined in equilibrium (i.e. the intersection between the supply and demand curves) so that a simultaneous relationship between them can occur. In such circumstances, a crucial assumption of OLS estimation, that the explanatory variables are distributed independently of the stochastic error term, is violated, resulting in biased and inconsistent empirical estimates. To determine how strong the endogeneity issue is in the series, eq. (5.1) is re-estimated using 2SLS; the estimates obtained are then compared with the OLS counterparts. Whenever the two sets of estimates depart from each other, the results are derived by privileging the 2SLS estimates, as they can better correct for endogeneity.

5.5 Empirical Results

In this section, OLS and 2SLS empirical estimates of eq. (5.1) are carried out for prices and volume of the products previously set out. Both the AIC and SBC criteria, which weight the bias/efficiency trade-off in slightly different ways, are utilised to determine the number of lags to include in the model. The model specification is tested with lag lengths from 1 to 7 in order to capture any potential weekly seasonality. The majority of the results suggest that the lag length of 1 is the most appropriate specification; although in certain cases a lag length of either 6 or 7 is more suitable, the improvement in both the AIC and SBC is minimal.[10] For this reason, and for consistency across all the series under scrutiny, the same model specification is applied with lag lengths equal to 1.

Tables from 5.4 to 5.7 present the results from the estimations of eq. (5.1) using OLS and 2SLS. Such estimates often deliver similar patterns of results across the two markets and conditions; however, whenever there is a departure between the two sets of estimates, 2SLS is prioritised, since it can account for the endogeneity that might affect the relationship between prices and volume.

5.5.1 The Price Dynamics

The coefficient β in Tables from 5.4 to 5.7 represents the relationship between changes in past and current prices of the iPhone 5s and Samsung Galaxy S4 models. The majority of the results between OLS and 2SLS are consistent, showing that the coefficients are significant at 1% level.

[10] Similarly, diagnostic tests for serial correlation and heteroscedasticity – as well as R-squared statistics – improve only marginally when additional lags are included in the specifications in use.

The absolute value of the coefficient is interpreted as elasticity, and it detects how responsive current prices are to changes in past prices. It is observed that such coefficients are of different magnitude, spanning from −0.166 (iPhone 5s 64GB MR) to −0.493 (iPhone 5s 32GB SR), showing a relatively low level of persistence in the time dynamics of prices. Overall, significant negative coefficients show that a positive change in past prices causes a reduction in current prices across all models and conditions, in both the US and UK markets. Such dynamics are strong, especially for iPhone 5s 32GB and 16GB, whereas they weaken for iPhone 64GB and Samsung Galaxy S4; this shows that for these products, the price dynamics is less anchored to past price levels, and it is therefore more erratic.

In the US, the new iPhone 5s 32GB exhibits the highest elasticity US (Table 5.5, β_{32GB} = 0.4545). As for Samsung Galaxy S4, the results indicate that only the coefficient for its SR variant is statistically significant (Table 5.7, β_{16GB} = 0.1481). In the UK, the patterns of responsiveness to changes in past prices are more conclusive compared to the US, with the iPhone 5s 32GB SR having the highest responsiveness to changes in past prices (Table 5.5, β_{32GB} = 0.4934). Similar to the results for the US markets, only one coefficient for Samsung Galaxy S4 is statistically significant, which is the MR variant (Table 5.7, β_{16GB} = 0.1786). Thus, the prices of the S4 models are more erratic than those of iPhone 5s 16GB, as they are not dependent at all on past prices. Therefore, they are potentially more difficult to forecast over time.

Next, the significance of the cross-lags of prices in eq. (5.1) is tested to investigate whether the prices of MR and SR products can explain the prices of their new counterparts, and vice versa (see Section 3.4.2.1). Similarly, an additional test is conducted to determine whether the prices of items in the US market can explain the prices of the equivalent items in the UK, and vice versa. When this type of analysis is carried out, very weak cross-interactions among the markets and conditions for both prices and volume are found. Such a pattern of results holds across the US and UK markets, suggesting that the price and volume dynamics across markets and conditions are independent, and not affected by any spillover effects. Consequently, the analysis is limited to eq. (5.1) with no cross-lags for prices and volume.

5.5.2 The Relationships between Price and Volume

The estimates of the parameter λ capture the relationship between changes in current price and changes in current volume of iPhone 5s and Samsung Galaxy S4. The small magnitude of the coefficient λ is a by-product of different scales of the dependent and independent variables in eq. (5.1), where the former is taken in log-first differences, and the latter is taken in first differences. The absolute values of the parameter represent the semi-elasticity of the change in current price to the change in current volume, and indicate how responsive current prices are to changes in volume. In other words, they signify the percentage change of price in response to a unit change in volume. All the parameter estimates are significant at 1% and 5% levels, except for a few cases where the results obtained from 2SLS estimations suggest otherwise.

Evidence of strong positive relationships between current prices and volume is found only for the MR variants in the US market; nevertheless, the same pattern survives for both the MR and SR products in the UK. This shows that, on average, the secondary markets for remanufactured smartphones are likely to have high profit potential – as the positive link between price and volume suggests that the main driving force in such markets is the demand from buyers. These positive relationships are also stronger across the UK markets than their US equivalents.

Strong negative relationships between the changes in current prices and volume can be established in the markets for new conditions of all products, with the exception of iPhone 5s 16GB. This result shows that such markets are not able to absorb increases in volume and they, therefore, require a drop in prices to boost the demand from buyers. Thus, *ceteris paribus*, it might be challenging for producers and/or sellers to reap additional profits by injecting additional volume of items in these markets. It is likely that this is the effect of the competition spreading across from the primary markets of new items by official sellers (i.e. Apple Stores and Samsung Stores).

Interestingly, the results indicate that all the markets for iPhone 5s 16GB have the most profit potential – as strong positive links between prices and volume are found. Again, this suggests that the main driving force in these markets is the demand from buyers. The positive relationships between the changes in current prices and volume survive across the US and UK markets for all three conditions. Also, the markets for iPhone 5s 16GB are the markets with the largest volume, and it is found that both US and UK markets seem to be driven by very similar market forces.

By directly comparing the markets for iPhone 5s 16GB and Samsung Galaxy S4, it is observed that these two markets are rather different in their dynamics, with strong positive links between price and volume for the former that drastically reduce for the latter – where the same link survives only in the UK markets for MR and SR items. Consequently, it appears that the markets for Samsung Galaxy S4 have much less profit potential for the sellers.

In terms of the semi-elasticity of prices to volume, it is found that the magnitudes are similar across the UK and US markets for all three conditions. Additionally, the results signify that, overall, the changes in current price of new conditions are the least responsive to the changes in current volume across all markets, compared to the markets for remanufactured products.

Based on the empirical results, the markets are ranked according to their profit potential as follows. The market with the most profit potential for the sellers is the market where positive links between price and volume can be established – in this case, the markets for all conditions of iPhone 5s 16GB. Markets for which it is not possible to establish any link between price and volume can also enable sellers to reap profits, since prices in such markets are not affected by volume; these markets exist mainly in the US, especially those for Samsung Galaxy S4. Finally, the markets with the least profit potential are those where a negative link between prices and volume occurs. This applies to most of the markets for new conditions of the products across both the US and UK markets.

5.5.3 Robustness Checks

The Box-Ljung statistics, as well as the LM and ARCH-LM tests, are reported in the bottom panels of Tables 5.4 – 5.7. They show that the residuals of the estimated models are affected by serial correlation and heteroscedasticity. Such features might drive a wedge between the finite sample properties of the OLS estimators and their asymptotic properties, so that inferences carried out using the asymptotic assumptions might lead to incorrect conclusions. Thus, the finite sample properties of the above estimators are investigated by carrying out a bootstrap analysis of eq. (5.1). More specifically, artificial datasets are constructed by re-sampling pairs (prices and volume) from the original datasets of 281 observations. To preserve the serial correlation present in the series, a re-sampling is carried out in blocks of as many as 7 observations. OLS estimates of eq. (5.1) are then carried out for each bootstrapped dataset. The above estimation exercise is repeated 1999 times so that the empirical distributions of the parameters α, β, and λ are obtained.

Table 5.4: Empirical estimates of eq. (5.1) for iPhone 5s 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0004	−0.0004	−0.0002	−0.0002	−0.0008	−0.0007	−0.0007	−0.0009	−0.0007	−0.0003	−0.0005	−0.0006
	(0.0013)	(0.0014)	(0.0027)	(0.0027)	(0.0013)	(0.0013)	(0.0015)	(0.0014)	(0.0022)	(0.0022)	(0.0015)	(0.0015)
	[−0.0027, 0.0014]	[−]	[−0.0045, 0.0042]	[−]	[−0.0025, 0.0010]	[−]	[−0.0031, 0.0021]	[−]	[−0.0047, 0.0031]	[−]	[−0.0030, 0.0020]	[−]
β	−0.2524***	−0.0574	−0.2746***	−0.1666*	−0.3338***	−0.1052	−0.1013*	−0.0460	−0.2645***	−0.3180***	−0.2438***	−0.2454***
	(0.0531)	(0.0844)	(0.0569)	(0.0891)	(0.0531)	(0.0778)	(0.0547)	(0.0904)	(0.0559)	(0.0590)	(0.0578)	(0.0569)
	[−0.3295, −0.1197]	[−]	[−0.4772, −0.0611]	[−]	[−0.4336, −0.1461]	[−]	[−0.1947, 0.0632]	[−]	[−0.4574, −0.1145]	[−]	[−0.4325, −0.1181]	[−]
λ	−0.0008***	−0.0010***	0.0007***	0.0008**	−0.0006***	−0.0004**	−0.0010***	−0.0009***	0.0021***	−0.0020	−0.0007***	0.0024**
	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0005)	(0.0011)	(0.0002)	(0.0011)
	[−0.0011, −0.0006]	[−]	[0.0002, 0.0012]	[−]	[−0.0008, −0.0004]	[−]	[−0.0014, −0.0008]	[−]	[0.0011, 0.0028]	[−]	[−0.0009, −0.0002]	[−]
R^2	0.265	0.236	0.110	0.103	0.222	0.162	0.182	0.209	0.143	0.031	0.088	0.048

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Q(4)	18.470	28.917	8.803	8.763	18.190	29.643	1.036	1.390	2.307	0.442	3.227	1.564
	(0.000)	(0.000)	(0.012)	(0.067)	(0.000)	(0.000)	(0.595)	(0.846)	(0.315)	(0.979)	(0.199)	(0.815)
LM(4)	23.260	36.313	15.810	9.246	28.080	42.629	5.625	1.774	12.280	0.451	11.280	1.753
	(0.001)	(0.000)	(0.015)	(0.055)	(0.000)	(0.000)	(0.466)	(0.777)	(0.056)	(0.978)	(0.079)	(0.781)
$Q^2(4)$	36.820	47.507	13.860	18.782	35.870	53.934	25.930	24.995	5.760	2.446	28.550	2.693
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.056)	(0.654)	(0.000)	(0.610)
ARCH(4)	36.030	59.668	13.330	19.440	38.390	74.813	30.520	28.121	5.391	2.390	30.410	2.619
	(0.000)	(0.000)	(0.009)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.249)	(0.664)	(0.000)	(0.623)

Notes: Sample period 28/01/2016–03/11/2016. OLS and 2SLS estimates of the parameters of eq. (5.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 5s 64GB. Instruments for 2SLS are ΔP(t-i) and ΔV(t-j) for i = 2, …, 7 and j = 1, …, 7.

Standard Deviations in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias-corrected confidence intervals based on 1999 bootstrap in squared brackets (DiCiccio and Efron (1996)).

Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.

Q(4) and $Q^2(4)$ are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw residuals. P-Values in parentheses.

LM(4) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 4. P-Values in parentheses.

ARCH(4) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 4. P-Values in parentheses.

Table 5.5: Empirical estimates of eq. (5.1) for iPhone 5s 32GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0006	−0.0006	−0.0002	−0.0012	−0.0007	−0.0001	−0.0011	−0.0007	−0.0012	−0.0010	−0.0003	−0.0013
	(0.0011)	(0.0011)	(0.0012)	(0.0018)	(0.0021)	(0.0018)	(0.0014)	(0.0011)	(0.0017)	(0.0018)	(0.0019)	(0.0021)
	[−0.0022, 0.0008]	[−]	[−0.0018, 0.0015]	[−]	[−0.0040, 0.0021]	[−]	[−0.0034, 0.0022]	[−]	[−0.0036, 0.0011]	[−]	[−0.0026, 0.0019]	[−]
β	−0.4545***	−0.4545***	−0.3668***	−0.3380***	−0.3822***	−0.2183***	−0.2797***	−0.2996***	−0.3325***	−0.3458***	−0.3802***	−0.4934***
	(0.0541)	(0.0541)	(0.0565)	(0.0718)	(0.0556)	(0.0667)	(0.0585)	(0.0738)	(0.0546)	(0.0567)	(0.0517)	(0.0850)
	[−0.6061, −0.2391]	[−]	[−0.4718, −0.2139]	[−]	[−0.5194, −0.1238]	[−]	[−0.4137, −0.0857]	[−]	[−0.4605, −0.1468]	[−]	[−0.4591, −0.1785]	[−]
λ	−0.0002***	−0.0002	−0.0001	0.0013**	0.0000	−0.0017***	−0.0001	−0.0003***	0.0015***	0.0011	−0.0010***	0.0026**
	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.0004)	(0.0002)	(0.0001)	(0.0003)	(0.0006)	(0.0002)	(0.0013)
	[−0.0004, −0.0001]	[−]	[−0.0003, 0.0002]	[−]	[−0.0002, 0.0001]	[−]	[−0.0004, 0.0003]	[−]	[0.0007, 0.0022]	[−]	[−0.0013, −0.0007]	[−]
R^2	0.284	0.251	0.126	0.132	0.140	0.048	0.070	0.021	0.185	0.175	0.290	0.313

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Q(4)	17.760	24.780	12.670	12.015	15.160	29.299	6.441	4.452	16.580	17.754	18.860	14.878
	(0.000)	(0.000)	(0.002)	(0.017)	(0.001)	(0.000)	(0.039)	(0.348)	(0.000)	(0.001)	(0.000)	(0.005)
LM(4)	31.310	38.359	28.770	17.463	17.290	49.369	12.930	8.695	19.860	24.918	34.730	21.267
	(0.000)	(0.000)	(0.000)	(0.002)	(0.008)	(0.000)	(0.044)	(0.069)	(0.003)	(0.000)	(0.000)	(0.000)
$Q^2(4)$	65.880	62.342	25.780	28.841	31.640	55.070	15.330	7.878	52.620	53.310	33.320	44.496
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.096)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(4)	83.970	38.359	23.950	29.754	28.370	73.325	16.330	7.469	50.920	50.952	37.360	49.102
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.113)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–03/11/2016. OLS and 2SLS estimates of the parameters of eq. (5.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 5s 32GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.

Standard Deviations in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias-corrected confidence intervals based on 1999 bootstrap in squared brackets (DiCiccio and Efron (1996)).

Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.

Q(4) and $Q^2(4)$ are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw residuals. P-Values in parentheses.

LM(4) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 4. P-Values in parentheses.

ARCH(4) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 4. P-Values in parentheses.

Table 5.6: Empirical estimates of eq. (5.1) for iPhone 5s 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0010 (0.0009) [−0.0024, 0.0003]	−0.0009 (0.0009) [−]	−0.0013 (0.0014) [−0.0036, 0.0003]	−0.0008 (0.0015) [−]	−0.0011 (0.0019) [−0.0042, 0.0016]	−0.0009(0.0019) [−]	−0.0008 (0.0015) [−0.0029, 0.0010]	−0.0008 (0.0015) [−]	−0.0013 (0.0013) [−0.0034, 0.0007]	−0.0013 (0.0013) [−]	−0.0012 (0.0022) [−0.0039, 0.0014]	−0.0008 (0.0020) [−]
β	−0.3076*** (0.0492) [−0.3762, −0.1563]	−0.1937*** (0.0648) [−]	−0.3846*** (0.0544) [−0.5357, −0.1960]	−0.2620*** (0.0713) [−]	−0.2837*** (0.0565) [−0.4820, −0.0348]	−0.3409***(0.0761) [−]	−0.3672*** (0.0488) [−0.4393, −0.1270]	−0.3497***(0.0599) [−]	−0.1937*** (0.0446) [−0.3112, −0.0514]	−0.1785*** (0.0628) [−]	−0.4188*** (0.0516) [−0.5147, −0.2501]	−0.3464*** (0.0618) [−]
λ	0.0002*** (0.0000) [0.0002, 0.0002]	0.0003*** (0.0000) [−]	0.0002*** (0.0001) [0.0001, 0.0004]	0.0008*** (0.0001) [−]	0.0001 (0.0001) [0.0000, 0.0002]	0.0001 (0.0001) [−]	0.0003*** (0.0000) [0.0003, 0.0005]	0.0003*** (0.0001) [−]	0.0009*** (0.0001) [0.0008, 0.0011]	0.0007*** (0.0001) [−]	0.0002*** (0.0000) [0.0001, 0.0003]	0.0002*** (0.0001) [−]
R^2	0.375	0.298	0.186	0.089	0.086	0.097	0.378	0.378	0.513	0.492	0.258	0.252

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Q(4)	11.520	11.063	21.620	22.761	20.810	21.388	15.930	14.015	8.701	4.777	48.150	27.654
	(0.003)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.013)	(0.311)	(0.000)	(0.000)
LM(4)	15.340	16.373	68.780	29.752	21.870	23.963	25.910	18.119	13.640	5.971	54.570	36.896
	(0.018)	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.034)	(0.201)	(0.000)	(0.000)
$Q^2(4)$	33.360	46.653	47.220	89.241	34.510	31.854	29.940	33.307	40.490	36.095	46.070	41.918
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(4)	28.730	40.515	33.570	63.687	35.060	31.472	27.740	30.184	46.510	37.756	46.410	37.845
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–03/11/2016. OLS and 2SLS estimates of the parameters of eq. (5.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 5s 16GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.

Standard Deviations in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias-corrected confidence intervals based on 1999 bootstrap in squared brackets (DiCiccio and Efron (1996)).

Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.

Q(4) and $Q^2(4)$ are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw residuals. P-Values in parentheses.

LM(4) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 4. P-Values in parentheses.

ARCH(4) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 4. P-Values in parentheses.

Table 5.7: Empirical estimates of eq. (5.1) for Samsung Galaxy S4 (16GB)

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0017** (0.0009) [−0.0006, −0.0036]	−0.0015** (0.0006) [−]	−0.0010 (0.0012) [0.0008, −0.0025]	−0.0009 (0.0010) [−]	−0.0012 (0.0009) [−0.0002, −0.0025]	−0.0009 (0.0009) [−]	−0.0019 (0.0028) [−0.0057, 0.0017]	5.83E-05 (0.0032) [−]	−0.0022 (0.0020) [−0.0049, 0.0008]	−0.0029 (0.0023) [−]	−0.0011 (0.0012) [−0.0036, 0.0009]	−0.0011 (0.0013) [−]
β	−0.1250** (0.0485) [0.0073, −0.2560]	−0.0470 (0.0563) [−]	−0.3380*** (0.0535) [−0.1769, −0.4569]	−0.1377 0.0984 [−]	−0.3583*** (0.0577) [−0.2333, −0.4556]	−0.1481* (0.0868) [−]	−0.3523*** (0.0488) [−0.4123, −0.1010]	−0.0676 (0.0736) [−]	−0.3772*** (0.0556) [−0.5438, −0.1288]	−0.1786** (0.0789) [−]	−0.2440*** (0.0593) [−0.4473, 0.0305]	−0.1177 (0.0846) [−]
λ	−0.0002*** (0.0000) [−0.0001, −0.0002]	−0.0003*** (0.0000) [−]	−0.0004*** (0.0001) [−0.0003, −0.0006]	−0.0002** (8.11E-05) [−]	−0.0001 (0.0001) [0.0001, −0.0002]	2.60E-05 (0.0002) [−]	−0.0020*** (0.0002) [−0.0027, −0.0016]	−0.0037*** (0.0005) [−]	0.0006* (0.0003) [0.0003, 0.0030]	0.0031*** (0.0008) [−]	−0.0003 (0.0002) [−0.0006, 0.0001]	0.0008 (0.0004) [−]
R^2	0.261	0.443	0.225	0.082	0.116	0.051	0.356	0.199	0.154	0.215	0.053	0.051

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Q(4)	17.21	4.931	5.661	5.922	17.81	14.228	16.39	27.787	14.37	6.679	4.326	6.414
	(0.000)	(0.295)	(0.059)	(0.205)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.154)	(0.115)	(0.170)
LM(4)	57.02	5.408	16.11	8.554	35.12	25.441	22.54	36.419	59.47	10.029	11.98	6.473
	(0.000)	(0.248)	(0.013)	(0.073)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.040)	(0.062)	(0.167)
$Q^2(4)$	5.506	0.221	19.43	23.218	29.92	24.818	32.58	45.097	48.04	47.965	74.55	30.199
	(0.063)	(0.994)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(4)	5.053	0.220	26.16	28.481	19.63	23.574	27.92	57.474	41.51	55.209	92.15	30.966
	(0.281)	(0.994)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–03/11/2016. OLS and 2SLS estimates of the parameters of eq. (5.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S4 (16GB). Instruments for 2SLS are ΔP(t-i) and ΔV(t-j) for i = 2, …, 7 and j = 1, …, 7.

Standard Deviations in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias-corrected confidence intervals based on 1999 bootstrap in squared brackets (DiCiccio and Efron (1996)).

Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.

Q(4) and Q2(4) are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw residuals. P-Values in parentheses.

LM(4) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 4. P-Values in parentheses.

ARCH(4) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 4. P-Values in parentheses.

A common feature of such empirical distributions is that they are leptokurtic, suggesting departures of the above estimators from their asymptotic properties. In fact, the K-S statistics reject the null of normality for a relatively large set of parameters in eq. (5.1).[11] Given the above evidence, bootstrapped confidence intervals could be a better tool than standard asymptotic intervals to carry out statistical inference. Therefore, the above empirical distributions are used to construct the BC confidence intervals (see DiCiccio and Efron (1996)). Such confidence intervals are set out in Tables 5.4 – 5.7. For comparison purposes, the bootstrap percentile intervals, as well as asymptotic intervals, are also computed.

The BC intervals differ only slightly from the percentile and asymptotic intervals, showing that the departures between finite sample and asymptotic properties appear negligible, so that inference based on asymptotic and finite sample properties leads to similar conclusions. Such a pattern of results holds across the four products, and for both the US and UK markets. A final robustness check is then conducted by carrying out both OLS and 2SLS estimations of eq. (5.1) where the daily average mean observations are replaced with daily median values for all the combinations of markets, models and conditions under scrutiny. All in all, the above estimation exercises deliver patterns of results very similar to those set out in Tables 5.4 – 5.7.[12]

A separate analysis is carried out for iPhone 5s 64GB, as the unit-root tests in use show that, unlike the remaining cohort of products under scrutiny, such series are stationary in levels. The

[11] Significant departures from normality are found in the parameters β and λ, whereas the constant parameter α is almost always normally distributed. Such a pattern of results holds across the two markets, four products and three conditions under scrutiny.

[12] The eq. (5.1) is also re-estimated using the non-converted GBP series for the UK markets and comparing such estimates with the results set out in Tables from 5.4 to 5.7 obtained using converted series. It is found that the two sets of results are relatively similar. Therefore, it is maintained that the exchange rates do not distort the price series under scrutiny.

analysis starts by fitting the model of eq. (5.1) to the log-price series in both levels and first-differences, from which inconsistent estimates for the parameter α, β and λ are obtained. Next, the stationarity of the residuals obtained from the two estimation exercises are evaluated. On the one hand, unit-root tests applied to the residuals generated by fitting the series in first-differences consistently reject the null at standard significance levels. On the other hand, it is found that the residuals obtained by fitting the log price series in levels are non-stationary. The same empirical exercise is carried out for both the US and UK series from which the same pattern of results set out above is obtained. Consequently, the original estimations are retained by treating the above series in level as non-stationary.

The effect of using log prices in levels or first-differences is then re-assessed by carrying out bootstrap simulations of the same type as those set out in the previous sections. The motivation for this type of analysis hinges on the evidence that the residuals obtained from eq. (5.1) are in general leptokurtic in comparison to normal distributions, with some levels of skewness when the above models are fitted to series in levels. Under such circumstances, the finite sample properties of the OLS estimators might depart from their asymptotic properties.

Therefore, the severity of the departure from the assumption of normality for the parameters α, β and λ, estimated over series in levels and first differences, are evaluated. For the model fitted to series in first differences, the empirical distributions of the above parameters resemble the related normal densities, suggesting moderate departures of OLS estimators from their asymptotic properties. The Anderson-Darling tests fail to reject the null of normality for the parameter α for the US, and for the parameters α and β for the UK series. The same evidence is less desirable for the models fitted to series in levels where the same tests soundly reject the null for all the 3 parameters estimated on US and UK series – signalling a more severe departure from the assumption of normality. Similar evidence holds for both US and UK series.

5.6 Discussion and Managerial Implications

The empirical results highlight a number of managerial implications, in terms of both the predictability of the price dynamics and the gauging of the profit potential of the markets under scrutiny. From the perspective of both manufacturers and sellers, in fact, it is paramount to be able to forecast future price levels of the products sold, as well as to properly evaluate how profitable specific markets of interest are. The empirical analysis of the price-volume series can certainly shed some light on these two important aspects.

Firstly, it is documented that the relationships between changes in past and current prices are not consistent across markets, models, and conditions. More specifically, such patterns are less evident in the markets for iPhone 5s 64GB and Samsung Galaxy S4. This shows that the price dynamics in these two markets are potentially more erratic than the rest of the markets under scrutiny, as current prices are less anchored to past price levels. The weak responsiveness to past levels of price is also particularly evident amongst new items across different models considered. This result can be explained by noting that such items benefit from a direct comparison to the equivalent items traded in primary markets (e.g. official sellers); as a result, the prices of new items traded on eBay platforms should be more strongly linked to the prices set in primary markets than to past values in secondary markets. Such links, of course, tend to fade away when remanufactured items are considered, as such a price anchor does not exist for secondary markets. Although remanufactured versions are offered at prices lower than those of new counterparts to increase buyers' purchase intention, the sellers have to match the prices of their competitors to stay competitive. Accordingly, remanufactured products have higher responsiveness to the change in past prices. The weak dependence on lagged values of prices, coupled with general low persistence of the price series, suggests that the time dynamics of prices might be difficult to forecast – especially for models such as iPhone 5s 64GB and Samsung Galaxy S4, as well as for all new conditions across the various models considered.

Secondly, the nature of the contemporaneous relationship between the changes in current prices and volume provides managers with a broad-brush picture of the profit potential of the markets under scrutiny. With respect to the standard demand-and-supply framework (see Chapter 2, Section 2.3), a negative contemporaneous link – as detected by the parameter estimates λ – suggests that the market is mainly driven by shifts in the supply. On the other hand, a positive link would suggest that shifts in the demand are what characterise the market. Consequently, it is possible to rank the markets in terms of their profit potential.

From the sellers' point of view, the markets with high profit potential are those characterised by a positive link between prices and volume. In such markets, in fact, consumer demand is the main driver, and sellers are able to inject larger volume of items without causing a downward pressure on prices. It is established that such positive links hold in the market for MR products in the US, and the markets for both MR and SR products in the UK. Thus, on average, the secondary markets for remanufactured smartphones are likely to have high profit potential. This may be due to the small number of vendors that dominate the market for this specific type of products. The sellers have more control over prices, since consumers do not have as many choices as they have by tapping into both primary and eBay markets for corresponding new items. This suggests that remanufacturers have more market power and can benefit from larger volume injected into the markets, unlike vendors of new items. The business of remanufactured items – especially MR – is therefore potentially more lucrative, indicating stronger appetite of buyers for this type of product as opposed to new items.

Moreover, it is shown that the markets for all conditions of iPhone 5s 16GB have the most profit potential. These markets are the largest in volume, and it appears that both the US and UK platforms are driven by similar market forces. Surprisingly, based on the direct comparison between iPhone 5s 16GB and Samsung Galaxy S4, it is found that the dynamics of these two models are distinct from each other, despite these products being considered as substitutes. In fact, the strong positive link between prices and volume found in the former drastically reduces when the latter is considered. Therefore, the market for Samsung Galaxy S4 has much less profit potential for the sellers. The second-best markets that sellers can trade in and, *ceteris paribus*, still reap sufficient profits, are those that present no significant link between prices and volume. For this type of markets, sellers can still inject a higher volume of items without causing any downward pressure on prices.

Lastly, the markets with the least potential in terms of profitability are those characterised by negative contemporaneous links between prices and volume. Such markets are mainly driven by supply forces, so that prices decrease when there is an increase in volume. It is established that this type of dynamic is predominant in the markets for new smartphones, suggesting that they are not capable of absorbing increases in volume without correspondent decreases in prices to boost the demand from buyers. As a result, in such markets, it might be difficult for sellers to make extra profit by injecting additional volume. Since the negative contemporaneous relationships are prevalent in the markets for new products, it is possible that this is the effect of the heightened competition stemming from primary markets of equivalent new items – official sellers – in the first place.

In addition to the aforementioned managerial insights, the reported results also contribute to the literature in several ways. Firstly, the established contemporaneous relationships between price and volume of new and remanufactured smartphones shed light on the efficiency of the online markets under scrutiny. According to the EMH (refer to Chapter 2, Section 2.3 for more details), a market is regarded as efficient when prices reflect all available information in the market, rendering it impossible to beat; in other words, when it is impossible for customers to purchase undervalued products, or for sellers to inflate the prices. Furthermore, in its weak form, past prices or volume changes should not help predict future prices in efficient markets. Therefore, the fact that it is possible to uncover meaningful patterns between price changes and volume in this study – or even between past prices and current prices – indicates that online markets can still be considered inefficient. This is somewhat unexpected, since a considerable amount of price information is available to both the buyers and sellers in online markets. Also, with the advent of the internet, information dissemination should be more prompt, meaning that it can be incorporated into prices more efficiently. As such, when traders attempt to arbitrate the market, participants should, in theory, be more likely to be aware of such an exploit. Nevertheless, it is also common knowledge that prices of the products on online platforms are often more expensive than those offered in the primary markets. The fact that online markets such as eBay are experiencing tremendous growth while seemingly not becoming more efficient merits further investigation outside the scope of this thesis.

Secondly, in the context of CLSCs and RLs, listing volume and its explanatory power towards price has been neglected so far (Jakowczyk *et al.*, 2017). Based on the established relationships between prices and volume, this chapter provides evidence of the usefulness of listing volume in predicting and explaining price movements of both new and remanufactured products. This finding contributes to the empirical studies on prices reviewed in Chapter 2 (Section 2.5), as a potential variable that may affect customers' WTP. The predictive power of listing volume is likely to also be beneficial in the field of research reviewed in Section 2.6, where the majority of the literature focuses on developing mathematical models. This is because researchers can now incorporate volume – a tangible variable – into their models instead of relying only on estimated demand functions, or price dynamics, to achieve 'optimal' price solutions.

Finally, although the study is performed with data from online market platforms, the impact of volume on price is not necessarily limited to such a context. The previously established price-volume nexuses indicate how market equilibrium (given by the time-varying intersection between demand and supply) fluctuates over time as a result of more / less volume demanded by consumers and supplied by producers. As mentioned earlier, the link can be positive, negative and there can also be no link. From the producers' perspective, it is important to measure how market reacts to change in volume – in other words, what the impact is on the price of items when the volume injected into the market changes; this is because the revenues are dependent upon both price and volume sold (i.e. Revenue = P x Q). Assuming that the initial price, P = 10, and volume, Q = 100, the revenue is equal to 1000. If, following an increase in Q from 100 to 110, the price falls from 10 to 9, then the revenue decreases to 110 x 9 = 990 < 1000. However, if – for the same change in Q, the price drops to 9.9, then the revenue becomes 110 x 9.9 = 1089 > 1000, yielding an increase in revenue compared to the initial value. In this sense, it is more profitable for the producer to decrease the price than increase the volume – an insight that would not be possible without access to data from secondary markets, where both price and volume vary over time. With data from primary markets, the prices are set at a given level with minimal changes throughout (e.g. the high street price of smartphones is more stable in each shop), but the volume sold changes often. Consequently, it is not possible to determine whether the total revenue of the company is set to increase, decrease, or perhaps stay the same, as a result of an increase in price or a decrease in volume offered. Thus, it is reasonable to say that a focus on primary markets alone prohibits the sensitivity analysis of revenue.

In the next chapter, the price-volume relationship for new and remanufactured smartphones is investigated further by incorporating additional product generations. This is to determine whether, as suggested above, life cycle stages represented by different product models affect the patterns reported in this chapter, and the validity of product cannibalisation effects.

Chapter 6

The Price-Volume Relationship for New and Remanufactured Smartphones across Product Life Cycles: Evidence for Cannibalisation Effect

“Change is inevitable,
change will always
happen, but you have to
apply direction to change,
and that's when it's
progress.”

Doug Baldwin

6.1 Introduction

This chapter is the last of the three empirical results chapters in this thesis. It aims to investigate the extent to which the cannibalisation problem occurs, based on the evolution of the relationships between price and volume of new and remanufactured smartphones, in order to fulfil the final research objective (see Chapter 2, Section 2.8). In the literature, the types of cannibalisation defined within the CLSCs and RLs context include internal and external cannibalisation (Atasu, Sarvary and van Wassenhove, 2008). Nevertheless, the definition given for each type of cannibalisation effect is not entirely applicable to this research (see Chapter 2, Section 2.7 for more information). This is because on eBay, both OEMs and independent remanufacturers can become sellers, which means that the cannibalisation effect that both parties experience is not strictly one or the other. In either instance, product cannibalisation occurs when the sales of remanufactured variants displace the sales of their new counterparts.

Another type of cannibalisation that relates to this study is within-category cannibalisation, which is defined by Van Heerde, Srinivasan and Dekimpe (2010). This type of cannibalisation can occur when customers switch from one brand to another, and when they purchase newer product generations instead of older ones. As such, these aforementioned definitions will be used to guide the interpretations and discussions of the empirical results in this chapter. The rest of Chapter 6 is organised as follows. Section 6.2 outlines the dataset used for the empirical exercise. Section 6.3 reports the preliminary data analysis results, in preparation for the estimation of the ARIMA models. Section 6.4 describes the model specifications used to perform the analysis. Section 6.5 presents the estimation results of the models previously covered in Section 6.4. Section 6.6 compares the reported results against the results presented in Chapter 5 to determine the cannibalisation effect amongst the smartphones in this study. Section 6.7 concludes by discussing the results and managerial insights.

6.2 Data Description

The dataset used in this chapter consists of daily listing prices and volume (referred to henceforth as “price” and “volume”) for iPhone 6s (64GB and 16GB) and iPhone 6 (64GB and

16GB), as well as Samsung Galaxy S6 (64GB and 32GB) and S5 (16GB). Each smartphone model has three conditions: N, MR, and SR, for a total of 21 homogenous items. In addition to their ample volume and comparable life cycle stages, these models are chosen for the fulfilment of the third research objective (see Chapter 2, Section 2.7), as they represent earlier stages of the product life cycle – introduction (iPhone 6s and Samsung Galaxy S6) and growth (iPhone 6 and Samsung Galaxy S5) – in order to explore the continuity of the relationship between price and volume previously explored in Chapter 5. Should discrepancies between price-volume links occur, they will be taken as evidence for product cannibalisation, which will be discussed in more details in Section 6.6.2. The dataset spans from 28th January 2016 to 20th July 2017, for a total of 540 observations. The average number of daily listings retrieved for each product is summarised in Table 6.1.

Table 6.1: The average number of listings per day of selected products

Product		**Specification**	**Platform**		**Corresponding Life Cycle Stage**
			eBay US	eBay UK	
Apple	iPhone 6s	64GB	352	176	Introduction
		16GB	630	256	
	iPhone 6	64GB	524	216	Growth
		16GB	844	420	
Samsung	Galaxy S6	64GB	206	46	Introduction
		32GB	1048	447	
	Galaxy S5	16GB	1978	538	Growth

6.3 Preliminary Data Analysis

In this section, the preliminary data analysis is performed on the data series previously set out in Section 6.2. This is to ensure that the properties of the data series under scrutiny are suitable for the analysis carried out using the subsequent empirical models. Figures 6.1 to 6.4 exemplify overall evolution of the prices and volume of iPhone 6s (64GB and 16GB) and iPhone 6 (64GB and 16GB), as well as Samsung Galaxy S6 (64GB and 32GB) and S5 (16GB). The products retrieved from eBay UK were originally listed in British Pound Sterling (GBP) and have been converted into USD using the corresponding daily exchange rate series taken from the Bank of England (Bank of England, 2017).

Overall, the price series in Figures 6.1 to 6.4 show downward trends throughout the entire data collection period. This is with an exception for the prices of new Samsung Galaxy S6 64GB where initially the prices decrease gradually before rising back up from August 2016 onwards. This price increase is less noticeable in the US (Figure 6.2) than its UK (Figure 6.4) counterpart. There exist also visible differences between the prices of new and remanufactured variants for all smartphone models. Notably, the price differences between new and remanufactured products are far more noticeable for Samsung Galaxy models compared to iPhone models, in both the US and UK markets. Furthermore, in both markets, the prices of all conditions of every smartphone model experience a sharp increase between December 2016 and January 2017, before plummeting back down and resuming the original trend – such a behaviour is less severe in the UK.

Figures 6.1 to 6.4 also portray overall evolution of the listing volume for all seven models (See Table 6.1) under scrutiny. The volume series in both the US and the UK markets fluctuate over time. Additionally, significant changes between December 2016 and January 2017 (similar to those documented for the prices) can also be found for volume series. To be more specific, the volume of each smartphone model decreases considerably between December 2016 and January 2017, before returning to the original level prior to the drop. Overall, it appears that the volume of MR and SR products behave relatively similar to each other. The volume of new items is generally the highest across all models. On the other hand, the volume of MR products is typically the lowest across all models under scrutiny.

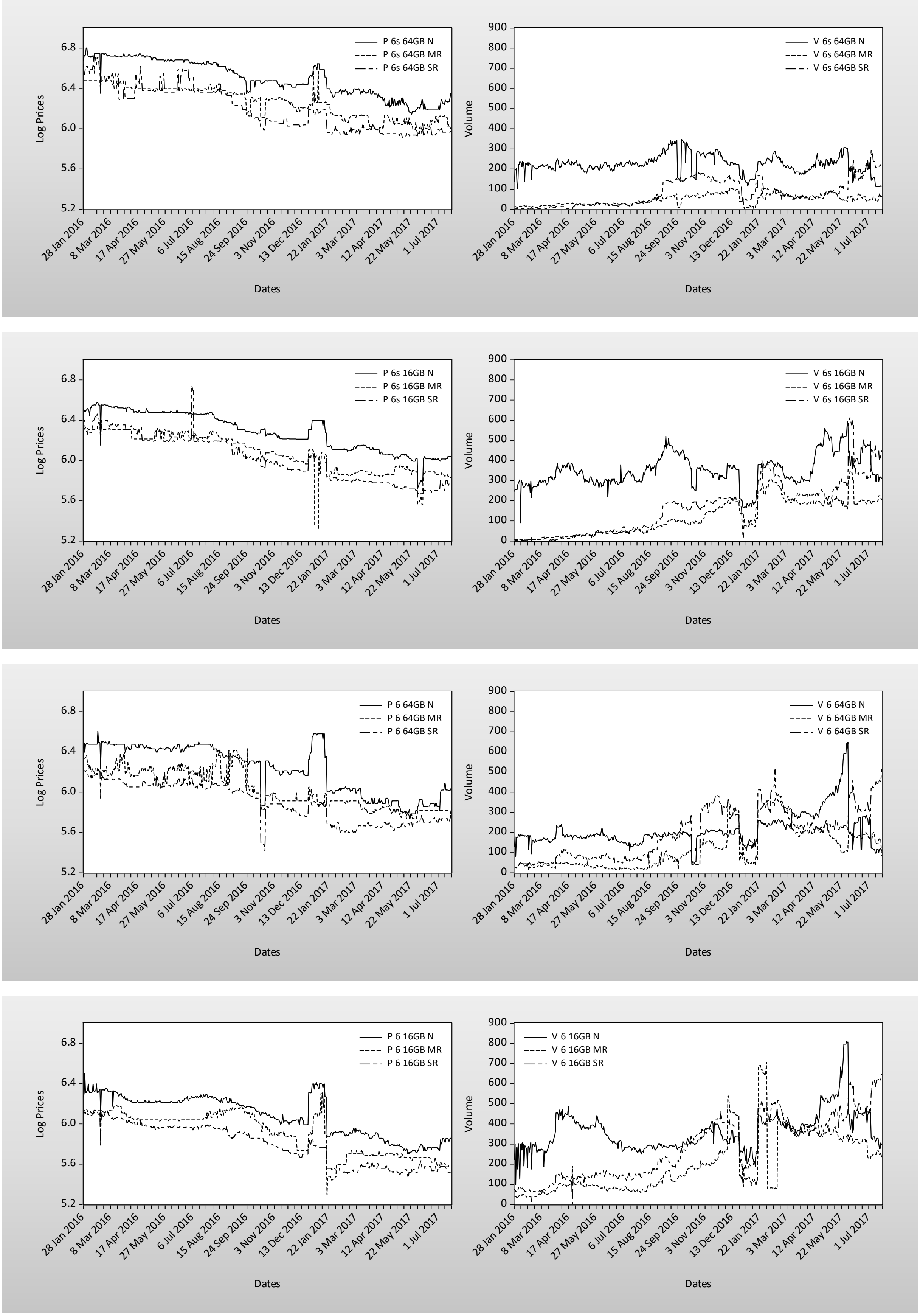

Figure 6.1: Price and volume of iPhone models in the US markets

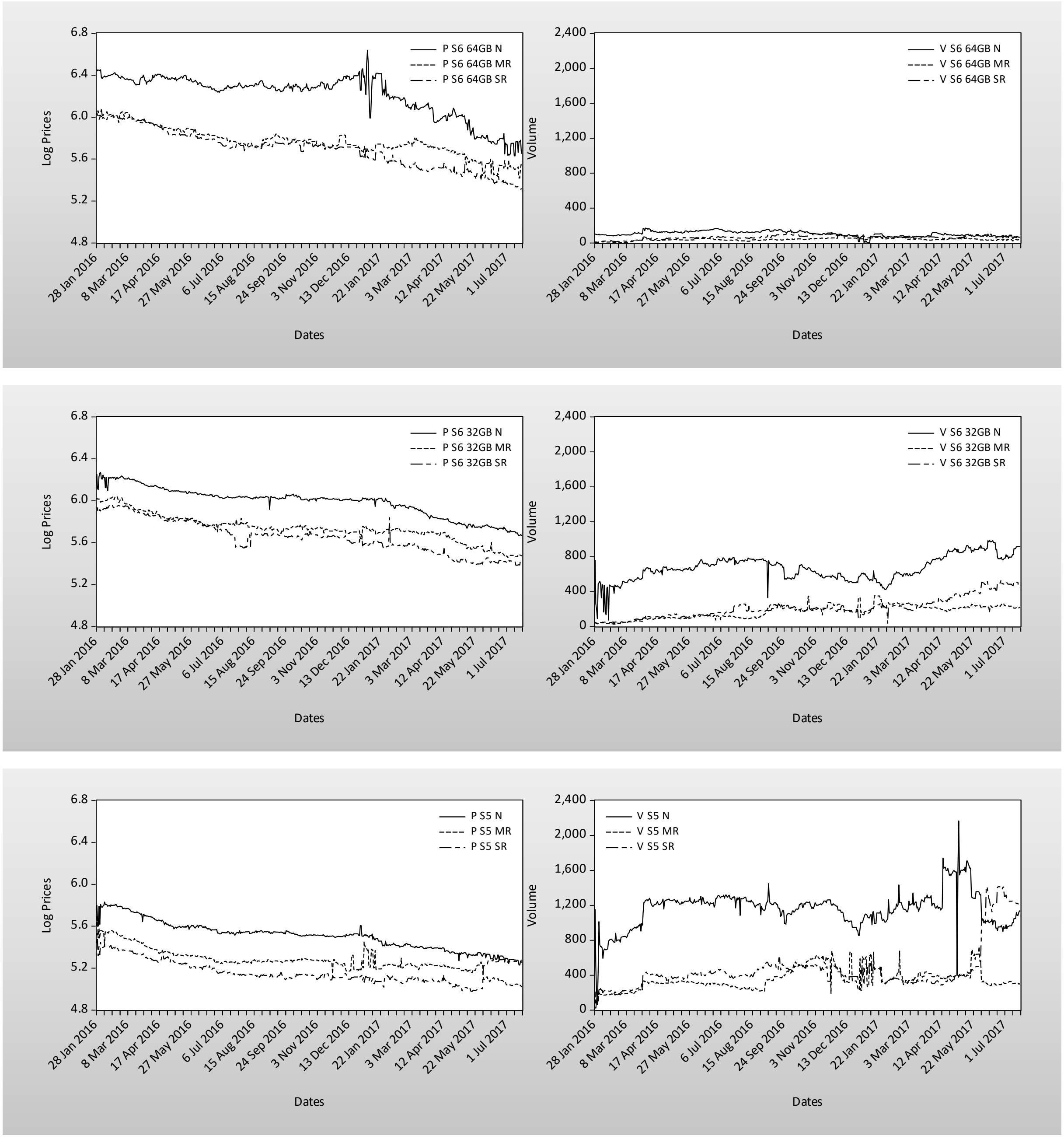

Figure 6.2: Price and volume of Samsung Galaxy models in the US markets

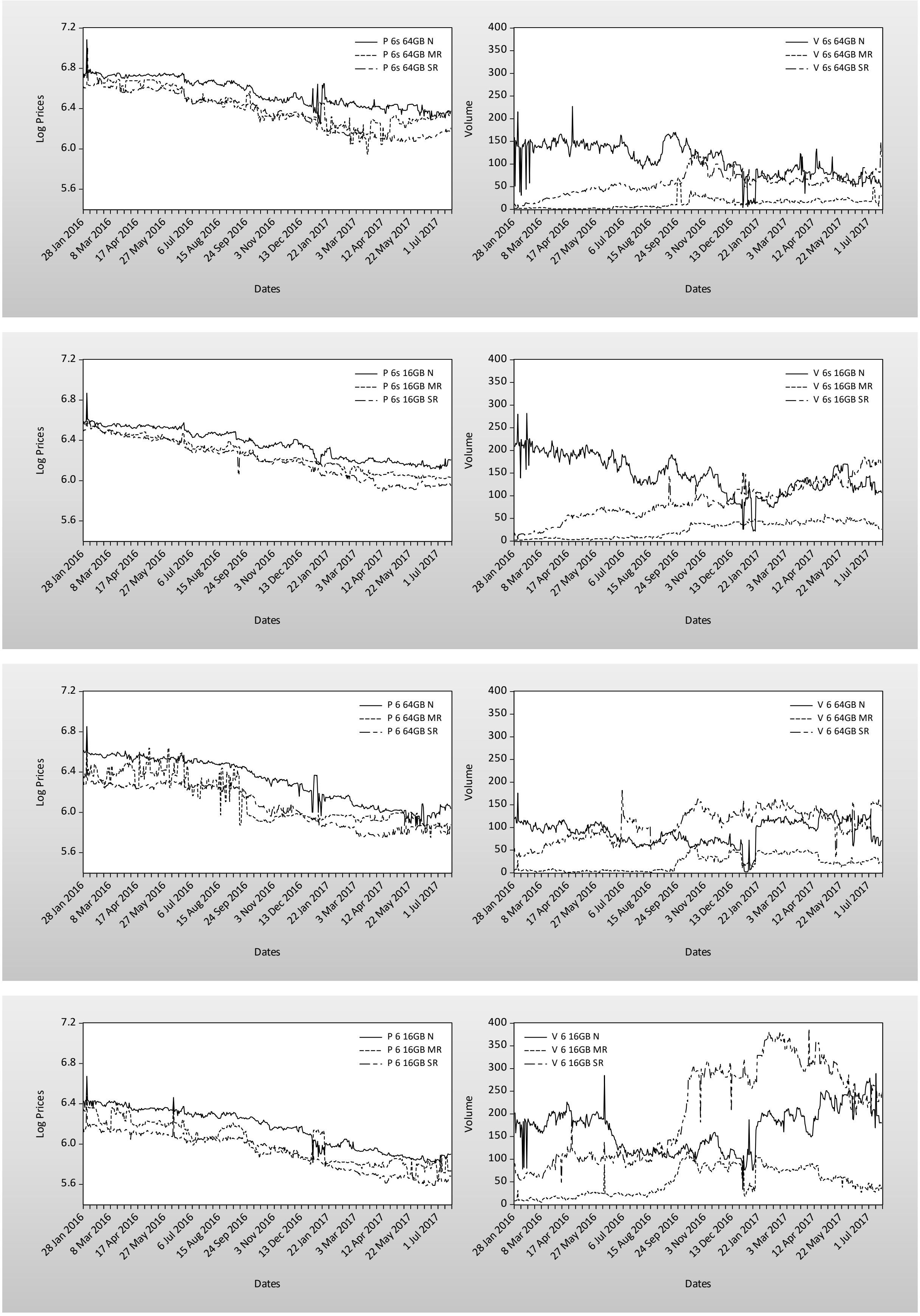

Figure 6.3: Price and volume of iPhone models in the UK markets

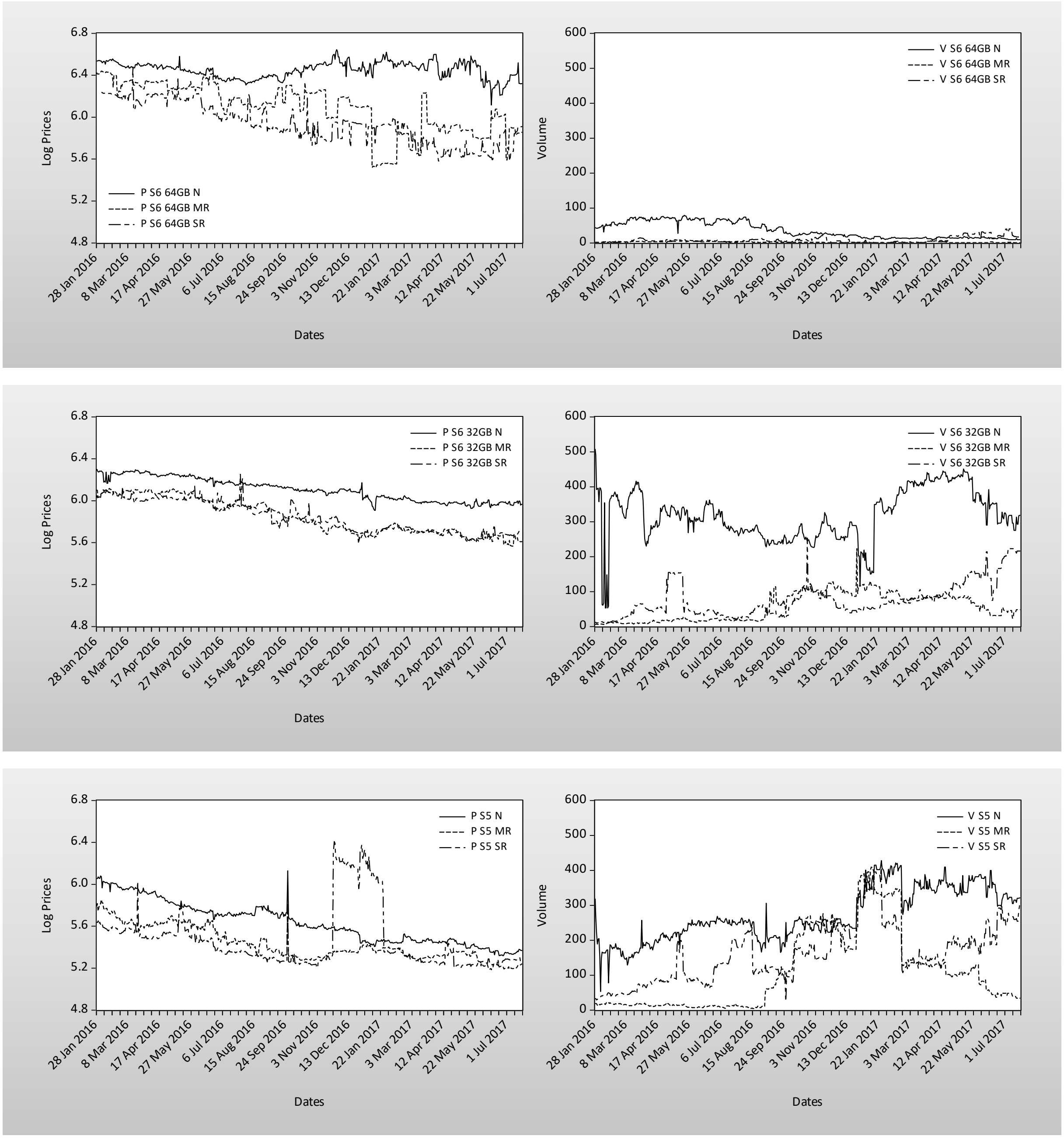

Figure 6.4: Price and volume of Samsung Galaxy models in the UK markets

Table 6.2 outlines the mean and median prices of iPhone 6s (64GB and 16GB) and iPhone 6 (64GB and 16GB), as well as Samsung Galaxy S6 (64GB and 32GB) and S5 (16GB) on eBay US and eBay UK. Overall, the prices of the products in the UK market are more expensive than those in the US counterpart. The mean prices of each smartphone item correspond directly to the capacity specification of the product model, regardless of the condition of the smartphone. In other words, the prices of iPhone 6s 64GB are higher than those of iPhone 6s 16GB, while the prices of Samsung Galaxy S6 64GB are higher than those of Samsung Galaxy S6 32GB. The same behaviour also applies when considering the listing prices of different conditions within a certain model, as new items have the highest listing price, followed by MR phones, then SR variants offered at the lowest price.

Table 6.2 also summarises the standard deviations of daily prices. In general, the deviations in the price setting are the highest for the new condition of iPhone and Samsung Galaxy models. The variations in the price setting of all product models under scrutiny are comparable in magnitude across the US and the UK markets (e.g. for iPhone 6s 64GB, SD_{US} = 120.27; SD_{UK} = 102.61). However, it is observed that the price settings of iPhone products are, typically, more volatile than those of Samsung Galaxy smartphones (e.g. iPhone 6s 64GB, SD_{US} = 120.27; Samsung Galaxy S6 64GB, SD_{US} = 92.51).

Table 6.2: Preliminary statistics of the dataset

Product Model				Statistics						
				Mean # of Daily Listings	**Mean Listing Prices (USD)**	**Median Listing Prices (USD)**	**SD**	**JB**	**Q(4)**	**$Q^2(4)$**
iPhone 6s	64GB	US	N	223.31	676.5	649.9	120.27	44.8 (0.000)	2072.3 (0.000)	2065.9 (0.000)
			MR	47.41	530.4	539.9	80.13	39.6 (0.000)	1930.4 (0.000)	1900.6 (0.000)
			SR	82.31	502.2	469.0	116.24	53.1 (0.000)	1961.8 (0.000)	1897.0 (0.000)
		UK	N	107.68	712.5	677.6	102.61	18.6 (0.000)	1923.9 (0.000)	1865.2 (0.000)
			MR	12.81	622.9	581.3	116.59	34.9 (0.000)	2005.7 (0.000)	2017.0 (0.000)
			SR	57.52	590.8	584.5	114.04	21.6 (0.000)	2054.6 (0.000)	1959.4 (0.000)
	16GB	US	N	350.27	547.1	539.0	101.88	39.9 (0.000)	2076.6 (0.000)	2076.9 (0.000)
			MR	118.45	438.7	439.9	91.93	435.6 (0.000)	1455.9 (0.000)	1861.4 (0.000)
			SR	162.43	423.3	409.9	99.80	28.74 (0.000)	1882.1 (0.000)	1675.0 (0.000)
		UK	N	145.73	586.4	582.2	88.95	23.72 (0.000)	2052.2 (0.000)	1995.4 (0.000)
			MR	24.89	526.3	501.5	87.26	36.13 (0.000)	2077.7 (0.000)	2060.3 (0.000)
			SR	87.89	503.1	494.9	96.87	34.24	2092.7	2083.5

Product Model				Statistics						
				Mean # of Daily Listings	**Mean Listing Prices (USD)**	**Median Listing Prices (USD)**	**SD**	**JB**	**Q(4)**	**$Q^2(4)$**
								(0.000)	(0.000)	(0.000)
iPhone 6	64GB	US	N	212.37	522.5	550.0	120.82	50.89 (0.000)	2017.4 (0.000)	2005.1 (0.000)
			MR	120.73	423.7	397.3	81.80	43.00 (0.000)	1844.3 (0.000)	1765.2 (0.000)
			SR	192.31	368.5	368.0	70.96	5.77 (0.000)	1807.5 (0.000)	1948.7 (0.000)
		UK	N	90.30	562.9	567.2	122.53	45.47 (0.000)	2054.3 (0.000)	2031.9 (0.000)
			MR	21.04	468.3	396.9	110.02	56.89 (0.000)	1768.8 (0.000)	1647.8 (0.000)
			SR	105.11	437.2	425.7	87.52	55.05 (0.000)	2084.3 (0.000)	2051.4 (0.000)
	16GB	US	N	362.37	448.1	476.3	87.39	38.68 (0.000)	2004.2 (0.000)	1966.4 (0.000)
			MR	200.08	375.4	415.0	75.03	44.94 (0.000)	1972.9 (0.000)	1941.4 (0.000)
			SR	282.66	335.5	339.9	66.32	45.28 (0.000)	2074.9 (0.000)	2064.0 (0.000)
		UK	N	166.61	478.4	490.6	93.02	38.57 (0.000)	2072.0 (0.000)	2032.4 (0.000)
			MR	49.23	412.3	389.6	82.02	37.85 (0.000)	1975.7 (0.000)	1948.0 (0.000)
			SR	205.45	377.8	390.9	69.45	24.56	2044.1	1961.1

Product Model				Statistics						
				Mean # of Daily Listings	**Mean Listing Prices (USD)**	**Median Listing Prices (USD)**	**SD**	**JB**	**Q(4)**	**$Q^2(4)$**
								(0.000)	(0.000)	(0.000)
Samsung Galaxy S6	64GB	US	N	103.00	507.3	537.7	92.51	71.98 (0.000)	1891.9 (0.000)	1814.7 (0.000)
			MR	39.31	322.4	314.9	43.29	9.95 (0.007)	2022.3 (0.000)	2020.6 (0.000)
			SR	65.21	301.3	303.4	54.98	16.57 (0.000)	2067.9 (0.000)	2068.2 (0.000)
		UK	N	36.01	634.6	643.3	49.00	9.49 (0.009)	1546.8 (0.000)	1531.2 (0.000)
			MR	2.63	451.5	457.1	98.47	24.81 (0.000)	1877.9 (0.000)	1885.0 (0.000)
			SR	8.31	380.0	370.9	83.82	254.82 (0.000)	1432.1 (0.000)	1629.9 (0.000)
	32GB	US	N	665.42	402.8	412.0	54.83	8.46 (0.015)	2057.8 (0.000)	2044.2 (0.000)
			MR	169.86	313.2	308.0	40.87	27.27 (0.000)	2044.1 (0.000)	2041.8 (0.000)
			SR	214.51	288.5	286.1	46.51	27.44 (0.000)	2069.8 (0.000)	2069.5 (0.000)
		UK	N	317.87	451.5	447.1	49.14	39.47 (0.000)	2044.9 (0.000)	2042.4 (0.000)
			MR	55.96	349.6	326.2	60.21	57.61 (0.000)	2095.5 (0.000)	2098.3 (0.000)
			SR	75.61	350.3	341.2	53.26	40.29	1972.6	1917.4

Product Model				Statistics						
				Mean # of Daily Listings	Mean Listing Prices (USD)	Median Listing Prices (USD)	SD	JB	Q(4)	$Q^2(4)$
								(0.000)	(0.000)	(0.000)
Samsung Galaxy S5	16GB	US	N	1157.57	249.7	249.1	34.62	28.91 (0.000)	2057.6 (0.000)	2049.8 (0.000)
			MR	354.94	190.0	192.4	23.14	148.41 (0.000)	1818.4 (0.000)	1791.1 (0.000)
			SR	467.43	177.1	169.9	19.60	61.98 (0.000)	1961.9 (0.000)	1940.6 (0.000)
		UK	N	271.74	285.1	270.1	59.15	44.63 (0.000)	2022.3 (0.000)	1975.4 (0.000)
			MR	108.45	230.6	215.0	37.96	66.77 (0.000)	1943.3 (0.000)	1908.1 (0.000)
			SR	159.85	248.6	210.8	92.54	672.46 (0.000)	1870.6 (0.000)	1811.0 (0.000)

Notes: Sample period 28/01/16–31/08/17. Preliminary statistics for New (N), Manufacturer-refurbished (MR) and Seller-refurbished (SR) iPhone 6s 64GB and 16GB, iPhone 6 64GB and 16GB, Samsung Galaxy S6 64GB and 32GB, and Samsung Galaxy S5 16GB.
JB is Jarque-Bera statistics for the null of normality in distribution. P-Values in parentheses.
Q(4) and $Q^2(4)$ are Ljung–Box statistics for serial correlation up to lag 4 in raw and squared raw series. P-Values in parentheses.

Table 6.2 also shows the average volume of iPhone 6s (64GB and 16GB) and iPhone 6 (64GB and 16GB), as well as Samsung Galaxy S6 (64GB and 32GB) and S5 (16GB) in the US and UK markets. In general, the average total volume of all products under scrutiny increase as the capacity specification of each model decreases. In other words, the average volume of iPhone 6s 64GB, for example, is lower than the average volume of its 16GB counterpart. This, again, implies that the demand pattern of each smartphone mirrors the one in primary markets, as the models with lower capacity specification were sold in larger volume than the higher-end models. Considering the number of products on offer in relation to the product condition, it appears that the N condition has the highest volume, while the MR variant has the lowest volume. Overall, there are more product listings in the US market than the UK. Interestingly, there are significantly fewer Samsung Galaxy S6 64GB on offer in both markets compared to not only its 32GB counterpart, but also the rest of the product models under scrutiny. Ultimately, the volume of Samsung Galaxy S5 16GB on eBay US seems to be the largest amongst all conditions and model specifications.

6.3.1 Empirical Distributions of the Data

Similar to the previous chapter, the first step of the analysis in this chapter is to take the logarithmic transformation of the price series.[13] Subsequently, both the Ng and Perron (2001) test and the KPSS (1992) test are applied to the log price series. The values of such statistics are reported in Tables 6.3 and 6.4.[14, 15] The top values are the statistics generated by taking both trend and intercept into account, whereas the values in the parentheses are those obtained by taking only the intercept into consideration. The empirical results indicate that all of the series are not stationary, as the unit-root tests within the Ng-Perron framework consistently fail to reject the null of integrated series at standard significance levels. Likewise, the KPSS tests consistently reject the null of stationarity at standard significance levels. All series under scrutiny are subsequently transformed by taking the first difference to achieve stationarity.

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[13] The logarithmic transformation makes it possible to reduce the level of heteroscedasticity in the series. The same transformation is not applied to the volume series as these may drop to zero on specific days, which is undefined on a logarithmic scale.

[14] Such statistics are applied as they have better size and stronger power than other unit-root tests when the data generating process is characterized by heteroscedasticity and serial correlation (see Ng and Perron, 2001).

[15] Additional tests such as the ADF and DF-GLS tests are also applied from which similar results as those set out in the two tables are obtained. Their results are not reported to save space.

Table 6.3: Unit root tests results for selected smartphones in the US

Product Model	Capacity	Variable	Condition	Lags	Ng-Perron				KPSS[e]
					MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 6s	64GB	Price	N	3	–10.32	–2.23	0.22	9.04	0.11
				(2)	(–0.61)	(–0.37)	(0.59)	(21.29)	(2.72)**
			MR	10	–10.22	–1.88	0.23	7.06	0.18*
				(9)	(0.58)	(0.37)	(0.65)	(30.97)	(2.75)**
			SR	3	–11.37	–2.29	0.20	8.52	0.26**
				(3)	(0.22)	(0.19)	(0.87)	(49.53)	(2.58)**
		Volume	N	17	–3.93	–1.18	0.30	20.60	0.25**
				(17)	(–2.41)	(–1.09)	(0.45)	(10.08)	(0.30)
			MR	6	–12.88	–2.37	0.19	6.77	0.28**
				(7)	(–4.85)	(–1.46)	(0.30)	(5.29)	(1.68)**
			SR	1	–11.25	–2.32	0.21	8.40	0.26**
				(6)	(–0.21)	(–0.09)	(0.43)	(15.69)	(1.63)**
	16GB	Price	N	2	–11.39	–2.27	0.25	7.28	0.23**
				(2)	(–0.12)	(–0.07)	(0.59)	(23.66)	2.75**
			MR	12	–10.60	–2.29	0.22	8.64	0.28**
				(12)	(–0.02)	(–0.01)	(0.68)	(29.36)	(2.95)**
			SR	14	–13.22	–2.59	0.19	6.61	0.19*
				(10)	(0.37)	(0.32)	(0.88)	(48.60)	(2.95)**
		Volume	N	1	–13.92	–2.53	0.19	5.48	0.22**
				(1)	(–6.84)	(–1.84)	(0.27)	(3.63)	(0.69)*
			MR	9	–12.97	–2.37	0.19	7.07	0.15*
				(8)	(–0.75)	(–0.40)	(0.53)	(0.53)	(2.58)**
			SR	8	–14.27	–2.70	0.18	6.56	0.06
				(8)	(0.09)	(0.04)	(0.46)	(17.40)	(2.66)**

Product Model	Capacity	Variable	Condition	Lags	Ng-Perron				KPSS[e]
					MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 6	64GB	Price	N	8	–15.40	–2.76	0.18	5.99	0.21*
				(7)	(–2.56)	(–0.99)	(0.39)	(8.96)	(2.41)**
			MR	4	–11.01	–2.23	0.25	6.38	0.18*
				(9)	(–0.15)	(–0.09)	(0.60)	(24.08)	(2.57)**
			SR	9	–17.38	–2.83	0.16	5.99	0.21*
				(8)	(–0.33)	(–0.23)	(0.69)	(28.36)	(2.79)**
		Volume	N	11	–14.51	–2.90	0.16	6.79	0.17*
				(10)	(–7.32)	(–1.91)	(0.26)	(3.36)	(1.22)**
			MR	2	–14.95	–2.91	0.16	5.63	0.22**
				(17)	(–6.02)	(–1.72)	(0.29)	(4.10)	(1.95)**
			SR	1	–17.15	–2.23	0.19	6.70	0.15*
				(1)	(–0.69)	(–0.25)	(0.37)	(12.26)	(2.28)**
	16GB	Price	N	2	–12.28	–2.48	0.20	7.43	0.25**
				(3)	(–1.83)	(–0.75)	(0.41)	(10.96)	(2.38)**
			MR	4	–14.49	–2.83	0.18	6.13	0.23**
				(4)	(–3.50)	(–1.09)	(0.31)	(6.99)	(2.50)**
			SR	2	–16.91	–2.34	0.17	6.69	0.21*
				(2)	(0.72)	(0.67)	(0.93)	(58.48)	(2.83)**
		Volume	N	16	–12.40	–2.38	0.19	7.94	0.22**
				(16)	(–3.29)	(–1.27)	(0.39)	(7.44)	(0.99)**
			MR	17	–14.65	–2.69	0.21	6.20	0.15*
				(17)	(–2.89)	(–1.13)	(0.39)	(8.30)	(2.34)**
			SR	1	–12.59	–2.27	0.19	6.56	0.17*
				(1)	(0.56)	(0.28)	(0.50)	(20.92)	(2.58)**

Product Model	Capacity	Variable	Condition	Lags	Ng-Perron				KPSS[e]
					MZa[a]	MZt[b]	MSB[c]	MPT[d]	
Samsung Galaxy S6	64GB	Price	N	18 (8)	–1.34 (2.59)	–0.55 (2.07)	0.41 (0.80)	38.15 (61.54)	0.59** (2.08)**
			MR	10 (16)	–6.38 (0.98)	–1.77 (1.27)	0.28 (1.29)	14.29 (112.00)	0.28** (2.45)**
			SR	14 (5)	–4.20 (1.62)	–1.40 (2.58)	0.33 (1.59)	21.18 (188.82)	0.29** (2.74)**
		Volume	N	10 (10)	–6.72 (–5.68)	–1.81 (–1.61)	0.27 (0.28)	13.58 (4.56)	0.30** (1.51)**
			MR	8 (8)	–10.76 (–2.74)	–2.19 (–1.15)	0.20 (0.42)	9.13 (8.86)	0.36** (1.07)**
			SR	2 (2)	–8.59 (–1.07)	–2.02 (–0.59)	0.24 (0.55)	10.80 (17.23)	0.50** (1.40)**
	32GB	Price	N	3 (2)	–5.25 (1.78)	–1.53 (2.49)	0.29 (1.40)	17.06 (151.73)	0.48** (2.57)**
			MR	5 (5)	–3.71 (1.47)	–1.36 (2.51)	0.37 (1.71)	24.51 (210.84)	0.32** (2.45)**
			SR	3 (3)	–16.16 (0.90)	–2.81 (1.02)	0.17 (1.14)	5.82 (86.84)	0.23** (2.68)**
		Volume	N	2 (2)	–6.88 (–6.36)	–1.78 (–1.72)	0.26 (0.27)	13.34 (4.05)	0.35** (0.97)**
			MR	18 (18)	–10.04 (–0.10)	–2.17 (–0.08)	0.22 (0.78)	9.42 (35.84)	0.40** (2.45)**
			SR	4 (3)	–10.85 (1.01)	–2.29 (0.72)	0.21 (0.71)	8.58 (38.96)	0.39** (2.28)**

Product Model	Capacity	Variable	Condition	Lags	Ng-Perron				KPSS[e]
					MZa[a]	MZt[b]	MSB[c]	MPT[d]	
Samsung Galaxy S5	16GB	Price	N	4 (4)	–4.70 (1.40)	–1.53 (2.79)	0.33 (1.99)	19.40 (278.03)	0.27** (2.67)**
			MR	15 (17)	–1.99 (1.27)	–0.99 (2.04)	0.50 (1.61)	45.90 (179.23)	0.34** (2.33)
			SR	1 (1)	–2.43 (–0.69)	–0.80 (–0.54)	0.33 (0.78)	26.64 (30.77)	0.49** (1.51)**
		Volume	N	4 (4)	–10.75 (–5.44)	-2.31 (–1.28)	0.22 (0.32)	8.50 (4.35)	0.19* (0.53)*
			MR	16 (4)	–8.16 (–6.18)	–1.93 (–1.74)	0.24 (0.28)	11.46 (4.02)	0.33** (1.10)**
			SR	6 (6)	–6.85 (0.37)	–1.70 (0.14)	0.25 (0.39)	13.48 (15.26)	0.26** (0.99)**

Notes: Sample period 28/01/16–20/07/17. Unit root tests are applied to series (log prices) in levels with constant and trend, and then with constant only (given in parentheses). * and ** denote statistical significance at 5% and 1% levels.
Ng-Perron test comprises of four test statistics, which are [a] MZa with critical values at 5% (1%) level equal to −17.30 (−23.80) for constant and trend (−8.10 (−13.80) for constant), [b] MZt with critical values at 5% (1%) level equal to −2.91 (−3.42) for constant and trend (−1.98 (−2.58) for constant), [c] MSB with critical values at 5% (1%) level equal to 0.17 (0.14) for constant and trend (0.23 (0.17) for constant), and [d] MPT with critical values at 5% (1%) level equal to 5.48 (4.03) for constant and trend (3.17 (1.78) for constant). [e] KPSS with critical values at 5% (1%) level equal to 0.15 (0.22) for constant and trend (0.46 (0.74) for constant). Tests computed using spectral GLS de-trended AR kernel based on Modified AIC.

Table 6.4: Unit root tests results for selected smartphones in the UK

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 6s	64GB	Price	N	15	10.99	–2.33	0.21	8.35	0.24**
				(7)	(0.40)	(0.30)	(0.76)	(38.37)	(2.85)**
			MR	17	–5.40	–1.44	0.27	16.32	0.43**
				(17)	(0.16)	(0.17)	(1.06)	(64.34)	(2.57)**
			SR	16	–2.67	–0.94	0.35	27.51	0.25**
				(1)	(-0.04)	(0.03)	(0.73)	(33.03)	(2.88)**
		Volume	N	6	–15.35	–2.77	0.18	5.95	0.15*
				(6)	(-0.66)	(-0.32)	(0.48)	(16.01)	(2.27)**
			MR	17	–9.36	–2.14	0.23	9.84	0.28**
				(17)	(-0.29)	(-0.14)	(0.48)	(17.33)	(1.97)**
			SR	15	–12.27	–2.43	0.20	7.68	0.44**
				(15)	(0.51)	(0.27)	(0.53)	(22.77)	(1.69)**
	16GB	Price	N	1	–16.31	–2.18	0.22	6.95	0.18*
				(1)	(0.04)	(0.03)	(0.72)	(32.67)	(2.88)**
			MR	8	–15.07	–2.62	0.17	6.79	0.23**
				(1)	(0.81)	(0.95)	(1.18)	(90.48)	(2.91)**
			SR	4	–14.00	–2.41	0.24	6.11	0.15*
				(4)	(0.91)	(1.12)	(1.23)	(99.81)	(2.90)**
		Volume	N	11	–8.63	–2.06	0.24	10.61	0.42**
				(11)	(–0.44)	(–0.27)	(0.60)	(22.62)	(2.02)**
			MR	9	–4.33	–1.13	0.26	18.40	0.31**
				(2)	(–0.78)	(–0.53)	(0.67)	(24.16)	(2.65)**
			SR	7	–10.51	–2.18	0.19	6.58	0.18*
				(3)	(1.04)	(0.82)	(0.79)	(46.69)	(2.68)**

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	**MZa[a]**	**MZt[b]**	**MSB[c]**	**MPT[d]**	
iPhone 6	64GB	Price	N	11	–4.47	–1.44	0.32	19.94	0.44**
				(11)	(0.99)	(1.67)	(1.68)	(183.88)	(2.87)**
			MR	13	–10.13	–2.25	0.22	9.01	0.33**
				(13)	(–0.24)	(–0.15)	(0.61)	(23.86)	(2.66)**
			SR	4	–6.01	–1.71	0.29	15.16	0.35**
				(4)	(0.71)	(0.73)	(1.04)	(70.72)	(2.77)**
		Volume	N	10	–10.87	–2.33	0.21	8.40	0.41**
				(11)	(–8.22)	(–1.94)	(0.24)	(3.31)	(0.47)**
			MR	1	–14.69	–2.67	0.18	6.47	0.32**
				(1)	(–4.82)	(–1.51)	(0.31)	(5.19)	(1.84)**
			SR	5	–16.64	–2.88	0.17	5.52	0.36**
				(5)	(–1.83)	(–0.78)	(0.42)	(11.18)	(1.94)**
	16GB	Price	N	7	–7.88	–1.94	0.25	11.69	0.39**
				(4)	(0.90)	(1.10)	(1.23)	(100.37)	(2.87)**
			MR	6	–12.30	–2.00	0.19	6.90	0.19*
				(8)	(0.01)	(0.01)	(0.64)	(27.40)	(2.71)**
			SR	8	–4.25	–1.43	0.34	21.16	0.49**
				(7)	(1.01)	(1.49)	(1.47)	(142.90)	(2.86)**
		Volume	N	9	–5.20	–1.61	0.31	17.49	0.58**
				(9)	(–4.40)	(–1.47)	(0.34)	(5.59)	(0.87)**
			MR	2	–9.66	–2.09	0.22	9.91	0.48**
				(2)	(–2.82)	(–1.16)	(0.41)	(8.59)	(1.58)**
			SR	4	–4.08	–1.32	0.32	21.25	0.37**
				(4)	(–0.33)	(–0.25)	(0.77)	(33.65)	(2.30)**

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
Samsung Galaxy S6	64GB	Price	N	7 (7)	–13.52 (–5.62)	–2.57 (–1.46)	0.19 (0.26)	6.90 (4.99)	0.27** (0.27)
			MR	7 (7)	–15.99 (–2.28)	–2.86 (–0.89)	0.18 (0.39)	6.09 (9.62)	0.16* (2.28)**
			SR	17 (12)	–5.44 (–0.41)	–1.36 (–0.32)	0.25 (0.79)	16.02 (33.82)	0.21* (2.63)**
		Volume	N	1 (1)	–7.65 (–2.66)	–1.95 (–0.98)	0.26 (0.37)	11.92 (8.61)	0.31** (2.56)**
			MR	17 (17)	–15.39 (–4.46)	–2.76 (–0.68)	0.18 (0.29)	5.99 (7.49)	0.15* (1.02)**
			SR	18 (18)	–9.27 (–2.02)	–2.15 (–0.82)	0.23 (0.40)	9.83 (10.39)	0.35** (1.02)**
	32GB	Price	N	18 (6)	–14.85 (0.73)	–2.01 (0.76)	0.19 (1.05)	6.24 (71.92)	0.20* (2.89)**
			MR	2 (2)	–16.62 (0.71)	–2.87 (0.65)	0.17 (0.92)	5.56 (56.36)	0.39** (2.76)**
			SR	12 (7)	–14.21 (0.04)	–2.59 (0.03)	0.18 (0.74)	6.84 (34.38)	0.25** (2.83)**
		Volume	N	1 (1)	–12.02 (–4.97)	–2.44 (–1.51)	0.20 (0.30)	7.64 (5.09)	2.23** (4.50)**
			MR	5 (5)	–4.35 (–1.26)	–1.34 (–0.74)	0.31 (0.59)	19.83 (17.78)	1.49** (4.94)**
			SR	5 (5)	–13.61 (–0.22)	–2.49 (–0.08)	0.18 (0.37)	7.41 (13.26)	0.72** (4.00)**

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
Samsung Galaxy S5	16GB	Price	N	5	–6.63	–1.70	0.26	13.83	0.72**
				(5)	(0.95)	(1.61)	(1.70)	(185.94)	(8.61)**
			MR	5	–6.83	–1.79	0.26	13.42	1.19**
				(5)	(0.55)	(0.57)	(1.04)	(67.99)	(7.33)**
			SR	5	–10.92	–2.34	0.21	8.35	0.53**
				(5)	(–7.61)	(–1.88)	(0.25)	(3.48)	(0.76)
		Volume	N	5	–5.15	–1.60	0.31	17.70	0.39**
				(5)	(–4.68)	(–1.53)	(0.33)	(5.24)	(6.80)**
			MR	5	–4.79	–1.43	0.30	18.35	1.32**
				(5)	(–2.93)	(–1.21)	(0.41)	(8.37)	(3.30)**
			SR	5	–14.81	–2.06	0.16	6.88	0.49**
				(5)	(–1.57)	(–0.62)	(0.39)	(11.21)	(4.72)**

Notes: Sample period 28/01/16–20/07/17. Unit root tests are applied to series (log prices) in levels with constant and trend, and then with constant only (given in parentheses). * and ** denote statistical significance at 5% and 1% levels.
Ng-Perron test comprises of four test statistics, which are [a] MZa with critical values at 5% (1%) level equal to −17.30 (−23.80) for constant and trend (−8.10 (−13.80) for constant), [b] MZt with critical values at 5% (1%) level equal to −2.91 (−3.42) for constant and trend (−1.98 (−2.58) for constant), [c] MSB with critical values at 5% (1%) level equal to 0.17 (0.14) for constant and trend (0.23 (0.17) for constant), and [d] MPT with critical values at 5% (1%) level equal to 5.48 (4.03) for constant and trend (3.17 (1.78) for constant). [e] KPSS with critical values at 5% (1%) level equal to 0.15 (0.22) for constant and trend (0.46 (0.74) for constant). Tests computed using spectral GLS de-trended AR kernel based on Modified AIC.

Once the log price series under scrutiny are transformed by means of first differences, their empirical distributions are examined. It is found that, despite resembling normal distributions, both the Jarque-Bera and Kolmogorov-Smirnov tests soundly reject the null of normality at standard significance levels for all series. Nevertheless, according to Field (2013), these aforementioned tests are more sensitive to the slightest departure from normality when the sample size is large. This, together with the fact that normality of variables is not a necessary requirement for OLS estimators, means the analysis can be carried out using the log-transformed series – with caution regarding non-normality and heteroscedasticity of residuals – instead of performing another bootstrap analysis.

6.4 Model Specifications

This section introduces different model specifications based on both the preliminary statistics presented in Section 6.3, and the application of the AIC and SBC. Considering the preliminary analysis of the price and volume series, it is clear that all the series under scrutiny are integrated of order one (i.e. each has a unit root); this means that the subsequent analysis is performed on the log-transformed series to remove the presence of a unit root, as stationarity is required in order to ensure that the asymptotic properties of standard linear regression models hold. The link between prices and volume is analysed using standard auto-regression models with the following specification:

$$\Delta P_t = \alpha + \sum_{p=1}^{P} \beta_p \Delta P_{t-1} + \lambda \Delta V_t + \varepsilon_t \qquad (6.1)$$

where ΔP_t is the daily change in price at time *t*, and ΔV_t is the daily change in volume at time *t*; ε_t is an error term, which is normally distributed with mean equals to 0 and variance ${\sigma_t}^2$. The specified model is estimated using OLS on daily series of 540 observations, where the most suitable lag length P is determined using both the AIC and SBC. The presence of heteroscedasticity and serial correlation in the residuals of each model is then determined by applying the Ljung-Box Q-stats, LM tests and ARCH-LM tests.

This chapter also takes into account the presence of GARCH-type volatility, since the empirical estimates are performed on non-normal daily series, by supplementing eq. (6.1) with GARCH dynamics. Such a model can capture volatility clusters in the disturbance terms, which facilitates the investigation into the effect of volume on the volatility of prices. The conditional variance dynamics are specified as:

$$\sigma_t^2 = \omega + \sum_{j=1}^{J} \alpha_j \varepsilon_{t-j}^2 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \qquad (6.2)$$

where ω is the long-run variance; j is the number of ARCH terms, and q is the number of GARCH terms. For the model to be stationary, $\alpha_j + \beta_q < 1$ and α_j, $\beta_q > 0$. The model is estimated by means of ML, where the most suitable lag lengths J, and Q are, likewise, determined using both the AIC and SBC.

In order to account for possible endogeneity in the price-volume relationships, eq. (6.1) is re-estimated using 2SLS methods. This is because the two variables, price and volume, might be jointly determined in equilibrium as a result of the intersection between supply and demand curves. Consequently, a simultaneous relationship between them can occur, leading to a serious violation of an important assumption of the OLS estimation – independent distribution of explanatory variables. In such cases, the resulting empirical estimates are considered biased and inconsistent. The severity of the endogeneity issue in the series is determined by comparing the estimates originally obtained using OLS against their 2SLS counterparts; if departures between the two sets of estimates are observed, the inferences are made based on the 2SLS estimates, as they can better correct for endogeneity.

6.5 Empirical Results

In this section, the empirical estimations of eq. (6.1) and eq. (6.2) are carried out for price and volume series previously set out using OLS and 2SLS to ensure the robustness of the results. Both the AIC and SBC criteria are utilised to determine the number of lags of AR- and GARCH-terms to include in the model; in order to capture any potential weekly seasonality, the model specification is tested with lag lengths from 1 to 7. For AR-terms, the results suggest different lag lengths for each series with significant improvement in both the AIC and SBC.[16] This means that it is not possible to apply the same model specification to all the series under scrutiny. It should be noted that the additional lags are included in the model so as to improve the overall fit, along with reducing chances of serial correlation, but only the first lag – yesterday's prices – are of interest. As for GARCH-terms, the results indicate that lag length 1 is appropriate for every series; the specification of each model is summarised in Table 6.5 below.

Table 6.5: The summary of model specifications

Product Model				**Model Specifications**
iPhone 6s	64GB	US	N	AR(2)-GARCH(1)
			MR	AR(7)-GARCH(1)
			SR	AR(3)-GARCH(1)
		UK	N	AR(5)-GARCH(1)
			MR	AR(3)-GARCH(1)
			SR	AR(6)-GARCH(1)
	16GB	US	N	AR(3)-GARCH(1)
			MR	AR(6)-GARCH(1)
			SR	AR(7)-GARCH(1)

[16] Similarly, diagnostic tests for serial correlation and heteroscedasticity – as well as R-squared statistics – improve considerably when additional lags are included in the specifications in use.

Product Model				Model Specifications
		UK	N	AR(4)-GARCH(1)
			MR	AR(5)-GARCH(1)
			SR	AR(3)-GARCH(1)
iPhone 6	64GB	US	N	AR(7)-GARCH(1)
			MR	AR(6)-GARCH(1)
			SR	AR(2)-GARCH(1)
		UK	N	AR(7)-GARCH(1)
			MR	AR(7)-GARCH(1)
			SR	AR(7)-GARCH(1)
	16GB	US	N	AR(2)-GARCH(1)
			MR	AR(6)-GARCH(1)
			SR	AR(5)-GARCH(1)
		UK	N	AR(5)-GARCH(1)
			MR	AR(6)-GARCH(1)
			SR	AR(5)-GARCH(1)
Samsung Galaxy S6	64GB	US	N	AR(6)-GARCH(1)
			MR	AR(2)-GARCH(1)
			SR	AR(4)-GARCH(1)
		UK	N	AR(3)-GARCH(1)
			MR	AR(4)-GARCH(1)
			SR	AR(6)-GARCH(1)
	16GB	US	N	AR(7)-GARCH(1)
			MR	AR(5)-GARCH(1)
			SR	AR(3)-GARCH(1)
		UK	N	AR(6)-GARCH(1)
			MR	AR(5)-GARCH(1)
			SR	AR(5)-GARCH(1)
Samsung Galaxy S5	32GB	US	N	AR(2)-GARCH(1)
			MR	AR(4)-GARCH(1)
			SR	AR(3)-GARCH(1)
		UK	N	AR(5)-GARCH(1)
			MR	AR(4)-GARCH(1)
			SR	AR(4)-GARCH(1)

Tables 6.6 – 6.12 outline the results from the OLS and 2SLS estimations of eq. (6.1). Both estimates generally deliver similar patterns of results across all models under scrutiny; nevertheless, whenever there is a discrepancy between the two sets of estimates, 2SLS results are prioritised over OLS as 2SLS estimators can better account for the endogeneity that can potentially affect the relationships between price and volume.

6.5.1 The Price Dynamics

The coefficients β_1 to β_7 in Tables 6.6 – 6.12 illustrate the relationships between changes in past and current prices of the iPhone and Samsung Galaxy models. Each coefficient corresponds to a specific day prior to the current time *t*; for instance, coefficient β_1 represents yesterday, β_2 represents the day before yesterday, and so on. In most cases, only the coefficient β_1 is significant, whereas the rest of the coefficients are not only lower in magnitude, but also are not statistically significant. This indicates a much weaker relationship, and hence, lower predictive power of prices beyond the day prior. As such, the results confirm the previous decision to only interpret coefficient β_1. It is observed that the majority of such a coefficient is significant at the 1% level, which is consistent between OLS and 2SLS results.

The absolute value of the coefficient β_1 represents price elasticity – the responsiveness of current prices to changes in past prices – which spans from −0.1160 (the lowest price elasticity found in iPhone 6s 16GB MR US) to −0.5471 (the highest price elasticity found in iPhone 6s 64GB SR UK). This signifies a relatively low level of persistence in the time dynamics of prices. The sign of the coefficients (i.e. positive or negative) indicates the nature of the relationship between changes in past price and changes in current price. Overall, the coefficients are significant and negative, showing that a positive change in past prices causes a reduction in current prices across all models and conditions in both the US and UK markets. Such dynamics are especially strong for the products in the UK, whereas they slightly weaken for US products, meaning that the price dynamics of the products in the US markets are less anchored to past price levels. In other words, the prices of smartphones in the US are more erratic than the UK.

Having discussed the overall pattern of price elasticity, this section continues to examine the degree of responsiveness of prices toward past prices of each product. Starting with the iPhone 6s, it appears that the prices of the new condition in the US (Table 6.6, $\beta_{1,\ 64GB}$ = 0.4233; Table 6.7, $\beta_{1,\ 16GB}$ = 0.2716) and the SR condition in the UK (Table 6.6, $\beta_{1,\ 64GB}$ = 0.5471; Table 6.7, $\beta_{1,\ 16GB}$ = 0.1789) exhibit the highest elasticity. In contrast, the MR condition in both US and UK markets (Table 6.6, $\beta_{1,\ 64GB\ US}$ = 0.3917; $\beta_{1,\ 64GB\ UK}$ = 0.1979; Table 6.7, $\beta_{1,\ 16GB\ US}$ = 0.1160; $\beta_{1,\ 64GB\ UK}$ = 0.1303) has the lowest responsiveness to changes in past prices. As for the iPhone 6, the MR variant in the US (Table 6.8, $\beta_{1,\ 64GB}$ = 0.5121; Table 6.9, $\beta_{1,\ 16GB}$ = 0.5196) and the UK (Table 6.8, $\beta_{1,\ 64GB}$ = 0.3043) has the highest elasticity in general. On the other hand, the new condition of the iPhone 6 has the lowest elasticity in general (Table 6.8, $\beta_{1,\ 64GB\ US}$ = 0.0921; $\beta_{1,\ 64GB\ UK}$ = 0.1897).

The results for the Samsung Galaxy S6 suggest that the new variant in the US (Table 6.11, $\beta_{1,\ 32GB}$ = 0.3448) and the SR variant in the UK (Table 6.10, $\beta_{1,\ 64GB}$ = 0.3002; Table 6.11, $\beta_{1,\ 32GB}$ = 0.3873) are the most sensitive to changes in past prices; this mirrors the results for the iPhone 6s presented earlier. In contrast, the MR variant in both the US and the UK (Table 6.10, $\beta_{1,\ 64GB\ US}$ = 0.2159; $\beta_{1,\ 64GB\ UK}$ = 0.0163) has the lowest price elasticity. Concerning the Samsung Galaxy S5, the new variant in the US (Table 6.11, $\beta_{1,\ 16GB}$ = 0.3858) and the MR condition in the UK (Table 6.12, $\beta_{1,\,16GB}$ = 0.5032) are the most responsive to changes in past prices, while the SR variant in both the US (Table 6.12, $\beta_{1,\,16GB}$ = 0.1378) and UK (Table 6.12, $\beta_{1,\,16GB}$ = 0.1594) markets has the lowest price elasticity. Accordingly, it appears that the Samsung Galaxy S6 and its S5 counterpart only have one thing in common – the new product variants in the US and the UK are the most responsive to changes in past prices.

Overall, the higher capacity models tend to be more sensitive to the changes in past prices, while the differences in the degree of responsiveness between the US and the UK are negligible. It is also observed that, in general, the magnitude of the coefficients are larger for iPhone models than Samsung Galaxy, indicating that the prices of iPhone products rely more heavily on past prices than Samsung Galaxy smartphones; this suggests that past prices of iPhone give a better indication of their current prices than past prices of Samsung Galaxy models.

Next, the investigation into whether the prices of MR and SR products can explain the prices of their new counterparts, and vice versa, is performed by testing the significance of the cross-lags of prices in eq. (6.1) using the VAR models (see Section 3.4.2.1 for more details). Additionally, the same test is conducted to determine whether the prices of items in the US market can explain the prices of the equivalent items in the UK, and vice versa. The results from such an exercise show virtually non-existent cross-interactions amongst the markets and conditions for both prices and volume. This suggests independence between the price and volume dynamics across markets and conditions, and a lack of spillover effects. In other words, a price (volume) decrease in one market / product condition is unlikely to result in a price (volume) decrease in another market / product condition. Accordingly, the analysis is limited to eq. (6.1) without cross-lags for prices and volume.

6.5.2 The Relationships between Price and Volume

The parameter λ in Tables 6.6 – 6.12 represents the relationship between changes in current price and changes in current volume of the smartphones under scrutiny. It can be seen that, compared to those of coefficient β_1, the magnitude of the coefficient λ is much smaller; this stems from the difference in scales of the dependent and independent variables in eq. (6.1), where the former is taken in log-first differences and the latter is taken in first differences. The majority of the parameter estimates are consistent between OLS and 2SLS estimators. The absolute value of the parameter is interpreted as semi-elasticity, which is the percentage change of price in response to a unit change in volume. In other words, it signifies how responsive current prices are to changes in volume. The magnitude of the coefficient λ ranges from −0.0001 (the lowest semi-elasticity found in Samsung Galaxy S6 32GB N UK) to −0.0041 (the highest semi-elasticity found in Samsung Galaxy S6 64GB SR UK). However, it is found that the magnitude in general is relatively similar across the US and the UK markets for all three conditions – except for Samsung Galaxy S6 64GB, which exhibits the highest sensitivity to changes in volume. The empirical results also signify that, overall, the changes in current price of new conditions are the least responsive to the changes in current volume across all markets compared to their remanufactured counterparts.

After examining the overall characteristics of semi-elasticity, the next focus of this section is on the sensitivity of prices towards changes in volume of each smartphone under scrutiny. Considering the iPhone 6s, the MR variant in both the US (Table 6.7, λ_{16GB} = 0.0006) and the UK markets (Table 6.7, λ_{16GB} = 0.0014) has the highest responsiveness of prices towards the changes in volume, whereas the SR condition (Table 6.6, $\lambda_{64GB\,US}$ = 0.0008; Table 6.7, $\lambda_{16GB\,US}$ = 0.0001) has the lowest sensitivity. Similar patterns are also observed for the iPhone 6, as prices of its MR variant in the US (Table 6.8, λ_{64GB} = 0.0011; Table 6.9, λ_{16GB} = 0.0008) respond the most to changes in volume. However, the same cannot be said for its UK counterpart, as the majority of the coefficients are not significant. On the other hand, the SR condition of the iPhone 6 in both the US (Table 6.8, λ_{64GB} = 0.0002; Table 6.9, λ_{16GB} = 0.0007) and the UK (Table 6.8, λ_{64GB} = 0.0007) markets exhibits the least sensitivity.

As for Samsung Galaxy S6, the N (Table 6.10, $\lambda_{64GB\,US}$ = 0.0008) and MR (Table 6.10, $\lambda_{64GB\,UK}$ = 0.0221; Table 6.11, $\lambda_{32GB\,UK}$ = 0.0004) variants are the most responsive towards the changes in volume. On the other hand, the SR (Table 6.10, $\lambda_{64GB\,US}$ = 0.0005) and the N (Table 6.10, $\lambda_{64GB\,UK}$ = 0.0021; Table 6.11, $\lambda_{32GB\,UK}$ = 0.0001) conditions are the least sensitive to changes in volume. Concerning the Samsung Galaxy S5, the SR variant (Table 6.12, $\lambda_{16GB\,US}$ = 0.0005) exhibits the highest responsiveness of prices towards the changes in volume, while the N condition (Table 6.12, $\lambda_{16GB\,UK}$ = 0.0007) shows the lowest semi-elasticity.

Moving on to the nature of the relationships between current prices and volume, the majority of iPhone products in the US markets exhibit strong negative patterns, meaning that the markets are saturated with products from sellers; consequently, price reduction is needed to attract demand from buyers when the volume is high. On the other hand, strong positive links between price and volume can be found for Samsung smartphones – except for the remanufactured variants of Samsung Galaxy S6 32GB – signifying that demand for such products is not affected by volume, as their prices increase even when the number of listings is high. This shows that the two products, iPhone and Samsung Galaxy, are actively competing with each other since Samsung Galaxy has more profit potential than iPhone. The patterns of the link between price and volume in the UK is significantly less conclusive than its US counterpart, as the relationships survive mainly for Samsung products.

Strong positive relationships between the changes in current prices and volume are observed in the markets for new items of all smartphones in this study, with the exceptions of iPhone 6 16GB and Samsung Galaxy S6 64GB. However, both the MR and SR variants of Samsung Galaxy S5 exhibit strong positive links between price and volume, suggesting that remanufactured variants of older product generations tend to have higher profit potential than remanufactured variants of newer product generations. This may stem from the preference of customers to purchase new conditions of the latest smartphone products.

It is possible to determine similarities and differences in dynamics by directly comparing two competing products either based on generation (e.g. iPhone 6s vs iPhone 6), specification (e.g. 64GB vs 16GB), or release date (e.g. iPhone 6s vs Samsung Galaxy S6). It is observed that the dynamics of iPhone products are incredibly similar across generations and specifications, but the same does not apply to Samsung Galaxy smartphones. For such products, the S5 model has the most profit potential of all, while the S6 32GB model has the least. When comparing iPhone against Samsung Galaxy models, the results suggest that both products experience similar dynamics in the US markets, indicating that their profit potential is comparable. In other words, when the profit potential of one product is high, the profit potential of the other is also high. However, the opposite is true for their UK counterparts, suggesting more active competition between products.

Table 6.6: Empirical estimates of eq. (6.1) for iPhone 6s 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0007	−0.0013	−0.0009	−0.0015	−0.0010	−0.0022	−0.0011*	−0.0015	−0.0008	−0.0012	−0.0010**	−0.0024*
	(0.0007)	(0.0012)	(0.0008)	(0.0014)	(0.0010)	(0.0017)	(0.0006)	(0.0013)	(0.0012)	(0.0016)	(0.0004)	(0.0013)
β_1	−0.4175***	−0.4233***	−0.3960***	−0.3917***	−0.2031***	−0.1993***	−0.4297***	−0.2711***	−0.2026***	−0.1979***	−0.5436***	−0.5471***
	(0.1247)	(0.1206)	(0.1114)	(0.1039)	(0.0485)	(0.0499)	(0.1357)	(0.1020)	(0.0706)	(0.0729)	(0.1519)	(0.1493)
β_2	−0.1607**	−0.1637**	−0.1584*	−0.1595**	−0.1848**	−0.1884**	−0.2029	−0.1858	−0.0866**	−0.0767*	−0.2988*	−0.2923*
	(0.0761)	(0.0794)	(0.0822)	(0.0813)	(0.0815)	(0.0829)	(0.1687)	(0.1594)	(0.0421)	(0.0432)	(0.1607)	(0.1639)
β_3	–	–	−0.0990*	−0.1004**	−0.1323***	−0.1345***	−0.1553	−0.0983	−0.0780	−0.0606	−0.1763	−0.1693
			(0.0576)	(0.0464)	(0.0484)	(0.0501)	(0.1140)	(0.0910)	(0.0738)	(0.0737)	(0.1307)	(0.1322)
β_4	–	–	−0.0988*	−0.0990*	–	–	−0.2184**	−0.2204**	–	–	−0.1416*	−0.1338
			(0.0527)	(0.0506)			(0.0973)	(0.0899)			(0.0811)	(0.0813)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
β_5	–	–	−0.0261 (0.0427)	−0.0247 (0.0419)	–	–	−0.1169** (0.0569)	−0.0882 (0.0769)	–	–	−0.1200** (0.0564)	−0.1109** (0.0558)
β_6	–	–	−0.1503* (0.0785)	−0.1511* (0.0799)	–	–	–	–	–	–	−0.0470 (0.0377)	−0.0416 (0.0366)
β_7	–	–	−0.1195 (0.1404)	−0.1012 (0.1428)	–	–	–	–	–	–	–	–
λ	0.0001 (0.0002)	0.0003 (0.0012)	−0.0000 (0.0005)	−0.0018 (0.0013)	−0.0004 (0.0003)	0.0008** (0.0004)	−0.0005** (0.0002)	−0.0001 (0.0002)	0.0013 (0.0008)	0.0024 (0.0018)	−0.0003* (0.0002)	−0.0005 (0.0008)
R^2	0.175	0.163	0.198	0.202	0.072	0.061	0.223	0.103	0.056	0.041	0.365	0.359
Q(8)	4.224 (0.646)	2.549 (0.959)	4.733 (0.030)	4.168 (0.842)	3.218 (0.666)	3.462 (0.902)	43.847 (0.000)	49.355 (0.000)	14.239 (0.014)	14.275 (0.075)	94.603 (0.000)	98.924 (0.000)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
LM(8)	9.837	4.693	11.084	17.134	3.940	3.590	99.500	53.008	22.839	16.824	152.500	157.033
	(0.277)	(0.790)	(0.197)	(0.029)	(0.863)	(0.892)	(0.000)	(0.000)	(0.004)	(0.032)	(0.000)	(0.000)
$Q^2(8)$	54.370	46.898	118.040	108.620	20.907	19.096	399.670	409.180	25.956	29.263	63.379	70.246
	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.014)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
ARCH(8)	53.408	44.423	94.643	86.594	19.423	17.863	233.729	202.744	21.739	23.931	84.668	81.483
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.022)	(0.000)	(0.000)	(0.005)	(0.002)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6s 64GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.
Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.7: Empirical estimates of eq. (6.1) for iPhone 6s 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0008	−0.0013	−0.0004	−0.0009	−0.0007	−0.0019	−0.0007	−0.0009	−0.0011**	−0.0012*	−0.0008	−0.0016**
	(0.0009)	(0.0012)	(0.0014)	(0.6862)	(0.3864)	(0.0019)	(0.0005)	(0.0006)	(0.0005)	(0.0524)	(0.0005)	(0.0008)
β_1	−0.2729***	−0.2716***	−0.1245***	−0.1160***	−0.1547***	−0.1481***	−0.3622***	−0.1295***	−0.2462***	−0.1303***	−0.2200***	−0.1789***
	(0.1663)	(0.1601)	(0.0765)	(0.0692)	(0.0106)	(0.0563)	(0.1204)	(0.0627)	(0.1036)	(0.0597)	(0.0721)	(0.0831)
β_2	−0.0964	−0.1089	0.0303	0.0090	−0.0588	−0.0590	−0.1176	−0.0398	−0.0345	0.0003	−0.2891***	−0.3036**
	(0.0774)	(0.0778)	(0.0406)	(0.0163)	(0.1279)	(0.0373)	(0.0945)	(0.0417)	(0.0835)	(0.0575)	(0.1050)	(0.1256)
β_3	−0.0136	−0.0240	0.0919	0.0793	−0.3786*	−0.3296	−0.0550	−0.0110	−0.1014*	−0.0824	−0.0861*	−0.0778*
	(0.0470)	(0.0481)	(0.0644)	(0.0636)	(0.0581)	(0.1955)	(0.0699)	(0.0324)	(0.0530)	(0.0538)	(0.0445)	(0.0427)
β_4	–	–	0.0548	0.0484	−0.1376***	−0.1203**	−0.0730**	−0.0305	−0.0591	−0.0449	–	–
			(0.0350)	(0.0377)	(0.0067)	(0.0510)	(0.0346)	(0.0495)	(0.0518)	(0.0523)		

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
β_5	–	–	−0.0426* (0.0804)	−0.0404* (0.0232)	−0.0626 (0.1196)	−0.0449 (0.0315)	–	–	0.0238 (0.0506)	0.0239 (0.0509)	–	–
β_6	–	–	−0.3855 (0.1518)	−0.3616 (0.2513)	−0.1234 (0.2780)	−0.0826 (0.1042)	–	–	–	–	–	–
β_7	–	–	–	–	−0.0869* (0.0560)	−0.0781* (0.0420)	–	–	–	–	–	–
λ	0.0001 (0.0002)	0.0006 (0.0004)	−0.0010*** (0.0002)	−0.0006*** (0.0006)	−0.0005*** (0.0001)	−0.0001*** (0.000)	0.0003 (0.0003)	0.0003 (0.0002)	−0.0012*** (0.0004)	−0.0014*** (0.0008)	−0.0007 (0.0008)	0.0002 (0.0005)
R^2	0.072	0.086	0.202	0.135	0.166	0.100	0.154	0.031	0.097	0.024	0.151	0.094
Q(8)	12.611 (0.027)	14.648 (0.066)	5.287 (0.071)	8.493 (0.387)	6.005 (0.014)	4.734 (0.786)	1.683 (0.794)	7.775 (0.456)	20.922 (0.000)	11.652 (0.167)	6.771 (0.238)	9.265 (0.320)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
LM(8)	12.927	22.135	30.264	51.988	14.981	10.309	263.216	14.985	42.932	15.340	28.835	13.388
	(0.114)	(0.005)	(0.000)	(0.000)	(0.060)	(0.244)	(0.000)	(0.059)	(0.000)	(0.053)	(0.000)	(0.099)
$Q^2(8)$	58.872	59.138	60.809	63.534	41.019	50.422	42.983	25.827	42.932	87.303	54.939	67.144
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(8)	61.184	59.670	59.001	61.637	39.604	50.396	18.443	23.763	69.176	62.406	71.330	82.070
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6s 16GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for i = 2, …, 7 and j = 1, …, 7.
Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.8: Empirical estimates of eq. (6.1) for iPhone 6 64GB

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0008	−0.0009	−0.0010	−0.0015	−0.0008	−0.0010	−0.0011**	−0.0025**	−0.0010	−0.0029	−0.0008*	−0.0017*
	(0.0014)	(0.0017)	(0.0013)	(0.0021)	(0.0014)	(0.0017)	(0.0005)	(0.0012)	(0.0010)	(0.0025)	(0.0005)	(0.0009)
β_1	−0.0954***	−0.0921***	−0.5100***	−0.5121***	−0.1649***	−0.1658***	−0.1804***	−0.1897***	−0.3018***	−0.3043***	−0.2298***	−0.2428***
	(0.0698)	(0.0699)	(0.1091)	(0.1059)	(0.0837)	(0.0839)	(0.0920)	(0.0990)	(0.0979)	(0.0978)	(0.0621)	(0.0629)
β_2	−0.0199	−0.0238	−0.3160***	−0.2935***	−0.0739*	−0.0823*	−0.2034**	−0.1648	−0.2709***	−0.2746***	−0.1959**	−0.2339**
	(0.0261)	(0.0264)	(0.0913)	(0.0862)	(0.0392)	(0.0468)	(0.0789)	(0.1181)	(0.0827)	(0.0841)	(0.0795)	(0.0999)
β_3	0.1301	0.1357	−0.0836	−0.0491	−	−	−0.3021***	−0.2882***	−0.2758***	−0.2844***	−0.1314***	−0.1415**
	(0.0940)	(0.0965)	(0.0705)	(0.0780)			(0.0795)	(0.1004)	(0.0485)	(0.0514)	(0.0490)	(0.0575)
β_4	−0.0168	−0.0192	0.0052	−0.0060	−	−	−0.1279	−0.0906	−0.2489***	−0.2570***	−0.0857**	−0.1027*
	(0.0577)	(0.0576)	(0.0566)	(0.0570)			(0.0795)	(0.1225)	(0.0586)	(0.0609)	(0.0413)	(0.0549)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
β_5	0.0053	0.0051	0.0936*	0.0801	–	–	−0.1872**	−0.1758	−0.1711***	−0.1760***	−0.0293	−0.0329
	(0.0417)	(0.0424)	(0.0541)	(0.0540)			(0.0867)	(0.1122)	(0.0484)	(0.0483)	(0.0318)	(0.0390)
β_6	−0.0316	−0.0343	0.1250**	0.1186**	–	–	−0.2023**	−0.2185**	−0.1529**	−0.1548**	−0.0620**	−0.0643**
	(0.0235)	(0.0280)	(0.0522)	(0.0532)			(0.0865)	(0.0892)	(0.0754)	(0.0758)	(0.0272)	(0.0312)
β_7	−0.2057	−0.2006	–	–	–	–	−0.1301**	−0.1167	−0.1615***	−0.1662***	−0.0610*	−0.0505
	(0.1760)	(0.1715)					(0.0552)	(0.0851)	(0.0496)	(0.0507)	(0.0339)	(0.0358)
λ	0.0000	0.0007	−0.0002**	−0.0011*	−0.0001***	−0.0002***	−0.0007*	−0.0013*	−0.0012	−0.0016	−0.0008**	−0.0007*
	(0.0002)	(0.0007)	(0.0001)	(0.0006)	(0.0001)	(0.0001)	(0.0004)	(0.0007)	(0.0008)	(0.0042)	(0.0004)	(0.0004)
R^2	0.061	0.065	0.227	0.221	0.030	0.024	0.1830	0.153	0.139	0.135	0.193	0.089
Q(8)	1.950	2.329	2.394	3.095	38.262	33.556	5.121	5.629	1.519	1.496	3.200	1.959
	(0.163)	(0.969)	(0.302)	(0.928)	(0.000)	(0.000)	(0.024)	(0.689)	(0.218)	(0.993)	(0.074)	(0.982)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
LM(8)	6.024	7.349	7.501	6.906	38.247	34.265	17.166	23.326	10.294	10.407	7.071	4.207
	(0.645)	(0.499)	(0.484)	(0.547)	(0.000)	(0.000)	(0.028)	(0.003)	(0.245)	(0.238)	(0.529)	(0.838)
$Q^2(8)$	63.971	60.847	152.780	146.060	107.410	101.410	194.700	271.730	29.199	27.794	83.274	91.490
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ARCH(8)	63.224	60.117	92.885	88.419	104.631	99.119	114.425	155.422	24.149	22.656	60.165	79.168
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6 64GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.
Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.
$Q(8)$ and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.9: Empirical estimates of eq. (6.1) for iPhone 6 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0010	−0.0014	−0.0009	−0.0014	−0.0007	−0.0026	−0.0012**	−0.0022**	−0.0011	−0.0018	−0.0012***	−0.0020**
	(0.0010)	(0.0015)	(0.0013)	(0.0017)	(0.0005)	(0.0017)	(0.0005)	(0.0010)	(0.0009)	(0.0016)	(0.0004)	(0.0009)
β_1	−0.3067***	−0.2009***	−0.3729***	−0.5196***	−0.4172***	−0.3989***	−0.5702***	−0.5087***	−0.2495***	−0.2049***	−0.5399***	−0.4137***
	(0.1213)	(0.0928)	(0.1037)	(0.2036)	(0.1798)	(0.1867)	(0.0745)	(0.0779)	(0.0886)	(0.0767)	(0.1069)	(0.1386)
β_2	−0.1363**	−0.0718	0.0263	−0.0490	−0.1984	−0.2081*	−0.3079***	−0.2180**	−0.0481	−0.0032	−0.3730***	−0.2525**
	(0.0635)	(0.0487)	(0.1074)	(0.1285)	(0.1217)	(0.1191)	(0.0841)	(0.0889)	(0.0489)	(0.0447)	(0.1035)	(0.1140)
β_3	–	–	0.2955	0.2162	−0.0695	−0.0640	−0.2205***	−0.1552**	−0.1203**	−0.0737	−0.2377***	−0.1590*
			(0.2066)	(0.1555)	(0.0631)	(0.0493)	(0.0759)	(0.0718)	(0.0553)	(0.0618)	(0.0875)	(0.0819)
β_4	–	–	−0.1097	−0.1844	−0.0502	−0.0056	−0.1909***	−0.1604***	−0.0775*	−0.0566	−0.1455**	−0.0904
			(0.0821)	(0.1332)	(0.0436)	(0.0530)	(0.0631)	(0.0529)	(0.0413)	(0.0403)	(0.0621)	(0.0588)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
β_5	–	–	−0.0285	0.0083	−0.1146***	−0.0314	−0.0356	−0.0223	−0.1171***	−0.1063**	−0.0602	−0.0383
			(0.0520)	(0.0406)	(0.0356)	(0.0677)	(0.0421)	(0.0393)	(0.0439)	(0.0445)	(0.0399)	(0.0362)
β_6	–	–	−0.0842	−0.0848	–	–	–	–	−0.1128**	−0.0941*	–	–
			(0.0755)	(0.0855)					(0.0513)	(0.0548)		
β_7	–	–	–	–	–	–	–	–	–	–	–	–
λ	−0.0003***	−0.0005***	−0.0002***	−0.0008****	−0.0004***	−0.0007***	−0.0000	−0.0001	−0.0012	0.0004	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0001)	(0.0004)	(0.0002)	(0.0003)	(0.0011)	(0.0012)	(0.0001)	(0.0001)
R^2	0.132	0.067	0.268	0.232	0.252	0.127	0.291	0.212	0.109	0.050	0.312	0.157
Q(8)	6.719	6.061	0.694	0.625	9.376	1.895	13.969	9.629	6.666	4.653	28.165	11.784
	(0.348)	(0.640)	(0.707)	(1.000)	(0.025)	(0.984)	(0.003)	(0.292)	(0.036)	(0.794)	(0.000)	(0.161)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
LM(8)	16.656	6.422	2.165	4.856	13.528	4.583	39.952	12.783	9.128	5.275	47.550	19.779
	(0.034)	(0.600)	(0.976)	(0.773)	(0.095)	(0.801)	(0.000)	(0.120)	(0.332)	(0.728)	(0.000)	(0.011)
$Q^2(8)$	18.469	5.679	121.330	112.850	43.823	39.939	34.779	44.872	32.052	5.086	13.802	34.207
	(0.018)	(0.683)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.748)	(0.087)	(0.000)
ARCH(8)	18.398	5.791	92.768	90.365	42.017	39.473	31.813	39.494	31.464	4.724	12.617	32.523
	(0.018)	(0.671)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.787)	(0.126)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6 16GB. Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.
Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.10: Empirical estimates of eq. (6.1) for Samsung Galaxy S6 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0013	−0.0023	−0.0010*	−0.0011	−0.0013***	−0.0021**	−0.0006	−0.0005	−0.0011	−0.0013	−0.0004	−0.0012
	(0.0008)	(0.0016)	(0.0006)	(0.0009)	(0.0005)	(0.0008)	(0.0008)	(0.0013)	(0.0020)	(0.0025)	(0.0010)	(0.0024)
β_1	−0.0698	−0.0887	−0.2280****	−0.2159***	−0.3185***	−0.3241***	−0.2730***	−0.2670***	−0.0257***	−0.0163***	−0.3445***	−0.3002***
	(0.1197)	(0.1266)	(0.0982)	(0.0948)	(0.0950)	(0.0433)	(0.0739)	(0.0735)	(0.0145)	(0.0241)	(0.0923)	(0.0842)
β_2	−0.2714***	−0.2703***	−0.1470*	−0.1512*	−0.1601**	−0.1472***	−0.1565***	−0.1497***	−0.0656	−0.0666*	−0.2079***	−0.1875***
	(0.0882)	(0.0800)	(0.0808)	(0.0781)	(0.0676)	(0.0455)	(0.0561)	(0.0548)	(0.0434)	(0.0377)	(0.0594)	(0.0582)
β_3	−0.2650***	−0.2564**	–	–	−0.0515	−0.0466	−0.1182**	−0.1130**	0.0035	0.0051	−0.2288***	−0.1852***
	(0.0959)	(0.1039)			(0.0447)	(0.0453)	(0.0509)	(0.0505)	(0.0097)	(0.0112)	(0.0611)	(0.0548)
β_4	−0.2175**	−0.1948**	–	–	−0.1156***	−0.1106**	–	–	−0.1163*	−0.1156*	−0.0732	−0.0635
	(0.0901)	(0.0976)			(0.0365)	(0.0431)			(0.0623)	(0.0611)	(0.0494)	(0.0488)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
β_5	−0.0695	−0.0588	–	–	–	–	–	–	–	–	−0.1138***	−0.0934**
	(0.0677)	(0.0768)									(0.0367)	(0.0367)
β_6	0.1067	0.1160	–	–	–	–	–	–	–	–	−0.1305*	−0.1230*
	(0.0696)	(0.0951)									(0.0732)	(0.0628)
β_7	–	–	–	–	–	–	–	–	–	–	–	–
λ	0.0005***	0.0008***	0.0007***	−0.0003***	0.0005***	0.0005***	−0.0026***	−0.0021***	−0.0153***	−0.0221***	−0.0064***	−0.0041***
	(0.0002)	(0.0004)	(0.0005)	(0.0026)	(0.0003)	(0.0003)	(0.0005)	(0.0012)	(0.0070)	(0.0102)	(0.0013)	(0.0024)
R^2	0.215	0.203	0.074	0.051	0.124	0.100	0.148	0.068	0.036	0.013	0.194	0.099
Q(8)	7.092	11.261	10.393	10.983	12.829	14.061	9.020	8.715	5.026	4.484	17.482	16.200
	(0.029)	(0.187)	(0.109)	(0.203)	(0.012)	(0.080)	(0.108)	(0.367)	(0.285)	(0.811)	(0.000)	(0.040)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
LM(8)	8.494	14.458	16.615	14.459	28.246	29.064	13.162	10.749	6.082	6.642	25.845	28.318
	(0.387)	(0.071)	(0.034)	(0.071)	(0.000)	(0.000)	(0.106)	(0.216)	(0.638)	(0.576)	(0.001)	(0.000)
$Q^2(8)$	178.150	198.680	85.401	73.649	28.504	27.161	69.623	61.796	2.200	3.955	57.137	43.543
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.974)	(0.861)	(0.000)	(0.000)
ARCH(8)	90.156	92.486	66.186	58.609	24.949	23.331	64.220	56.703	2.150	3.853	60.588	44.941
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.000)	(0.000)	(0.976)	(0.870)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S6 64GB. Instruments for 2SLS are ΔP(t-i) and ΔV(t-j) for i = 2, …, 7 and j = 1, …, 7.
Adjusted R^2 is calculated as 1-(1-R^2)/(T-1/T-k).
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.11: Empirical estimates of eq. (6.1) for Samsung Galaxy S6 32GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0011***	−0.0021***	−0.0009***	−0.0019***	−0.0004	−0.0008	−0.0006*	−0.0011	−0.0008	−0.0013	−0.0007	−0.0013
	(0.0003)	(0.0005)	(0.0003)	(0.0007)	(0.0005)	(0.0009)	(0.0003)	(0.0007)	(0.0005)	(0.0008)	(0.0007)	(0.0013)
β_1	−0.3647***	−0.3448***	−0.3679***	−0.3287***	−0.3224***	−0.2626***	−0.3129***	−0.2839***	−0.1895***	−0.1988***	−0.3805***	−0.3873***
	(0.0744)	(0.0857)	(0.0765)	(0.0811)	(0.0848)	(0.0834)	(0.0972)	(0.0954)	(0.0546)	(0.0588)	(0.1533)	(0.1546)
β_2	−0.1687***	−0.2214***	−0.2258***	−0.2074***	−0.1150**	−0.1247*	−0.1673**	−0.1664**	−0.1396**	−0.1542***	−0.1726***	−0.1757***
	(0.0582)	(0.0832)	(0.0544)	(0.0553)	(0.0454)	(0.0685)	(0.0754)	(0.0831)	(0.0602)	(0.0568)	(0.0747)	(0.0728)
β_3	−0.1030*	−0.1222	−0.1392***	−0.1605**	−0.0657*	−0.0839	−0.1213	−0.0790	−0.0476	−0.0084	0.0178	0.0124
	(0.0539)	(0.0725)	(0.0491)	(0.0779)	(0.0370)	(0.0551)	(0.0811)	(0.0910)	(0.0495)	(0.0384)	(0.0758)	(0.0761)
β_4	−0.0591	−0.0993	−0.1459***	−0.1404***	–	–	−0.1596***	−0.1189**	−0.0683	−0.0640*	−0.0726	−0.0784
	(0.0702)	(0.0737)	(0.0464)	(0.0481)			(0.0493)	(0.0528)	(0.0406)	(0.0364)	(0.0584)	(0.0580)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
β_5	0.0622 (0.0863)	0.0340 (0.0910)	−0.0660 (0.0493)	−0.1051* (0.0571)	–	–	−0.1577*** (0.0575)	−0.1414* (0.0751)	−0.1115** (0.0507)	−0.0827*** (0.0445)	−0.1320*** (0.0680)	−0.1398*** (0.0680)
β_6	−0.1084 (0.0767)	−0.1599** (0.0807)	–	–	–	–	−0.0881* (0.0452)	−0.0791 (0.0512)	–	–	–	–
β_7	0.0016 (0.0447)	−0.0331 (0.0392)	–	–	–	–	–	–	–	–	–	–
λ	0.0001*** (0.0001)	0.0001*** (0.0001)	−0.0003*** (0.0001)	−0.0002*** (0.0001)	−0.0006*** (0.0003)	−0.0008*** (0.0004)	0.0002*** (0.0001)	0.0001*** (0.0001)	−0.0005*** (0.0002)	−0.0004*** (0.0002)	0.0003 (0.0003)	0.0002 (0.0004)
R^2	0.317	0.247	0.251	0.105	0.424	0.190	0.210	0.107	0.131	0.057	0.175	0.159
Q(8)	9.286 (0.002)	7.794 (0.454)	0.194 (0.979)	1.290 (0.996)	15.8490 (0.007)	1.995 (0.981)	3.195 (0.202)	1.526 (0.992)	6.613 (0.085)	5.937 (0.654)	9.918 (0.019)	11.033 (0.200)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
LM(8)	78.489	60.300	1.151	3.242	20.064	7.997	7.139	16.010	11.513	8.389	15.028	14.041
	(0.000)	(0.000)	(0.997)	(0.918)	(0.010)	(0.434)	(0.522)	(0.042)	(0.174)	(0.396)	(0.059)	(0.081)
$Q^2(8)$	106.820	106.550	34.577	41.894	48.082	30.416	49.129	59.087	16.604	7.312	205.120	193.460
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.035)	(0.503)	(0.000)	(0.000)
ARCH(8)	48.619	33.016	37.063	46.912	48.864	29.288	45.955	29.876	13.774	6.470	126.714	121.124
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.088)	(0.595)	(0.000)	(0.000)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S6 32GB. Instruments for 2SLS are $\Delta P(t\text{-}i)$ and $\Delta V(t\text{-}j)$ for $i = 2, \ldots, 7$ and $j = 1, \ldots, 7$.
Adjusted R^2 is calculated as $1\text{-}(1\text{-}R^2)/(T\text{-}1/T\text{-}k)$.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

Table 6.12: Empirical estimates of eq. (6.1) for Samsung Galaxy S5 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
α	−0.0008**	−0.0016***	−0.0010**	−0.0015***	−0.0006	−0.0004	−0.0013***	−0.0031**	−0.0010	−0.0023	−0.0010	0.0004
	(0.0003)	(0.0004)	(0.0005)	(0.0012)	(0.0004)	(0.0007)	(0.0005)	(0.0013)	(0.0007)	(0.0014)	(0.0022)	(0.0037)
β_1	−0.6672***	−0.3858***	−0.2968***	−0.2016	−0.1931***	−0.1378***	−0.5151***	−0.4604***	−0.4976***	−0.5032***	−0.1826***	−0.1594***
	(0.1791)	(0.0709)	(0.1113)	(0.1312)	(0.0535)	(0.0439)	(0.1520)	(0.1297)	(0.1729)	(0.1746)	(0.1470)	(0.1435)
β_2	−0.2291***	−0.2020***	−0.0626	−0.1231	−0.0324	−0.0739	−0.2899**	−0.2791**	−0.2859*	−0.2930*	−0.0891	−0.0829
	(0.0850)	(0.0667)	(0.0789)	(0.1050)	(0.0512)	(0.0439)	(0.1421)	(0.1314)	(0.1499)	(0.1516)	(0.0704)	(0.0626)
β_3	–	–	−0.1037**	−0.0815	−0.1745***	−0.0522	−0.2182*	−0.2178*	−0.1575	−0.1600	−0.0762**	−0.0658**
			(0.0446)	(0.1587)	(0.0634)	(0.0415)	(0.1180)	(0.1150)	(0.1083)	(0.1113)	(0.0299)	(0.0307)
β_4	–	–	−0.0836**	−0.0701	–	–	−0.1624*	−0.1642*	−0.0801*	−0.0773*	−0.0688***	−0.0462****
			(0.0411)	(0.0600)			(0.0871)	(0.0884)	(0.0411)	(0.0428)	(0.0231)	(0.0228)

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
β_5	–	–	–	–	–	–	−0.1297 (0.0903)	−0.1200 (0.0883)	–	–	–	–
β_6	–	–	–	–	–	–	–	–	–	–	–	–
β_7	–	–	–	–	–	–	–	–	–	–	–	–
λ	0.0000 (0.0000)	−0.0000 (0.0000)	0.0004*** (0.0000)	0.0003*** (0.0001)	0.0002*** (0.0001)	0.0005*** (0.0001)	0.0002*** (0.0002)	0.0007*** (0.0003)	0.0000*** (0.0002)	0.0001*** (0.0002)	0.0006*** (0.0007)	−0.0027*** (0.0018)
R^2	0.357	0.146	0.659	0.140	0.252	0.023	0.248	0.260	0.193	0.195	0.041	0.036
Q(8)	31.315 (0.000)	42.436 (0.000)	1.241 (0.871)	10.237 (0.249)	15.492 (0.008)	4.954 (0.763)	0.995 (0.802)	4.250 (0.834)	4.826 (0.306)	4.324 (0.827)	0.627 (0.960)	0.529 (1.000)

Parameter	US						UK					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
LM(8)	150.076	44.040	5.150	23.676	29.180	7.511	9.589	7.410	10.597	9.111	0.757	4.678
	(0.000)	(0.000)	(0.742)	(0.003)	(0.000)	(0.483)	(0.295)	(0.493)	(0.226)	(0.333)	(0.999)	(0.791)
$Q^2(8)$	231.740	68.670	45.177	106.420	4.233	0.832	55.538	33.575	35.321	34.483	15.465	6.865
	(0.000)	(0.000)	(0.000)	(0.000)	(0.836)	(0.999)	(0.000)	(0.000)	(0.000)	(0.000)	(0.051)	(0.551)
ARCH(8)	124.998	58.519	13.043	86.089	3.931	0.787	50.100	30.106	33.127	32.320	15.258	6.601
	(0.000)	(0.000)	(0.110)	(0.000)	(0.863)	(0.999)	(0.000)	(0.000)	(0.000)	(0.000)	(0.054)	(0.010)

Notes: Sample period 28/01/2016–20/07/2017. OLS and 2SLS estimates of the parameters of eq. (6.1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S5 16GB. Instruments for 2SLS are ΔP(t-i) and ΔV(t-j) for i = 2, …, 7 and j = 1, …, 7.
Adjusted R^2 is calculated as $1-(1-R^2)/(T-1/T-k)$.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.
ARCH(8) is the ARCH LM test for the null of no heteroscedasticity in residuals up to lag 8. P-Values in parentheses.

6.5.3 Robustness Checks

The bottom panels of Tables 6.6 – 6.12 outline the Box-Ljung statistics, as well as the LM and ARCH-LM tests. The test statistics show that some residuals of the estimated models are affected by serial correlation, but all are affected by heteroscedasticity. Such features are addressed using the heteroscedasticity- and autocorrelation-consistent (HAC) estimator to ensure that the homoscedasticity assumption of the OLS estimator holds. Nevertheless, since the presence of conditional volatility as detected by the ARCH-LM tests is prevalent in every model, an opportunity arises to investigate the relationship between price volatility and volume. Consequently, the empirical exercise proceeds with the use of GARCH models.

Tables 6.13 – 6.19 report the results from the estimations of eq. (6.2) using ML. The majority of the estimates are consistent between the equation generated by means of OLS and by means of 2SLS, indicating that the GARCH models are able to capture conditional volatility in the residuals well. The models are then used to test whether daily change in volume, as measured by ΔV_t and ΔV_t^2, affect daily volatility of prices; this is done by supplementing the GARCH(1,1) specification sequentially with explanatory variables ΔV_t and ΔV_t^2. The empirical results reveal that such variables are not statistically significant for a vast majority of the series under scrutiny. Therefore, it is concluded that there is no link between volatility in daily volume and volatility in daily price.

Table 6.13: Empirical estimates of eq. (6.2) for iPhone 6s 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0003***	0.0005***	0.0002***	0.0001******	0.0004***	0.0004***	0.0001***	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ε^2	0.0829**	0.0897	0.7478***	0.2567***	0.1462***	0.1464***	0.1625***	0.3327***	0.1558***	0.1160***	0.2568******	0.2381******
	(0.1791)	(0.0709)	(0.0369)	(0.0165)	(0.0291)	(0.0309)	(0.0292)	(0.0219)	(0.0094)	(0.0069)	(0.0553)	(0.0452)
σ^2	0.4390***	0.1835***	0.5246***	0.7918***	0.6231***	0.5969***	0.6771***	0.6364***	0.8482***	0.8740***	0.5041***	0.5442***
	(0.1376)	(0.2305)	(0.0181)	(0.0097)	(0.0501)	(0.0559)	(0.0400)	(0.0210)	(0.0050)	(0.0052)	(0.0684)	(0.0528)
Q(8)	3.787	3.489	3.126	2.562	2.393	2.763	8.836	8.799	13.434	11.045	37.747	36.935
	(0.876)	(0.900)	(0.926)	(0.959)	(0.967)	(0.948)	(0.356)	(0.360)	(0.098)	(0.199)	(0.000)	(0.000)
$Q^2(8)$	0.184	0.193	9.341	1.517	9.207	9.080	8.418	4.211	2.929	2.157	9.036	7.397
	(1.000)	(1.000)	(0.314)	(0.992)	(0.325)	(0.336)	(0.394)	(0.838)	(0.939)	(0.976)	(0.339)	(0.494)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6s 64GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.14: Empirical estimates of eq. (6.2) for iPhone 6s 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0001***	0.0001***	0.0001***	0.0001******	0.0005***	0.0005***	0.0000***	0.000***	0.0000***	0.0000***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ε^2	0.1833***	0.3589**	0.1122*	0.6104***	0.0571**	0.0650**	0.1518***	0.1054***	0.1666***	0.1208***	0.0954******	0.0530******
	(0.0447)	(0.1419)	(0.0617)	(0.0862)	(0.0226)	(0.0268)	(0.0338)	(0.0202)	(0.0216)	(0.0163)	(0.0213)	(0.0126)
σ^2	0.7194***	0.4022***	0.5164***	0.7545***	0.6015***	0.5860***	0.7099***	0.8528***	0.7521***	0.8163***	0.5255***	0.5510***
	(0.0290)	(0.0129)	(0.0225)	(0.0221)	(0.1260)	(0.1291)	(0.0351)	(0.0276)	(0.0232)	(0.0212)	(0.0650)	(0.0726)
Q(8)	6.518	5.533	20.897	8.853	6.382	6.054	13.710	3.777	14.455	5.989	4.391	4.825
	(0.589)	(0.699)	(0.007)	(0.355)	(0.604)	(0.641)	(0.090)	(0.877)	(0.071)	(0.648)	(0.820)	(0.776)
$Q^2(8)$	1.952	1.741	1.331	0.304	0.959	1.362	1.598	1.393	1.242	3.144	0.804	1.456
	(0.982)	(0.988)	(0.995)	(1.000)	(0.998)	(0.995)	(0.991)	(0.994)	(0.996)	(0.925)	(0.999)	(0.993)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6s 16GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.15: Empirical estimates of eq. (6.2) for iPhone 6 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0003***	0.0003***	0.0000***	0.0000***	0.0002***	0.0003***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000**	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ε^2	0.2562***	0.2545***	0.1503***	0.1336***	0.0779***	0.0882***	0.1400***	0.1196***	0.2063***	0.2113***	0.2042***	0.1942****
	(0.0318)	(0.0317)	(0.0165)	(0.0162)	(0.0233)	(0.0247)	(0.0206)	(0.0142)	(0.0124)	(0.0129)	(0.0326)	(0.0205)
σ^2	0.6588***	0.6578***	0.8508***	0.8664***	0.7473***	0.7348***	0.8751***	0.8826***	0.8554***	0.8552***	0.6846***	0.7708***
	(0.0211)	(0.0213)	(0.0100)	(0.0111)	(0.0436)	(0.0417)	(0.0093)	(0.0063)	(0.0056)	(0.0056)	(0.0390)	(0.0176)
Q(8)	3.715	4.338	10.982	10.345	17.893	16.202	2.571	2.715	7.326	5.964	2.401	7.841
	(0.882)	(0.825)	(0.203)	(0.242)	(0.022)	(0.040)	(0.958)	(0.951)	(0.502)	(0.651)	(0.966)	(0.449)
$Q^2(8)$	5.114	4.993	1.310	1.095	14.910	16.838	0.473	1.063	5.826	6.273	2.555	2.150
	(0.745)	(0.758)	(0.995)	(0.998)	(0.061)	(0.032)	(1.000)	(0.998)	(0.667)	(0.617)	(0.959)	(0.976)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6 64GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.16: Empirical estimates of eq. (6.2) for iPhone 6 16GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0000	0.0000***	0.0002***	0.0001***	0.0000***	0.0003***	0.0002***	0.0002***	0.0002***	0.0000***	0.0002**	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
ε^2	0.2221***	0.2820***	0.1785***	0.1071***	0.7071***	0.9762***	0.9326***	1.0119***	0.0813***	0.2215***	0.0490***	0.0927***
	(0.0219)	(0.0269)	(0.0383)	(0.0122)	(0.0299)	(0.0614)	(0.0524)	(0.0573)	(0.0172)	(0.0181)	(0.0401)	(0.0727)
σ^2	0.8788***	0.8625***	0.6810***	0.8224***	0.6096***	−0.0859***	0.0149	−0.0080	0.7949***	0.8345***	0.4149*	−0.0755
	(0.0087)	(0.0088)	(0.0401)	(0.0126)	(0.0227)	(0.0345)	(0.0381)	(0.0315)	(0.0320)	(0.0069)	(0.2290)	(0.3005)
Q(8)	3.146	2.797	10.746	12.761	10.532	4.492	32.323	21.046	5.063	6.124	38.131	21.101
	(0.925)	(0.946)	(0.217)	(0.120)	(0.230)	(0.810)	(0.000)	(0.007)	(0.751)	(0.633)	(0.000)	(0.007)
$Q^2(8)$	0.476	0.374	0.828	0.392	1.459	0.262	2.331	1.701	0.610	0.729	0.095	0.058
	(1.000)	(1.000)	(0.999)	(1.000)	(0.993)	(1.000)	(0.969)	(0.989)	(1.000)	(0.999)	(1.000)	(1.000)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 6 16GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.17: Empirical estimates of eq. (6.2) for Samsung Galaxy S6 64GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0020***	0.0000***	0.0014***	0.0017***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0011)	(0.0000)	(0.0002)	(0.0003)
ε^2	0.2307***	0.2963***	0.0810***	0.0689***	0.1335***	0.1191***	0.1187***	0.1013***	−0.0141***	−0.0031***	0.1331***	0.1401***
	(0.0200)	(0.0245)	(0.0122)	(0.0091)	(0.0157)	(0.0143)	(0.0119)	(0.0121)	(0.0004)	(0.0004)	(0.0408)	(0.0347)
σ^2	0.8119***	0.7725***	0.9078***	0.9165***	0.8402***	0.8437***	0.8910***	0.8971***	0.5824*	0.9990***	0.3105***	0.2659***
	(0.0091)	(0.0092)	(0.0135)	(0.0105)	(0.0125)	(0.0126)	(0.0080)	(0.0101)	(0.2287)	(0.0003)	(0.1096)	(0.1016)
Q(8)	24.205	20.720	11.569	11.153	11.145	10.776	8.907	6.456	8.684	5.297	17.537	16.712
	(0.002)	(0.008)	(0.171)	(0.193)	(0.194)	(0.215)	(0.350)	(0.596)	(0.370)	(0.725)	(0.025)	(0.033)
$Q^2(8)$	4.864	4.300	1.416	2.030	4.700	5.515	6.867	11.593	2.390	19.310	3.212	2.584
	(0.772)	(0.829)	(0.994)	(0.980)	(0.789)	(0.701)	(0.551)	(0.170)	(0.967)	(0.013)	(0.920)	(0.958)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S6 64GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.18: Empirical estimates of eq. (6.2) for Samsung Galaxy S6 32GB

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0000	0.0000***	0.0002***	0.0001***	0.0000***	0.0001***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ε^2	0.1178***	0.0507***	0.1196***	0.1423***	0.0820***	0.7977***	0.3320***	0.2606***	0.0423***	0.0400***	0.3095***	0.2444***
	(0.0239)	(0.0141)	(0.0409)	(0.0254)	(0.0155)	(0.0721)	(0.0531)	(0.0287)	(0.079)	(0.0077)	(0.0199)	(0.0169)
σ^2	0.6284***	0.7750***	−0.3241***	0.5725***	0.8530***	0.0552***	0.4863***	0.6819***	0.9257***	0.9132***	0.8122***	0.8498***
	(0.0621)	(0.0359)	(0.0770)	(0.0695)	(0.0230)	(0.0147)	(0.0673)	(0.0284)	(0.0112)	(0.0119)	(0.0079)	(0.0060)
Q(8)	17.351	10.806	1.661	0.433	10.725	9.537	10.439	6.208	10.087	9.051	6.189	7.780
	(0.027)	(0.213)	(0.990)	(1.000)	(0.218)	(0.299)	(0.236)	(0.624)	(0.259)	(0.338)	(0.626)	(0.455)
$Q^2(8)$	1.303	0.423	2.261	7.232	6.827	0.542	6.065	2.887	3.644	2.515	0.992	0.800
	(0.996)	(1.000)	(0.972)	(0.512)	(0.555)	(1.000)	(0.640)	(0.941)	(0.888)	(0.961)	(0.998)	(0.999)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S6 32GB.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

Table 6.19: Empirical estimates of eq. (6.2) for Samsung Galaxy S5

Parameter	**US**						**UK**					
	N		**MR**		**SR**		**N**		**MR**		**SR**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ω	0.0001***	0.0000***	0.0000***	0.0000***	0.0001***	–	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ε^2	0.2113***	0.0806***	0.1056***	0.1637***	0.0827***	–	0.3320***	0.2606***	0.0423***	0.0400***	0.3095***	0.2444***
	(0.0544)	(0.0196)	(0.0091)	(0.0113)	(0.0228)		(0.0531)	(0.0287)	(0.079)	(0.0077)	(0.0199)	(0.0169)
σ^2	0.5105***	0.7936***	0.8451***	0.8577***	0.5150***	–******	0.4863***	0.6819***	0.9257***	0.9132***	0.8122***	0.8498***
	(0.0603)	(0.0353)	(0.0099)	(0.0053)	(0.1132)		(0.0673)	(0.0284)	(0.0112)	(0.0119)	(0.0079)	(0.0060)
Q(8)	49.955	24.092	3.608	2.491	13.174	–***	10.439	6.208	10.087	9.051	6.189	7.780
	(0.000)	(0.002)	(0.891)	(0.962)	(0.106)		(0.236)	(0.624)	(0.259)	(0.338)	(0.626)	(0.455)
$Q^2(8)$	0.768	2.051	1.454	0.485	1.100	–***	6.065	2.887	3.644	2.515	0.992	0.800
	(0.999)	(0.979)	(0.993)	(1.000)	(0.998)		(0.640)	(0.941)	(0.888)	(0.961)	(0.998)	(0.999)

Notes: Sample period 28/01/2016–20/07/2017. ML estimates of the parameters of eq. (6.2) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S5.
Q(8) and $Q^2(8)$ are Ljung–Box statistics for serial correlation up to lag 8 in raw and squared raw residuals. P-Values in parentheses.
LM(8) is the Lagrange Multiplier test for the null of no serial correlation in raw residuals up to lag 8. P-Values in parentheses.

6.5.4 The Progression of Relationships across Product Life Cycles

6.5.4.1 The Responsiveness to Past Prices and Volume

As previously mentioned, each smartphone generation represents a specific product life cycle stage for its corresponding brand (see Table 6.1 for more details). By comparing the results obtained in this chapter against the results reported in Chapter 5, it is possible to explore the evolution of the relationships under scrutiny across the smartphones' product life cycles.

The first aspect that this section considers is elasticity – or the responsiveness of price to the changes in past price – and it is found that a clear distinction between life cycle stages can be made. When the smartphones are in their introductory stage (e.g. iPhone 6s and Samsung Galaxy S6), their new condition has the highest sensitivity to changes in past prices, and the MR variant has the lowest. Nevertheless, when the products progress through the growth and mature stages (e.g. iPhone 6 / 5s and Samsung Galaxy S4), the sensitivity of new items becomes weaker, while the MR condition becomes more responsive. In other words, the results reveal that the prices of the new condition of smartphones under scrutiny react less and less towards past price changes as they progress through the stages of their respective product life cycles. On the other hand, as the remanufactured versions of the smartphones mature, their prices react more and more strongly to past price changes. This pattern of results is consistent between iPhone and Samsung Galaxy smartphones.

The next aspect that this section considers is the semi-elasticity between price and volume. It is observed that the changes do not appear to be as distinctive across product life cycle stages compared to the elasticity between past and current prices. For every life cycle stage of iPhone products, the prices of the MR and the SR variants are the most and least sensitive to changes in volume, respectively. This means that volume may be a good predictor of the prices of both remanufactured versions of smartphones, albeit more so for the MR variant as the changes are more distinct. However, when taking into account the new variant of the smartphones under scrutiny, the changes become more prominent, as the responsiveness of prices to changes in volume evolves through the product life cycle. To be more specific, the new condition of the products in their introductory and growth stages (e.g. iPhone 6s / 6 and Samsung Galaxy S6 / S5) initially exhibits the least responsiveness, before becoming the most responsive once the products reach maturity (e.g. iPhone 5s and Samsung Galaxy S4). This indicates that, for new condition of smartphones, volume is a more reliable predictor of the prices when the products are mature.

6.5.4.2 The Cannibalisation Effect

It has been established in the previous chapter that the nature of the relationships between prices and volume (i.e. positive or negative) signifies the profit potential of each market. Specifically, the markets exhibiting positive price-volume link have the most profit potential since prices increase even when the volume is high. In contrast, the markets with negative relationship between prices and volume have the least profit potential because when the volume increases, prices decrease. In this chapter, the insights are extended further to reveal complementary and substitution effects based on the profit potential of different smartphone models.

For products to coexist comfortably within the same market, their profit potential should be similar, meaning that the same type of relationship between current prices and volume is to be expected (i.e. positive vs positive / negative vs negative). Such product pairs are regarded as complementary. When the products are considered substitutes, it is expected that one will have more profit potential than the other; in other words, both products should have opposite price-volume links (i.e. positive vs negative). This substitution effect can be taken as evidence for different types of product cannibalisation, depending on the comparison made. For clarity, when comparing between Apple and Samsung products, the differing profit potential signifies substitution effects, whereas when considering multiple product generations within the same brand (i.e. iPhone 6s vs iPhone 6), difference in profit potential suggests cannibalisation within category. Finally, evidence of internal and / or external cannibalisation can be observed when comparing the profit potential of new products against their remanufactured counterparts.

This section uses the aforementioned concepts to analyse the complementary and substitution (and, in some cases, cannibalisation) effects in each market location (US / UK) across the following dimensions: life cycle stages (introduction, growth, mature), conditions (N, MR, SR), capacities (64GB vs 16GB), and brands (Apple vs Samsung). As such, the nature of the links between prices and volume of each smartphone model, and their corresponding profit potential, are summarised in Table 6.20 below. The same table also contains details from the previous chapter for comparison purposes.

Table 6.20: Summary of the relationships between price and volume and profit potential

Results	**Product Model**		**US**			**UK**		
			N	**MR**	**SR**	**N**	**MR**	**SR**
This chapter	iPhone 6s	64GB	+	–	+ **	–	+	–
		16GB	+	– ***	– ***	+	– *	+
	iPhone 6	64GB	+	– *	– ***	– *	–	– *
		16GB	– **	– **	– *	–	+	+
	Samsung Galaxy S6	64GB	+ **	–	+ *	– *	– **	– *
		32GB	+ **	– *	– *	+ *	– *	+
	Samsung Galaxy S5	16GB	–	+ **	+ ***	+ **	+	–
Previous chapter	iPhone 5s	64GB	– ***	+ **	– **	– ***	–	+ **
		16GB	+ ***	+ ***	+	+ ***	+ ***	+ ***
	Samsung Galaxy S4	16GB	– ***	– **	+	– ***	+ ***	+

Notes: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

In the US, when comparing the profit potential of the products in the introduction stage (i.e. iPhone 6s and Samsung Galaxy S6) against the products in the growth stage (i.e. iPhone 6 and Samsung Galaxy S5), weak evidence of within-category cannibalisation amongst iPhone products can be observed. This is because the majority of the products share the same price-volume links (positive for new condition and negative for MR and SR), with the exceptions of iPhone 6s and 6 16GB, where iPhone 6s cannibalises the profit potential of iPhone 6. Evidence for within-category cannibalisation effect between Samsung Galaxy S6 and S5, however, is stronger. It is found that the new S6 cannibalises the new S5, while the remanufactured S5 cannibalises the remanufactured S6.

The cannibalisation effect is more prominent when taking into account the products in the mature stage of the life cycle. Starting with the new condition, it is documented that the products in the earlier stages of the life cycle (i.e. introduction and growth) cannibalise the profit potential of the smartphones in the mature stage. For instance, the iPhone 6s and 6 64GB cannibalise the profit potential of the iPhone 5s 64GB, while the iPhone 6 16GB is cannibalised by both iPhone 6s and 5s 16GB. As for Samsung Galaxy products, the S6 cannibalises both the S5 and S4. Concerning the remanufactured variants, the results suggest that the remanufactured condition of the products in the mature stage (iPhone 5s and Samsung Galaxy S4) cannibalises the profit potential of those in the introduction and growth stage (iPhone 6s / 6 and Samsung Galaxy S6 / S5).

The next dimension for comparison is the product condition. Starting with the smartphones in the introduction stage of the product life cycle (i.e. iPhone 6s and Samsung Galaxy S6), clear evidence of cannibalisation from new condition to remanufactured variants is found – this is with the exception of the iPhone 6s 64GB where both new and SR conditions complement each other. It is also documented that both MR and SR variants of the introductory smartphones can be considered complementary, with the exception of the iPhone 6s and Samsung Galaxy S6 64GB, where the SR condition cannibalises the profit potential of its MR counterpart. As for the products in the growth stage (i.e. iPhone 6 and Samsung Galaxy S5), the cannibalisation effect remains for both iPhone 6 64GB and Samsung Galaxy S5. Specifically, the new condition of iPhone 6 64GB cannibalises the profit potential of its remanufactured counterparts, while the remanufactured conditions of the Samsung Galaxy S5 cannibalise the new variant instead.

The patterns for the iPhone 6 16GB indicate that all three conditions (N, MR, and SR) can coexist comfortably. Additionally, both MR and SR variants of the smartphones in the growth stage complement each other. Concerning the mature smartphones (i.e. iPhone 5s and Samsung

Galaxy S4), there is clear evidence of cannibalisation effect from remanufactured products towards their new equivalent – this is with the exception of iPhone 5s 16GB, where all three conditions complement each other.

With regards to the capacity specifications, the results for the smartphones in the introduction stage (i.e. iPhone 6s and Samsung Galaxy S6) suggest the lack of cannibalisation effect for all conditions. Nevertheless, when considering the products in the growth stage (only iPhone 6, as Samsung Galaxy S5 has only one specification – 16GB), evidence of the cannibalisation from 64GB towards 16GB is found for the new variant, whereas the MR and SR variants of both specifications coexist comfortably within the same market. As for the products in the mature life cycle stage (again, only iPhone 5s), the patterns reveal that both the new and SR conditions of the iPhone 5s 16GB cannibalise the profit potential of their 64GB counterparts, but the MR variants of both specifications complement each other.

When comparing between the iPhone and Samsung Galaxy smartphones in the US, it can be seen that when the products are in their introductory stage (iPhone 6s and Samsung Galaxy S6), they coexist comfortably within the same market. Nonetheless, evidence of product substitution is found when the products progress to the growth stage of the life cycle; that is, the new iPhone 6 can be considered as a substitute for the new Samsung Galaxy S5, while the remanufactured Samsung Galaxy S5 substitutes its iPhone 6 equivalent. As for the mature smartphones, it is observed that the substitution effect between the iPhone 5s 16GB and Samsung Galaxy S4 is stronger than between the iPhone 5s 64GB and Samsung Galaxy S4. This is because both new and MR variants of the iPhone 5s 16GB can be considered substitutes for the Samsung Galaxy S4, while only the MR condition of the iPhone 5s 64GB is considered a substitute. Evidence of substitution effect is also found from the Samsung Galaxy S4 SR to its iPhone 5s 64GB counterpart.

Concerning the UK markets, the results indicate that the new condition of the smartphones in the introduction (i.e. iPhone 6s and Samsung Galaxy S6) and growth (i.e. iPhone 6 and Samsung Galaxy S5) stages complement each other in most cases. This is with the exception of iPhone 16GB, where the 6 cannibalises the profit potential of its 6s equivalent. In contrast, evidence of within-category cannibalisation is stronger when taking into account remanufactured variants. Specifically, the MR condition of the iPhone 6s 64GB cannibalises the iPhone 6 64GB, while the MR condition of the iPhone 6 16GB cannibalises the iPhone 6s 16GB. On the other hand, the SR variant of both products complement each other.

As for Samsung Galaxy smartphones, the MR condition of the S5 cannibalises the MR condition of both Samsung Galaxy S6 64GB and 32GB. Similarly, the SR variant of the Samsung Galaxy S6 32GB cannibalises the profit potential of the 64GB and S5. When taking into account the products in the mature life cycle stage (i.e. iPhone 5s and Samsung Galaxy S4), it is observed that the new condition of the smartphones coexist comfortably in most cases – except for the Samsung Galaxy S4, where its profit potential is cannibalised by the products in the earlier stages of the life cycle. Considering the MR and SR variants, evidence of the within-category cannibalisation from smartphones in the mature stage towards those in the introduction and growth stages is found.

Taking into account the cannibalisation between product conditions, evidence suggests that all variants of the smartphones in the introduction stage of the life cycle (i.e. iPhone 6s and

Samsung Galaxy S6) complement each other – except for the MR variant of the iPhone 6s 16GB and Samsung Galaxy S6 32GB, which is substituted by the new and SR counterparts. As for the products in the growth stage (iPhone 6 and Samsung Galaxy S5), all conditions of both smartphones can also coexist comfortably within the same market, apart from the remanufactured iPhone 6 that cannibalises the profit potential of its new equivalent. This particular observation is also applicable to the smartphones in the mature stage (i.e. iPhone 5s and Samsung Galaxy S4), as the new variant can be substituted by remanufactured conditions. This is with the exception of the iPhone 5s 16GB since every condition complement each other.

Moving on to the capacity specifications, evidence of the cannibalisation effect from lower capacity specification (16GB and 32GB) towards the higher capacity counterpart (64GB) is found for the smartphones in the introduction life cycle stage (i.e. iPhone 6s and Samsung Galaxy S6). This is with the exception of the MR variant of both iPhone 6s 16GB and Samsung Galaxy S6 32GB, where the former is cannibalised by its 64GB equivalent, and the latter coexists comfortably within the same market. Concerning the products in the growth stage (only iPhone 6, as Samsung Galaxy S5 has only the 16GB capacity), the new condition of both the 64GB and 16GB complement each other, while the remanufactured variants of the 16GB cannibalise the profit potential of the remanufactured 64GB. Evidence of cannibalisation from the 16GB to the 64GB is the strongest for mature smartphones (i.e. iPhone 5s). This is because every condition of the iPhone 5s 64GB can be substituted by its corresponding 16GB counterpart.

Considering the substitution effect between Apple and Samsung products in the UK, the majority of the smartphones in the introduction stage of their product life cycles (i.e. iPhone 6s and Samsung Galaxy S6) are not substitutes. However, evidence of substitution is found when the products progress to the growth stage (i.e. iPhone 6 and Samsung Galaxy S5), where Samsung Galaxy S5 can be considered a substitute for its iPhone 6 counterpart. On the contrary, the results indicate that when the smartphones reach maturity (i.e. iPhone 5s and Samsung Galaxy S4), most of them can coexist comfortably within the same market. This is, of course, with the exception of iPhone 5s 64GB MR, as it is substituted by the MR variant of the Samsung Galaxy S4.

To conclude this section, the final dimension to be considered is the comparison between the US and UK markets. For the smartphones in the introduction stage of their product life cycles (i.e. iPhone 6s and Samsung Galaxy S6), evidence of the cannibalisation from new condition in the US towards the new condition in the UK is found. However, the results indicate that the remanufactured variants in both markets complement each other. Moving on to the growth stage (i.e. iPhone 6 and Samsung Galaxy S5), it is observed that most smartphones coexist comfortably between markets – except for the iPhone 6 16GB, where its remanufactured variants cannibalise the profit potential of their US counterparts. Finally, concerning mature products (i.e. iPhone 5s and Samsung Galaxy S4), it is documented also that most smartphones are not considered substitutes, especially the iPhone 5s 16GB.

6.6 Discussion and Managerial Implications

By carrying out the analysis of the price-volume relationships for generations of smartphone products, it is possible to shed some light on the progression of their profit potential, together with the degree of substitutability and cannibalisation effect of different smartphones under scrutiny. The ability to evaluate the long-term profit potential of the markets of interest and the understanding of how different product models react to each other are imperative for both OEMs and online sellers; as such, a number of managerial implications are discussed below.

Firstly, it is documented that the relationships between changes in past and current prices are more evident in the UK markets than the US, showing that the price dynamics in the US markets are potentially more erratic – and less predictable using past price levels – than the UK; this is consistent in all generations, including the iPhone 5s and Samsung Galaxy S4 from the previous chapter. However, the product life cycles do play a role in influencing the elasticity of prices. Compared to the mature smartphones, the responsiveness to past price levels of new conditions are stronger for the smartphones in the introduction and growth stages, whereas the MR variants are the least sensitive. Such an inconsistency can be explained by noting that at the current stage of the product life cycle, new variants are competing both within the primary and secondary markets, rather than solely within secondary markets. This is because sellers in the secondary markets have certain attributes which help attract customers that primary market sellers lack, such as low search cost, ease, and in some cases, the ability to beat the launch dates. As such, the price anchors are not as restrictive compared to when the products reach maturity. In contrast, the number of remanufactured items in the market is incredibly low, which means that the market is dominated by a few sellers (i.e. oligopolistic setting; see Chapter 2, Section 2.3). This, coupled with the lack of demand from customers due to their preference for new conditions over remanufactured counterparts, results in the low sensitivity of prices (refer to Chapter 2, Section 2.3 for more details). Overall, the time dynamics of prices remain a challenge to forecast due to the weak dependence on lagged price values and general low persistence of the price series.

Secondly, the results suggest that the relationships between changes in prices and volume are consistent between markets, and in some cases, product life cycle stages. It is also documented that the patterns of results are more conclusive in the US than the UK, indicating that volume may have more predictive power in such markets. It is found that the MR variant of all products under scrutiny is the most responsive to changes in volume, which is consistent with the results from the previous chapter. Nevertheless, the product life cycles do affect new conditions, as the price sensitivity starts off low before increasing when the smartphones progress through the life cycle stages. With respect to the profit potential of different markets and product life cycle stages, it is established that the product life cycles play a significant role. This is because the majority of the remanufactured items of the smartphones in the introduction and growth stages now have lower profit potential, compared to the previously reported results. Such a pattern can be explained by the preference of customers towards new condition of the most up-to-date models over their remanufactured counterparts. Once the products become obsolete, the demand for new items dissipates while the demand for remanufactured variants increases; this is reflected by the high profit potential uncovered in the previous chapter.

Thirdly, the comparison between profit potential of different items sheds light on the complementary and substitute effects of the smartphones under scrutiny. According to the supply-demand framework covered in Section 2.3 (Chapter 2), the prices of complementary items should react the same way to changes in demand or supply. In contrast, the products are considered substitutes when the prices react differently. The results reveal that remanufactured variants of the smartphones in different life cycle stages cannibalise each other, as the remanufactured condition of mature smartphones have more profit potential than those of introduction and growth stages. Similarly, the new variant of the most up-to-date products have more profit potential than mature ones, indicating that smartphones in different product life cycle stages are actively competing with each other. As such, these observations can be taken as evidence of within-category cannibalisation. Interestingly, it is established that the MR and SR variants do not cannibalise each other, as both of them have similar profit potential. Different product specifications (e.g. 64GB vs 16GB) also mostly complement each other – with an exception for iPhone 5s, whose 16GB variant can be considered a substitute for its 64GB counterpart. Perhaps the most surprising of all, the results show that both iPhone and Samsung Galaxy smartphones are not considered perfect substitutes. This is based on the fact that the profit potential of both products is comparable in most cases. Overall, the degree of cannibalisation is lower in the UK than in the US markets.

Finally, the results presented in this chapter may, at first glance, appear to validate the concern that OEMs and remanufacturers have regarding cannibalisation effects of remanufactured products – but this is certainly not the case. Strong evidence is found for within-category cannibalisation from smartphones in the introduction stage to those in the growth and mature stages, which is to be expected. Nevertheless, remanufactured products are only a threat to their own kind, and to obsolete items. This is based on the fact that with the most recent smartphones, the new condition has more profit potential than their remanufactured counterparts.

The profit potential of remanufactured variants, on the other hand, only overtake the profit potential of the new condition of mature product models. For OEMs, this means that they can potentially overcome the cannibalisation effect by delaying the launch of the most updated variant of their smartphones and limit the supply to only two generations (i.e. introduction and growth) in the markets. In doing so, it is possible to still make profits from the remanufactured variant of the older generation (e.g. growth) and the new condition of the more recent model (e.g. introduction). Such a finding supports the notion made by Atasu, Sarvary and Van Wassenhove (2008) that it is better for OEMs to lose sales to their own remanufactured products, instead of losing them to independent remanufactures. As for remanufacturers, they should focus on obtaining and remanufacturing the cores of the oldest generation (e.g. mature) first, because they are the ones with the most profit potential. If they are able to obtain cores of the second generation (e.g. growth) for remanufacturing purposes, they should wait until the third generation (e.g. introduction) is launched into the market before releasing them. However, if the remanufacturers wish to generate profits early, it is possible for them to list remanufactured products of the more recent generations (e.g. growth) in the UK market, as the profit potential of such items is higher in general.

Having performed three empirical exercises in this study, it is now possible to answer the central research question in relation to the dynamic behaviour of prices, and the use of data analytics to improve pricing decisions. This will be done in the concluding chapter by discussing the overall results and contributions, along with limitations of this research and further research avenues.

Chapter 7

Conclusions and Future Work

"Si vis pacem, para bellum"

Vegetius

In this concluding chapter, the thesis is reflected upon to locate the main findings in the extant literature, and determine the extent to which the research questions and objectives have been fulfilled. The outline of this chapter is as follows. Section 7.1 summarises the main findings of this study in relation to the research questions posed at the beginning of this thesis. Section 7.2 reviews the overall research in terms of how well each research objective is achieved, the effectiveness of the methodology, and notable insights. Section 7.3 discusses the contributions of this research to the CLSCs and RLs and other related literatures. Section 7.4 concludes the chapter by considering the limitations of this study, together with possible extensions to the work carried out in this thesis.

7.1 Research Questions and Main Findings of the Study

In this section, the main findings of this research are summarised in light of the research questions, which are:

(1) How do online prices of new and remanufactured smartphones behave over time?

(2) Can volume be used to predict prices in online secondary markets?

(3) Do remanufactured smartphones cannibalise the profit potential of their new counterparts?

The overall objective is to provide insights to ease the operationalisation of remanufacturing activities by addressing the challenges in terms of pricing decisions, competition between new and remanufactured products, and product cannibalisation. This research focus is justified because, despite proven benefits of remanufacturing activities presented in the literature, OEMs are not fully taking advantage of such a practice due to the fear of intensified competition between new and remanufactured products, and potential cannibalisation effects.

Based on the application of FDA and econometrics models in this study, it can be concluded that remanufacturing of smartphones is a viable option for OEMs to engage in as an environmentally-friendly, yet profitable, practice. With regards to the behaviour of online prices (research question 1), the results reveal that the price dynamics of new and remanufactured smartphones are incredibly similar, meaning that the presence of remanufactured variants does not complicate the pricing decisions that OEMs need to make. Since it is found that the price dynamics of both product conditions fluctuate most during the introduction and mature stages of their respective product life cycles, it is possible for OEMs and online sellers to focus their efforts during these life cycle stages.

Concerning the predictive power of volume (research question 2), it is found that volume can be used to understand price movements better in some markets as evident by established price-volume links. Furthermore, the nature of the relationship between prices and volume sheds light on the profit potential of new and remanufactured smartphones. In particular, it is discovered that remanufactured smartphones have high profit potential in online marketplaces, especially when their new counterparts reach maturity. This signals an opportunity for OEMs and third-party remanufacturers to generate additional profits by selling remanufactured variants of mature smartphones alongside their introductory products.

Finally, regarding the potential of cannibalisation effect between new and remanufactured smartphones (research question 3), evidence of product cannibalisation is found from remanufactured conditions to their new counterparts only when the smartphones are mature. The same effect is stronger when comparing between product generations – be it new or remanufactured variants. In other words, OEMs should concern themselves more with the threat of cannibalisation from newer generations and / or competitors than the threat of cannibalisation from remanufactured smartphones. Overall, it is argued that these results are evidence of the benefits of smartphone remanufacturing, which outweigh its associated risks.

7.2 Review of the Research

This section reflects on the overall study by considering each research objective with regards to how well it is achieved and whether it helps answer the main research questions. Each corresponding methodology is examined to determine its effectiveness, while notable insights are also considered with respect to the literature.

The first research objective is to investigate price dynamics in terms of speed and timing of price changes at different stages of the product life cycle (Chapter 4). The use of FDA helps shed light on the temporal nature of the prices of new and remanufactured smartphones beyond simple trends by revealing precisely how much the prices change daily and when prices change the most. This information is embedded in the data themselves, which would not be uncovered if the research relied on mathematical models that assume dependency between price levels and external factors such as demand. By devising a novel approach in this study that allows the bridging of different series, it is possible to obtain a comprehensive view of an entire product life cycle, while shortening the data collection period. This is important, as modern data analytics require prompt processing of the datasets, which means that time-saving methods play a crucial role. However, it is appropriate to acknowledge that the approach relies on one small, but important, characteristic of the data; that is, the mean price of each series at the connecting point should not differ too significantly.

The fulfilment of the first research objective not only helps answer the first research question concerning the behaviour of online smartphone prices, but also uncovers insights that could help sellers trade more efficiently. Specifically, the results show that the dynamics of the prices of both new and remanufactured products are, unexpectedly, incredibly similar; this contradicts the findings from auction research reported in the works of Shmueli and Jank (2006) and Reddy and Dass (2006). The generated insights also reveal two specific stages of a product life cycle – introduction and mature – where prevalent price fluctuations occur, which should ease the decision-making process of the sellers, at least during the growth stage. Nevertheless, this finding is unexpected, because it would usually be predicted that prices during the growth stage of the product life cycle will fluctuate more dramatically than in other stages due to increased competition. When new sellers enter the market during the growth stage, incumbent sellers would typically be expected to adopt a competitive pricing strategy; hence, there should have been more price movements than were revealed in this research.

Next, this section proceeds to consider the second research objective, which is to explore the price-volume relationship of new and remanufactured smartphones across different online platforms (Chapter 5). The analysis of the link between price and volume is done using an ARIMA model, and is inspired by the literature on EMH. Such a method is well-developed, but perhaps becomes less influential in a saturated area like stock markets. For online marketplaces where an understanding of the market structure is still limited, an econometrics model is an excellent first step.

The realisation of the second research objective helps answer the second research question regarding the predictive power of volume and sheds light on the market structure of focal markets. The finding that volume is a powerful predictor of price in the online secondary markets studied confirms that these markets are inefficient in the weakest form as defined by the EMH. This is, on the one hand, not surprising as prices on the internet are not consistently lower than high street shops, signalling that the competition within online marketplaces are not perfect. On the other hand, online platforms are still regarded as being near perfect as a result of the availability of information, low barrier to entry and exit, and homogeneity of products. Therefore, evidence of imperfection in online secondary markets despite such markets possessing important characteristics of a perfect market warrants further research.

The dependency of prices on volume also introduces volume as an important factor that can be used to understand prices better. This means that researchers can potentially take advantage of this tangible variable, instead of making assumptions about demand and supply functions. Furthermore, it is observed that there exist certain markets that do not conform to the overarching law of supply and demand where, assuming that the demand does not change, an increase in supply should lead to a decrease in price. The finding is, however, that an increase in supply causes prices to increase. Conceivably, new listings in such markets are priced higher than current listings, which is counterintuitive. It is also surprising that some models of mature smartphones still have high profit potential, notwithstanding the existence of remanufactured variants, since the demand should have subsided or shifted towards newer generations.

All in all, it can be said that the second objective has also been addressed in this thesis. The findings indicate that the competition between new and remanufactured smartphones is not as fierce as initially thought; as such, OEMs can potentially reap additional profits by selling both new and remanufactured conditions of smartphones simultaneously through online secondary markets. This further highlights the importance of a better understanding on how the online market functions, and potential winning factors beyond the best price that sellers can focus their efforts on.

The final research objective is to examine the degree to which product cannibalisation occurs based on the changes in price-volume links of new and remanufactured smartphones across product life cycles (Chapter 6). This is done by applying similar econometrics models as Chapter 5, but with modifications and extensions to take into account the changing characteristics of the dataset – the AR-GARCH. By handling volatility clusters detected in the series due to the length of the observation period, it is possible to ensure the robustness of the relationships between price and volume obtained from the dataset. Accordingly, econometrics models are necessary to achieve this research objective and reveal evidence of different product cannibalisation types.

By achieving the final research objective, it is possible to answer the last research question that focuses on the cannibalisation effect between new and remanufactured smartphones. Based on the reported results, the substitution effect between Apple and Samsung Galaxy smartphones is not as strong as predicted. This is unanticipated since the two products are considered main competitors. Potentially, the fierce competition between Apple and Samsung does not transfer from the OEMs to sellers – both online and offline. This reflection stems from the observation that most flagship stores sell both Apple and Samsung smartphones, and it is up to the customers to decide which to purchase. Likewise, some online sellers do offer both brands of smartphones within the market they are based in. As such, the focus of these sellers may be less on the competition between products in their portfolio, and more on the competition against each other. The finding of cannibalisation between generations of smartphones means that online sellers should be more cautious when carrying multiple product generations. Yet, how the sellers in online markets can best manage their portfolios to avoid adverse effects of generational cannibalisation remains to be determined.

The results also show that the cannibalisation effect from remanufactured variants to new condition is weak, which is in line with some of the CLSCs and RLs literature (e.g. Akan, Ata, and Savaşkan-Ebert (2013); Ovchinnikov, Blass and Raz (2014); Ramani and De Giovanni

(2017)). This is perhaps much-needed evidence for the viability of smartphone remanufacturing for OEMs to fully engage in such an activity without additional governmental pressure.

Ultimately, it can be said that this research would not be able to generate the aforementioned insights without the use of data analytics tools such as FDA and econometrics models. The knowledge that the findings have contributed to can be used by OEMs and online sellers to make more informed pricing decisions and stay ahead of competitors in a fiercely active online market. The importance of advanced data analytics is widespread in the literature (Manyika, 2011; Tsai *et al.*, 2015), especially with the advent of big data. Nevertheless, this research attests to the benefits of these traditional analytics tools, whose concepts may be implemented in a larger scale to process the tremendous amount of data characterising industries today.

7.3 Contributions to the Literature

Having discussed main findings and notable results thus far, this section addresses the contributions of this thesis to the literature by referring to the gaps previously identified in Chapter 2. Additionally, it raises a number of important questions that need to be addressed to further advance the understanding in specific areas of the literature that this thesis engages with.

The first gap in the literature relates to the virtual non-existence of understanding on the price dynamics of new and remanufactured smartphones in a BIN setting. In the extant literature, very few researchers focus on determining the speed and timing of price changes; they utilise auction data to illustrate that prices of homogeneous products can be very different from each other (Bapna, Jank and Shmueli, 2008; Reddy and Dass, 2006; Wang, Jank and Shmueli, 2008). Researchers have yet to investigate the price dynamics of live-listing products over the course of their life cycles. This is important as BIN not only constitutes a large portion of online marketplaces, but also requires sellers to take more control of the prices over a longer period of time, compared to auctions. Chapter 4 addresses this gap by providing a first glimpse into the price formation process of each smartphone brand, specification, condition, and origin. Such a finding contributes to not only CLSCs and RLs literature, but also e-commerce research in general.

The new knowledge of the behaviour of prices of remanufactured smartphones in the long run contributes to the CLSCs and RLs literature in the following ways. First, it sheds light on how online secondary markets react to such products at each stage of their life cycle. Second, it reveals that the pricing of remanufactured products is currently done in a similar way to their new counterparts, despite proven impact of WTP on price levels in the literature (e.g. Guide and Li (2010); Quariguasi-Frota-Neto, Bloemhof and Corbett (2016); Xu, Zeng and He (2017)). As such, it is likely that the role of WTP may not be as prevalent in a BIN setting. Third, it unveils the interplay between the product life cycle and the pricing strategy that online sellers use. The counterintuitive pricing approach adopted in the growth life cycle stage, on the one hand, highlights a lack of understanding of the behaviours of online sellers in the extant literature. On the other hand, it signals that the characteristics, or even stages, of the life cycle of online products might differ from those of offline products. As a result, it may be fruitful to pursue the research of the differences between them.

In addition to filling the gap originally identified in the CLSCs and RLs literature, the findings presented in Chapter 4 raise further important questions in relation to the perception of remanufactured conditions themselves: If remanufactured smartphones are viewed as inferior to their new counterparts, why do their prices fluctuate in a comparable pattern? Is it possible that the perception of inferiority only applies to buyers and not sellers? Could it be due to the naivety of online sellers that they adjust the prices of remanufactured products in the same way as they do for new products? By addressing these questions, future researchers could further advance the CLSCs and RLs literature beyond the scope of this thesis.

As for the contribution to e-commerce research, this thesis attempts to link observable variables such as mean prices and the number of sellers as potential drivers of the dynamic behaviours. This provides a foundation for further research into the factors that can influence price dynamics of live-listing products – something that is yet to be done in the extant literature. Additionally, this thesis uses a simple statistical method to enhance the performance of FDA by reducing the arbitrariness of the smoothing process. This can increase the robustness of the method itself and ensure the validity of the results. The novel approach of constructing longer data series using an existing statistical method also introduces a more efficient way of data collection that is suitable for the fast-moving environment that characterises the business today.

The findings presented in Chapter 4 further contribute to e-commerce research by raising questions that can expand the knowledge on the relationship between product life cycles and the pricing behaviour of online sellers: Is it possible that the pricing behaviours may not be as closely linked to the life cycle stages as initially thought? Could it be that new sellers price their products at the same level as current sellers instead of lower, thus price matching does not occur? Maybe the market saturates much earlier than it is predicted? If so, why does it last for the majority of the product life cycle before prices begin to change considerably again?

The second gap in the literature concerns the limited understanding of the structure of online marketplaces, and the focus on local competition prevalent in the CLSCs and RLs literature (see, for example, Wu (2015); Liu *et al.* (2018); Zheng *et al.* (2019)). It is speculated in the literature that online markets are nearly perfect based on their characteristics (Kuttner, 1998; Srinivasan, Anderson and Ponnavolu, 2002; Hsieh, Chiu and Chiang, 2005). Nevertheless, many researchers provide evidence for imperfection (Degeratu, Rangaswamy and Wu, 2000; Lynch and Ariely, 2000; Suri, Long and Monroe, 2003), but the exact market structure is yet to be discovered. Much attention has been paid to the competition between OEMs and independent remanufacturers (for instance, the works of Jung and Hwang (2011), Abbey, Blackburn and Guide (2015), and Zheng *et al.* (2019)), but the literature has not considered the competition between sellers in a BIN setting – especially when remanufactured products coexist. For online sellers to operate in a more informed manner, knowledge of online trading mechanisms and competition between new and remanufactured products is beneficial. Chapter 5 fulfils this by confirming the inefficiency of online secondary markets for smartphones and identifying volume as a powerful predictor of prices. This contributes to both the economic and finance literature and CLSCs and RLs literature.

The evidence of inefficiency of the online market contributes to the economic and finance literature in a few ways. First, it signals that the EMH may not be applicable to online secondary markets where new and remanufactured products coexist. Second, it indicates that the MDH is relevant to online marketplaces. This means that information asymmetry exists in electronic markets, as prices depend on volume and thus do not immediately reflect all available information (Karpoff, 1987). Third, it illustrates that the market structure differs between stages of the product life cycle. Finally, this particular finding leads onto certain key questions that need to be addressed in future research: Are online products really homogenous considering possible influences from non-price attributes such as seller ratings, shipping costs, and delivery times? Maybe there exist certain price collusions online given the chance that consumers react to price changes slower than sellers do? Is it possible that electronic markets are still developing despite the expansive growth witnessed currently? Focusing on these questions may lead to an advancement of the literature's understanding of online markets.

The established price-volume links contribute to the CLSCs and RLs literature in the following ways. First, it suggests that volume can be used to understand price better. Most, if not all, of the existing studies that focus on finding optimal prices for new and remanufactured products have yet to include volume – be it sold or offered – into their mathematical models (for instance, the works of Ferrer and Swaminathan (2006); Majumder and Groenevelt (2001); Abbey, Blackburn and Guide (2015), instead of solely attempting to estimate customer demand; as such, this finding may lead to a more accurate estimation of selling prices. Second, it sheds light on the profit potential of different markets – information that was not available before. Third, it casts doubt on the applicability of the traditional product life cycle concept to online secondary markets that host both new and remanufactured smartphones, since some mature products are found to have high profit potential.

Based on the findings presented in Chapter 5, the thesis puts forward questions that allow researchers to better pursue understanding of the trading mechanisms of online markets: Could it be that online sellers do not follow the law of supply and demand? Maybe they are yet to take advantage of available information on the internet and adjust their pricing strategies? Perhaps certain desirable characteristics of products that are missing from newer generations are sufficient to attract the demand back to mature products?

Finally, the third gap in the literature concerns the lack of evidence of a cannibalisation effect of remanufactured products in online secondary markets. Some of the literature in CLSCs and RLs such as the works of Yan *et al.* (2015) and Gan *et al.* (2017) suggest that OEMs should offer remanufactured products through a different channel than their new counterparts to avoid product cannibalisation; this may mean e-channels, but more and more sellers are also marketing the new condition online. As such, evidence of the extent of a cannibalisation effect in an online setting is necessary to alleviate OEMs' concerns. Chapter 6 provides evidence that new and remanufactured smartphones can coexist in online marketplaces, which contradicts the findings reported by Ferrer and Swaminathan (2011), Mitra (2016), and De Giovanni and Ramani (2018). Additionally, it reveals an opportunity for OEMs to generate additional profits by offering remanufactured versions of their mature smartphones, instead of risking potential loss of sales caused by multiple product generations. To illustrate, OEMs typically offer three smartphone generations within the same market – introductory, growth, and mature – while it has been established in this thesis that these smartphones cannibalise each other's profit potential. In contrast, the risk of cannibalisation from remanufactured smartphones should only be of concern when considering mature smartphones, since the remanufactured condition has higher profit potential than the new condition. Therefore, it is possible that OEMs will generate more profit by selling new conditions of introductory and growth smartphones and remanufactured versions of mature smartphones than by selling only new versions of all three generations.

7.4 Limitations of the Study and Future Directions

After reflecting upon the research findings and contributions to the literature, this section proceeds to examine limiting factors in this research that may impact the findings and the applicability of the results. It then concludes by discussing possible extensions to this study.

The limitations to this study are as follows. First, this research selects smartphone models based on their popularity to ensure that the uncovered insights are beneficial to OEMs and sellers. This means that the patterns captured using FDA and econometrics models may not be transferrable to less popular smartphones. Second, the data collection period is not long enough to cover the entire product life cycles, due to the time constraint of this research. Although the researcher has used statistical methods to construct a longer dataset in order to replicate the supposed product life cycle and ensure its validity, it is possible that the actual dynamics can differ than those presented in this thesis. Last, the scarcity of previous research that focuses on similar topics, despite meaning that this study is novel in its nature, limits the accumulation of a firm theoretical foundation in this thesis.

As for future directions, it is possible to extend this study in the following ways. First, using data series that can cover the entire product life cycles to compare between the dynamics uncovered using the constructed dataset and the dynamics captured using the actual dataset. This facilitates the investigation into the strength of the statistical methods used, and further development of an approach that can significantly shorten the data collection period. Should online platforms make market data publicly available to academics like stock markets do, this area of research can grow exponentially. Second, using a series of explanatory variables, such as the number of sellers, starting prices, and ending prices, to determine if they play a role in affecting the exhibited price dynamics of live-listing smartphones. This empirical exercise would shed light on the key variables that govern the price dynamics, enabling further developments of more advanced forecast models that can predict future prices with higher accuracy. Third, similar research can be done using sold listing data, where the impact of market variables, such as seller ratings and item condition, on the prices and their dynamic behaviours can be determined.

Finally, to further contribute to the knowledge of online secondary markets, it is possible to use series for prices and volume as proxies for the demand and supply functions of online market platforms. Given the difficulty in accurately estimating such functions, the above empirical exercise could be carried out as long as data on both the volume of transactions and prices paid by buyers are available. The former, in fact, could be used to estimate the supply function, whereas the latter could be used to estimate the demand function. Such a study would be useful for both manufacturers and sellers, as online platforms also host the trading of new items, and the demand and supply estimated on online secondary markets can be taken as a good proxy for the demand and supply of primary markets.

As well as the aforementioned extensions that may be applied to this study, researchers may expand beyond the scope of this thesis by pursuing the key questions put forth in Section 7.3. This will allow further development – and even potentially a fundamental shift in perception – of traditional concepts such as product life cycle, market efficiency, and pricing behaviour, as they apply to an online secondary market setting.

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