The price-volume relationship for new and remanufactured smartphones

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Abstract

Despite the rapid expansion of secondary markets for remanufactured electronic goods, the understanding of their empirical dynamics such as the price-volume relationship is still rather limited. In this study, we investigate such dynamics over time for new, manufacturer- and seller-refurbished smartphones using data from eBay UK and eBay US. We find significant negative relationships between price and volume for new smartphones indicating that the profit potential of such markets for sellers is limited. We show, instead, that the price-volume relationships for remanufactured smartphones are positive and significant – suggesting that the secondary markets for such items are potentially highly profitable. Overall, our empirical results suggest that the UK markets have higher profit potential than their US counterparts. The proposed analysis is a further step toward a better understanding of the price dynamics of new and remanufactured smartphones – and it enables both manufacturers and OEMs to better evaluate the profit potential of one of the fastest growing segments of consumer electronic goods.

Key words: price-volume relationship, remanufacturing, eBay, regression analysis

1. Introduction

In the past decade, the rapid advancement in innovation and technology has significantly accelerated the development of consumer electronics. Nowadays, a vast amount of consumer electronics is being traded globally. One of the fastest growing segments is the smartphone industry, where approximately 1.53 billion units were sold in 2017 while the sales forecast can potentially soar to 1.77 billion by 2021 (International Data Corporation, 2017a). Despite the general trend of increased durability of such items, the end-of-use cycle of smartphones has shortened considerably due to software obsolescence and the desire of the consumers to upgrade their handsets to the newest generation.

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, the 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 is 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). Remanufacturing is considered profitable as it allows OEMs to retain the features and technologies of a new item where the finished products can be remarketed and sold in secondary markets (Guide *et al.*, 2003; Vorasayan and Ryan, 2006; Guide *et al.*, 2008). In this study we use the terms "refurbished" and "remanufactured" interchangeably as synonyms (see e.g. Ovchinnikov (2011), Subramanian and Subramanyam (2012), Abbey et al. (2015) and Quariguasi Frota Neto et al. (2016)).

Despite remanufacturing being a multi-million-dollar industry, the current literature appears to have only just begun to empirically investigate market-related issues. In the literature of closed-loop supply chains (CLSCs) and reverse logistics (RLs) (more specifically, remanufacturing), the majority of research focuses on the quantitative modelling perspective (see for example, Chen and Chang (2013), and Gan *et al.* (2016), see also Govindan *et al.* (2015) for a review), case studies (see De Brito *et al.* (2005) for a review) or theoretical frameworks (see for example, Subramoniam *et al.* (2010), Subramoniam *et al.* (2013), and Agrawal *et al.* (2015)). Such prescriptive and normative studies do not simulate exact market conditions as they rely on selected influencing factors whose importance is still not yet established in a generalised business environment (Souza, 2013; Prahinski and Kocabasoglu, 2006). Moreover, Guide and Van Wassenhove (2009) note that empirical analyses of such markets can allow for the development of more sophisticated analytical models. Therefore, the necessity to conduct further empirical research has become inevitable. The reviews by Guide and Van Wassenhove (2006; 2009) and Atasu *et al.* (2008) also strongly emphasise the need for empirical market-oriented studies in CLSCs and RLs.

In this study, we contribute to the existing CLSCs and RLs literature by shedding light on the time-series dynamics characterising the relationship between prices and volumes of remanufactured smartphones. The unravelling of such a link is important for producers and sellers, as it provides a first glance as to how prices react to changes in volumes, and vice versa. In fact, the sign and magnitude of the elasticity of prices to volumes is what determines the sensitivity of revenues and, in the final analysis, the profit potential of a given market. For instance, a profitable market would be a market in which prices increase following an increase in the quantities offered. Conversely, a less profitable market would be a market in which prices fall due to an increase in quantities. Moreover, the understanding of the link between prices and quantities is of paramount importance for primary markets of new items, which constitute by far the largest portion of trading volumes. However, the estimation of the price-volume link in such markets is problematic, as prices remain fixed at the level set by the producers and they do not change over time as a result of the interaction of demand and supply. On the other hand, secondary markets such as e-trading platforms constitute an ideal setting to investigate such a link for a number of different reasons. Firstly, in e-trading platforms the auction prices fluctuate on an intraday basis as a result of the market forces interactions, delivering long time series of prices and quantities which can be studied empirically. Secondly, such platforms host markets for new and remanufactured items of a large variety of models, enabling investigation of the extent to which the dynamics of the price-volume relationship of a given item is dependent on those of items which are substitute. Finally, the same platforms host exchanges for new items – so that 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.

To the best of our knowledge, there are no previous studies in the CLSCs and RLs literature addressing the above issues. In this study, we fill these gaps by investigating the relationship between price and volume in the secondary market (eBay) for new and remanufactured smartphones (iPhone 5s and Samsung Galaxy S4). We examine such relationships across different platforms (eBay UK and eBay US), brands (Apple and Samsung), models (iPhone 5s 64GB, 32GB, 16GB, and Samsung Galaxy S4), and conditions (new, manufacturer-refurbished, and seller-refurbished) as the above features can affect consumer purchase decisions and seller trading strategies. We carry out the empirical analysis using daily series for prices and volumes gathered from the above platforms over the period spanning from 28th January 2016 to 3rd November 2016. This empirical approach enables a better understanding as to how the price-volume relationships evolve on the eBay UK and US platforms, across different brands, model variants, and conditions – as well as to what extent they are dependent on the presence of competitor items. It also facilitates a comparison across the different markets under scrutiny, distinguishing markets with high-profit potential from those are potentially less profitable.

We make use of standard autoregressive (AR) models which make it possible to unravel the links between the prices and volumes of the different products under scrutiny and, at the same time, control for any other variables that might determine the dynamics of prices over time. Such models are estimated by means of Least Squares (OLS) and bootstrap simulations, and then re-estimated by using 2-Stage Least Squares (2SLS) to account for the potential endogeneity occurring between prices and volumes. Our empirical results for both UK and US markets are quite similar. We find, in fact, strong negative relationships between price and volume of new smartphones. This suggests that for such markets the profit potential is limited - as an increase in volume results in downward pressures on prices. Interestingly, we find strong positive links between price and volume of remanufactured smartphones. Thus, the secondary markets for remanufactured smartphones are potentially highly profitable as they are mainly driven by the demand from buyers. We also show that the most profitable market for the sellers is the market for every condition of iPhone 5s 16GB. Moreover, the markets for iPhone 5s 16GB and Samsung Galaxy S4 have distinct dynamics despite the products being considered as substitutes.

The structure of this study is organised as follows. Section 2 reviews the related literature. Section 3 describes the dataset in greater detail. Section 4 discusses the empirical methodology used to investigate the price-volume relationships. Section 5 discusses the empirical results. Discussion and managerial insights are presented in Section 6. This is followed by conclusions in Section 7.

2. Literature Review

2.1 Empirical Research on Willingness to Pay for New and Remanufactured Products

According to Jiménez-Parra *et al.* (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 *et al.*, 2014), functionality of the products (Mugge *et al.*, 2017), perceived environmental benefits (Hazen *et al.*, 2016, Khor and Hazen, 2017; Mugge *et al.*, 2017), and how up-to-date the products are (Quariguasi-Frota-Neto and Bloemhof, 2011; Jakowczyk *et al.*, 2017). However, consumers also perceive remanufactured products as the economic substitutes of the corresponding new counterparts. They are often willing to purchase remanufactured products when the price is lower than the price of the new counterparts. This claim is empirically evaluated by Guide and Li (2010) who find a clear difference in consumer’s willingness to pay (WTP) between new and remanufactured products for consumer and commercial goods such as jigsaws and security devices. Other scholars 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), less robust remanufacturers’ reputation (Subramanian and Subramanyam, 2012), consumers’ low tolerance of ambiguity in terms of perceived quality (Hazen *et al.*, 2012; Wang *et al.*, 2013, Wang and Hazen, 2016, Hazen *et al.*, 2017), and disgust caused by contacts of products with previous owners (Abbey *et al.*, 2015) are among the determinants of the above price gap.

Recently, Pang *et al.* (2015) empirically analysed the 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, 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 *et al.* (2017). Quariguasi-Frota-Neto *et al.* (2016) investigated how customers perceived 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 relative to new products. They also found that customers were willing to pay a premium for remanufactured products in comparison with used items. Customers need more reassurance for used iPods through the 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 *et al.* (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, finding that buyers tend to pay a premium for seller-refurbished iPads in comparison to used ones, and that such premia are even higher for new and manufacturer-refurbished iPads.

Several other studies look into brand preferences in order to investigate whether brand name affects customers' 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 risks in terms of quality (van Weelden *et al.*, 2016). Nevertheless, there are conflicting views regarding this matter. A study by Abbey *et al.* (2015) 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 tires. 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 *et al.* (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 the OEM. This negative effect differs across brands and product categories.

The above studies are all based on datasets in cross-sectional format, where only the prices at which transactions occur are observed and then matched with a number of market, seller and item's features occurring at the same time as the transactions (see for example, Pang *et al.*, 2015). In this sense, such studies lack the time dimension – as they neglect to analyse the time-series properties of prices. In this study, we take a slightly different approach, as we focus on a number of homogeneous items (i.e. specific models of smartphones) and we look at the time dynamics of listing prices in order to unravel any existing link between these last and their volumes.

Studying the link between prices and volumes enables researchers to shed light on some important features of the markets under scrutiny. The sign and magnitude of the price-volume link, in fact, provide a broad-brush picture of the profit potential of a given market. For instance, a market characterized by a positive link would be a market with high-profit potential, where producers can inject larger volumes of goods without causing a downward pressure on prices. Conversely, a less profitable market would be a market in which prices fall following an increase in the volumes supplied. Moreover, the analysis of the above link can also help identify empirical models able to predict over time the price levels of given items. These are the main contributions of our study to CLSCs and RLs literature.

We investigate the price-volume relationship in a time-series setting over a long-time span of 10 months by retrieving daily prices and volumes from the eBay platforms for new and remanufactured iPhone 5s and Samsung Galaxy S4. We carry out the above analysis by drawing on the economic literature on price-volume relationships. Such literature is well developed for some specific areas of empirical finance, such as the strands of research on the Mixture of Distributions Hypothesis (MDH), Efficient Market Hypothesis (EMH), and the futures markets for stocks, commodities and natural resources. All the above studies are based on the idea that prices over time evolve as a function of a number of driving forces, and that among these, the volumes of units exchanged (along with prices and volumes of substitute items) are an important determinant. We provide below an overview of such strands of research.

2.2 Empirical Research on Price-Volume Relationship

The relationship between prices and volumes has been extensively analysed in the literature on the Mixture of Distributions Hypothesis (MDH). The MDH is a popular paradigm that has been used widely to describe how prices and volumes evolve over time (see, among other, Karpoff, 1987). It hinges on the idea that prices and volumes are jointly determined by the preferences of market participants which can change as a result of the arrival over time of specific types of information. These include, for example, past levels of prices and quantities for the focus and substitute items. The MDH has been tested typically using series of prices and volumes of financial securities such as shares. A related strand of research has focused on the predictability of prices of financial securities using explanatory variables such as past levels of prices, volumes exchanged, balance sheet data as well as various sources of private information (see Fama and Malkiel, 1970). A large number of empirical studies have shown that prices of financial securities can be predicted by using the volumes of securities traded (see, among others, Rogalski, 1978; Hiemstra and Jones, 1994; and Brida *et al.*, 2016).

The link between prices and volume has also been investigated extensively in futures markets of commodities. This strand of studies has shown that the above links can have complicated dynamics characterized by causality, non-linearity, co-integration and dependence on market trends. For instance, Malliaris and Urritia (1998) set up a stochastic model which relates prices with volumes, and test it on a set of futures contracts for agricultural commodities. Their empirical results show that the price-volume links are strongly negatively interrelated in both the short- and long-run. He and Chen (2011) gauge the price-volume links in the Chinese and US commodity markets for hard winter wheat, soy meal, soybean and corn, showing that the above links are characterized by non-linear dependency and power-law cross-correlation. Abdullahi *et al.* (2014) show that the trading volumes on the West Texas Intermediate (WTI) and Brent crude oil futures markets can forecast the returns in such markets. Using the same data, Moosa and Silvapulle (2000) document the presence of a linear causality running from volumes to prices, but not vice versa. Magkonis and Tsouknidis (2017) examine whether the price-volume link occurs in the markets for petroleum-based commodities, and document the existence of time-varying spillover effects between futures trading volumes and prices. Alizadeh and Tamvakis (2016) investigate the price-volume relationship in the markets for WTI and gas futures contracts, showing that the impact of volumes on prices is time-varying and dependent on market trends.

Unlike the literature on financial markets, the strand of research on price-volume relationships in markets where real assets are traded is rather scant - with a limited number of studies that have analysed the markets for electricity, second-hand dry bulk ships, and pharmaceutical drugs. Saâdaoui (2013) study the relationship between electricity spot prices and related trading volumes in the European Energy Exchange market, documenting a strong causal link that is bidirectional and that changes with the time-horizon considered. Syriopoulos and Roumpis (2006) focus on the markets for second-hand dry bulk ships and tankers and document positive causal links between prices and volumes. Alizadeh and Nomikos (2003), using data for a similar variety of vessels obtain similar results. Focusing on the markets for pharmaceutical drugs, Bhattacharya and Vogt (2003) test empirically a theoretical pricing model using quarterly retail quantity and price series for a large cohort of β-blockers, and show that there is a positive causal impact of volumes on prices.

2.3 Summary

Based on recent market trends there is clear evidence that the remanufacturing industry will continue to grow in the near future. This, coupled with the ever-growing sales volume of consumer electronics in the primary market, highlights the importance of understanding the secondary market itself as an intensely active channel for remanufactured products. The volume, or the total number of listings in our study, represents the market size from the suppliers' perspective and the options available from the consumer perspective, and it can potentially yield insights into the trading mechanism of secondary markets beyond those that can be afforded solely by analysing WTP (Jakowczyk *et al.*, 2017). As for price, much attention has been paid to the external factors affecting prices such as customers' perception and the brand name. However, the effect of price on the future prices of consumer electronics in the secondary market has not yet been studied empirically. There also exists an invaluable opportunity to investigate the role of volume and price further to shed more light on the structure of the secondary market where new and remanufactured products coexist.

3. Data Description

Our data consist of daily listing prices and volumes for iPhone 5s (64GB, 32GB, and 16GB) and Samsung Galaxy S4 (16GB). Each specific model has three product conditions: new (N), manufacturer-refurbished (MR) and seller-refurbished (SR) for a total of 12 homogeneous items. 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 inspection processes where they are cleaned, repaired to full working order and ensured that they are in excellent condition.

Listings for the above items are retrieved through the use of eBay's application programming interfaces (APIs) from eBay UK and eBay US. We select iPhone 5s and Samsung Galaxy S4 for three reasons. Firstly, the volumes of daily listings for these two smartphones are 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 S4 were released in 2013, which makes them comparable in terms of the stage of the product life cycle. We take life cycle stage into account as it affects the price and demand of consumers which, in turn, influence the interaction between prices and volumes. Therefore, we select the products at the same stage of the life cycle 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 the 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 S4 16GB) and, of course, cross-brand comparisons between iPhone 5s 16GB and Samsung S4 16GB. The sampling period spans from the 28th of January 2016 to the 3rd of November 2016, for a total of 281 observations. On average, we have retrieved 846 daily iPhone 5s listings from eBay UK and 1,782 listings from eBay US. As for Samsung Galaxy S4, we have retrieved on average 283 and 763 daily listings from eBay UK and eBay US, respectively.

3.1. Preliminary Statistics

Figures 1 and 2 illustrate the overall evolution of the prices and volumes of the iPhone 5s (64GB, 32GB and 16GB) and Samsung 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 UK and US. Interestingly, the price difference between new and remanufactured products is less noticeable for the Samsung 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. The two figures also depict the overall evolution of the listing volume for the four models under scrutiny. Such volumes fluctuate over the entire period, with a significant decrease in all New and SR items around August 2016 for the UK markets. The quantities then accumulate back afterward and continue 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 UK gradually increases over the entire period, whereas the same series for the US markets are more erratic. 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 amounts 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 New.

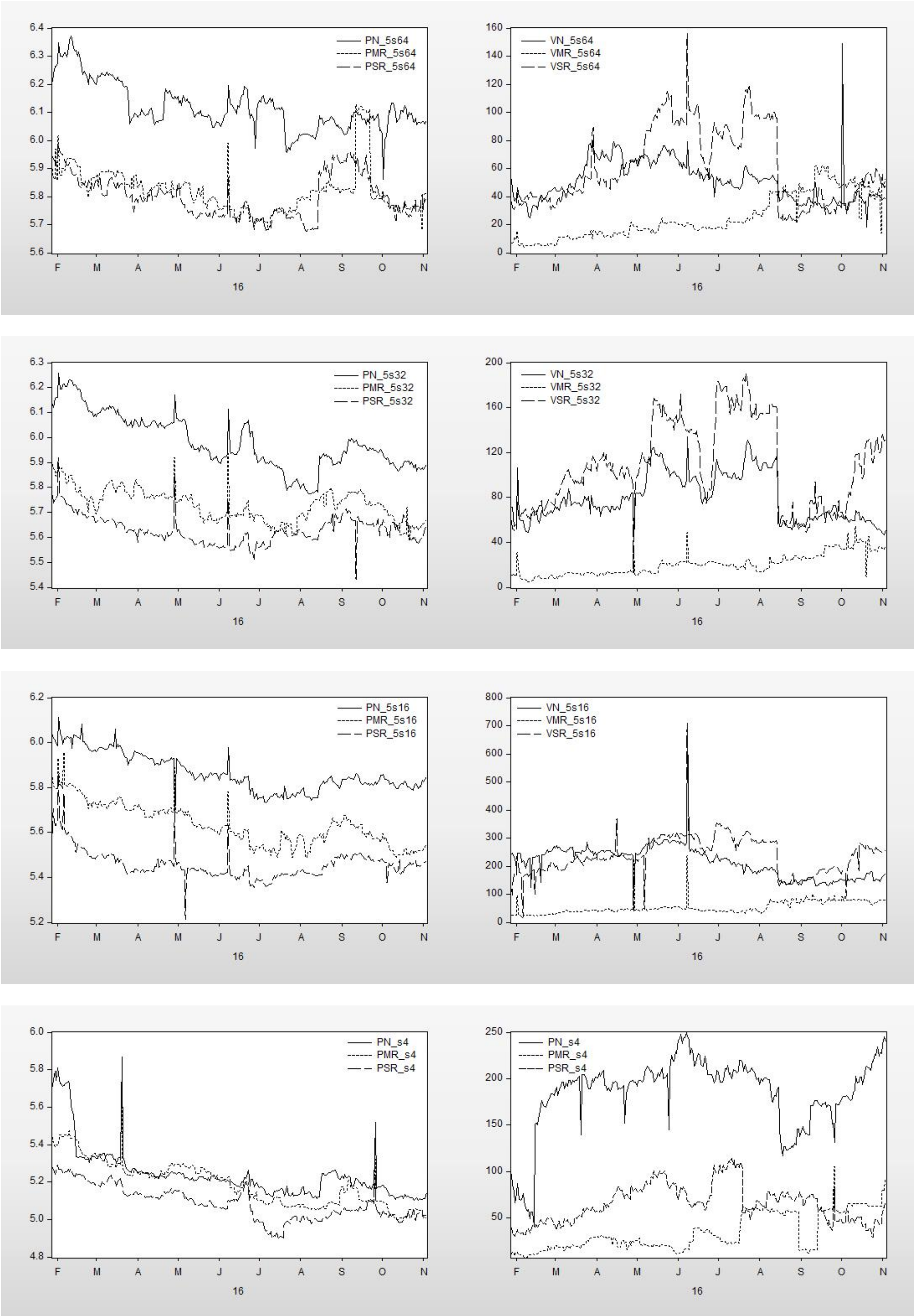

Figure 1: Price and Volume of iPhone 5s and Samsung Galaxy S4 in the UK markets.

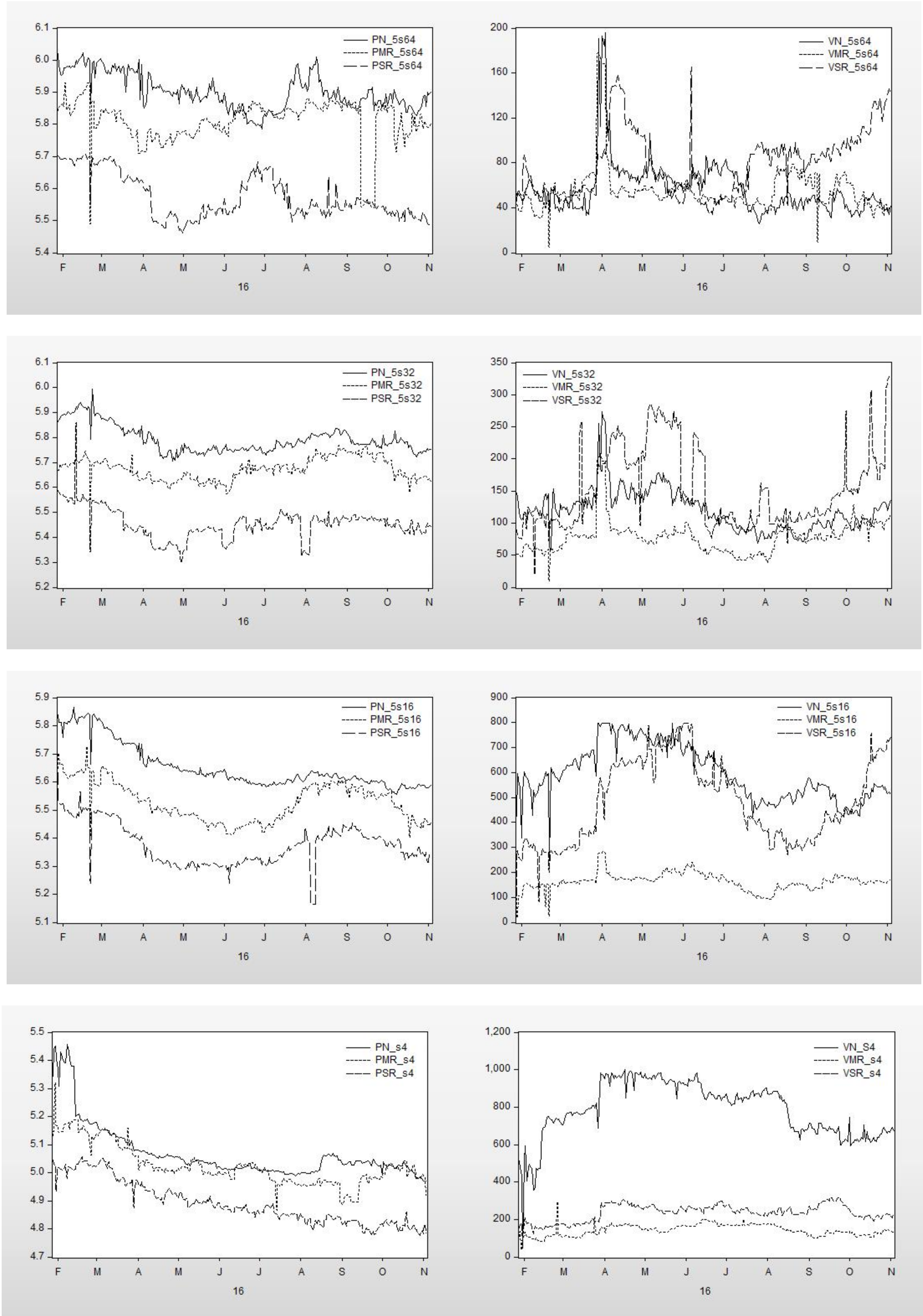

Figure 2: Price and Volume of iPhone 5s and Samsung Galaxy S4 in the US markets.

Table 1 illustrates the average prices of iPhone 5s and Samsung S4 on eBay UK and US. The mean prices of iPhone are directly proportional to the capacity of the product model regardless of the condition of the product. In other words, the price of iPhone 5s 64GB is higher than those of iPhone 5s 32GB and 16GB, respectively, for every condition of the item 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 S4 are similar to those for iPhone 5s 16 GB. The same table depicts the standard deviations of the daily prices. The deviations in the price setting are the highest for the new version of iPhone 5s and Samsung S4 across the UK and US markets. On the other hand, similar discrepancies in price are found for the two remanufactured versions in most models. In general, the variations in the price setting of both iPhone 5s and Samsung S4 are larger in the UK than the US. Finally, the price settings of iPhone 5s 16GB are, in general, more volatile than those of Samsung S4.

Table 1 shows also the average volumes of iPhone 5s and Samsung Galaxy S4 in the UK and US markets. Overall, the mean total volume of iPhone 5s increases as the capacity specification of the model decreases, so 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 quantities than the iPhone 5s 64GB and 32GB. Interestingly, there are more iPhone 5s 16GB on offer than Samsung S4 in both the UK and the US 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.

Product Model				Statistics						
				Vol	Mean	Median	SD	JB	Q(4)	$Q^2(4)$
iPhone 5s	64GB	UK	N	50.73	455.7	444.6	39.79	52.22 (0.000)	923.3 (0.000)	940.2 (0.000)
iPhone 5s	64GB	UK	MR	25.06	338.4	336.4	29.70	552.6 (0.000)	707.3 (0.000)	691.1 (0.000)
iPhone 5s	64GB	UK	SR	60.55	331.2	328.0	25.45	20.08 (0.000)	889.3 (0.000)	889.8 (0.000)
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)
iPhone 5s	64GB	US	MR	55.45	333.7	340.1	22.21	360.2 (0.000)	536.3 (0.000)	552.0 (0.000)
iPhone 5s	64GB	US	SR	79.44	264.0	256.1	18.64	29.61 (0.000)	923.6 (0.000)	926.4 (0.000)
iPhone 5s	32GB	UK	N	79.12	398.7	385.1	44.98	14.84 (0.001)	1016 (0.000)	1014 (0.000)
iPhone 5s	32GB	UK	MR	20.20	308.8	309.7	20.63	8.106 (0.017)	735.7 (0.000)	708.1 (0.000)
iPhone 5s	32GB	UK	SR	108.3	279.4	277.3	16.14	257.4 (0.000)	576.5 (0.000)	556.5 (0.000)
iPhone 5s	32GB	US	N	120.1	328.2	322.2	18.36	71.07 (0.000)	938.8 (0.000)	934.6 (0.000)
iPhone 5s	32GB	US	MR	77.80	291.5	291.4	12.80	6.556 (0.038)	806.4 (0.000)	813.8 (0.000)
iPhone 5s	32GB	US	SR	153.3	234.2	233.7	15.11	1622 (0.000)	576.2 (0.000)	496.4 (0.000)
iPhone 5s	16GB	UK	N	214.3	354.1	345.2	30.60	20.80 (0.000)	937.6 (0.000)	936.7 (0.000)
iPhone 5s	16GB	UK	MR	52.78	281.1	276.7	26.91	26.86 (0.000)	910.6 (0.000)	882.1 (0.000)
iPhone 5s	16GB	UK	SR	235.4	235.2	232.0	16.70	1879 (0.000)	625.6 (0.000)	586.9 (0.000)
iPhone 5s	16GB	US	N	596.8	286.3	276.9	23.84	80.69 (0.000)	1012 (0.000)	1007 (0.000)
iPhone 5s	16GB	US	MR	162.7	252.2	251.1	17.62	12.93 (0.002)	898.8 (0.000)	890.1 (0.000)
iPhone 5s	16GB	US	SR	479.9	216.6	214.6	16.24	10.99 (0.004)	753.3 (0.000)	762.5 (0.000)
Samsung Galaxy S4	16GB	UK	N	184.4	191.7	184.4	33.15	1192 (0.000)	768.3 (0.000)	719.0 (0.000)
Samsung Galaxy S4	16GB	UK	MR	34.35	180.8	179.9	22.66	26.80 (0.000)	926.9 (0.000)	881.1 (0.000)
Samsung Galaxy S4	16GB	UK	SR	64.87	162.5	160.3	14.77	11.68 (0.003)	980.9 (0.000)	975.4 (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)
Samsung Galaxy S4	16GB	US	MR	142.4	152.4	149.5	11.40	65.98 (0.000)	929.6 (0.000)	909.7 (0.000)
Samsung Galaxy S4	16GB	US	SR	235.6	133.4	131.0	10.50	28.60 (0.000)	1025 (0.000)	1025 (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 1: Preliminary statistics of the dataset

3.2. Empirical Distributions of the Data

We start our analysis by taking the logarithmic transformation of the price series.[1] We then feed both the Ng and Perron (2001) test for the null of integrated series and the KPSS test for the null of stationarity with the log price series, and report the values of such statistics in Tables 2 and 3.[2,3] 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 non-stationary series are subsequently transformed by taking the first difference to achieve stationarity.

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

Once we take the first differences of the log price series, we examine their empirical distributions. These last 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. We, therefore, carry out the analysis by

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

[2] We make use of such statistics 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).

[3] We apply additional tests such as the ADF and DF-GLS tests and obtain similar results as those set out in the two tables. We do not report their results to save space.

using the log-transformed series, and by controlling for potential distortions generated by departures from normality of the above series by using bootstrap analysis (see DiCiccio and Efron 1996).

Product Model	Capacity	Variable	Condition	Ng-Perron					KPSS[e]
				Lags	MZa[a]	MZt[b]	MSB[c]	MPT[d]	
iPhone 5s	64GB	Price	N	1 (1)	-16.79 (-5.12)	-2.21 (-1.51)	0.18 (0.30)	5.39 (5.01)	0.26** (1.24)**
			MR	1 (1)	-18.99* (-11.02)*	-3.08* (-2.31)*	0.16* (0.21)*	4.81* 2.39*	0.11 (0.36)
			SR	1 (1)	-7.51 (-2.85)	-1.90 (-1.14)	0.25 (0.40)	12.22 (8.45)	0.25** (0.50)*
		Volume	N	6 (6)	-6.75 (-5.94)	-1.82 (-1.67)	0.27 (0.28)	13.51 (4.31)	0.35** (0.61)**
			MR	14 (15)	-5.61 (1.11)	-1.65 (0.90)	0.29 (0.81)	16.19 (49.46)	0.21* (1.72)**
			SR	1 (1)	-8.03 (5.96)	-1.98 (-1.72)	0.25 (0.29)	11.43 (4.12)	0.36** (0.46)*
	32GB	Price	N	1 (1)	-11.26 (-0.99)	-2.34 (-0.52)	0.21 (0.52)	8.24 (16.56)	0.27** 1.45**
			MR	5 (3)	-6.29 (-0.79)	-1.75 (-0.44)	0.55 (0.33)	14.49 (18.59)	0.19* (0.91)**
			SR	5 (5)	-4.15 (-1.10)	-1.36 (-0.65)	0.33 (0.60)	21.19 (18.94)	0.41** (0.53)*
		Volume	N	2 (2)	-9.85 (-7.42)	-2.15 (-1.92)	0.22 (0.22)	9.55 (3.80)	0.35** (0.47)*
			MR	5 (5)	-11.47 (-0.12)	-2.38 (-0.06)	0.21 (0.51)	8.02 (19.21)	0.18* (1.65)**
			SR	1 (1)	-9.32 (-4.65)	-2.16 (-1.43)	0.23 (0.31)	9.77 (5.47)	0.27** (0.49)*
	16GB	Price	N	3 (3)	-6.10 (-0.40)	-1.57 (-0.30)	0.26 (0.76)	14.85 (31.89)	0.42** (1.51)**
			MR	9 (2)	-3.23 (-0.28)	-1.18 (-0.18)	0.37 (0.65)	26.36 (26.28)	0.26** (1.53)**
			SR	9 (9)	-2.50 (-0.67)	-1.01 (-0.48)	0.40 (0.73)	32.32 (28.07)	0.36** (0.59)*
		Volume	N	7 (6)	-5.73 (-2.78)	-1.69 (-1.08)	0.30 (0.39)	15.90 (8.52)	0.32** (1.29)**
			MR	15 (8)	-6.85 (-1.26)	-1.85 (-0.61)	0.27 (0.48)	13.31 (14.31)	0.15* (1.50)**
			SR	4 (4)	-6.80 (-2.52)	-1.84 (-1.02)	0.27 (0.41)	13.42 (9.25)	0.30** (0.36)*
Samsung Galaxy S4	16GB	Price	N	3 (2)	-3.84 (-0.07)	-1.31 (-0.05)	0.34 (0.81)	22.76 (23.14)	0.29** (1.20)**
			MR	4 (3)	-11.89 (0.58)	-2.43 (0.46)	0.20 (0.80)	7.71 (43.50)	0.18* (1.74)**
			SR	1 (1)	-9.66 (-0.49)	-2.14 (-0.31)	0.22 (0.63)	9.72 (23.71)	0.28** (1.42)**
		Volume	N	2 (2)	-4.82 (-0.52)	-1.55 (-0.28)	0.32 (0.54)	18.91 (19.08)	0.25** (0.51)*
			MR	15 (15)	-16.97 (2.08)	-2.01 (1.07)	0.18 (0.51)	5.49 (27.42)	0.20* (1.46)**
			SR	2 (2)	-6.72 (-3.48)	-1.82 (-1.26)	0.27 (0.36)	13.57 (7.03)	0.39** (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.

Table 2: 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	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)*
			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 (160.28)	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 3: Unit Root Tests Results for iPhone 5s and Samsung Galaxy S4 in the US.

4. Methodology

Since the preliminary analysis of the price and volume series has shown that such series are all integrated of order one, the empirical analysis which follows is carried out on the same series in first differences, as their stationarity is a necessary condition for the asymptotic properties of standard linear regression models to hold. We analyse the link between prices and volumes by means of standard auto-regression models which take the following specification:

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

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 σ_ϵ^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 Akaike (AIC) and Schwarz Information Criterion (SIC). We then investigate the presence of heteroscedasticity and serial correlation in the residuals of the above models by applying Ljung 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.(1) with GARCH dynamics, and by estimating this particular model through Maximum Likelihood (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). Moreover, the reduced number of available data-points makes it difficult to achieve a maximum in the Likelihood function and ascertain that such maximum is global rather than local – casting, therefore, doubts on the opportunity to adopt GARCH models. We, therefore, choose not to model any GARCH dynamics and carry out estimation of eq.(1) by using OLS which is less affected by small sample bias.

We then control for any undesirable effect that departures from normality, heteroscedasticity, and serial correlation might have on our empirical estimates by carrying out WLS estimates as well as bootstrap simulations of eq.(1). Given the limited number of observations available, we use bootstrap analysis to assess to what extent the finite sample properties of our 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, we re-estimate eq.(1) by 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 in 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 gauge how strong the endogeneity issue is in our series, we re-estimate eq.(1) using 2SLS and compare the estimates obtained with the OLS counterparts. Whenever the two sets of estimate depart from each other, we comment on our results by privileging the 2SLS estimates as they can better correct for endogeneity.

5. Empirical Results

In this section, we carry out OLS and 2SLS empirical estimates of eq.(1) for prices and volumes of the products previously set out. To determine the number of lags to include in the model we utilise both the AIC and SIC criteria which weight the bias/efficiency trade-off in slightly different ways. We test the model specification 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 SIC is minimal.[4] For this reason, and for consistency across all the series under scrutiny, we apply the same model specification with lag lengths equal to 1.

Tables from 4 to 7 present the results from the estimations of eq. (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, we consider 2SLS which can account for the endogeneity that might affect the relationship between prices and quantities.

5.1 The Price Dynamics

The coefficient β in Tables from 4 to 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 the 1% level. The absolute value of the coefficient is interpreted as elasticity, and it detects how responsive are current prices to changes in past prices. We observe 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, the significant negative coefficients show that a positive change

[4] 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.

in past prices causes a reduction in current prices across all models and conditions in both the UK and US markets. Such dynamics are strong especially for iPhone 5s 32GB and 16GB, whereas they weaken for iPhone 64GB and Samsung Galaxy S4 showing that for these products the price dynamics is less anchored to past level of prices, and it is therefore potentially more erratic.

In the UK, the iPhone 5s 32GB SR has the highest responsiveness to changes in past prices. As for Samsung Galaxy S4, the results indicate that only the coefficient for its MR variant is statistically significant. Thus, the prices of the S4 models are potentially more erratic than those of iPhone 5s 16GB as they are not dependent at all on past levels of prices, and therefore potentially more difficult to forecast over time. In the US, the patterns of responsiveness to changes in past prices are less conclusive compared to the UK, with the new iPhone 5s 32GB exhibiting the highest elasticity. Similar to the results for the UK markets, only one coefficient for Samsung Galaxy S4 is statistically significant, that is the SR variant.

We then check whether cross-lags of prices are significant in eq.(1). More specifically, we investigate whether the prices of MR and SR products can explain the prices of their new counterparts, and vice versa. Similarly, we test whether the prices of items in the US market can explain the prices of the equivalent items in the UK, and vice versa. When we carry out this type of analysis, we find very weak cross-interactions among the markets and conditions for both prices and volumes. Such pattern of results holds across the US and UK markets, and it suggests that the price and volume dynamics across markets and conditions are independent and not affected by any spill-over effects. Consequently, we limit our analysis to eq.(1) with no cross-lags for prices and volumes.

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 the by-product of the different scale of the dependent and the independent variable in eq.(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 the volume. In other words, it signifies the percentage change of price in response to a unit of 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.

We find evidence of strong positive relationships between current prices and volumes for both the MR and SR products in the UK. Nevertheless, the same pattern survives only for the MR variants in the US market. This shows that, on average, the secondary markets for remanufactured smartphones are potentially highly profitable - as the positive link between price and quantity 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 the US.

Strong negative relationships between the changes in current prices and volumes 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 volumes and they, therefore, require a drop in prices to boost the demand from buyers. Thus, it might be challenging for producers and/or sellers to reap additional profits by injecting additional quantities 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 retailers (i.e. Apple Stores and Samsung Stores).

Interestingly, our results indicate that all the markets for iPhone 5s 16GB are the most profitable - as we find strong positive links between prices and quantities. 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 volumes survive across the UK and US markets for all three conditions. Also, the markets for iPhone 5s 16GB are the markets with the largest volume and we find that both UK and US markets seem to be driven by very similar market forces.

By directly comparing the markets for iPhone 5s 16GB and Samsung Galaxy S4, we observe that these two markets are rather different in their dynamics, with strong positive links between price and quantity 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 are much less profitable for the sellers.

In terms of the semi-elasticity of prices to volumes, we find that the magnitudes are similar across the UK and US markets for all three conditions. Additionally, the results signify that, overall, the changes in the 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, we rank the markets according to their profitability as follows. The most profitable market for the sellers is the market where positive links between price and quantity can be established. In this case, the markets for all condition 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 average profits since prices in such markets are not affected by volumes. Such markets exist mainly in the US, especially those for Samsung Galaxy S4. Finally, the least profitable markets are those where a negative link between prices and volumes occurs. This applies to most of the markets for new conditions of the products across both the UK and US.

Parameter	US						UK					
	N		MR		SR		N		MR		SR	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
α	-0.0004 (0.0013) [-0.0027, 0.0014]	-0.0004 (0.0014) [-]	-0.0002 (0.0027) [-0.0045, 0.0042]	-0.0002 (0.0027) [-]	-0.0008 (0.0013) [-0.0025, 0.0010]	-0.0007 (0.0013) [-]	-0.0007 (0.0015) [-0.0031, 0.0021]	-0.0009 (0.0014) [-]	-0.0007 (0.0022) [-0.0047, 0.0031]	-0.0003 (0.0022) [-]	-0.0005 (0.0015) [-0.0030, 0.0020]	-0.0006 (0.0015) [-]
β	-0.2524*** (0.0531) [-0.3295, -0.1197]	-0.0574 (0.0844) [-]	-0.2746*** (0.0569) [-0.4772, -0.0611]	-0.1666* (0.0891) [-]	-0.3338*** (0.0531) [-0.4336, -0.1461]	-0.1052 (0.0778) [-]	-0.1013* (0.0547) [-0.1947, 0.0632]	-0.0460 (0.0904) [-]	-0.2645*** (-0.0559) [-0.4574, -0.1145]	-0.3180*** (0.0590) [-]	-0.2438*** (0.0578) [-0.4325, -0.1181]	-0.2454*** (0.0569) [-]
λ	-0.0008*** (0.0001) [-0.0011, -0.0006]	-0.0010*** (0.0002) [-]	0.0007*** (0.0002) [0.0002, 0.0012]	0.0008** (0.0004) [-]	-0.0006*** (0.0001) [-0.0008, -0.0004]	-0.0004** (0.0002) [-]	-0.0010*** (-0.0001) [-0.0014, -0.0008]	-0.0009*** (0.0002) [-]	0.0021*** (0.0005) [0.0011, 0.0028]	-0.0020 (0.0011) [-]	-0.0007*** (0.0002) [-0.0009, -0.0002]	0.0024** (0.0011) [-]
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
Q(4)	18.470 (0.000)	28.917 (0.000)	8.803 (0.012)	8.763 (0.067)	18.190 (0.000)	29.643 (0.000)	1.036 (0.595)	1.390 (0.846)	2.307 (0.315)	0.442 (0.979)	3.227 (0.199)	1.564 (0.815)
LM(4)	23.260 (0.001)	36.313 (0.000)	15.810 (0.015)	9.246 (0.055)	28.080 (0.000)	42.629 (0.000)	5.625 (0.466)	1.774 (0.777)	12.280 (0.056)	0.451 (0.978)	11.280 (0.079)	1.753 (0.781)
$Q^2(4)$	36.820 (0.000)	47.507 (0.000)	13.860 (0.000)	18.782 (0.001)	35.870 (0.000)	53.934 (0.000)	25.930 (0.000)	24.995 (0.000)	5.760 (0.056)	2.446 (0.654)	28.550 (0.000)	2.693 (0.610)
ARCH(4)	36.030 (0.000)	59.668 (0.000)	13.330 (0.009)	19.440 (0.001)	38.390 (0.000)	74.813 (0.000)	30.520 (0.000)	28.121 (0.000)	5.391 (0.249)	2.390 (0.664)	30.410 (0.000)	2.619 (0.623)

Notes: Sample period 28/01/2016–03/11/2016. LS and 2SLS estimates of the parameters of eq.(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 are in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias Corrected confidence intervals based on 1,999 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 4: Empirical Estimates of eq.(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	-0.0006 (0.0011) [-0.0022, 0.0008]	-0.0006 (0.0011) [-]	-0.0002 (0.0012) [-0.0018, 0.0015]	-0.0012 (0.0018) [-]	-0.0007 (0.0021) [-0.0040, 0.0021]	-0.0001 (0.0018) [-]	-0.0011 (0.0014) [-0.0034, 0.0022]	-0.0007 (0.0011) [-]	-0.0012 (0.0017) [-0.0036, 0.0011]	-0.0010 (0.0018) [-]	-0.0003 (0.0019) [-0.0026, 0.0019]	-0.0013 (0.0021) [-]
β	-0.4545*** (0.0541) [-0.6061, -0.2391]	-0.4545*** (0.0541) [-]	-0.3668*** (0.0565) [-0.4718, -0.2139]	-0.3380*** (0.0718) [-]	-0.3822*** (0.0556) [-0.5194, -0.1238]	-0.2183*** (0.0667) [-]	-0.2797*** (0.0585) [-0.4137, -0.0857]	-0.2996*** (0.0738) [-]	-0.3325*** (-0.0546) [-0.4605, -0.1468]	-0.3458*** (0.0567) [-]	-0.3802*** (0.0517) [-0.4591, -0.1785]	-0.4934*** (0.0850) [-]
λ	-0.0002*** (0.0001) [-0.0004, -0.0001]	-0.0002 (0.0001) [-]	-0.0001 (0.0001) [-0.0003, 0.0002]	0.0013** (0.0006) [-]	0.0000 (0.0001) [-0.0002, 0.0001]	-0.0017*** (0.0004) [-]	-0.0001 (-0.0002) [-0.0004, 0.0003]	-0.0003*** (0.0001) [-]	0.0015*** (0.0003) [0.0007, 0.0022]	0.0011 (0.0006) [-]	-0.0010*** (0.0002) [-0.0013, -0.0007]	0.0026** (0.0013) [-]
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
Q(4)	17.760 (0.000)	24.780 (0.000)	12.670 (0.002)	12.015 (0.017)	15.160 (0.001)	29.299 (0.000)	6.441 (0.039)	4.452 (0.348)	16.580 (0.000)	17.754 (0.001)	18.860 (0.000)	14.878 (0.005)
LM(4)	31.310 (0.000)	38.359 (0.000)	28.770 (0.000)	17.463 (0.002)	17.290 (0.008)	49.369 (0.000)	12.930 (0.044)	8.695 (0.069)	19.860 (0.003)	24.918 (0.000)	34.730 (0.000)	21.267 (0.000)
$Q^2(4)$	65.880 (0.000)	62.342 (0.000)	25.780 (0.000)	28.841 (0.000)	31.640 (0.000)	55.070 (0.000)	15.330 (0.000)	7.878 (0.096)	52.620 (0.000)	53.310 (0.000)	33.320 (0.000)	44.496 (0.000)
ARCH(4)	83.970 (0.000)	38.359 (0.000)	23.950 (0.000)	29.754 (0.000)	28.370 (0.000)	73.325 (0.000)	16.330 (0.003)	7.469 (0.113)	50.920 (0.000)	50.952 (0.000)	37.360 (0.000)	49.102 (0.000)

Notes: Sample period 28/01/2016–03/11/2016. LS and 2SLS estimates of the parameters of eq.(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, .., 7 and j=1,..,7.
Standard Deviations are in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias Corrected confidence intervals based on 1,999 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: Empirical Estimates of eq.(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	-0.0010 (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
Q(4)	11.520 (0.003)	11.063 (0.026)	21.620 (0.000)	22.761 (0.000)	20.810 (0.000)	21.388 (0.000)	15.930 (0.000)	14.015 (0.007)	8.701 (0.013)	4.777 (0.311)	48.150 (0.000)	27.654 (0.000)
LM(4)	15.340 (0.018)	16.373 (0.003)	68.780 (0.000)	29.752 (0.000)	21.870 (0.001)	23.963 (0.000)	25.910 (0.000)	18.119 (0.001)	13.640 (0.034)	5.971 (0.201)	54.570 (0.000)	36.896 (0.000)
$Q^2(4)$	33.360 (0.000)	46.653 (0.000)	47.220 (0.000)	89.241 (0.000)	34.510 (0.000)	31.854 (0.000)	29.940 (0.000)	33.307 (0.000)	40.490 (0.000)	36.095 (0.000)	46.070 (0.000)	41.918 (0.000)
ARCH(4)	28.730 (0.000)	40.515 (0.000)	33.570 (0.000)	63.687 (0.000)	35.060 (0.000)	31.472 (0.000)	27.740 (0.000)	30.184 (0.000)	46.510 (0.000)	37.756 (0.000)	46.410 (0.000)	37.845 (0.000)

Notes: Sample period 28/01/2016–03/11/2016. LS and 2SLS estimates of the parameters of eq.(1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) iPhone 5s 16GB. Instruments for 2SLS are ΔP(t-i) and ΔV(t-j) for i=2, .., 7 and j=1,..,7.
Standard Deviations are in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias Corrected confidence intervals based on 1,999 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 6: Empirical Estimates of eq.(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	-0.0017** (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 (1.53E-04) [-]	-0.0020*** (0.0002) [-0.0027, -0.0016]	-3.70E-03*** (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
Q(4)	17.21 (0.000)	4.931 (0.295)	5.661 (0.059)	5.922 (0.205)	17.81 (0.000)	14.228 (0.007)	16.39 (0.000)	27.787 (0.000)	14.37 (0.000)	6.679 (0.154)	4.326 (0.115)	6.414 (0.170)
LM(4)	57.02 (0.000)	5.408 (0.248)	16.11 (0.013)	8.554 (0.073)	35.12 (0.000)	25.441 (0.000)	22.54 (0.001)	36.419 (0.000)	59.47 (0.000)	10.029 (0.040)	11.98 (0.062)	6.473 (0.167)
$Q^2(4)$	5.506 (0.063)	0.221 (0.994)	19.43 (0.000)	23.218 (0.000)	29.92 (0.000)	24.818 (0.000)	32.58 (0.000)	45.097 (0.000)	48.04 (0.000)	47.965 (0.000)	74.55 (0.000)	30.199 (0.000)
ARCH(4)	5.053 (0.281)	0.220 (0.994)	26.16 (0.000)	28.481 (0.000)	19.63 (0.000)	23.574 (0.000)	27.92 (0.000)	57.474 (0.000)	41.51 (0.000)	55.209 (0.000)	92.15 (0.000)	30.966 (0.000)

Notes: Sample period 28/01/2016–03/11/2016. LS and 2SLS estimates of the parameters of eq.(1) for New (N), Manufacturer refurbished (MR) and Seller refurbished (SR) Samsung Galaxy S4 (16GB). Instruments for 2SLS are $\Delta P(t-i)$ and $\Delta V(t-j)$ for i=2, .., 7 and j=1,..,7.
Standard Deviations are in parentheses. *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively. Bias Corrected confidence intervals based on 1,999 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 7: Empirical Estimates of eq.(1) for Samsung Galaxy S4 (16GB)

5.3 *Robustness Checks*

The Box-Ljung statistics, as well as the LM and ARCH-LM tests, reported in the bottom panels of Tables 4 to 7, 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 inference carried out by using the asymptotic assumptions might lead to incorrect conclusions. Thus, we investigate the finite sample properties of the above estimators by carrying out a bootstrap analysis of eq.(1). More specifically, we construct artificial data-sets by re-sampling pairs (prices and volumes) from our original datasets of 281 observations. To preserve the serial correlation present in our series, we carry out a re-sampling in blocks of as many as 7 observations. For each bootstrapped dataset, we carry out OLS estimates of eq.(1). We then repeat the above estimation exercise 1,999 times so that we obtain the empirical distributions of the parameters α, β, and λ.

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.(1).[5] Given the above evidence, bootstrapped confidence intervals could be a better tool than standard asymptotic intervals to carry out statistical inference. We, therefore, use the above empirical distributions to construct the Bias-Corrected (BC) confidence intervals (see DiCiccio and Efron (1996)). Such confidence intervals are set out in Tables 4 to 7. For purposes of comparison, we also compute the bootstrap percentile intervals as well as asymptotic intervals.[6]

The BC intervals differ only slightly from the percentile and asymptotic intervals, showing that the departures between finite sample and asymptotic properties appear

[5] We find significant departures from normality in the parameter beta and lambda, whereas the constant parameter alpha is almost always normally distributed. Such pattern of results holds across the two markets, four products and three conditions under scrutiny.
[6] The percentile and asymptotic intervals for eq.(1) are not reported to save space, but are available from the authors upon request.

negligible so that inference based on asymptotic and finite sample properties leads to similar conclusions. Such pattern of results holds across the four products, and for both the UK and US markets under scrutiny. We then conduct a final robustness check by carrying out both OLS and 2SLS estimations of eq.(1) where we replace daily average mean observations 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 4 to 7.[7]

We then carry out a separate analysis for the iPhone 5s 64GB as the unit-root tests in use show that – unlike the remaining cohorts of products under scrutiny – such series are stationary in levels. We start by fitting the model of eq.(1) to the log-price series in both levels and first-differences, and notice that we obtain inconsistent estimates for the parameter alpha, beta and lambda. We then evaluate the stationarity of the residuals obtained from the two estimation exercises. 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, we find 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, and we obtain the same pattern of results set out above. Consequently, we retain the original estimations by treating the above series in level as non-stationary.

We then re-assess the effect of using log prices in levels or first-differences 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.(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,

[7] We also re-estimate eq.(1) using the non-converted GBP series for the UK markets and compare such estimates with the results set out in Tables from 4 to 7 obtained using converted series. We find that the two sets of results are relatively similar. Therefore, we maintain that the exchange rates do not distort the price series under scrutiny.

the finite sample properties of the OLS estimators might depart from their asymptotic properties.

We, therefore, evaluate how severe is the departure from the assumption of normality for the parameters alpha, beta and lambda estimated over series in levels and first differences. 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 (AD) tests fail to reject the null of normality for the parameter alpha and beta for the UK, and for the parameter alpha for the US series. The same evidence is less neat for the models fitted to series in levels where the same tests soundly reject the null for all the 3 parameters estimated on UK and US series– signalling a more severe departure from the assumption of normality.[8] Similar evidence holds for both UK and US series.

6. Discussion and Managerial Insights

Our 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 level of prices of the products sold, as well as to properly evaluate how profitable are specific markets of interest. The empirical analysis of the price-volume series enables us to shed some light on these two important aspects.

Firstly, we document that the relationships between changes in past and current prices are not consistent across the two 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

[8] The empirical distributions for the parameters alpha, beta and lambda for the model fitted to series in levels and first differences are not reported to save space, but are available from the authors upon request.

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 among the new items across the different models considered. We make sense of this result by noting that such items benefit from a direct comparison to the equivalent items traded in primary markets (e.g. official retailers). 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, tends to fade away when we consider remanufactured items, as such price anchor does not exist for secondary markets. Although the remanufactured versions are offered at the prices lower than those of new counterparts to attract buyers' purchase intention, the sellers have to match the prices of their competitors to stay competitive. Therefore, remanufactured products have higher responsiveness to the change in past prices. The weak dependence on lagged values of prices, coupled with the 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 the new conditions across the various models considered.

Secondly, the nature of the contemporaneous relationship between the changes in current prices and volumes provide managers with a broad-brush picture of the profit potential of the markets under scrutiny. With respect to the standard demand-and-supply framework, 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. Accordingly, it is possible to rank the markets in terms of their profitability. Of course, from the sellers' point of view the markets with high-profit potential are those characterised by a positive link between prices and quantities. In such markets, in fact, consumer demand is the main driver and sellers are able to inject larger volumes of items without causing a downward pressure on prices. We established that such positive links hold in the markets for both MR and SR products in the UK, and the market for MR products in the US. Thus, on average the secondary markets for remanufactured smartphones are potentially highly profitable. This may be due to the small number of vendors that dominate the market for this specific type of products. As there is limited competition within such markets, the sellers have more control over prices since consumers do not have as many choices as they have by tapping into primary and eBay markets for corresponding new items. This suggests that remanufacturers have more market power and can benefit from larger quantities 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 products as opposed to new items.

Moreover, we show that the markets for all conditions of iPhone 5s 16GB are the most profitable. These markets are the largest in volume, and it appears that both the UK and US platforms are driven by similar markets forces. Interestingly, based on the direct comparison between iPhone 5s 16GB and Samsung Galaxy S4, we find 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 volumes found in the former drastically reduced when the latter is considered. Therefore, the market for Samsung Galaxy S4 is much less profitable for the sellers.

The second best markets that sellers can trade in and still reap sufficient profits are those that present no significant link between prices and volumes. For this type of markets, in fact, 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 volumes. Such markets are mainly driven by supply forces, so that prices decrease when there is an increase in volumes. We document that this type of dynamics are predominant in the markets for new smartphones, suggesting that they are not capable of absorbing increases in quantity without correspondent decreases in prices to boost the demand from buyers. As a result, in such markets it might be difficult for sellers to reap extra profits by injecting additional volumes. 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 coming from primary markets of equivalent new items - official retailers in the first place.

7. Conclusions

In recent years, the markets of remanufactured smartphones have witnessed a sharp increase in sales volume due to their shortened product lifecycle. Nevertheless, the understanding of the characteristics of such secondary markets is limited in the current literature of CLSCs and RLs. In fact, such strands of research have focussed on a number of aspects such as auction dynamics, pricing strategies, as well as buyers' willingness to pay, whereas the investigation of the price-volume links in markets for remanufactured electronics has remained so far largely unexplored. The understanding of the stochastic properties of price-volume relationships is important because it sheds light on the fundamental mechanisms driving the markets for remanufactured electronics. The unravelling of price-volume links, in fact, can provide a glimpse into each market's profit potential - as the sign and magnitude of the elasticity of price to volume indicate the responsiveness of revenues to changing market conditions.

In this study, we empirically investigate the dynamic relationships between price and volume of new and remanufactured smartphones on eBay UK and eBay US using daily series for the period 28th January 2016 - 3rd November 2016. The empirical results show significant negative links between current and past changes in prices (i.e. any increase in past prices is followed by a decrease in current prices) for the smartphones in both UK and US secondary markets. In terms of magnitude, the new product conditions are less responsive to such changes than their remanufactured counterparts. This may stem from the direct competition of primary markets (e.g. from official retailers) that new products face. Also, the prices of the new products set on the primary market act as an anchor for their respective prices in the secondary market. On the other hand, the stronger responsiveness of remanufactured items might stem from the fact that sellers of such items must compete against each other by matching their prices with those set by the competitors. Therefore, the current prices of remanufactured smartphones are more responsive to the changes in past prices than their new counterparts.

When we focus on the relationships between prices and volumes, we find significant negative contemporaneous relationships for new smartphones, which means that these markets are the least profitable for sellers. Again, the additional competition from the sellers in primary markets may play an important role in affecting the link between price and quantity. In contrast, we document significant positive contemporaneous price-volume links for remanufactured smartphones suggesting that these markets are highly profitable. Since the markets for remanufactured items by OEM-approved sellers are thin markets, the competition is less fierce and such sellers retain market power. Consequently, prices increase when there is an upsurge in volume as sellers of this particular product condition are more likely to set new prices at higher levels than the current prices. The same pattern exists in the markets for every condition of iPhone 5s 16GB in both the UK and US markets, which are not only the largest in size but also the markets with the highest profit potential.

In this study, we focus on iPhone 5s and Samsung Galaxy S4 mainly due to the availability of the data observations in all product conditions. However, both products were released in 2013, which means that they are likely to be in the mature stage of their respective product life cycles. Therefore, it is possible that the relationships established in this study might be affected by this feature of the items under scrutiny. At the time the data collection was carried out, the price and volume series for iPhone 6s UK / US were much shorter than the 281 observations we managed to collect for iPhone 5s. Moreover, the product models chosen in this study are the most appropriate as they guarantee a sufficient amount of observations per day to reliably represent the markets. For these reasons, we opted for the iPhones 5s series in this study. That said, a possible extension of the paper would be the use of prices and volumes series for the iPhone 6s as well. This would enable a cross-model comparison between two generations of iPhones. Nevertheless, this would provide an interesting extension to our paper, as it allows an investigation of whether the price-volume relationships change across different generations of products.

Another possible development of this study would consist of using series for prices and quantities to estimate the demand and supply functions of secondary markets. This empirical exercise would be useful for both manufacturers and sellers as such platforms host the trading of new items, and the demand and supply estimated on these markets can be taken as a good proxy for the demand and supply of primary markets. Given the identification problem that comes with the estimation of such functions, the above empirical exercise could be carried out as long as data on both the volume of transactions and bids made by buyers are available. The former, in fact, can be used to estimate the supply function, whereas the latter is necessary to estimate the demand function. We leave this empirical exercise as a possible avenue for further research.

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