FACULTY OF ECONOMICS AND
BUSINESS ADMINISTRATION

THE EFFECT OF A NEW PRODUCT INTRODUCTION ON THE PRICES OF EXISTING PRODUCTS

With data from the smartphone industry

Word count: 17,617

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Master's dissertation submitted to obtain the degree of:

Master in Business Engineering: Operations management

Academic year: 2018-2019

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Preface

This master dissertation will be the final piece in obtaining my master degree in Business Engineering. I would like to thank my promotor, Prof. Dr. Dries Benoit, for offering the interesting subject, and Dieter Oosterlinck for his guidance and constructive feedback. Finally, I would like to thank my friends and family for their support during my entire education.

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List of abbreviations

KBT Kleenex Bath Tissue

OS Operating system

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INTRODUCTION

This research aims to investigate the effect of a product introduction on the prices of existing products on the smartphone market. There is little research conducted in this field and the only equivalent investigation that was found is the one of Hausman & Leonard (2003). They analyzed one product introduction in the bath tissue industry. The research for this master dissertation is based on this and can, therefore, be seen as an extension to the application of panel data analyses to investigate the effect of a product introduction on the prices of existing products.

As no industry is the same, it is important to gather information about the smartphone market dynamics. The first section will elaborate more on this and starts with some introductory figures regarding the smartphone industry. Then, the related operating system industry is briefly discussed. This section will end with discussing smartphone innovation characteristics and the new entrants. Secondly, the important factors that play a role in the smartphone-decision-making process of a customer are presented. Thirdly, the manufacturers' launch decisions are discussed with a focus on strategic and tactical launch decisions that improve a successful product launch. The last two sections of the literature review both discuss research that is more related to product launches. The fourth section looks in more detail at a case study that generally investigates whether competitive reactions follow a product launch in a certain industry. The fifth section focuses on the bath tissue industry research. This section ends with a comparative analysis of the bath tissue industry and smartphone industry and proposes remediation options for the statistical analysis of the smartphone data.

The second part contains the actual research performed with data from the smartphone market. Different linear panel data models are applied and compared in order to select the best estimation method. Then the brands' launching and termination strategies are compared. Because many brands have the intention to terminate their old smartphone models when they launch a new model, statistical analysis cannot be performed and these brands are only empirically investigated.

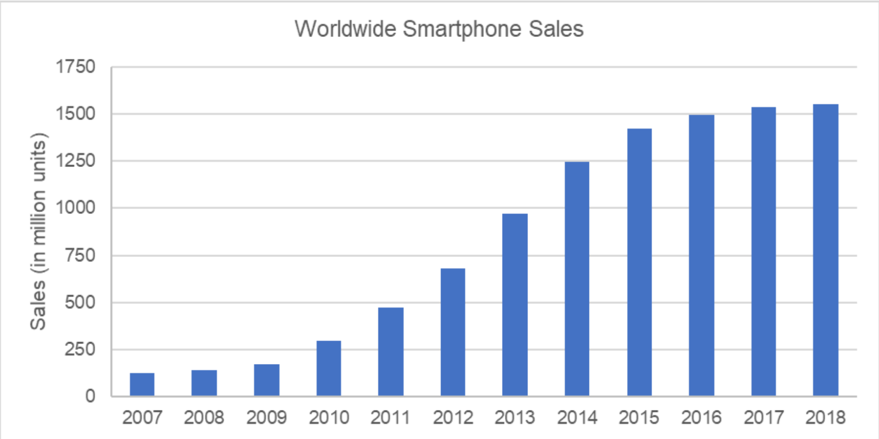
This master dissertation ends with a general conclusion and the limitations of the research.

LITERATURE REVIEW

1 The smartphone industry

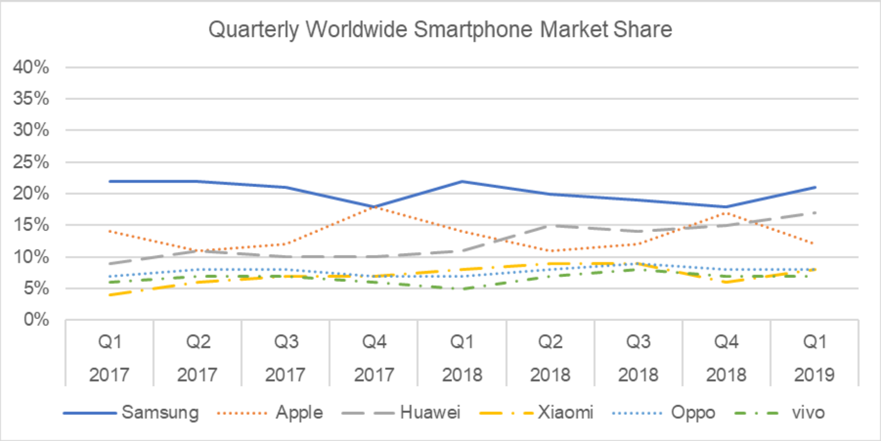
1.1 Numerical introduction

Devices with telephony and computing features have been around for decades (R. Want 2014). Due to various emerging technologies, smartphone market incumbents do not only compete at price-level, but they also compete by offering superior and differentiating levels of product specifications (Koski & Kretschmer, 2007; Riikonen , Smura, & Töyli, 2016). Smartphones are becoming increasingly homogeneous and the smartphone industry is reaching its saturation state, so it becomes important to differentiate (Koski & Kretschmer, 2007). Graph 1 illustrates the number of worldwide sold smartphones to end consumers from 2007 until 2018. Remarkably, the number of sold devices is still increasing, but the growth rate is slowing down. This drives frequent innovative product launches and consequently new market strategies become essential to continue the growth of the smartphone companies (Kim, Wong, Chang, & Park, 2016; Koski & Kretschmer, 2007). This also means that the market is primarily dominated by replacement demand (Koski & Kretschmer, 2007; Riikonen, Smura, Kivi, & Töyli, 2013).



Graph 1 - The number of smartphones sold to end users worldwide since 2007 (in million units) (Holst, 2019b)

In 2018, smartphone sales exceeded the amount of 500 billion American dollars ("Global smartphone sales exceeded $500 billion in 2018," 2019). This large amount is not equally divided over the more than 600 smartphone market incumbents. The worldwide six best-selling smartphone brands in the last two years account for 62% up to 73% of the entire smartphone sales volume. Graph 2 illustrates the quarterly worldwide market share for the top six best-selling smartphone companies of the moment in terms of the number of shipped units. The corresponding market shares are exhibited in Table 1.



Graph 2 - Quarterly Worldwide Smartphone Market Share (“Global Smartphone Share,” 2017)

Global Smartphone Shipments Market Share (%)	2017 Q1	2017 Q2	2017 Q3	2017 Q4	2018 Q1	2018 Q2	2018 Q3	2018 Q4	2019 Q1
Samsung	22%	22%	21%	18%	22%	20%	19%	18%	21%
Apple	14%	11%	12%	18%	14%	11%	12%	17%	12%
Huawei	9%	11%	10%	10%	11%	15%	14%	15%	17%
Xiaomi	4%	6%	7%	7%	8%	9%	9%	6%	8%
Oppo	7%	8%	8%	7%	7%	8%	9%	8%	8%
vivo	6%	7%	7%	6%	5%	7%	8%	7%	7%
Others	38%	35%	35%	34%	33%	30%	29%	29%	27%

Table 1 - Quarterly Worldwide Smartphone Market Share (“Global Smartphone Share,” 2017)

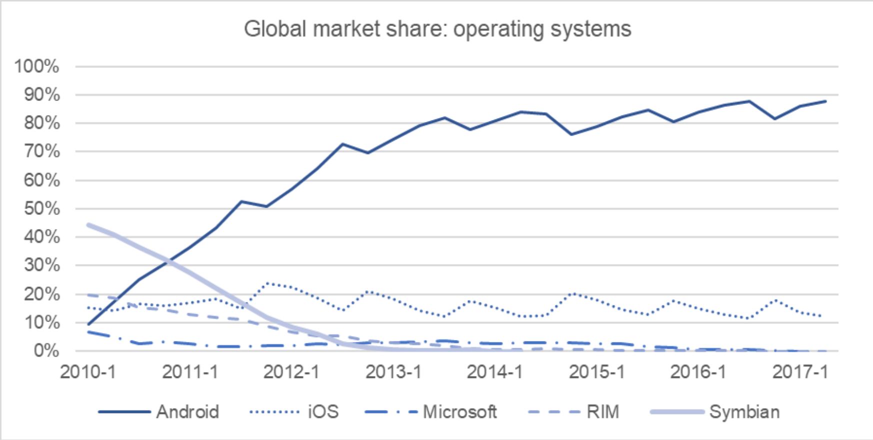
From 2017 until the first quarter of 2019, the smartphone market is mainly led by three companies. Samsung has been leading the market with a market share that fluctuates around 20%. Apple and Huawei follow Samsung and alternate between the second and the third place. However, especially in the fourth quarter, Apple comes very close to the market share of Samsung. This is probably caused by Apple’s new product launches taking place every year around October. The other three brands, Xiaomi, Oppo and Vivo, are extremely popular in Asia, which makes them part of the worldwide top six. (“Global Smartphone Share,” 2017)

1.2 The role of the operating system

With the emergence of the smartphone came the development and implementation of the operating system in the mobile phone industry (Lin & Ye, 2009). The operating system is the standardly installed main software program that allows its users to install, execute and run applications (Kenney & Pon, 2019; “What is an Operating System (OS)?,” n.d.). Neither the operating system industry, nor the smartphone industry are solely represented by respectively pure software, or hardware producers (Cecere, Corrocher, & Battaglia, 2015; Lin & Ye, 2009). The operating system determines the number of available applications for its users, and the more available applications, the more appealing it is to the customers.

Today’s operating systems’ market leaders are two completely different companies. The market leader is Google’s Android, an open-source system that is widely used by several smartphone providers. The second place goes to Apple’s iOS, a closed source software that is only installed on

Apple products and developed by Apple developers. Graph 3 illustrates the evolution of the leading smartphone operating systems, measured in terms of device sales to end-consumers, from 2009 until 2017.



Graph 3 - Global market share held by the leading smartphone operating systems sales to end users from the first quarter of 2010 until the second quarter of 2017 (Holst, 2019a)

The operating system market looked very different at the beginning of 2010 compared to the beginning of 2017. The market of the operating systems was very unstable and uncertain: OS Symbian and RIM were the market leaders until the advent of today's market leaders Google's Android and Apple's iOS (S. P. Hall & Anderson, 2009). A lot of companies, like Nokia, continued to produce Symbian-based smartphones when the top producers started imitating and improving the iPhone concept (Cecere et al., 2015).

OS Symbian, the first popular operating system, was launched in 1998 and jointly owned by a few hardware companies: Nokia, Panasonic, Psion, Samsung, Siemens, and Sony Ericsson (S. P. Hall & Anderson, 2009; Kamboj & Gupta, 2012; Lin & Ye, 2009). 2009 was a turning point: OS Symbian first accounted for more than 50% of the smartphone OS market share, and then quickly fell after the emergence of Google's Android. The partnership had enormous difficulties with developing applications and several companies dropped out. Nokia was the last partner that launched Symbian phones, until it announced in 2011 that it would switch operating systems and start using Windows Mobile, which later failed too. (Kenney & Pon, 2019; Tilson, Sorensen, & Lyytinen, 2012)

Google's Android has been the main Operating System provider since late 2010 and has been leading the market ever since (Cecere et al., 2015). Google bought Android in 2005 when smartphones became popular. Initially, there were quite some problems with the devices when using Google, and Google formed a conglomerate of companies, 'the Open Handset Alliance', to tackle this issue. It turned Android into a world-class operating system that was offered freely to any manufacturer that wanted to use it. This also benefited the users who were not limited to use a single kind of hardware for the operating system. From 2013 onward, Android's market share in the smartphone industry has been fluctuating around 85%, while Apple's iOS has been fluctuating around 15%, absorbing almost the entire market and leaving less than 1% to all other operating systems.

1.3 Innovation

The goal of stimulating replacement demand as a consequence of the increasing market saturation can be achieved by shortening the smartphone life cycles and quickly launching innovative software and hardware (Cecere et al., 2015; Koski & Kretschmer, 2007; Zhou, Gupta, Kinoshita, & Yamada, 2017). Innovation can be classified in many ways. For the smartphones, vertical and horizontal innovation seem the most appropriate (Cecere et al., 2015; Han & Cho, 2016; Koski & Kretschmer, 2007). Koski & Kretschmer (2007) define horizontal innovation as adding additional product characteristics to the product, whereas vertical innovation are improvements of those horizontal innovations (Cecere et al., 2015; Han & Cho, 2016; Koski & Kretschmer, 2007). Vertical innovations are mostly perceived as quality improvements and consequently lead to a higher price, whereas horizontal innovations are mostly perceived differently by the customers, which makes them more difficult to compare (Koski & Kretschmer, 2007).

In the early stages of the market development of horizontal or vertical innovations, there is always uncertainty which leads to the development of different designs (Cecere et al., 2015). Different hardware improvements are implemented until one is successful and preferred by the customer (Koski & Kretschmer, 2007). Some of these innovations will become part of the smartphone standard, such as a camera on both sides of the phone, and consequently become part of the dominant design of the smartphone industry (Cecere et al., 2015; Koski & Kretschmer, 2007; Schilling, 2013). Due to continuous innovation and the temporary character of the smartphone models, the dominant design is only satisfying as long as there is commercial interest among the market incumbents and the potential customer base (Cecere et al., 2015; Han & Cho, 2016). When the dominant design emerges, it is important as a company to react quickly and jump on the bandwagon. A general phenomenon is a decrease of the number of competing firms, where only the best-performing ones can survive (Cecere et al., 2015; Schilling, 2013). Innovations that do not become a permanent part of the dominant design, but are maintained by one or a few brands, create differentiation and lead to the creation of niche markets in the smartphone industry (Koski & Kretschmer, 2007). Consequently, several brands' new launches have similar specifications (Cecere et al., 2015; Schilling, 2013). This illustrates the generation concept, i.e. when a series of released smartphones with similar technologies show major performance improvements compared to previous generations (Riikonen et al., 2013). Zhou et al. (2017) state that when a new generation is released, the value of the previous generations decreases, a phenomenon also called cannibalization, which is further discussed in section 3.

1.4 New entrants

The uncertainty of innovative smartphone specifications creates opportunities for new entrants to obtain a share from the industry's sales (Cecere et al., 2015). The enormous value of the smartphone market and the immense popularity of smartphones attract other companies to enter the market and start producing smartphones. On top of that, it would not be the first time in the mobile phone industry that market incumbents are outcompeted by new entrants (Han & Cho, 2016).

New entrants can beat innovative smartphone generations by the combination of the core strength of their initial industry with their new-to-the-market ideas (Koski & Kretschmer, 2007). In 2007, Apple, then a popular computer and software company, announced its entry into the smartphone market with the launch of the iPhone 2G and completely disrupted and commercialized the market by enabling the device to play audio and video files (Cecere et al., 2015). A few months later, in 2008, Samsung released the 'Samsung Instinct' and thereby directly competed with Apple's iPhone for market share in the smartphone industry (Capatina & Draghescu, 2015; Cecere et al., 2015). More than ten years later, Samsung still leads the smartphone market, followed by Apple and the growing company Huawei.

The smartphone industry still seems to be an attractive industry for online companies. Amazon, one of the largest e-commerce companies and Yandex, the number one Russian search engine, entered the smartphone market with the main purpose of strengthening their core business (Humphries, 2018). Their profit-generating strategy does not primarily rely on the sales of devices, but mostly on the use of the devices, and thus the company's website and apps (Gibbs, 2014; Humphries, 2018). Both companies had a hard time to convince customers of the worthiness and value of their devices compared to the market leaders.

Amazon launched its first smartphone, the 'Fire Phone', in 2014. For the Fire Phone to be successful it should have had at least an attractive price or an astonishing design, but Amazon's smartphone had neither (Wohlsen, 2015). In terms of pricing, the Fire Phone was categorized as Apple's and Samsung's high-end devices, while having equal or fewer specifications (Gibbs, 2014; Wohlsen, 2015). Another reason for its failure was that people did not need an Amazon device to use its services (Gibbs, 2014). One year later, Amazon shut down the production of the Fire Phone.

The most popular Russian search engine Yandex launched its first smartphone at the end of 2018 (Aris, 2019; Humphries, 2018). The company targets the Russian market, offering an Android-based device with all the Russian localized tools pre-installed (Humphries, 2018). Compared to the Fire Phone, this smartphone competes with the market leaders by offering a highly qualitative device at a lower price (Humphries, 2018). However, the latest articles announce disappointing sales figures because Yandex was unable to sell more than 500 devices during the first month after the launch (Aris, 2019).

2 Customers

The success of a smartphone launch also depends on the attractiveness of the design and the features perceived by the customers. It is a challenge for the manufacturers to find out the different needs and requirements of customers and offer smartphones accordingly (Wollenberg, 2016). The smartphone industry used to target only business people as the phone specifications initially focused on communication (Capatina & Draghescu, 2015). Especially the introduction of the iPhone in 2007 that allowed to listen to music and watch videos, commercialized the individual and personal use of the smartphone, broadened the target audience considerably and led to the further expansion of the smartphone's specifications (Goggin, 2009).

These extensive specification options lead to diverse customer needs and requirements resulting in an industry with fierce competition, offering a wide variety of devices (Chen, Chen, & Lin, 2016; Wollenberg, 2016). The competition in the smartphone market is characterized by competing for market share, which is determined by customer sales. The major brands are getting more and more competitive with the aim of attracting as many customers as possible while keeping existing customers (Chen et al., 2016; Kim et al., 2016).

Manufacturers should understand this diversity among the customers' preferences and launch smartphones and functionalities accordingly (Chen et al., 2016; Wollenberg, 2016). It is important to capture the factors that influence the customer's choice of smartphone, and find out which ones mainly affect the purchase of a smartphone while comparing alternatives (Chen et al., 2016; Jisana, 2014; Wollenberg, 2016). The concepts of customer attraction, satisfaction and loyalty are key (Chen et al., 2016).

There are several possibilities to distinguish the influences on a smartphone decision-making process. Three types of factors are distinguished: internal factors, external factors, and previously made choices, which are further set out below (Wollenberg, 2016). Finally, the results in terms of customer satisfaction and customer loyalty are discussed.

2.1 Internal factors

The internal factors of a smartphone-purchase decision-making process are related to the product and its properties. Examples of these are the price, the camera resolution, the screen size…. The price is important in the decision, as it restricts the customer to buy a smartphone up to a certain budget (Chen et al., 2016; Wollenberg, 2016). From a manufacturer's point of view, it is essential to identify the relevant functionalities for the targeted customer segments. They should find out the significant general functionalities, the less important ones and the versioning functionalities, such as storage capacity and color, where the customer has to make a choice at the moment of purchase. As a result, a lot of research has been conducted, and some of the results are discussed below.

Liu & Liang (2014) identified 15 important smartphone specifications and investigated which of those specifications are key in the choice of a new smartphone, distinguished per gender and brand. It appeared that the customers' choice was mainly influenced by the exterior design and display resolution. Wollenberg (2016) investigated customer age and gender differences concerning smartphone feature factors that affected the decision-making process when buying a smartphone, customer satisfaction, and customer loyalty. He found significant results for different characteristics that influence the decision-making process, the most important being internet facility, camera, battery life, screen size, and screen quality. Chen e.a. (2016) identified the next features as highly important in the decision-making process: exterior design, price, internal functions of the smartphone and battery life. The design or appearance represents the first impression and is therefore one of the most important determinants of the purchasing decision (Chen et al., 2016). Also price plays an important role: many people believe that the price is partly a representation of the quality, but not the most important factor regarding a purchase decision (Çelik, Eygü, & Oktay, 2015; Chen et al., 2016). Kim e.a. (2016) investigated a whole decision model concerning the smartphone decision process. They found that smartphone design, functions, usability, customer support (after-sales service) and corporate image had a significant positive effect on customer satisfaction. Unlike other studies, the applications and the price of the device appeared to be not significant in this study.

2.2 External factors

External factors are defined as the influences of the environment by friends' and family's opinions and online reviews for example (Chen et al., 2016). Kotler & Keller (2016) recognize that customers are culturally, socially and politically influenced by their environment. Little research has been conducted on the effect of the environment on an individual's smartphone choice (Chen et al., 2016).

An applicable concept is the network effect theory. Applied to the smartphone industry, it is the value that a smartphone user reaps when a larger portion of the market adopts the same smartphone or smartphone brand (Cecere et al., 2015; Lin & Ye, 2009; Schilling, 2013). Apple's Airdrop, for example, is an iOS application that makes sharing files easier, but only has added value for users when people they want to share files with also possess an iPhone. On top of that, Schilling (2013) states that the more customers use a certain smartphone brand, the more complementary goods, such as smartphone cases, will be available. This also contributes as an external factor to preferring a certain smartphone brand.

2.3 Previously made decisions

Lastly, as the sales volume of the smartphone industry is largely dependent on replacement purchases, the majority of customers have already made a purchase decision in the past. When a customer is satisfied with its previous purchase, he may consider buying a smartphone from the same brand. A new purchase decision results in customer loyalty when a device is bought from the same smartphone brand the customer possessed before. Customer dissatisfaction, on the other hand, may lead to brand churning and the purchase of another brand (Chen et al., 2016). It is common knowledge that it is important to retain customers because it costs less to retain customers than to attract new ones (Anderson and Mittal, 2000). If, however, customer dissatisfaction exceeds the switching costs, which are the costs related to the change to another brand, chances are high that customers will choose another smartphone brand (Kim et al., 2016). An important note here is that if the other manufacturers fail to provide better and more attractive smartphones, the customers will stay with their current smartphone brand (Ha & Park, 2013; Kim et al., 2016).

Ultimately internal factors, external factors and previously made decisions can result in satisfied customers. Satisfied customers become loyal customers when they stay loyal to the brand and always buy their smartphones from the same brand (Kim et al., 2016). It is strategically important to aim for loyal customers, as their willingness to pay is higher, they are willing to wait longer for a specific new launch and they are more inclined to recommend the brand to others (Chen et al., 2016; Giddens, 2010; Liu & Liang, 2014; Wollenberg, 2016).

3 Product introductions

Many industries survive by customers' recurring purchases. The smartphone industry survives and establishes its enormous sales by launching innovative products. It counts on the customers' technological preferences resulting in replacement purchases (Capatina & Draghescu, 2015; Kotler & Keller, 2016; Wollenberg, 2016). This makes successful product launches a priority, especially because, according to E. Hultink (2002), 70% to 80% of the new product launches fail each year. Before introducing a new product, it is as such important to make the right decisions regarding the essential factors that will affect the successfulness of a product launch.

In literature, two broad types of launch decisions from technical innovations are identified: strategic and tactical launch decisions (Di Benedetto, 1999; Hultink, Griffin, Hart, & Robben, 1997; Schilling, 2013). Strategic decisions primarily answer the questions: what, where, when and why related to launching a product (Calantone & Di Benedetto, 2007; Di Benedetto, 1999). These decisions focus on the degree of innovativeness, the market or industry situation, and are best made at an early stage in the new product's development. Together with the launch strategy, they typically precede the tactical decisions, that are more detailed and focus more on how a product is launched (Calantone & Di Benedetto, 2007).

The concepts of several frameworks regarding the successful launching strategy can be classified as either strategic or tactical decisions. The first one is the marketing mix, where the right combination of product, place, price, and promotion would contribute to a successful launch decision (Hultink et al., 1997; Schilling, 2013). Product and place decisions can be classified as strategic because they answer the questions of what and where. Price and promotion decisions are more related to how a product is launched on the market and are therefore classified as tactical decisions. Schilling (2013) also identified five determinants that are key in launching a product: the launch timing, licensing and compatibility, pricing, marketing, and distribution. The launch timing determines when to introduce a product to the market and can be classified as a strategic decision. The other four decisions determine more how the product will enter the market and are classified as tactical decisions.

It is important to develop the optimal mix of strategic and tactical decisions, which will lead to an effective product launch that is found to guarantee more product success (Calantone & Di Benedetto, 2007). The following paragraphs will elaborate on the different strategic and tactical decisions and apply them to the smartphone industry.

3.1 Strategic decisions

3.1.1 What?

It is crucial to launch a new smartphone with specifications that are significantly different from its previous generations and from the devices of the competition (Capatina & Draghescu, 2015). To achieve a high sales volume, it is important to meet and exceed the needs and wishes of potential customers (Wollenberg, 2016). Due to the increased heterogeneity and the various customer requirements, the versioning strategy, where smartphone models are launched in vertically differentiating types, is widely used in the smartphone industry (Bhargava, Kim, & Sun, 2013; Goggin, 2009). It is common that when choosing a new smartphone, customers still need to choose between a variety of options, such as storage capacity, color… that will influence the price. In the meantime, older products, with outdated technologies and features, will become cheaper, which is an opportunity for late adopters to buy a smartphone at a lower price (Riikonen et al., 2016; Schilling, 2013). This enables smartphone companies to generate profits from each generation (Schilling, 2013).

3.1.2 When?

The launch timing of a technologically innovative product should be chosen strategically. There are advantages but also disadvantages related to launching a product too early or too late. It is also important to determine the perfect timing by considering the following events: the competitor's innovations, cannibalization and the actual timing of a new smartphone model release in the calendar year. This will be discussed in the following paragraphs.

The advantages of launching a product too early are mainly associated with the benefits of being a first-mover. They mainly help shape the brand's reputation (Calantone & Di Benedetto, 2007). In the smartphone industry, this means being the first brand that includes a certain software or hardware innovation in a new smartphone. Many studies suggest that this smartphone brand will be remembered as the original and most preferred smartphone brand of that time. When a first successful move has been made, it is important for the competing firms to quickly follow and not stay behind. One of the first and most memorable smartphone introductions was the launch of the first iPhone, also known as the iPhone 2G. Its cutting-edge launch was presented to the public in January 2007 and the iPhone 2G was available for purchase in June of that year (Capatina & Draghescu, 2015). Apple had one year to gain market share before competitors HTC and Samsung followed with a competing Android-based model in 2008 (Capatina & Draghescu, 2015; Hruska, 2017). Nowadays, Apple and Samsung are still market leaders.

At the very beginning of new technological innovations, uncertainty may exist among the customers. These innovations may create confusion and customers may wait for the launch of competing models with similar technologies (Capatina & Draghescu, 2015; Schilling, 2013). The currently popular multilens camera system, in which more than one lens is added at the frontside and/or the backside of the smartphone, may serve as an example (C. Hall, 2019; Ralph, 2017). The dual camera was initially launched in 2011 by the companies HTC and LG allowing users to record 3D content (C. Hall, 2019; Ralph, 2017). Those companies failed to convince the market and it was not until 2016 that they became widely adopted in especially the newly launched high-end smartphone models. With the trend of improving smartphone camera quality and replacing digital cameras, smartphone manufacturers enabled smartphones to take photos and videos with multiple effects (Ralph, 2017). This example shows that good products and features can fail when customers aren't ready and when they are launched too early (Schilling, 2013).

In high-tech markets it is important to be at the ultimate top of the technology, because even if the popular dual camera is only three years old, smartphone brands are already looking at further developing the technology because development and life cycles are becoming shorter and shorter (Beard & Easingwood, 1996). The development can go in two ways: an additional camera at the backside or a dual-camera at the frontside of the smartphone (C. Hall, 2019). As the dual front camera is rather rare, a triple back camera has been introduced by Huawei in 2019, with their model: the Huawei Mate 20 (C. Hall, 2019).

On the other hand, if a product or product specification is launched too late on the market, the company can lose its reputation as a market leader and lose market share rapidly (Schilling, 2013). When a company reacts too late to a new technology, it could already have missed the chance of persuading first adopters to pay a higher price for their new product. A textbook example is the failure of Nokia. Until the early 2000s, Nokia was the market leader in the mobile phone industry. Nokia quickly lost market share after the launch of the first iPhone in 2007 and reoccurring problems with Symbian, their operating system (D. Lee, 2013). The OS problems caused the layback at software level and their market share was taken by Apple and other fast following competitors (Bouwman et al., 2014; D. Lee, 2013).

New products will not only compete with products from rival firms, but they will also compete with the brand's own, previously-launched products. When newly introduced products clash with other products, produced by the same company, it is called cannibalization (Schilling, 2013; Vukasovič, 2012). Smartphone companies must choose the optimal launch timing to optimize the cash flows by maximizing the sales of their smartphone products (Schilling, 2013).

Finally, the timing of the launch in the calendar year. Schilling (2013) proposes December as an interesting month to launch new products. Manufacturers can reap the benefits of increasing their sales as their new product may serve as a gift. However, Aris (2019) states that launching a new smartphone at a high introduction price in December may not be a good idea as previously launched smartphones tend to lower their prices in that month. Only brand loyal customers may be willing to wait for their favorite brand launch and pay the high introduction price at the end of the year (Hruska, 2017; Udland, 2015; Vukasovič, 2012).

The two remaining questions in the strategic decision-making process when launching smartphones are ‘where’ and ‘why’. These topics are not discussed extensively in the literature. Below they are briefly applied to the smartphone industry.

3.1.3 Where?

In terms of demographics, it is important to release the smartphone where it is easily available to the target audience (Capatina & Draghescu, 2015). Most smartphone manufacturers target an audience that is not restricted to national borders, however, this is not the goal of all smartphone producers. Yandex, for example, only targeted the Russian market and has not had any intention yet of reaching a broader audience (Aris, 2019; Humphries, 2018).

3.1.4 Why?

The reason why smartphone producers keep launching new products is mainly explained by the intense competition and their intention to maintain market share (Cecere et al., 2015). Hardware in particular, because the software can be updated, becomes quickly outdated caused by the continuous technology evolution and consequently new products are launched to maintain a competitive edge (Cecere et al., 2015). The competition in the smartphone industry is intense and having a stake in every smartphone generation is important to be able to compete in the market. Even before the smartphone market saturation, new devices accounted for almost half of the sales in the mobile phone industry (Di Benedetto, 1999).

3.2 Tactical decisions

Compared to strategic decisions, tactical decisions are made in later stages because they are easier and less expensive to adjust (Hultink et al., 1997; Schilling, 2013). This certainly does not make them less important; the literature also focuses more on tactical decisions compared to strategic decisions (Hultink et al., 1997). The tactical decisions we are dealing with here are: licensing and compatibility, distribution, marketing, and pricing.

Licensing and compatibility decisions provide an answer to the questions on how compatible the product will be with previous generations or with products from the competition and determine the degree of openness or closedness regarding newly used technologies. The pricing decision will position the product in the product’s price range with competing products and classify it as lowly- or highly-priced. The distribution decision determines how the product will be made available to the customers and the marketing decision determines how to reach the target audience.

3.2.1 Licensing and compatibility

Regarding licensing and compatibility, smartphone manufacturers decide on how compatible the product should be with previous generations or with products from the competition and determine the degree of openness regarding newly used technologies in order to protect their successful innovations.

The more open a technology is, the faster the adoption and the more the production of complementary goods will be stimulated (Schilling, 2013). The intense competition nourishes the patent battles for smartphone hardware and software innovations, as well as for horizontal and vertical innovations (Cecere et al., 2015). Android is an open-source OS whereas Apple's iOS is closed. Samsung thanks its popularity partly to the wide market penetration of Android (Cecere et al., 2015). At some point in time the operating systems of outdated models are not supported anymore, which stimulates sales of new models (Cecere et al., 2015; Y. Lee & O'connor, 2003; Schilling, 2013).

Compatibility, for the smartphone industry, especially backward compatibility, means that innovations of a new generation also work with previous generations (Y. Lee & O'connor, 2003; Schilling, 2013; Venkitachalam, Namboodiri, Joseph, Dee, & Burdsal, 2015). This is especially the case for complementary goods such as smartphone cases that should be repurchased when the dimensions of the new generation change, the charger connection changes… because the old accessories are not compatible with the newer versions anymore.

3.2.2 Distribution

The main goal of smartphone distribution is being able to reach the target audience (Capatina & Draghescu, 2015). Most smartphone producers choose to widely spread their devices and use as many distribution channels as possible, compared to a few other manufacturers that choose to only sell via direct sales. Apple, for example, chooses to sell their devices online, in their own stores and via other intermediaries (Capatina & Draghescu, 2015). On the other hand, OnePlus is selling their devices exclusively online, which enables lower costs (Bacon, 2016). Another advantage of selling via web stores is that smartphones are no longer restricted to the geographical locations from physical stores, and consequently their smartphones are available in the entire world (Khurana, 2019). However, smartphone manufacturers that choose to solely sell their devices through online channels miss out on the potential purchase from a customer that goes to a physical store (Abhishek, 2017).

3.2.3 Marketing

Via marketing tools, the audience becomes aware of the innovative technologies and release date and thus, the availability of a new smartphone. Schilling (2013) discusses the top three marketing methods for technological innovations: advertising, promotions and public relations.

Advertising is an opportunity to shape perceptions and expectations and create a desire for innovative technologies, and convince the public of the differences with the competition (Schilling, 2013). New technologies mainly appeal to early adopters who like to take the risk and try out new things. Promotions, especially price promotions, may convince later adopters of the purchase. Public relations are responsible for the image of the smartphone brand. OnePlus, for example, exclusively gives the right to buy their smartphone models online and invite a limited amount of friends than can buy them too (Bacon, 2016).

3.2.4 Pricing

The pricing strategy of a smartphone company is of utmost importance (Calantone & Di Benedetto, 2007; Mohd Suki, 2013; Zhou et al., 2017). The pricing strategy should take into account that pricing is not only a way to increase the revenues, but it is also important for building a relationship with the customers (Capatina & Draghescu, 2015). Apple, for example, decreased the price of its first iPhone by $200 already two months after the launch (Capatina & Draghescu, 2015; Hafner & Stone, 2007). In order not to ruin the relationship with the early adopters that bought the iPhone 2G in those first two months, they were compensated by allocating them a $100 App store credit (Capatina & Draghescu, 2015; Hafner & Stone, 2007). As such, the pricing strategy should not only decide upon decisions regarding the introduction price but also pay attention to decisions on the pricing after the introduction.

The introduction price immediately determines the smartphone's position in the entire range of available smartphones (Schilling, 2013). Riikonen e.a. (2016) found that the variation in the mobile handsets' introduction price is for 71% to 76% determined by a selection of features from the smartphone, representing its innovativeness. The versioning strategy discussed in section 3.1.1 allows for price discrimination, where products with different vertical specifications are priced differently.

Most of the innovative models follow a market skimming strategy, where a high introduction price represents the innovativeness compared to the previous generations and the price gradually goes down over time (Hultink et al., 1997; Riikonen et al., 2016; Schilling, 2013). The price level of the smartphones is subjective because customers value the innovativeness of new smartphones differently but, in general, the assumed gradual decrease in the prices seems to fit the smartphone market. In section 7, the average and median prices from several smartphone brands are discussed. Remarkably, all of these models show an average or median price decrease when they are on the market.

Of course, these decisions are not independently decided upon and they will affect one another. Especially for the price decisions, it is important to be coordinated with the other strategic and tactical launch decisions discussed in this paragraph (Capatina & Draghescu, 2015). This is also illustrated in section 1.4 where the introduction of Amazon's Fire Phone is discussed. Its high price positioned the Fire Phone with the high-end devices of the market leaders but failed to compete with their more qualitative features. Production, distribution and marketing decisions will influence the manufacturing cost which may increase the selling price of the smartphone (Capatina & Draghescu, 2015).

4 Reactions from the competition

Innovative smartphone launches are a means of survival in a highly competitive industry. All of the smartphone manufacturers strive for a purchase from the customer and a new product launch may provoke a reaction from the competition. Below, two pieces of research regarding competitive reactions to product launches are discussed. The first research focuses on the resulting competitive reactions to the existing products' marketing mix. The second paper focuses on the perceived signals of the market incumbents that lead to competitive reactions as a result of the new product's launch decisions. The perception of the market incumbents can then result in fast and/or strong competitive reactions.

Debruyne e.a. (2002) investigated competitive reactions regarding the existing products' marketing mix of 509 industrial product launches. The general results show that in 61.3% of the introduction cases researched, a competitive reaction was provoked, which means that in 38.7% of the cases competitors did not react to a rival product introduction. In cases where they did, a price change was the main reaction: in 43.6% of the product launch cases, competitors reacted by changing their prices. The second place went to changing the product assortment, which was the case in 35.5% of the product launches. 23.9% of the competitors reacted with a promotion stunt and only 3.2% reacted more radically by changing their distribution channel.

Based on extensive literature research, Debruyne e.a. (2002) built a conceptual framework in order to identify the significant factors that could influence or provoke a competitive reaction on an existing product's marketing mix (product, price, place, and promotion). In this framework, three groups of factors are identified: the characteristics of a new product introduction, the market characteristics and the characteristics of the innovator.

Firstly, the characteristics of a new product are defined by:

- The innovativeness of the new product compared to existing products; they range from incremental to radical product improvements. Incremental improvements are expected to compete more with the existing products of market incumbents; this is why Debruyne et al. (2002) expect the likelihood of a competitive reaction to be higher for incremental improvements compared to radical improvements.
- The marketing effort represented by the advertisement budget. When the advertisement budget is higher than the one from the market incumbents, the likelihood of a competitive reaction is expected to be higher.
- The targeting strategy. Three distinct strategies are identified: the undifferentiated strategy, the niche strategy, and the selective strategy. The difference between the latter two strategies entails that a selective strategy adjusts its marketing mix for each of the selected market segments whereas niche strategy focuses more on a low-competitive market segment. As the selective strategy directly competes in each targeted market segment, the chances of a competitive

reaction are assumed to be larger than when an undifferentiated or a niche strategy is used. (Debruyne et al., 2002)

Secondly, the market characteristics, assuming that the chance of a competitive reaction is higher when the market growth is higher. Finally, the characteristics of the innovator entail the previous successes and reputation in the market of the launching company. If the launching company has already experienced successes with its past product launches, the likelihood of a competitive reaction is higher. (Debruyne et al., 2002)

The first hypothesis of this research is supported, suggesting that innovative products (with incremental improvements) have the highest chance of provoking a competitive reaction. Secondly, a higher advertisement budget also leads to a higher likelihood of provoking a competitive reaction. Thirdly, the results regarding the targeting strategy are mixed. The likelihood of a competitive reaction as a consequence of the selective strategy is only significantly higher compared to the niche strategy, but not compared to the undifferentiated strategy. Fourthly, a higher growth market results in a higher likelihood of a competitive reaction, so in a lower growth market this likelihood decreases. Lastly, previous successes of the launching company do not lead to a higher likelihood of a competitive reaction. (Debruyne et al., 2002)

E. J. Hultink & Langerak (2002) also constructed a similar framework to that of Debruyne e.a. (2002), in which the launch decisions, the characteristics of the industry, and the characteristics of the launching company do not directly influence the competitive reaction of the market incumbents, but influence their perception of the new product introduction. Dependent on the launching decisions, in this research explained by the broad targeting strategy, the penetration pricing, the advertising intensity, and the product advantage, a market incumbent may perceive a new product introduction as a hostile market signal, as a commitment market signal, or as a consequence market signal. The latter refers to the incumbent’s perception that the new product would affect his profitability. The relation of the launch decisions and the perception from the market incumbents is also expected to be dependent on the market and entrant characteristics.

The results are fourfold. Firstly, when market incumbents perceive a product introduction as a hostile or a commitment market signal they will react strongly, whereas when the product introduction is perceived as a consequence market signal, the market incumbents will only react fast. Secondly, each of the four launch decisions included in this research will lead to one or two incumbent perceptions. New products with a higher product advantage compared to the incumbent’s existing products generate hostile and consequence market signals. A broad targeting strategy leads to consequence signals; more narrow targeting strategies, such as the selective and niche strategy discussed by Debruyne et al. (2002), lead to commitment market signals. Both the penetration pricing and high advertisement intensity create commitment market signals. Thirdly, the growth of the market strengthens the relationships between the launch decisions and the market signals, whereas a product introduction in a high-growth market will lead to a fast and strong competitive reaction.

Lastly, an aggressive reputation of the launching firms weakens the relationship of the launch decisions and the market signals.

5 Effect of a product introduction on prices

In literature, the competitive effect of a product introduction focusing on the prices of existing products has not been looked into extensively. When the subject is explored, the focus is primarily on the resulting effect of customers’ spending and welfare (Hausman & Leonard, 2003). This section will cover a discussion of the research done by Hausman & Leonard (2003). They investigated the competitive effect of product introduction on customer welfare in the bath tissue market.

5.1 Research introduction

Hausman & Leonard (2003) examined the effect of Kimberly Clark’s new bath tissue product ‘Kleenex Bath Tissue’ (hereafter KBT) with the purpose of finding out how customer welfare is influenced by a product introduction. The entire competitive launch effect is estimated by splitting the effect of a new product launch into two parts: the price effect and the variety effect.

The price effect is the consequence of changing the competitive structure of the bath tissue industry by adding a new product in the set of bath tissue products’ choices and it investigates how this affects the prices of competing products. The variety effect, on the other hand, implies that the product introduction results in having an additional choice for the customers, in this case, an extra bath tissue product. The variety effect is heavily influenced by the customers’ perception of the substitutability of the new product, compared to the existing products. The total welfare effect results from the sum of these two effects.

The total welfare effect resulted in 7.3% of the total consumer bath tissue expenditure, which is roughly equally divided between the price effect and the variety effect. The price effect represents 3.8% and the variety effect represents 3.5% of the total consumer welfare effect. In the following paragraphs, the methodology and the estimation of especially the price effect will be elaborated as it largely corresponds to the focus and goal of this master dissertation. Then, the bath tissue industry is compared to the smartphone industry and finally, the applicability of the estimation of the price effect to the smartphone research is discussed.

5.2 Bath tissue industry research

Researchers collected weekly sales data via the scanners in a selected series of supermarkets in 30 different cities of the United States. Next to Kleenex’ KBT, bath tissue products of the six largest brands were selected to be included in the research. The products’ identification code made it possible to weekly monitor the sales of the selected products, their prices, the sold quantities… for 196 weeks, from January 1992 until September 1995.

KBT was not launched simultaneously in the 30 cities, which made it necessary to make a distinction in terms of the moment of launch. The 30 cities were divided into three groups. A first group represented 17 cities where KBT was already introduced before the data was collected. This is particularly interesting because these cities can be used as a control group to detect price changes in the weekly data that are not caused by the product launch. In the remaining 13 cities, KBT was not yet introduced at the start of the investigation. This group was further divided into two groups based on the date of the launch of KBT, respectively in July 1993 and May 1994. The price data in these last two groups contain pre- and post-launch data which makes it possible to detect price changes caused by the introduction of KBT.

5.2.1 Price effect

The price effect represents the price change in the prices of the existing bath tissue products that result from the KBT introduction. It was estimated twice, using a direct and indirect approach.

5.2.1.1 The direct approach

The direct approach estimated the price effect by using an OLS-regression on pre- and post-launch data in combination with a Newey-West correction for possible correlation in the standard error terms. Hausman & Leonard (2003) estimated the following equation for each of the investigated existing bath tissue brands:

$$\log p_{it} = \alpha_i + W_t + M_{it}\delta_1 + I_{it}\delta_2 + \varepsilon_{it}$$

p_{it} is the price of the existing bath tissue brand's product in week t and city i. It is a semi-log model as the logarithm is taken from the dependent variable, p_{it}. For an absolute change in an independent variable, its coefficient will estimate the percentual change in the independent variable (Gujarati & Porter, 2009).

Hausman & Leonard (2003) used a typical analytical method for investigating panel data, namely the two-way fixed effects model. The first two variables, α_i and W_t, represent the fixed effects for respectively the cities and the weeks. They filter out city- and week-specific changes in p_{it} that may be caused by other events in a certain city or week. By introducing dummy variables for each week and each city, these changes in the price for each bath tissue product are not considered in the calculation of the effect of the introduction of KBT. (Gujarati & Porter, 2009)

As mentioned before, the cities could be divided into three groups based on the introduction time of KBT. It is possible that cities in the group of the last introduction would anticipate and already react to the introduction of KBT launched in the second group of cities. M_{it} equals one for the cities i from the third group in the weeks between July 1993 and May 1994.

The last variable, I_{it}, is the most important one as its coefficient will measure the searched price effect caused by the launch of KBT. It is a dummy variable that equals one in those weeks where KBT has been introduced and is available for purchase.

By using a semi-log model, the percentual change due to the change of M_{it} and I_{it} can be found by the following operation: $100(\exp(\delta_k) - 1)$ (with k = 1 for independent variable M_{it}, and k = 2 for independent variable I_{it} (Gujarati & Porter, 2009). Only these outcomes of the regression are mentioned in the study as the percentual price change as a result of the introduction of KBT per bath tissue product. The regression is performed per brand which makes it possible to analyze and compare the price changes of the different products. The percentual price changes are all significant and negative, which means the brands reacted to the KBT introduction by decreasing their prices. The resulting price decreases vary from 0.6% to a maximum price drop of 8.2%.

The results for M_{it}, on the other hand, were not significant for all brands, suggesting that the bath tissue brands have different strategies as to when to react to a product introduction. Some brands dropped their prices in all the cities, including the third group of cities where KBT had not yet been introduced, whereas some brands waited for the actual introduction of KBT in the city to drop their prices.

In the following sections, the indirect approach for the price effect and the variety effect are discussed. Both of these models need an estimated model of the post-introduction demand structure combined with an assumed model of the competition in the industry. As this approach requires more data than only retail prices, such as sales quantities, total expenditure per time period, etc., these approaches cannot be conducted in the research of this master's dissertation.

5.2.1.2 The indirect approach

Compared to the direct price approach, the indirect price approach offers a methodology to estimate the price effect based on post-introduction prices only. This approach needs an estimation of the overall demand of the bath tissue market and an assumed structure of the competition in the bath tissue industry.

The objective of this approach is to use the demand structure and the marginal costs, from the market and the industry incumbents, to estimate the equilibrium prices as if KBT would have never been introduced. In the bath tissue research, the marginal costs were not available, which is why they must be estimated. This is done by solving the equilibrium conditions from the assumed competition model, the Nash-Bertrand model, by using the prices and the estimated demand structure. Finally, the indirect price effect is calculated by taking the percentual difference of the actual after-launch prices and the estimated prices without KBT.

Hausman & Leonard (2003) would check the equality of the coefficients from the direct approach compared to the indirect approach and conclude that the results are mixed. For four out of the six brands the coefficients from both approaches are not statistically different, which is not the case for the two other brands. In the calculation of the overall customer welfare effect, the estimates of this approach are used to represent the price effect.

5.2.2 Variety effect

Hausman & Leonard (2003) state that "the variety effect associated with KBT, evaluated at the post-introduction prices of the other brands, is the increase in the expenditure function that would result from raising the price of KBT from its actual level to its virtual level, i.e., the price level that sets KBT demand to zero" (p. 253). The variety effect is estimated by dividing the difference between the actual and the virtual price in all cities by the total bath tissue expenditure. As additional data, such as sales data, personal disposable income per city, etc. are necessary to estimate this effect is not available and the effect is outside the scope of this research, the variety effect will not be further discussed and we refer the interested reader to the research of Hausman & Leonard (2003).

5.3 Differences with the smartphone industry

The direct approach to estimate the price effect is interesting since it is applied to the same type of data we possess, and no sales information is required. However, there are some crucial differences between the bath tissues and the smartphones that may play a role in the analysis and the results of the smartphone data. Those will be discussed below.

Firstly, in the bath tissue industry product introductions are rather rare. The data used was collected over three years and only one product introduction was discussed. Furthermore, the brands' products involved were sufficient to conduct the analysis and we can assume that those products have not exited the market. Compared to this, the smartphone market is characterized by innovative launches and terminations of the production of older smartphone models with outdated technologies. A production termination in the bath tissue industry is most likely a bad sign instead of a strategic decision.

Secondly, KBT is introduced as a Kleenex brand extension by Kimberly Clark that strived for growth and extension of the Kleenex brand in other product categories of the tissue industry as KBT was their first bath tissue product. Unlike the smartphone industry, bath tissue producers limit their number of products in a certain product category in order to avoid cannibalizing any other product from their own tissue brand. In the smartphone industry product launches are a way to maintain market share and to survive by keeping a certain level of technologic competitiveness. Product introductions are therefore much more common in the smartphone industry. This will make it impossible to conduct a long-term analysis based on one product introduction.

Thirdly, bath tissue products are consumer goods that are bought repeatedly, in large quantities at low product prices. The price of a bath tissue product is directly related to its quality, which can be ranked from economy to premium. Bath tissue products are also bought more frequently than smartphones; this means that when customers are not satisfied with their bath tissue products, they can buy another brand the next time. Smartphones, however, require more brand and purchase consideration, their prices are high, and they are used for a longer period of time. Smartphone prices are higher when the usefulness of their properties increases, such as storage capacity, camera resolution….

Fourthly, prices of bath tissue products are fairly constant and seem to respond only to certain events such as the product introduction of KBT. Smartphone prices will not react to all the production introductions of each brand in the smartphone industry, but they may go down gradually and react only to certain product introductions. Moreover, a percentual reduction in prices of 10% results in a way higher absolute price change in the smartphone industry than in the bath tissue industry.

Fifthly, it took over 2 years for the KBT introduction to reach the physical supermarkets in thirty cities in the United States. The prices in this research come from online web stores that sell smartphones. Due to the intense competition between the web stores as well as between the smartphone brands, it will probably take less time for new models to be available in-store.

5.4 Applicability to the smartphone industry research

The differences that may be important for further research in the smartphone market are the period considered and the selection of the available existing smartphone models. Statistics Belgium, or Statbel, the official Belgian organization that is responsible for calculating the Belgian consumer price index, experiences similar problems when including the consumer electronics in the calculations of the consumer price index (Roels & Van Loon, 2018). They identified three problems:

- The time on the market is short and product launches are frequent. There is a high inflow of innovative smartphone products, but also a high outflow of the previously launched models. It is difficult to follow the price evolution of a certain smartphone model in the long term.
- Older consumer electronics tend to leave the market at a lower price than their initial introduction price. This would imply that, as assumed, the prices of smartphones will not stay constant in between launches, but there is a downward trend.
- The innovative consumer electronics have other features or specifications and, usually, are of higher quality compared to previous generations.

To take these remarks into account, the reviewed time period should be shorter in order to keep the effect of a product introduction isolated and exclude influences from other product launches. Secondly, it will also be important to search and select the appropriate existing smartphones that are still available and are not terminated during the launch period.

RESEARCH

6 Research question

Do product launches affect the prices of existing products in their market? It seems to be the case in the bath tissue industry, but will this also be the case in other industries such as the smartphone industry, despite the differences discussed in the previous section? This research investigates the effect of a smartphone introduction on the prices of existing smartphones. It is based on a dataset of collected prices through a process of web crawling and contains data of all the available smartphones from November 2015 until October 2017, at various online web stores in Belgium and the Netherlands.

7 Methodology

In the following paragraphs, the influence of a product introduction on the prices of existing products is examined by implementing different panel data models that are then compared and tested in order to select the best estimation method. Two Apple launches will be analyzed:

- The launch of the iPhone 7 and the iPhone 7 Plus in September 2016
- The launch of the iPhone 8 and the iPhone 8 Plus in September 2017 and the iPhone X, six weeks later, in November 2017.

For the second launch, additional data with price information after October 12th 2017 was requested and received. This data is only used in section 7.3.4.6. All other paragraphs are based on the original data set with price information from November 26th, 2015 until October 12th 2017.

7.1 Dataset composition

The data mentioned above comes from the web crawling site: www.tweakers.net. During the 99-week period, two different types of CSV files were composed. The first one contained weekly information, gathered every Thursday of the week. For every available phone that day the URL-code, the web store, the price, and a data stamp were collected. The second type of files contained monthly information on the offered phones of that month with all of their detailed specifications. In order to facilitate the analysis, the week files were merged into one large dataset in Excel to construct a pivot table and a pivot graph. As a result, it was possible to check which smartphones already existed and which were newly launched in a certain week. The pivot table made it easy to get the minimum, maximum, and average price per smartphone per week, but also the median price was calculated, via column functions. Neither the minimum nor the maximum prices are used because they focus on the extreme offerings of a certain store in a week and may be a temporary offer or a package deal with complementary goods. As the dataset contains too much data to filter these observations out, these price deviations can be minimized by using the average and the median price of a certain smartphone in a certain week. The average and median prices make it possible to conduct a graphical analysis of the price and to get a general idea about the general price trend, which enables us to detect and disregard ordinary price shifts. Further statistical analysis is performed using the statistical software tool R Studio.

7.2 Brand selection

In total, the dataset contains 942.524 prices from 106 different phone brands. When the brands are ranked according to the number of prices in the dataset, Apple comes first, followed by Samsung. Both brands together represent 35.23% of the total number of prices and the top 10 accounts for 76.60%. The share of each brand’s number of prices is shown in Figure 1. After Samsung and Apple, the market shares of the remaining brands drop enormously.

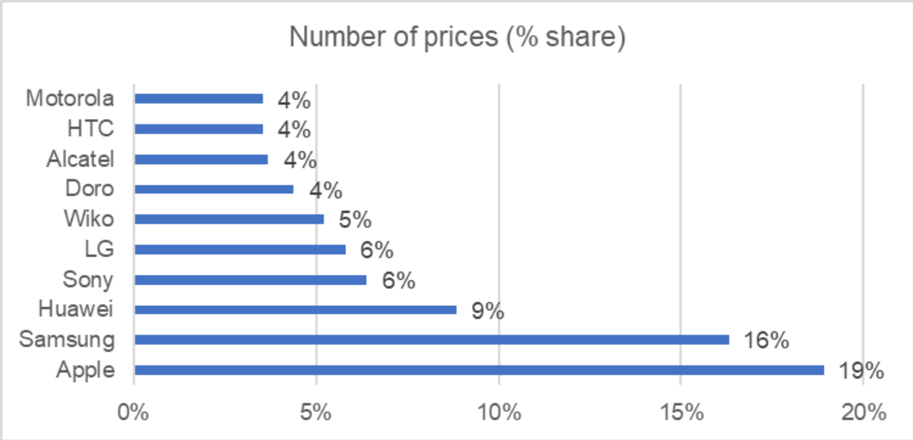
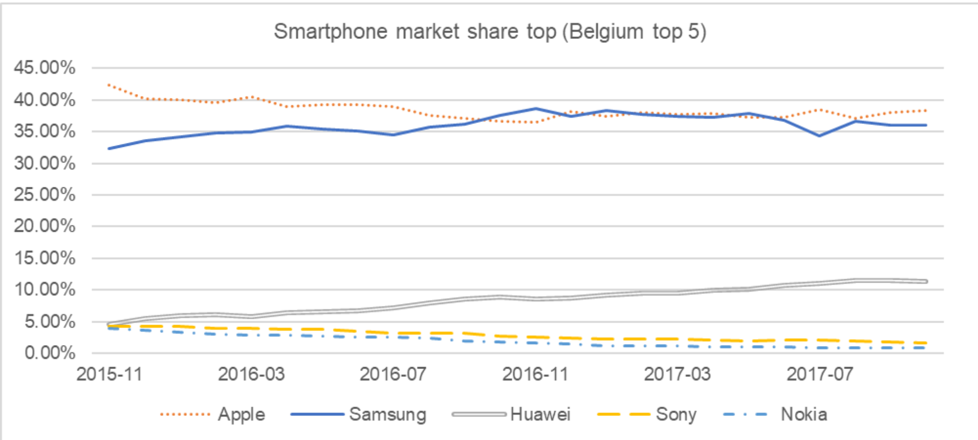
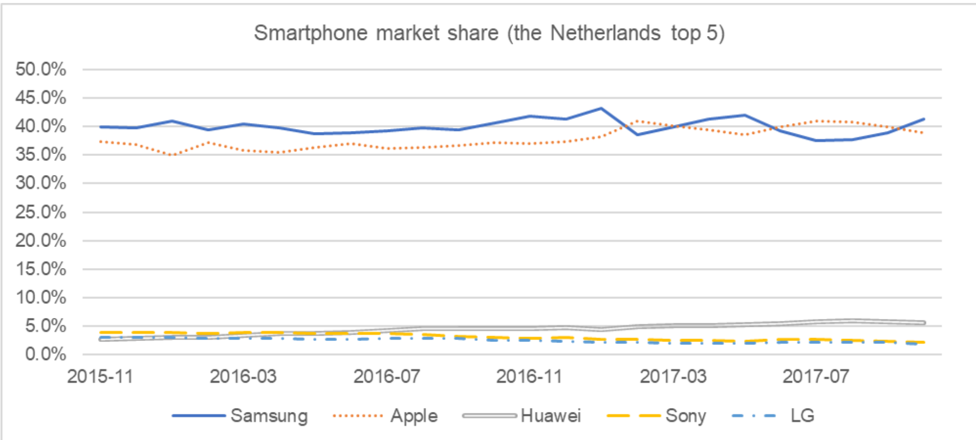


Figure 1 - Number of prices (% share of total)

As tweakers.net scrawls the Belgian and the Dutch web stores for smartphone prices, these numbers should be validated by comparing them with the Belgian and Dutch market shares. The market shares for the top 5 smartphone vendor companies from November 2015 until October 2017 are respectively presented in Graph 4 and Graph 5. To keep a clear overview, only the top 5 companies are presented in the graphs.



Graph 4 - Smartphone market share Belgium (top 5 companies) ("Mobile Vendor Market Share Belgium," n.d.)



Graph 5 - Smartphone market share the Netherlands (top 5) ("Mobile Vendor Market Share Netherlands," n.d.)

Figure 1 largely matches the market share structures in Belgium and the Netherlands. In both countries, Apple and Samsung lead the market with a remarkably large market share compared to the other three brands. This is why only those two brands are investigated extensively in this analysis.

In the following paragraphs, the price effects on Apple smartphones are statistically discussed. Firstly, the existing smartphone models, of which the prices will be examined, are introduced. Then, Apple's product introductions during those 99 weeks are presented. Afterward, graphical observations of the price trend are discussed and the statistical procedure for the price effect is conducted. Finally, the differences in launch and termination strategies of Apple compared to Samsung, Huawei, Sony, LG, and HTC are shortly discussed and a selection of their models is empirically analyzed.

7.3 Apple

7.3.1 Available smartphone models

At the end of November 2015, multiple generations of Apple's iPhone are being sold. There are still prices available for the iPhone 4 and iPhone 5 series, but their production is discontinued as of the end of 2015, which is why they are not considered in this analysis. The web stores will then probably want to sell the stock they still have as the number of stores that offer these models decreases heavily. The models discussed in this analysis are the iPhone 6s-series models. They came out just before the data was collected in October 2015. Six different versions were released: an iPhone 6s and an iPhone 6s Plus with each three different storage capacity options: 16GB, 64GB and 128GB.

7.3.2 iPhone launches

Apple has been known to launch its new models once a year around October. In the period of the data collection, there were two exceptions: the twofold launch of the iPhone SE. In March 2016, the 16GB and the 64GB versions were launched. One year later, Apple released the 32GB and 128GB version of the device. Below, the iPhones that were launched during the data collection will shortly be discussed. Device introductions are detected on a weekly level and are identified when their identification number appears for the first time in that week.

7.3.2.1 iPhone SE

The launch of the iPhone SE breaks Apple's pattern to announce and release the new generations each year around September and October. The iPhone SE-models (16GB and 64GB) were launched in week 12 of 2016, which is the week of 24 March 2016. One year later, in the week of 30 March 2017, Apple launched the 32GB and 128GB version. These models are part of Apple's ninth generation just like the iPhone 6s-series, launched in October 2015.

7.3.2.2 iPhone 7 (10th generation)

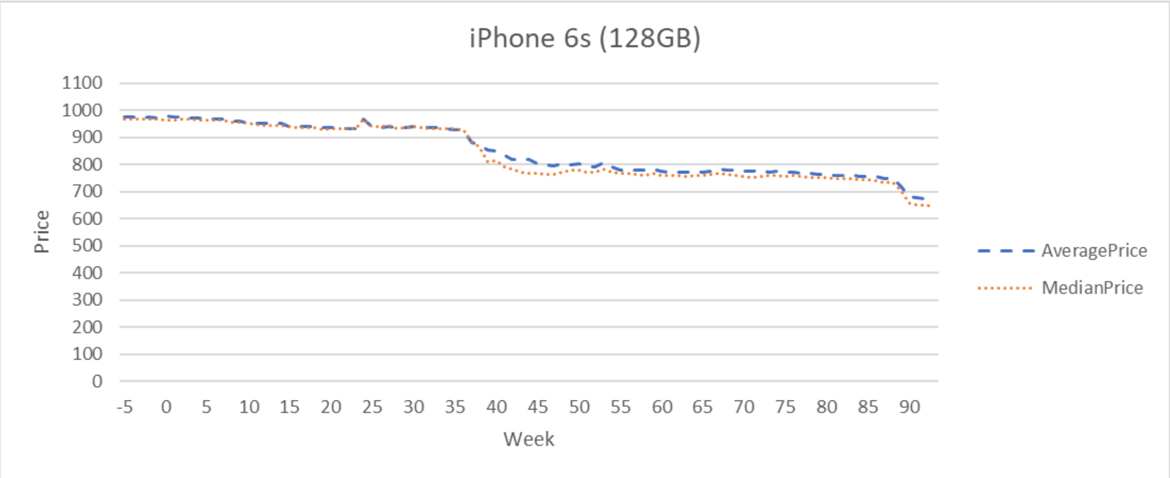
In September 2016, the iPhone 7 and the iPhone 7 Plus were launched together with the launch of the 32GB versions of the iPhone 6s and iPhone 6s Plus. Apple's tenth generation came with three storage options, i.e. 32GB, 128GB and for the first time the maximal storage capacity of 256GB.

7.3.2.3 iPhone 8 and iPhone X (11th generation)

Approximately one year later, the eleventh generation of the iPhone was launched, in September 2017. The iPhone 8 and iPhone 8 Plus are only available with a storage capacity of 64GB and 256GB. Six weeks later, the iPhone X was released in November 2017. This iPhone is launched with the same storage capacities of 64GB and 256GB.

7.3.3 Graphical observations

Observing the average and median price trend of a smartphone model can already reveal a lot about the price trend of a smartphone model. It can help with the presupposition of assumptions and the search for relevant price effects. Graph 6 shows the average and the median prices of one smartphone model, the iPhone 6s (128GB), from November 2015 until October 2017. The graph starts at week -5, the period from week -5 until week 0 representing the last six weeks in 2015. Week 1 is the first week of 2016, week 53 is the first week of 2017, and the last week of data available, week 93, corresponds to the beginning of October 2017. Another important remark is that the price jump in week 24 is caused by an error from the web crawling process in that particular week. As a correction is not possible for data collection in that week, the data of week 24 will not be included in the analysis.



Graph 6 - Median and average price iPhone 6s (128GB)

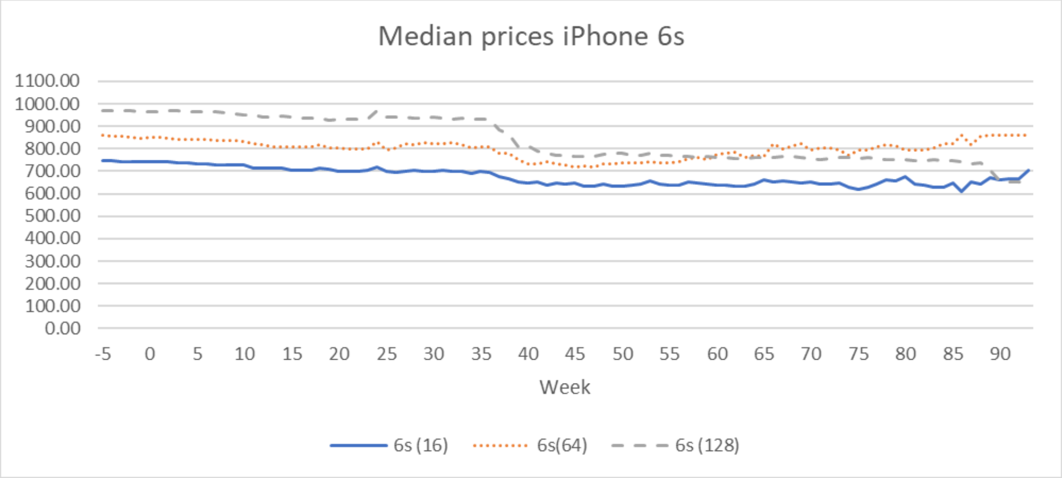
From this graph, we can put forward the following assumptions, which may be useful for further analysis:

- As mentioned before, during the 99-week data collection period, Apple has four different release dates. They take place in week 12, week 37, week 65 and week 90. Only two of these launches, those of week 37 and week 90, are extremely noticeable in the graph: they correspond to the launch of the iPhone 7 and the launch of the iPhone 8 with approximately one year in between. None of the launch timings of the iPhone SE, in week 12 and week 65, seem to have an effect on the average price nor the median price of the iPhone 6s (128GB).
- Looking at the price trend between the two notable launches, we see that the prices do not remain constant, and we observe a slightly downward trend. The iPhone 6s (128GB) has an average price of €977.71 and a median price of € 969.00 in week -5, which drops to € 928.61 for the average price and €929.36 for the median price in week 36, just before the launch of the iPhone 7 (Table 2). This means that over 42 weeks (from week -5 until week 36), the average price decreased on average by €1.17 per week and the median price decreased on average by €0.94 per week.

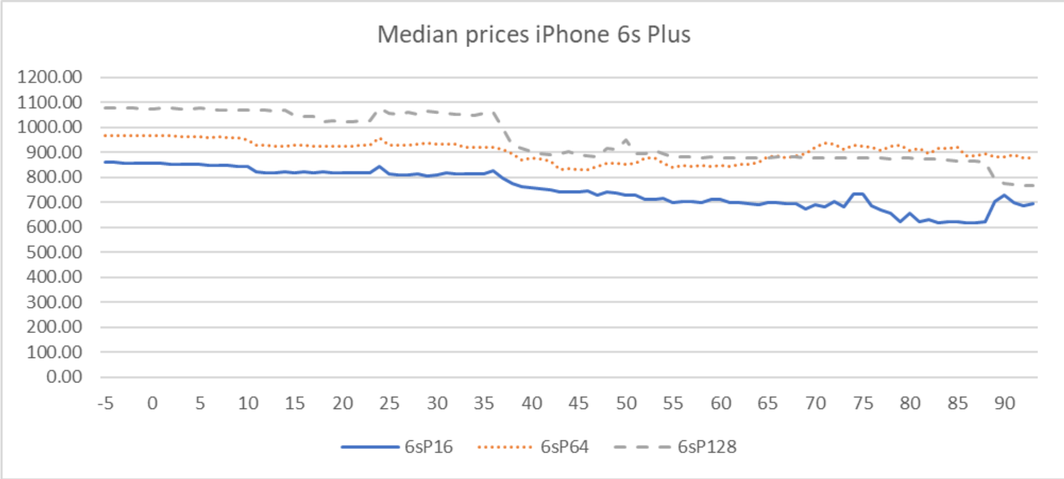
iPhone 6s (128GB)	Week -5	Week 36	Difference	Average decrease/week
Average price	€ 977.71	€ 928.61	€ 49.10	- € 1.17/week
Median price	€ 969.00	€ 929.36	€ 39.64	- € 0.94/week

Table 2 - Weekly average and median price decrease

As mentioned before, Apple releases its models with a difference in storage capacity. It may be interesting to see whether those differences result in a difference in price reaction. Graph 7 shows the median price trend of the different storage capacity models of the iPhone 6s. Graph 8 displays the same for the iPhone 6s Plus.



Graph 7 - Median prices iPhone 6s



Graph 8 - Median prices iPhone 6s Plus

There is definitely a change point for these smartphone models at week 36, which is the week before the launch: the price drops faster than before the launch. The following assumptions can be made:

- All of the iPhone prices seem to react to the launch in week 37 with a decrease.
- For both the iPhone 6s and the iPhone 6s Plus, the price of the smartphone with the highest capacity, 128GB, seems to react the strongest to the product launch in week 37. For the two other categories of storage capacities, it is unclear which price reacts the strongest.
- The price fluctuations after week 60, especially for the models with a storage capacity of 16GB and 64GB, are due to the fact that the number of offerings decreases considerably, and the median will vary each week from then onward.
- In week 12, the first versions of the iPhone SE are launched. This seems to have an effect on the price of the iPhones with 16GB and 64GB storage capacity. The iPhone with 128GB storage capacity does not seem to react to this product launch.
- In week 65, the second versions of the iPhone SE are launched. Due to a lack of data points resulting in volatile median prices, only the models with a storage capacity of 128GB can be considered. Neither the iPhone 6s (128GB) nor the iPhone 6s Plus (128GB) seem to react to the launch of this set of models.
- In week 90, only the models with a storage capacity of 128GB still have enough offerings to enable us to make some assumptions, and it seems that again they react strongly to the launch of the next generation, the iPhone 8 and iPhone X.

7.3.4 Procedure

For each smartphone the weekly prices for several web stores are available. This enables us to conduct a panel or longitudinal data analysis and use specific estimation tools and techniques that take the week-specific (time-series) and store-specific data (cross-sectional series) into account in order to estimate the effect of a product introduction. The free software tool, RStudio, offers these tools in several packages to conduct significant panel data analysis.

In the bath tissue research, which is discussed in section 5, the two-way fixed effects model is used to estimate the effect of the KBT introduction for each specific brand. This modeling technique is a specific technique used to estimate panel data models and will also be included in this analysis. However, what is not included in the bath tissue study are the statistical tests which investigate if the two-way fixed effects model is indeed an appropriate model for estimating the launch effect in the bath tissue industry. Below, this will be discussed in detail for one smartphone model, the iPhone 6s Plus (128GB). The same procedure is performed for the other smartphone models for which the results are shown in Appendix A until Appendix I. The results of all these different iPhone model analyses will be elaborated thereafter.

The different panel data models will be discussed in the following paragraphs, but first, an important remark must be made. Many of the techniques and tools used in the analysis require a balanced data set, this means that the number of observations for each cross-section should be equal, or the observations for each period should be equal. The data set contains several missing values, which is why some adjustments have been made.

The number of weeks included in the dataset is reduced considerably. As we are only interested in the launch effect in week 37, we will investigate ten weeks before and ten weeks after the launch, from week 26 until week 46. The reasons why are twofold:

- First of all, as mentioned in section 5.4 the reviewed time period should be shorter in order to isolate the launch effect and exclude the effects of other product launches. As the surrounding Apple product launches take place in week 12 and week 65, a launch interval is chosen of ten weeks before and after the launch in week 37.
- Secondly, as some of the statistical tools used from the plm-package require a balanced data set, thus the number of missing values should be minimized. By reducing the number of periods, the number of missing values goes down as well. Only the stores with a maximum of two missing values over those 21 weeks are selected. The missing data points are interpolated using the prices before and after the missing value. When the missing value is located at the beginning or the end of the period, only the price of the period before, respectively afterward is taken into account. The following paragraphs describe the procedure that is followed to select the panel data model that is best used to estimate the product launch effect on the prices of existing products.

7.3.4.1 Exploratory analysis

In Figure 2, the prices from the iPhone 6s Plus (128GB) are plotted for every included week for sixteen stores. In most stores, we can see a clear downward shift around week 37. However, from this plot, it appears that some stores do not react at all to the new product introduction, such as the last store on the second row, or the last store on the fourth row.

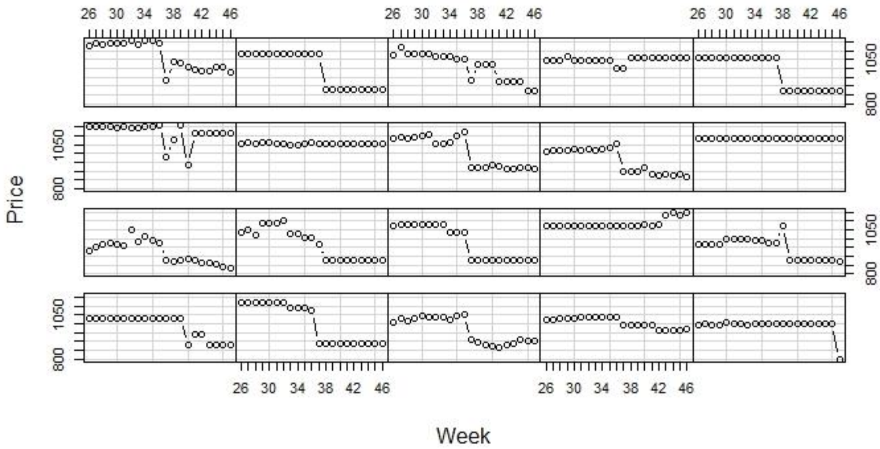


Figure 2 - Plotted data per store

7.3.4.2 Forecasting

When time effects, also used in two-way effects, are implemented, an error message is returned. This is caused by the fact that the launch variable is the same for every model. This causes estimation problems because these time effects can be interpreted as dummy variables for each time period and in this case, the launch variable can be written as a linear combination of the dummy variables of week 37 until week 46. In the bath tissue industry, this problem did not occur as for each bath tissue brand, there were cities in which KBT had already been introduced and for which the launch coefficient was never equal to one. In this case, web stores seem to offer new smartphone models immediately after the release, which is necessary to stay competitive. This is why on top of the data set selection mentioned above, a forecast was added. Several forecasting methods need more than 52 data points to forecast a time series. This is why the 'forecast.ets' function from excel was used to forecast the median price of the iPhone 6s Plus (128GB). The median prices of the iPhone 6s-series from week -5 until week 36 were used to forecast the future price trend as if the launch in week 37 had never happened. This forecasted data is added to the dataset as the web store 'Forecast'. For the iPhone 7-series, the prices from week 66 to week 89 were used.

7.3.4.3 Panel data analysis

The 'plm'-package from R Studio offers linear panel data models in order to estimate the effect of the product launch. These models will be introduced and compared to select the model that is best fit to estimate the launch effect. In order to use this package properly, the data has to be read as panel data, and the cross-sectional and time-series information are transmitted via the 'pdata.frame-command'. Then, only one more variable has to be defined: just like in the bath tissue research, a launch variable is introduced, whereby the launch effect is captured. It is a binary variable that turns to one in the week 37 and remains one until week 46.

7.3.4.3.1 Pooled OLS-regression

The first model that can be mentioned, is the pooled ordinary least squares regression, also called the constant coefficient model. It is a very basic model that pools all the observations, thereby assuming that the intercept and the regression coefficient are the same for every store, and thus ignoring the cross-sectional and time-series nature of the data. The following formula estimates the pooling model for the iPhone 6s Plus (128GB) (Econometrics Academy, 2013; Gujarati & Porter, 2009):

$$p_{st} = \beta_1 + \beta_2 * launch_{st} + \varepsilon_{st}$$

The dependent variable, p_{st}, represents the price of iPhone 6s Plus (128GB) for store s in week t and $launch_{st}$ represents the launch variable that indicates when the new generation is launched. The coefficient β_2 will estimate the price change as a result of the launch in week 37.

The results from the pooling regression model are presented in Table 3. According to this model, both the estimated intercept, β_1, and the launch coefficient, β_2, are significant. The price of the iPhone 6s Plus (128GB) would decrease on average by € 97.68 when the new smartphone models are launched. It may be intuitively clear that the pooling or OLS-regression model is not the optimal one as the differences between the stores and the weeks are not considered when estimating one launch coefficient for the entire dataset. This increases the possibility that the error term is correlated with the launch variable and, as a consequence, the launch coefficient may be biased and inconsistent. (Gujarati & Porter, 2009; Torres-Reyna, 2010)

```
                          Pooling Model

Call:
plm(formula = Price ~ Launch, data = PMdata, model = "pooling")

Balanced Panel: n = 26, T = 21, N = 546

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-152.613  -64.691   -7.750   39.705  209.470

Coefficients:
             Estimate Std. Error t-value  Pr(>|t|)
(Intercept) 1049.2950     4.2416 247.384 < 2.2e-16 ***
Launch       -97.6823     6.2683 -15.584 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    4190200
Residual Sum of Squares: 2897000
R-Squared:      0.30863
Adj. R-Squared: 0.30736
F-statistic: 242.844 on 1 and 544 DF, p-value: < 2.22e-16
```

Table 3 - Pooling model

Figure 3 shows the heterogeneity between the stores. Each point in the figure represents a 95%-confidence interval around a store's mean. Both the range and the average of the prices seem to vary enormously, which is in favor of the assumed store heterogeneity. Figure 4 on the other hand, shows the 95%-confidence interval of the average prices of all the stores per week. The range of the 95%-confidence intervals seems to increase after the launch. This indicates that not all the stores included in this data set adjust their prices simultaneously after the launch, which also strengthens the assumption that the web stores have different pricing strategies. It may be better to look for another model that can take these heterogeneities into account. (Torres-Reyna, 2010)

Two other commonly used panel data models are the fixed effects model and the random effects model. The fixed effects model, or the within model, considers heterogeneity across the individuals and/or time, in this case the stores' and the weeks' heterogeneity, in order to estimate the coefficient of the launch effect. The explanation and implementation of the fixed effects models will make the random effects model clearer; the latter is explained after the fixed effects models (Colonescu, 2016; Torres-Reyna, 2010).

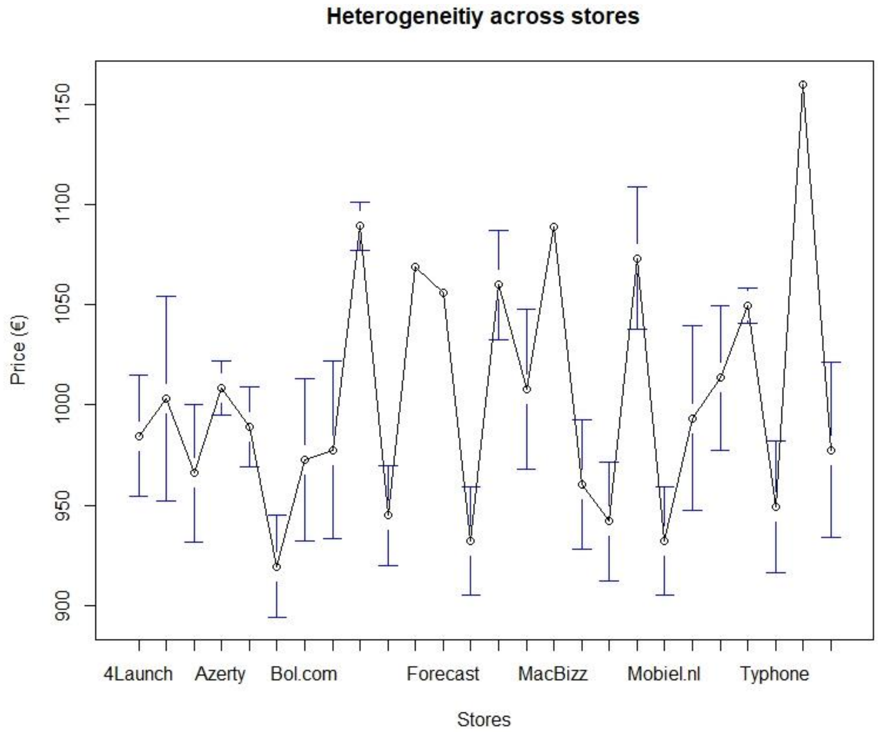


Figure 3 - Heterogeneity across stores

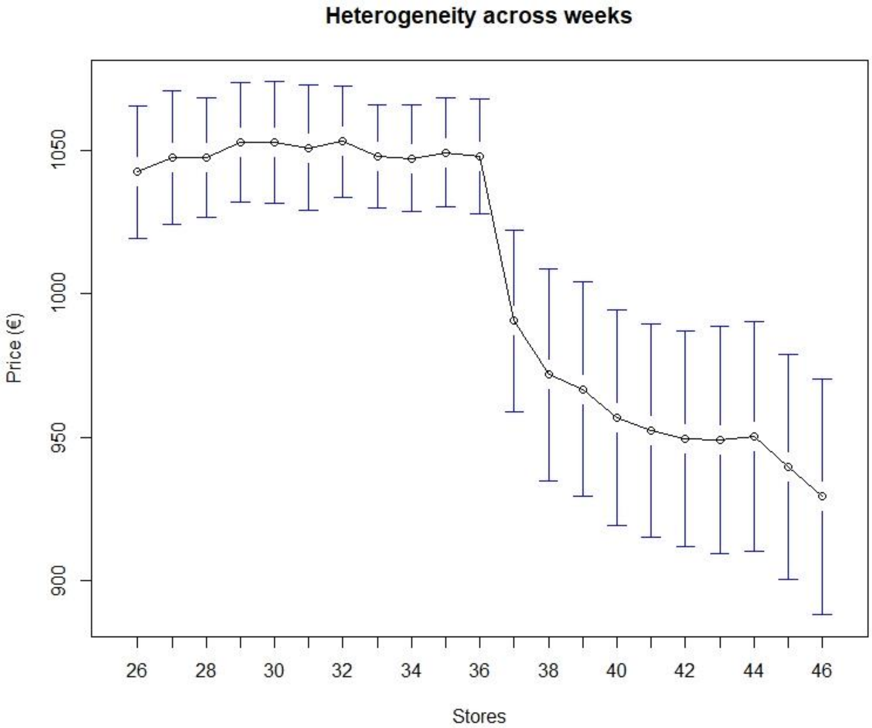


Figure 4 - Heterogeneity across weeks

7.3.4.3.2 Fixed effects estimators

The fixed effects model also uses OLS-estimation, but in the plm-formula, the fixed effects for the stores and/or the weeks are included in order to absorb any effect particular to the stores and/or the weeks. There are three different possibilities: either to only use the store-specific effect (individual fixed effects), the week-specific effect (time fixed effects) or to use a combination of the two, the two-way fixed effects model, where both the individual and time fixed effects are included. The latter model is used in the bath tissue research, but it is unclear whether the authors have investigated if that model is the optimal one and considered other options. This is why this analysis includes all three models and compares them to each other for each smartphone in order to deliver a full analysis and make a clear model selection. R Studio offers a special package for panel data analysis, 'plm', which is used in order to estimate linear panel models. Below, the three possible effects are discussed, and their significance is tested.

7.3.4.3.2.1 One-way (individual) fixed effects

This model only takes the factor variable 'store' into account, this means that for every store a dummy variable is created that will absorb the effects particular to each store, i.e. the heterogeneity amongst the stores. The following formula estimates the one-way fixed effects model for the iPhone 6s Plus (128GB) (Gujarati & Porter, 2009; Torres-Reyna, 2010):

$$p_{st} = \beta_{1s} + \beta_3 * launch_{st} + \varepsilon_{st}$$

The dependent variable, p_{st}, represents the price of iPhone 6s Plus (128GB) for store s in week t and $launch_{st}$ represents the launch variable that indicates when the new generation is launched. β_{1s} is the individual-specific fixed effect and represents a separate intercept for each store s. The coefficient β_3 will estimate the price change as a result of the launch in week 37.

The estimated model is shown in Table 4. The estimated Launch coefficient indicates how much the price changes on average per store when the variable Launch changes by one unit, which is only once in week 37. By using the 'effect = "individual" command in the plm equation, an intercept is estimated for each store. In the standard summary of the model these intercepts are not included, but via the 'fixef()-command' they become visible. Table 5 presents the individual-specific effects of each store. (Croissant & Millo, 2008; Crowson, 2019a; Econometrics Academy, 2013)

```
                 Oneway (individual) effect Within Model

Call:
plm(formula = (Price) ~ Launch, data = PMdata, effect = "individual",
    model = "within", index = c("Store", "Week"))

Balanced Panel: n = 26, T = 21, N = 546

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-138.9812  -36.7425   -1.8598   35.1561  136.6140

Coefficients:
       Estimate Std. Error t-value  Pr(>|t|)
Launch -97.1722     3.9489 -24.608 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    2296300
Residual Sum of Squares: 1059800
R-Squared:      0.53847
Adj. R-Squared: 0.51535
F-statistic: 605.531 on 1 and 519 DF, p-value: < 2.22e-16
```

Table 4 - One-way (individual) fixed effects model

```
                  Estimate Std. Error t-value   Pr(>|t|)
4Launch            1030.860     10.039 102.689 < 2.2e-16 ***
ACES Direct        1049.679     10.039 104.563 < 2.2e-16 ***
Afuture            1012.285     10.039 100.838 < 2.2e-16 ***
Azerty             1054.629     10.039 105.056 < 2.2e-16 ***
BCC                1035.153     10.039 103.116 < 2.2e-16 ***
Belsimpel.nl        965.753     10.039  96.203 < 2.2e-16 ***
Bol.com            1018.775     10.039 101.485 < 2.2e-16 ***
Centralpoint.nl    1023.749     10.039 101.980 < 2.2e-16 ***
Conrad.nl          1135.415     10.039 113.104 < 2.2e-16 ***
Coolblue.nl         991.225     10.039  98.740 < 2.2e-16 ***
FOKA Superstore    1115.273     10.039 111.097 < 2.2e-16 ***
Forecast           1055.974      9.861 107.086 < 2.2e-16 ***
GSMWijzer.nl        978.308     10.039  97.454 < 2.2e-16 ***
hifinesse          1106.089     10.039 110.183 < 2.2e-16 ***
Informatique       1054.114     10.039 105.005 < 2.2e-16 ***
MacBizz            1135.273     10.039 113.090 < 2.2e-16 ***
Max ICT B.V.       1006.409     10.039 100.253 < 2.2e-16 ***
Media Markt         988.209     10.039  98.440 < 2.2e-16 ***
Megekko            1119.353     10.039 111.504 < 2.2e-16 ***
Mobiel.nl           978.308     10.039  97.454 < 2.2e-16 ***
PC-Score Renkum BV 1039.558     10.039 103.555 < 2.2e-16 ***
SiComputers        1059.802     10.039 105.572 < 2.2e-16 ***
Staples.nl         1095.996     10.039 109.177 < 2.2e-16 ***
Typhone             995.273     10.039  99.144 < 2.2e-16 ***
Valeda.nl          1206.291     10.039 120.164 < 2.2e-16 ***
YourMacStore       1023.844     10.039 101.990 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 5 - Individual fixed effects

When the heterogeneity across stores is taken into account, the estimated Launch coefficient is a little higher than the one estimated with the pooled OLS-model presented in Table 3. The standard error of the launch coefficient has dropped from 6.65 to 4.66. As a consequence of the introduction of the individual fixed effects, where an intercept is estimated for each store, the degrees of freedom also decreased. (Torres-Reyna, 2010)

There is an intuitive preference of using the fixed effects model compared to the pooled OLS-model, but this can also be analyzed with a statistical F-test for individual effects. The null hypothesis of this test states that there are no significant individual effects on the estimated fixed effects model. The result of this test is presented in Table 6. The p-value is lower than 0.05, by which we can reject the null hypothesis and assume that the individual fixed effects model is a better choice than the pooled OLS-model. (Croissant & Millo, 2008; Econometrics Academy, 2013; Torres-Reyna, 2010)

```
            F test for individual effects

data:  (Price) ~ Launch
F = 35.987, df1 = 25, df2 = 519, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Table 6 - F test for individual fixed effects

7.3.4.3.2.2 One-way (time) fixed effect model

Instead of analyzing for individual fixed effects, we could implement individual time fixed effects controlling for heterogeneity across the weeks. The following formula estimates the time fixed effects model for the iPhone 6s Plus (128GB) (Gujarati & Porter, 2009; Hausman & Leonard, 2003):

$$p_{st} = \beta_{2t} + \beta_3 * launch_{st} + \varepsilon_{st}$$

The dependent variable, p_{st}, represents the price of iPhone 6s Plus (128GB) for store s in week t and $launch_{st}$ represents the launch variable that indicates when the new generation is launched. β_{2t} is the time-specific fixed effect and represents a separate intercept for each time period t. The coefficient β_3 will then estimate the price change as a result of the launch in week 37.

Table 7 shows the resulting model. The launch coefficient is higher than the one estimated by the pooling model (in Table 3) and the individual fixed effects model (Table 4). The standard error of the Launch coefficient is equal to 23.68, which is much higher than the ones in Table 3 and Table 4.

R Studio offers two tests to control for the significance of time fixed effects: The F test for time effects and the Lagrange Multiplier test. They are presented in Table 8 and Table 9. They both have a null hypothesis that states that the time effects are not significant. Both the p-values are greater than 0.05, which means that we cannot reject the null hypothesis that the one-way time fixed effects are not significant. However, the launch coefficient does not become insignificant. (Croissant & Millo, 2008; Econometrics Academy, 2013; Torres-Reyna, 2010)

```
                    Oneway (time) effect Within Model

Call:
plm(formula = (Price) ~ Launch, data = PMdata, effect = "time",
    model = "within", index = c("Store", "Week"))

Balanced Panel: n = 26, T = 21, N = 546

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-126.3119  -56.9937   -8.1387   36.2742  232.5781

Coefficients:
       Estimate Std. Error t-value  Pr(>|t|)
Launch -103.766     23.675 -4.3828 1.416e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    2927700
Residual Sum of Squares: 2824200
R-Squared:      0.035362
Adj. R-Squared: -0.0032967
F-statistic: 19.2092 on 1 and 524 DF, p-value: 1.4159e-05
```

Table 7 - One-way (time) fixed effects model

```
              F test for time effects

data:  (Price) ~ Launch
F = 0.67501, df1 = 20, df2 = 524, p-value = 0.8522
alternative hypothesis: significant effects
```

Table 8 - F-test for time effects

```
      Lagrange Multiplier Test - time effects
        (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 1.3389, df = 1, p-value = 0.2472
alternative hypothesis: significant effects
```

Table 9 - Lagrange Multiplier Test - time fixed effects

7.3.4.3.2.3 Two-way fixed effects model

In the two-way fixed effects model, both the individual specific and time-specific variables are included in order to estimate the launch effect. The following formula estimates the two-way fixed effects model for the iPhone 6s Plus (128GB) (Gujarati & Porter, 2009):

$$p_{st} = \beta_{1s} + \beta_{2t} + \beta_3 * launch_{st} + \varepsilon_{st}$$

The dependent variable, p_{st}, represents the price of iPhone 6s Plus (128GB) for store s in week t and $launch_{st}$ represents the launch variable that indicates when the new generation is launched. β_{1s} and β_{2t} represent respectively the individual-specific and the time-specific fixed effects. The coefficient β_3 will then estimate the price change as a result of the launch in week 37.

The resulting model is presented in Table 10. If both the individual and time fixed effects are included in the model, the resulting coefficient was overestimated by both of the one-way models. There are also two tests to verify the significance of a two-way fixed effects model. They have a null hypothesis that states that the two-way fixed effects are not significant. Their results are presented in Table 11 and Table 12. Both tests have a p-value lower than 0.05, which indicates that there are significant two-way effects. (Croissant & Millo, 2008; Torres-Reyna, 2010)

```
                     Twoways effects Within Model

Call:
plm(formula = (Price) ~ Launch, data = PMdata, effect = "twoways",
    model = "within", index = c("Store", "Week"))

Balanced Panel: n = 26, T = 21, N = 546

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-124.1987  -33.8512   -0.1598   31.0184  137.0577

Coefficients:
       Estimate Std. Error t-value  Pr(>|t|)
Launch  -96.036     19.821 -4.8451 1.692e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1033900
Residual Sum of Squares: 987430
R-Squared:      0.04493
Adj. R-Squared: -0.043113
F-statistic: 23.4747 on 1 and 499 DF, p-value: 1.692e-06
```

Table 10 - Two-way fixed effects model

```
             F test for twoways effects

data:  (Price) ~ Launch
F = 21.444, df1 = 45, df2 = 499, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Table 11 - F-test for two-way effects

```
              Lagrange Multiplier Test
         (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 2070.9, df = 1, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Table 12 - Lagrange Multiplier Test

The tests for the individual fixed effects indicated that they were significant and the tests for the time fixed effects were not significant. After investigating the significance of the two-way effects, where both the individual-specific and the time-specific effects are investigated, the latter seems the best option from the three possible fixed effects models.

The biggest advantage of using a fixed effects model is that its estimators are always consistent, even when the true model should be estimated with another plm-model. However, the disadvantage of the fixed effects models is the loss in degrees of freedom as a consequence of the estimation of the individual-specific and/or the time-specific intercepts. The random effects model proposes a solution to this problem. (Crowson, 2019a; Econometrics Academy, 2013; Gujarati & Porter, 2009; Torres-Reyna, 2010)

7.3.4.3.3 Random effects model

The random effects model proposes to express the heterogeneity across stores and time periods through the error term. Instead of treating the intercepts fixed for every store and/or time period, they are assumed to be a random variable with an estimated average value (see Table 13 for the results of the random effects model). We are stating that the stores in this analysis are part of a larger population of stores, which is true, as we know that some stores could not be included in this analysis.

The differences of each of the stores and/or time periods will then be captured by the error term. In this way, the error term of the model will exist of an individual-specific error term, a time-specific error term and the idiosyncratic term, which is the combined time series and cross-section error. The big assumption that must hold for the random effects estimators to be consistent, is the fact that the individual error components and the time error components are not correlated with each other and not correlated across both cross-section and time series units. (Crowson, 2019a; Econometrics Academy, 2013; Gujarati & Porter, 2009; Meier, n.d.)

The following formula estimates the random effects model for the iPhone 6s Plus (128GB):

$$p_{st} = \beta_1 + \beta_2 + \beta_3 * launch_{st} + w_{st} \text{ (with } w_{st} = \gamma_s + \delta_t + \varepsilon_{st})$$

The dependent variable, p_{st}, represents the price of iPhone 6s Plus (128GB) for store s in week t and $launch_{st}$ represents the launch variable that indicates when the new generation is launched. For each store the intercept β_{1s} consists of two parts: the common mean value for the intercept, β_1, and the store-specific error term γ_s, which is captured in the composite error term w_{st}. Identically, for each time period, β_{2t} consists out of two parts: the common mean value for the intercept, β_2, and the time period-specific error term δ_t, which is also captured in the composite error term w_{st}. β_3 is the time-specific fixed effect and represents a separate intercept for each time period t. The coefficient β_2 will then estimate the price change as a result of the launch in week 37.

The results from the random effects model are presented in Table 13. The launch coefficient is significant and almost equals the estimated coefficient from the individual fixed effects model. It is important to verify whether the individual error terms and the time error terms are not correlated with the regressor. This can be done by performing the Hausman test. The null hypothesis of this test states that the unique error terms are correlated with the regressors, in which the random effects model is preferred. If the Hausman test is significant, the fixed effects model should be used. The Hausman test is presented in Table 14. As the p-value is greater than 0.05, we cannot reject the null hypothesis and prefer the random effects model over the fixed effects model. (Croissant & Millo, 2008; Crowson, 2019b; Gujarati & Porter, 2009; Torres-Reyna, 2010)

```
                    Twoways effects Random Effect Model
                      (Swamy-Arora's transformation)

Call:
plm(formula = (Price) ~ Launch, data = PMdata, effect = "twoway",
    model = "random", index = c("Store", "Week"))

Balanced Panel: n = 26, T = 21, N = 546

Effects:
                  var  std.dev share
idiosyncratic 1978.810   44.484 0.353
individual    3548.902   59.573 0.634
time            70.408    8.391 0.013
theta: 0.8392 (id) 0.2793 (time) 0.2774 (total)

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-133.872  -33.033   -5.799   33.647  131.991

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept) 1049.0552    12.1987  85.997 < 2.2e-16 ***
Launch       -97.1586     5.2859 -18.381 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1738600
Residual Sum of Squares: 1072500
R-Squared:      0.38311
Adj. R-Squared: 0.38198
Chisq: 337.845 on 1 DF, p-value: < 2.22e-16
```

Table 13 - Random effects model

```
                    Hausman Test

data:  (Price) ~ Launch
chisq = 0.0034559, df = 1, p-value = 0.9531
alternative hypothesis: one model is inconsistent
```

Table 14 - Hausman test

The random effects model is thus preferred to estimate a consistent coefficient of the launch variable from the iPhone 6s Plus (128GB).

7.3.4.4 Regression diagnostics

Fixed effects estimators are always consistent, the random effects estimators are only consistent if the null hypothesis of the Hausman test is not rejected. In order for the estimations to be efficient as well, some diagnostics must be checked and should be controlled for. (Torres-Reyna, 2010)

7.3.4.4.1 Cross-sectional dependence (contemporaneous correlation)

Cross-sectional dependence means that the error terms across individuals, here the stores, are correlated. There are two tests to verify for cross-sectionally dependent residuals or contemporaneous correlation: the Breusch-Pagan LM test and the Pesaran CD test. Both tests have a null hypothesis that states that the residuals across cross-sections are not correlated. In this case, we will only use the Pesaran CD test as the Breusch-Pagan LM test performs badly when the number of individuals (N) is larger than the number of periods (T). In this case, the number of periods is 21 and the number of stores is 26, thus the number of stores is greater than the number of periods and the use of the Breusch-Pagan LM test is recommended. The Pesaran CD test is presented in Table

15, the p-value is greater than 0.05, which means that we cannot reject the null hypothesis and assume that there is no cross-sectional dependence in the random effects model. (Croissant & Millo, 2008; Torres-Reyna, 2010)

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = 0.90552, p-value = 0.3652
alternative hypothesis: cross-sectional dependence
```

Table 15 - Pesaran test for cross-sectional dependence

7.3.4.4.2 Serial correlation

Serial correlation or autocorrelation within units leads to lower standard errors. The Breusch-Godfrey/Wooldridge test has a null hypothesis that states that there is no serial correlation. This test is presented in Table 16 and has for the iPhone 6s Plus (128GB) a p-value of less than 0.05 whereby we reject the null hypothesis and assume that there is serial correlation in the random effects model. (Croissant & Millo, 2008; Torres-Reyna, 2010)

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 284.46, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Table 16 - Breusch-Godfrey/Wooldridge test

7.3.4.4.3 Testing for unit roots/stationarity

It is important to test for stationarity. The null hypothesis from the augmented Dickey-Fuller test is defined as the presence of a unit root and the alternative hypothesis is that the data is stationary. In Table 17 the results of this test are presented. The p-value is less than 0.05, so we can reject the null hypothesis and assume that the data is stationary. (Croissant & Millo, 2008; Torres-Reyna, 2010)

```
                        Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -6.5382, Lag order = 2, p-value = 0.01
```

Table 17 - Augmented Dickey-Fuller Test

7.3.4.4.4 Heteroskedasticity

The null hypothesis of the Breusch-Pagan test is that the variance of the error terms is constant. The test in Table 18 has a p-value of less than 0.05, which means that the variance of the errors terms is not constant, thus there is heteroskedasticity. (Croissant & Millo, 2008; Torres-Reyna, 2010)

```
             Breusch-Pagan test

data:  randommodel
BP = 94.123, df = 1, p-value < 2.2e-16
```

Table 18 - Breusch-Pagan test

7.3.4.4.5 Accounting for serial correlation and heteroskedasticity

The four performed tests made clear that we have to control for serial correlation and heteroskedasticity in the two-way random effects model. We can account for these ‘problems’ by computing a robust covariance matrix. The ‘Arellano’ covariance estimator is used because it accounts for heteroskedasticity and serial correlation. (Croissant, n.d.; Croissant & Millo, 2008; Torres-Reyna, 2010)

```
t test of coefficients:

             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 1049.0552     9.8595 106.4003 < 2.2e-16 ***
Launch       -97.1586    18.8091  -5.1655  3.37e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 19 - Robust covariance matrix

7.3.4.5 Results

The procedure, explained in section 7.4.3, is performed for all Apple models from the 6s-series. The resulting launch coefficient and its standard error are presented in Table 20 and the tests themselves can be found in Appendix A to Appendix E. The two-way random effects model is also used for the estimation of the launch coefficient of the iPhone 6s (128GB) and the two-way fixed effects model is used to estimate the launch coefficient of the remaining iPhones: the iPhone 6s (16GB), the iPhone 6s (64GB), the iPhone 6s Plus (16GB) and the iPhone 6s Plus (64GB).

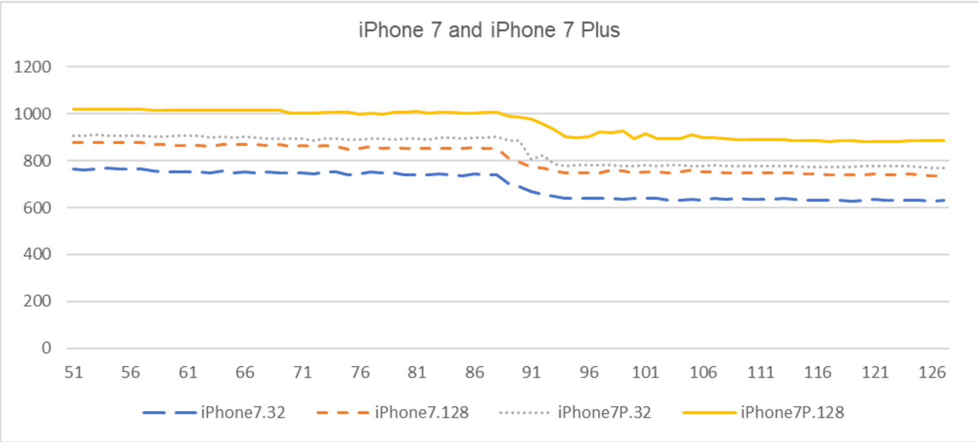
Model	Launch coefficient	Standard error	Median price at W36	%Decrease
6s 16GB	-23.06	4.69	695.11	-3.32%
6s 64GB	-40.15	5.84	806.38	-4.98%
6s 128GB	-107.74	22.29	929.36	-11.59%
6s Plus 16GB	-57.05	8.55	825.94	-6.91%
6s Plus 64GB	-49.21	8.26	919.78	-5.35%
6s Plus 128GB	-97.16	18.81	1059.28	-9.17%

Table 20 – Regression results

The six investigated models all reacted significantly to the introduction of new Apple models in week 37. The launch coefficient, estimated by either the two-way fixed effects model or the two-way random effects model, is for every investigated model significant and negative. This means that the prices of the models examined decreased when the new generation Apple smartphones were launched in week 37. Within the 6s-series and the 6s-Plus-series, the relative price reduction, calculated by dividing the estimated price reduction by the median price at week 36, is not in order of the storage capacity size. A model with the highest storage capacity of 128GB reduced more in price than the models with less storage capacity of 16GB and 64GB. Whereas for the iPhone 6s-series, the 64GB decreased more, in relative and absolute terms, than the 16GB, the opposite is true for the iPhone 6s Plus-series, where the 16GB decreased more in relative and absolute terms than the 64GB version.

7.3.4.6 The launch of the iPhone 8, the iPhone 8 Plus and iPhone X

The launches of Apple's new generation, the iPhone 8, iPhone 8 Plus and iPhone X, take place in week 90 and week 96, the iPhone X entering the market six weeks after the first two. On request further data was supplied so that the effect of a new introduction on the latest launched generation could be investigated once again. In Graph 9, the median prices of the iPhone 7 and iPhone 7 Plus are presented. Due to the spread introductions in week 90 and week 96, the price decrease seems to last longer compared to the effect of the iPhone 7 and the iPhone 7 Plus launches on the prices of the iPhone 6s-series. The same procedure as described in section 7.3.4.3 is followed to estimate the effect of the product launch; only an extra launch variable is introduced to estimate the effect of the second launch. The resulting tables can be found in Appendix F until Appendix I and the coefficient results are discussed below.



Graph 9 - Median price trend from the iPhone 7 and iPhone 7 Plus

The four investigated models all reacted significantly to the introduction on both launch dates in week 90 and week 96. The launch effects of each iPhone 7 (Plus) model were estimated with the two-way random effect model. The resulting launch coefficients are presented in Table 21 and Table 22 for respectively the launch coefficient for the effect of the iPhone 8 and iPhone 8 Plus and the launch coefficient for the effect of the iPhone X. The resulting coefficients are all negative for each of the models, meaning that the price of the existing models significantly decreased when the new smartphones were launched. So far, these findings correspond to the ones discussed in 7.3.4.5; however, the price of the 32GB-model decreases faster relative to its median price from the week before the launch compared to the 128GB-model. This last observation is the opposite from what was found in 7.3.5.4.

Model	Launch coefficient	Standard error	Median price at W89	%Decrease
7 32GB	-47.06	10.49	704.25	-6.68%
7 128GB	-37.06	9.54	810.51	-4.57%
7 Plus 32GB	-48.06	9.59	885.39	-5.43%
7 Plus 128GB	-38.07	9.45	992.62	-3.84%

Table 21 - Regression results (Launch of the iPhone 8 and iPhone 8 Plus in week 90)

Model	Launch coefficient	Standard error	Median price at W95	%Decrease
7 32GB	-30.08	9.59	639.00	-4.71%
7 128GB	-17.44	8.36	749.23	-2.33%
7 Plus 32GB	-28.88	8.32	780.11	-3.70%
7 Plus 128GB	-17.51	6.4	900.50	-1.94%

Table 22 - Regression results (Launch of the iPhone X in week 96)

7.4 Other smartphone brands

Of course, Apple is not the only smartphone brand, but it is the one with the most explicit launch and termination strategy. This may cause the effect of a product introduction of existing models of other brands to be different than the ones of Apple. The numbers in the following analysis are based on the Tweakers identification code, where models are identified based on their storage capacity and color. For example, iPhone 6s (128 GB) was brought out in four colors and thus has 4 identification codes.

Table 23 gives an overview of the model launches and terminations for six widely sold smartphone brands. The second column 'Models at the start' shows the number of models that were already available on November 26th, 2015, when the data collection stated. The third column shows the number of models that were launched onto the market over the following 98 weeks. The fourth column shows the total number of models that were available during part of the 99 weeks as the sum of the first two columns. The last two columns show the number and percentage of models that were terminated before week 99 and the models that were still sold at the end of the data collection, in week 99.

	Models at the start	Models launched	Total		Models terminated		Models continued	
Apple	69	117	186	100%	58	31.18%	128	68.82%
Samsung	234	167	401	100%	277	69.08%	124	30.92%
Huawei	89	126	215	100%	115	53.49%	100	46.51%
Sony	87	93	180	100%	105	58.33%	75	41.67%
LG	87	84	171	100%	109	63.74%	62	36.26%
HTC	55	80	135	100%	79	58.52%	56	41.48%

Table 23 - Overview model launches and terminations

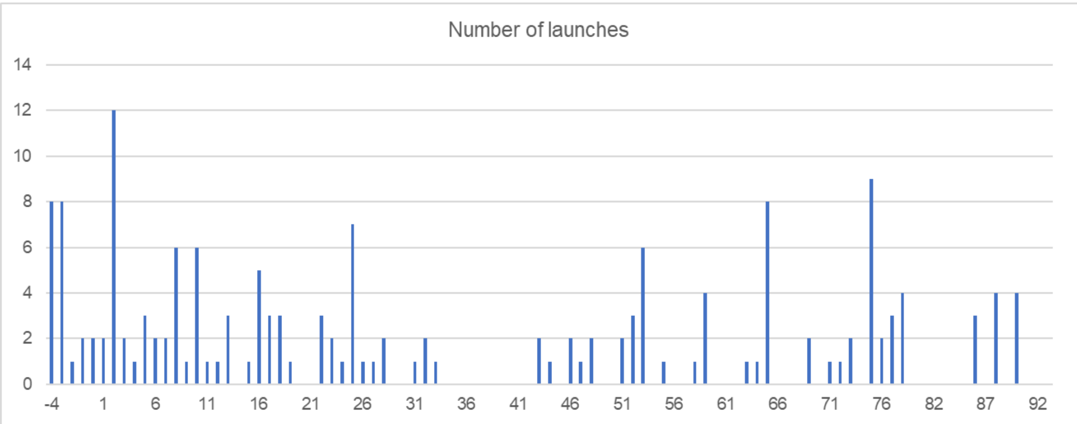
From Table 23, it is clear that Apple's strategy really stands out from the others. Except for HTC, Apple has the lowest number of models at the start of the data and it launches the third most smartphone models in 99 weeks. From its available models (column 'Total'), it has terminated the lowest number of models, in absolute and relative terms. The other brands terminate more than half of their available models during those 99 weeks. Apple is also the only brand that terminates fewer models (column 'Of the market') than were already available at the start of the data collection (column 'Models at start'). For the other brands, the opposite is the case. We can state with certainty that these brands also terminated models that were launched during those 99 weeks.

In the following paragraphs, Samsung is empirically discussed. As it will become clear, it was not possible to investigate the price effect at a statistical level, as done for Apple in section 7.3.4. Thereafter, Huawei, Sony, LG, and HTC are briefly discussed as well.0

7.4.1 Samsung

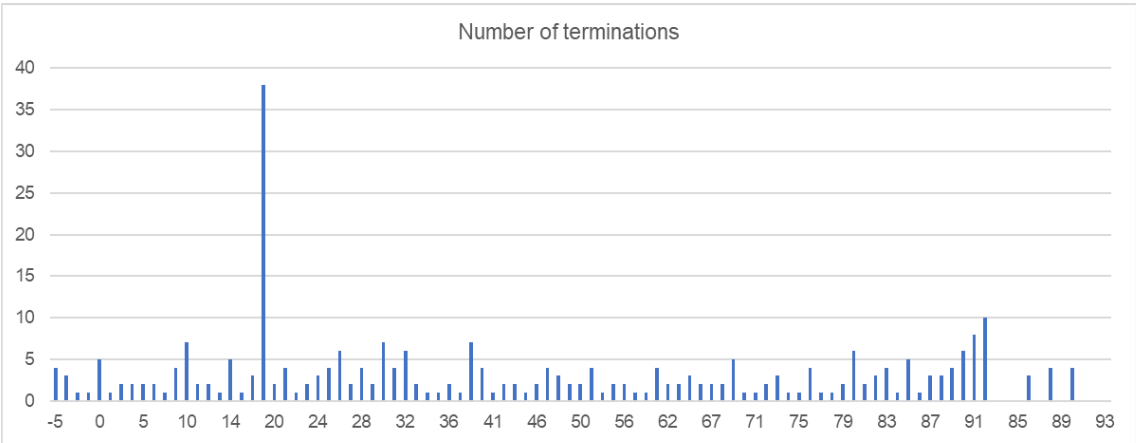
7.4.1.1 Number of launches

In November 2015, Samsung had 234 smartphone models on the market. Over the next 98 weeks, Samsung launched 167 models, which means that on average more than one model per week was launched. Graph 10 shows the distribution of those Samsung launches over the 99 weeks. In 58 out of 97 weeks, where the first and the last week are not included, a new Samsung model was launched.



Graph 10 - Samsung launches (November 2015 - October 2017)

Graph 11 shows the number of terminations of Samsung over those 99 weeks. In 88 weeks, one or more Samsung models were permanently terminated. There is one week that stands out, week 19, where 38 models were permanently removed and no longer sold by any of the web stores.

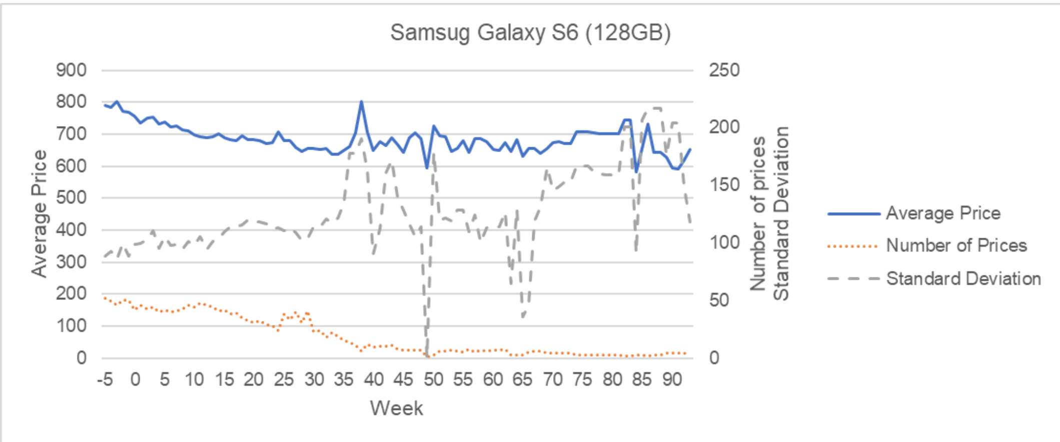


Graph 11 - Samsung terminations (November 2015 - October 2017)

7.4.1.2 Existing models

Unlike Apple's structured series launches of smartphone and generations, it is difficult to find some kind of structure for Samsung. In general, the prices of these models are very volatile. Samsung model prices have a decreasing trend, similar to Apple model prices, but when the number of offerings reduced, the volatility, measured by the standard deviation of al the prices in a certain week, increases. Most Samsung smartphones are from the Galaxy-series. Other models are not considered any further as the data for these models is rather limited. Within this Galaxy series, several other series exist: Ace, Alpha, Core, Europe, Express, Fame, Grand…. The series with the most data, for which Samsung still launches models today, are the Galaxy A-series, the Galaxy J-series, the Galaxy Note, and the Galaxy S-series. A common trend for these models seems to be that each year a newer version of a model is launched, for example, the Samsung Galaxy A5 2016, and at that moment the older version is exited. In this situation, it is difficult to statistically examine the effect of a product introduction on the prices of existing products as those existing products cease to exist.

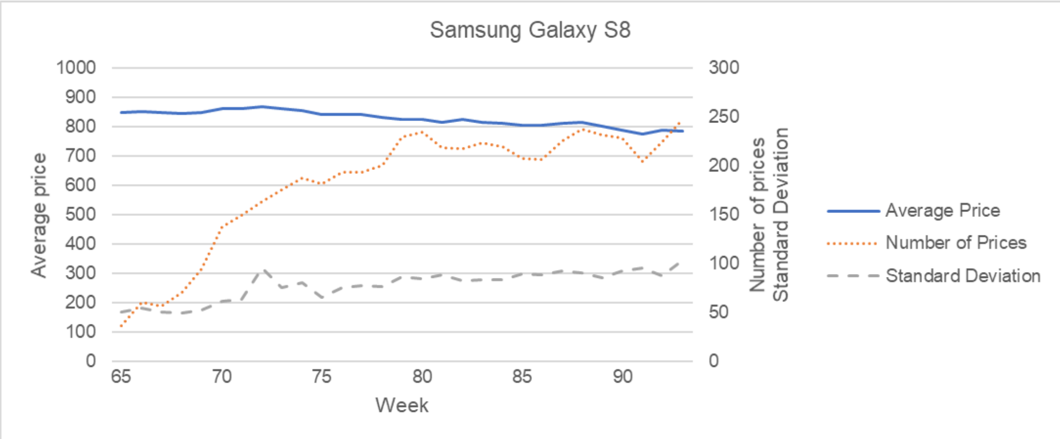
Graph 12 shows this phenomenon. The average price decreases until week 35 when prices become very volatile. This comes with an already decreasing number of offerings that is floating above zero and an incredible increase of the standard variation in the prices. Taking a look back at Graph 10, we can conclude that there are no launches of new Samsung models around week 35. So, the reason behind this volatility and decrease in offerings cannot be linked to a product introduction by Samsung.



Graph 12 - Samsung S6 (128GB)

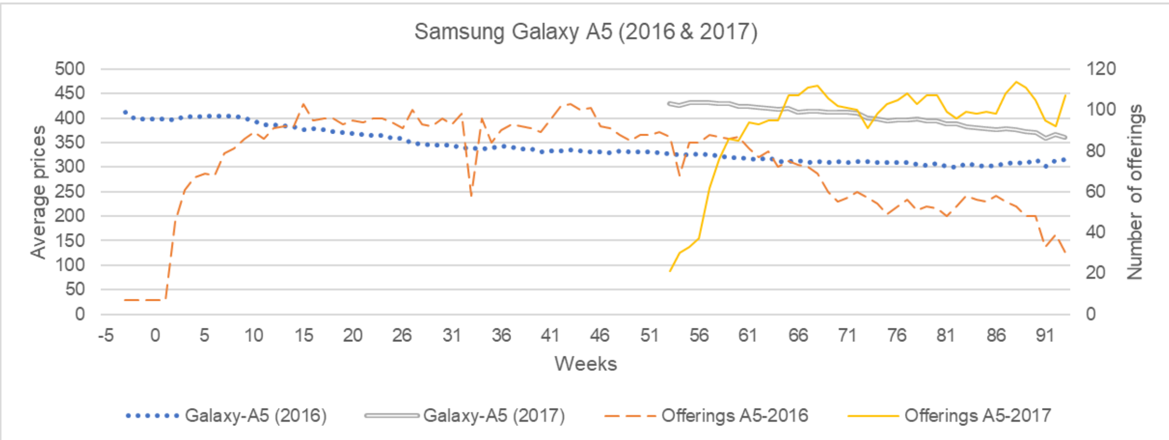
7.4.1.3 New models

Whereas the prices of existing models become rather volatile at the end of their life span, new models do not seem to react to anything. Their graphs show a gradual decrease per week in the average price, just like Apple's smartphones in between two launches. The Samsung models seem to wait for the newer version, with volatile prices as a consequence of web stores wanting to still sell their stock before these models are removed from the market. The Samsung S8 – 32GB, launched in week 65, shows a gradual decrease of the average price, and an increase in the number of web stores offering this model, and from week 80 on a constant standard deviation of the prices around 100 (Graph 13).



Graph 13 - Samsung Galaxy S8

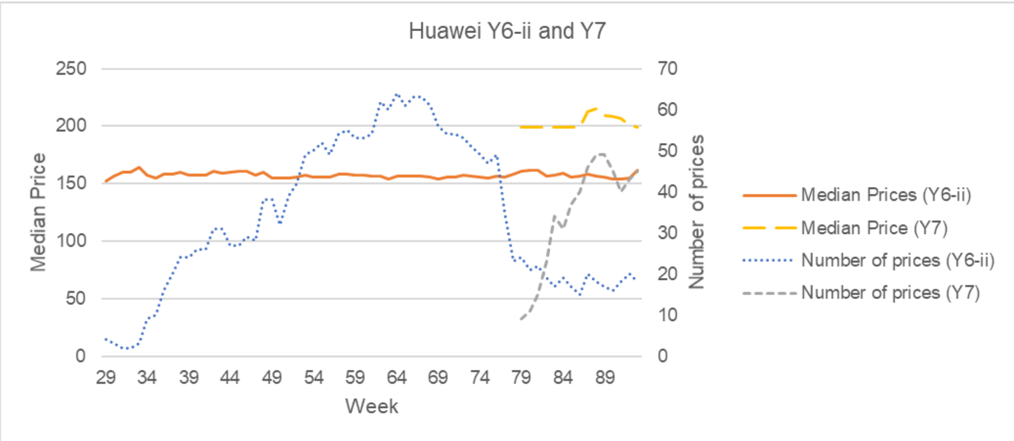
There are also models for which the prices do not go down when their new version is launched. This is illustrated in Graph 14 with the Samsung Galaxy A5 versions from 2016 and 2017. The Samsung Galaxy A5 (2016) median price decreases gradually every week, and this does not change when its 2017-version is launched in week 53. Only the number of offerings of the older version of the Samsung Galaxy A5 starts to decrease when the number of offerings of the newer version starts to increase.



Graph 14 - Samsung Galaxy A5 (2016 & 2017)

7.4.2 Huawei

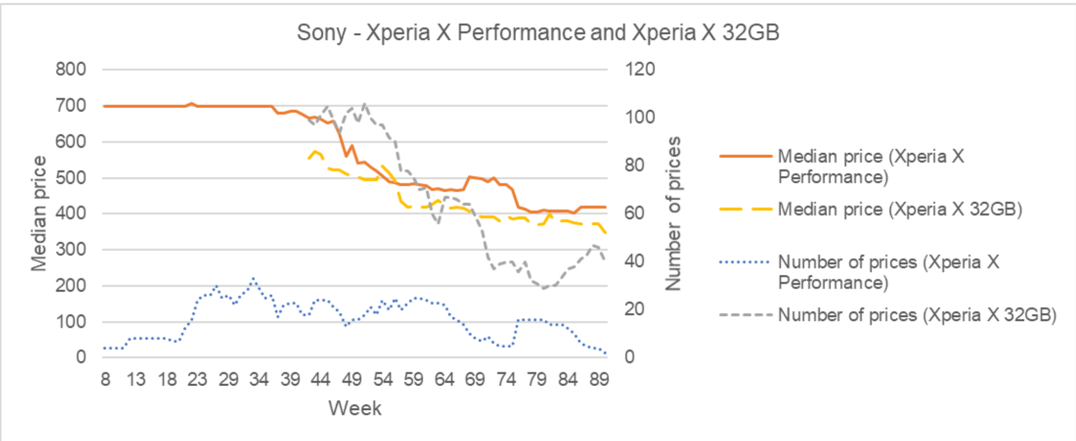
Graph 15 illustrates this short life cycle phenomenon for two Huawei smartphone models. Huawei Y6 ii is launched in week 29. In Graph 15, the blue dotted line shows that the number of prices, which represents the number of web stores that offer this model, increases, reaches a top at week 64 and then decreases enormously with an immense drop, from around week 70. This is followed by the new launch of the Huawei Y7 in week 78. The Huawei Y6 ii median price does not seem to react to the launch of the Huawei Y6. However, the median price of the Huawei Y7 increases accordingly with the number of offerings, suggesting that web stores offer the new model at a higher price than before the median price increase.



Graph 15 – Huawei: Y6 ii and Y7

7.4.3 Sony

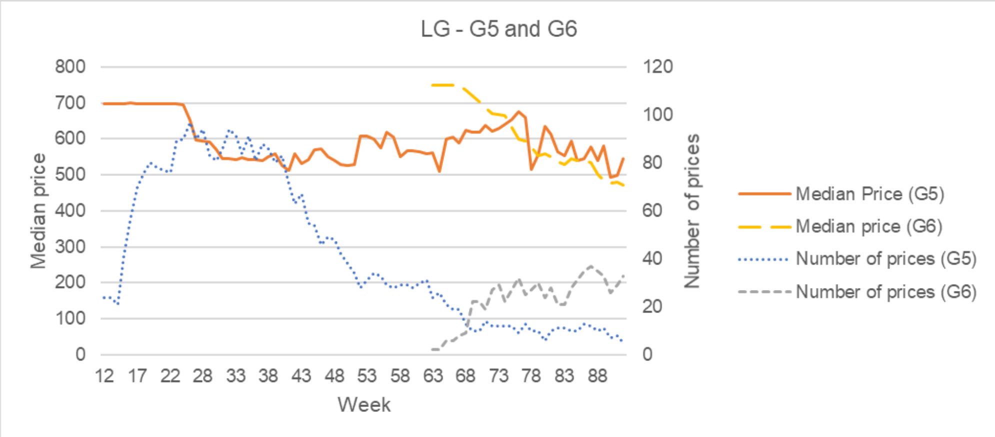
Due to the enormous number of Sony smartphones and their very short time on the market, it is difficult to find out which smartphone models are each other's successors. In Graph 16, Sony Xperia X Performance represents a smartphone that was launched in week 8 of the data collection period. The total number of prices is never really high for this model and fluctuates around 40. When the Sony Xperia X (32GB) is launched, the number of offerings starts to drop, and the median price drops as well.



Graph 16 – Sony: Xperia X Performance and Xperia X (32GB)

7.4.4 LG

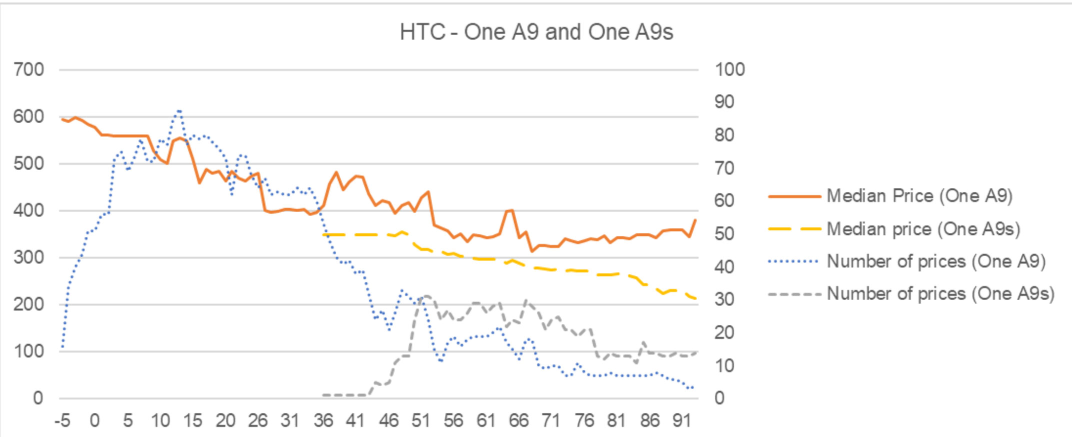
The LG G5 is launched in week 12. In week 27, there is a major drop in the median price. According to the number of launches, there is a launch in week 28, week 29, week 30 and week 31. This makes it difficult to relate the price decrease to a certain smartphone launch. Around week 40, the number of web stores offering the LG G5 drops immensely and the median price of LG G5 is very volatile. Only in week 64, the LG G6 is launched.



Graph 17 – LG: G5 and G6

7.4.5 HTC

It seems as if the HTC one A9 model was launched just before the data collection period started as the number of offerings is still increasing at the start of Graph 18. There seems to be a permanent price drop in week 15. As HTC launches four models in week 15 that are not from the One A-series, we cannot really identify to which launch the model is reacting. As of week 35, the number of offerings decreases hugely, which corresponds to the launch of the succeeding model, One A9s, in week 36.



Graph 18 – Sony: One A9 and One A9s

GENERAL CONCLUSION

This paper investigates the effect of a new product introduction on the prices of existing products in the smartphone market. Literature and available research show that the smartphone market has a constant inflow of new models, high outflow of existing models and a downward price trend during the short life span of the smartphones on the market. The available price data confirms this is also valid for the Belgian and Dutch smartphone market.

Investigation of the prices and availability of Apple iPhones revealed that when a new generation of Apple smartphones is released, the prices of the existing Apple iPhones decrease significantly. When the Apple iPhone 7 and the iPhone 7 Plus models were launched, the prices of the iPhone 6s and the iPhone 6s Plus decreased by 3.3% to 11.6%. The launch of the iPhone 8 and the iPhone 8 Plus caused a price decrease of the iPhone 7 and iPhone 7 Plus models of 3.8% to 6.7%. Six weeks later, the launch of the iPhone X caused an additional price decrease of 1.9% to 4.7%.

Comparing the launch and termination strategies of the main smartphone incumbents on the Belgian and Dutch smartphone market, there is a clear difference between Apple and the others. When Samsung, Huawei, Sony, LG, and HTC continuously launch new models, they terminate older models much faster and do not adjust the prices of existing models when new products are launched. Apple, on the contrary, not only keeps its iPhones longer on the market, but the prices of the preceding generations also decrease significantly as a reaction to the new generation launch.

LIMITATIONS

The first limitation of this master's dissertation is the absence of extensive research in this domain. Only one similar case study, conducted in the bath tissue industry, was found to serve as a basis for the analysis of the effect of a product launch on the prices of existing smartphones. Secondly, there is no sales information, such as sold quantities per model, included in the analysis. Consequently, each of the included prices in the analysis has the same weight. Web stores with high prices that may sell low quantities compared to web stores with low to moderate prices that may sell more devices are treated equally in the analysis.

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APPENDIX

Appendix A – iPhone 6s (16GB)

Test for fixed effects

```
        F test for individual effects

data:  (Price) ~ Launch
F = 108.27, df1 = 28, df2 = 579, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
        F test for time effects

data:  (Price) ~ Launch
F = 0.68481, df1 = 20, df2 = 587, p-value = 0.8432
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 1.4051, df = 1, p-value = 0.2359
alternative hypothesis: significant effects
```

Tests for two-way effects

```
        F test for twoways effects

data:  (Price) ~ Launch
F = 72.863, df1 = 48, df2 = 559, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 4213.1, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
        Hausman Test

data:  (Price) ~ Launch
chisq = 1.8491, df = 1, p-value = 0.1739
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return a significant launch coefficient, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. However, further analysis (regression diagnostics) showed that cross-sectional dependence is present in the random effects model, but not in the two-way fixed effects model. As the two-way fixed effects model is significant and its estimators are consistent, we will continue with the fixed effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = 0.894, p-value = 0.3713
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 329.79, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -5.8787, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  fixedtwowaymodel
BP = 13.519, df = 1, p-value = 0.0002362
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 6s 16GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the ‘Arellano’ method because it controls for serial correlation and heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

       Estimate Std. Error t value  Pr(>|t|)
Launch  -23.056      4.687 -4.9191 1.145e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix B – iPhone 6s (64GB)

Test for fixed effects

```
        F test for individual effects

data:  (Price) ~ Launch
F = 71.803, df1 = 27, df2 = 559, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
        F test for time effects

data:  (Price) ~ Launch
F = 1.3804, df1 = 20, df2 = 566, p-value = 0.1249
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 0.87537, df = 1, p-value = 0.3495
alternative hypothesis: significant effects
```

Tests for two-way effects

```
        F test for twoways effects

data:  (Price) ~ Launch
F = 53.297, df1 = 47, df2 = 539, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 3442, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
              Hausman Test

data:  (Price) ~ Launch
chisq = 2.334, df = 1, p-value = 0.1266
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return a significant launch coefficient, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. However, further analysis (regression diagnostics) showed that cross-sectional dependence is present in the random effects model, but not in the two-way fixed effects model. As the two-way fixed effects model is significant and its estimators are consistent, we will continue with the fixed effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = -1.5347, p-value = 0.1248
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 319.49, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -5.6332, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  fixedtwowaymodel
BP = 11.719, df = 1, p-value = 0.0006187
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 6s 64GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the ‘Arellano’ method because it controls for heteroskedasticity and serial correlation. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

       Estimate Std. Error t value  Pr(>|t|)
Launch -40.1522     5.8351 -6.8811 1.654e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix C – iPhone 6s (128GB)

Test for fixed effects

```
            F test for individual effects

data:  (Price) ~ Launch
F = 32.557, df1 = 27, df2 = 559, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
               F test for time effects

data:  (Price) ~ Launch
F = 1.8109, df1 = 20, df2 = 566, p-value = 0.01686
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 4.9746, df = 1, p-value = 0.02572
alternative hypothesis: significant effects
```

Tests for two-way effects

```
              F test for twoways effects

data:  (Price) ~ Launch
F = 23.428, df1 = 47, df2 = 539, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
Lagrange Multiplier Test - two-ways effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 2064.6, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                    Hausman Test

data:  (Price) ~ Launch
chisq = 0.3672, df = 1, p-value = 0.5445
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return a significant launch coefficient, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. Further analysis is conducted on the random effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = 1.2688, p-value = 0.2045
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
     Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 307.21, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -6.9151, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
Breusch-Pagan test

data:  randommodel
BP = 58.304, df = 1, p-value = 2.246e-14
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 6s 128GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the 'Arellano' method because it controls for heteroskedasticity and serial correlation. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

            Estimate Std. Error t value  Pr(>|t|)
(Intercept)  932.464     11.851 78.6821 < 2.2e-16 ***
Launch      -107.743     22.291 -4.8334 1.716e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix D – iPhone 6s Plus (16GB)

Test for individual fixed effects

```
            F test for individual effects

data:  (Price) ~ Launch
F = 36.511, df1 = 25, df2 = 519, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time fixed effects

```
              F test for time effects

data:  (Price) ~ Launch
F = 1.3883, df1 = 20, df2 = 524, p-value = 0.1214
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 1.0053, df = 1, p-value = 0.316
alternative hypothesis: significant effects
```

Tests for two-way effects

```
             F test for twoways effects

data:  (Price) ~ Launch
F = 24.429, df1 = 45, df2 = 499, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 2095.7, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                    Hausman Test

data:  (Price) ~ Launch
chisq = 0.22834, df = 1, p-value = 0.6328
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return a significant launch coefficient, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. However, further analysis (regression diagnostics) showed that cross-sectional dependence is present in the random effects model, but not in the two-way fixed effects model. As the two-way fixed effects model is significant and its estimators are consistent, we will continue with the fixed effects model.

Regression diagnostics

Cross-sectional dependence

```
Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = 0.13466, p-value = 0.8929
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 302.04, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -6.2633, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
          Breusch-Pagan test

data:  fixedtwowaymodel
BP = 3.5037, df = 1, p-value = 0.06123
```

Accounting for serial correlation

Out of the tests conducted in the regression diagnostics of the iPhone 6s Plus 16GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the 'Arellano' method because it controls for heteroskedasticity and serial correlation. The resulting launch coefficient and standard error are presented below.

```
                    t test of coefficients:

       Estimate Std. Error t value  Pr(>|t|)
Launch  -57.054      8.545  -6.677 6.517e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix E – iPhone 6s Plus (64GB)

Test for fixed effects

```
           F test for individual effects

data:  (Price) ~ Launch
F = 61.3, df1 = 26, df2 = 539, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
              F test for time effects

data:  (Price) ~ Launch
F = 1.2788, df1 = 20, df2 = 545, p-value = 0.1864
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 0.096691, df = 1, p-value = 0.7558
alternative hypothesis: significant effects
```

Tests for two-way effects

```
             F test for twoways effects

data:  (Price) ~ Launch
F = 41.963, df1 = 46, df2 = 519, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 3058.7, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                   Hausman Test

data:  (Price) ~ Launch
chisq = 1.278, df = 1, p-value = 0.2583
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return a significant launch coefficient, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. However, further analysis (regression diagnostics) showed that cross-sectional dependence is present in the random effects model, but not in the two-way fixed effects model. As the two-way fixed effects model is significant and its estimators are consistent, we will continue with the fixed effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch
z = -1.2911, p-value = 0.1967
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch
chisq = 314.62, df = 21, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -6.1239, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  fixedtwowaymodel
BP = 32.075, df = 1, p-value = 1.484e-08
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 6s Plus 64GB, we can conclude that we only have to account for serial correlation. We will still use the ‘Arellano’ method because it controls for serial correlation and heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

       Estimate Std. Error t value  Pr(>|t|)
Launch -49.2060     8.2637 -5.9545 4.812e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix F – iPhone 7 (32GB)

Test for individual fixed effects

```
            F test for individual effects

data:  (Price) ~ Launch + Launch2
F = 62.268, df1 = 29, df2 = 752, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
               F test for time effects

data:  (Price) ~ Launch + Launch2
F = 2.4283, df1 = 27, df2 = 754, p-value = 7.949e-05
alternative hypothesis: significant effects
```

```
   Lagrange Multiplier Test - time effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 22.27, df = 1, p-value = 2.369e-06
alternative hypothesis: significant effects
```

Tests for two-way effects

```
            F test for twoways effects

data:  (Price) ~ Launch + Launch2
F = 35.914, df1 = 55, df2 = 726, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch
chisq = 4166.4, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                    Hausman Test

data:  (Price) ~ Launch + Launch2
chisq = 0.58011, df = 2, p-value = 0.7482
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return significant coefficients for Launch and Launch2, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. Further analysis is conducted on the random effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch + Launch2
z = 1.6945, p-value = 0.09018
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch + Launch2
chisq = 461.59, df = 27, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -6.4096, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  randommodel
BP = 16.901, df = 2, p-value = 0.0002138
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 7 32GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the ‘Arellano’ method because it controls for both the serial correlation and the heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

            Estimate Std. Error t value  Pr(>|t|)
(Intercept) 725.0277     8.9808 80.7308 < 2.2e-16 ***
Launch      -47.0609    10.4980 -4.4829 8.469e-06 ***
Launch2     -30.0794     9.5904 -3.1364  0.001774 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix G – iPhone 7 (128GB)

Test for fixed effects

```
          F test for individual effects

data:  (Price) ~ Launch + Launch2
F = 71.798, df1 = 27, df2 = 726, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
          F test for time effects

data:  (Price) ~ Launch + Launch2
F = 0.54447, df1 = 26, df2 = 727, p-value = 0.9695
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - time effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 3.2488, df = 1, p-value = 0.07148
alternative hypothesis: significant effects
```

Tests for two-way effects

```
          F test for twoways effects

data:  (Price) ~ Launch + Launch2
F = 38.878, df1 = 53, df2 = 700, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
    (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 5054.7, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                Hausman Test

data:  (Price) ~ Launch + Launch2
chisq = 1.164, df = 2, p-value = 0.5588
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return significant coefficients for Launch and Launch2, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. Further analysis is conducted on the random effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch + Launch2
z = -1.6706, p-value = 0.0948
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch + Launch2
chisq = 429.72, df = 27, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -5.4375, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  randommodel
BP = 26.332, df = 2, p-value = 1.915e-06
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 7 128GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the ‘Arellano’ method because it controls for both the serial correlation and the heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

            Estimate Std. Error t value  Pr(>|t|)    
(Intercept) 833.0447     8.5172 97.8076 < 2.2e-16 ***
Launch      -37.0613     9.5443 -3.8831 0.0001122 ***
Launch2     -17.4383     8.3551 -2.0871 0.0372113 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix H – iPhone 7 Plus (32GB)

Test for fixed effects

```
              F test for individual effects

data:  (Price) ~ Launch + Launch2
F = 46.588, df1 = 23, df2 = 622, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
                 F test for time effects

data:  (Price) ~ Launch + Launch2
F = 0.41528, df1 = 26, df2 = 619, p-value = 0.9958
alternative hypothesis: significant effects
```

```
    Lagrange Multiplier Test - time effects
      (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 4.8868, df = 1, p-value = 0.02706
alternative hypothesis: significant effects
```

Tests for two-way effects

```
               F test for twoways effects

data:  (Price) ~ Launch + Launch2
F = 22.61, df1 = 49, df2 = 596, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
  Lagrange Multiplier Test - two-ways effects
      (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 3228.1, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                      Hausman Test

data:  (Price) ~ Launch + Launch2
chisq = 0.62803, df = 2, p-value = 0.7305
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return significant coefficients for Launch and Launch2, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. Further analysis is conducted on the random effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch + Launch2
z = 0.65853, p-value = 0.5102
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch + Launch2
chisq = 386.91, df = 27, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -5.7627, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
            Breusch-Pagan test

data:  randommodel
BP = 21.473, df = 2, p-value = 2.174e-05
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 7 Plus 32GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the 'Arellano' method because it controls for both the serial correlation and the heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

            Estimate Std. Error t value  Pr(>|t|)
(Intercept) 883.8129     9.0246 97.9334 < 2.2e-16 ***
Launch      -48.0628     9.5871 -5.0133 6.923e-07 ***
Launch2     -28.8808     8.3205 -3.4710 0.0005531 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix I – iPhone 7 Plus (128GB)

Test for fixed effects

```
          F test for individual effects

data:  (Price) ~ Launch + Launch2
F = 75.519, df1 = 22, df2 = 596, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Tests for time effects

```
             F test for time effects

data:  (Price) ~ Launch + Launch2
F = 0.28107, df1 = 26, df2 = 592, p-value = 0.9999
alternative hypothesis: significant effects
```

```
   Lagrange Multiplier Test - time effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 7.3159, df = 1, p-value = 0.006835
alternative hypothesis: significant effects
```

Tests for two-way effects

```
           F test for twoways effects

data:  (Price) ~ Launch + Launch2
F = 35.339, df1 = 48, df2 = 570, p-value < 2.2e-16
alternative hypothesis: significant effects
```

```
 Lagrange Multiplier Test - two-ways effects
     (Breusch-Pagan) for balanced panels

data:  Price ~ Launch + Launch2
chisq = 4260.2, df = 2, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Hausman test for random effects

```
                  Hausman Test

data:  (Price) ~ Launch + Launch2
chisq = 0.74182, df = 2, p-value = 0.6901
alternative hypothesis: one model is inconsistent
```

Model selection

Since the two-way effects are statistically significant and return significant coefficients for Launch and Launch2, both the individual and the time effects will be used in the final model. From the Hausman test, we can conclude that the random effects model is a better choice than the fixed effects models. The p-value is larger than 0.05 and the null hypothesis that states that the random effects model would result in inconsistent parameters cannot be rejected. Further analysis is conducted on the random effects model.

Regression diagnostics

Cross-sectional dependence

```
 Pesaran CD test for cross-sectional dependence in panels

data:  (Price) ~ Launch + Launch2
z = 0.65076, p-value = 0.5152
alternative hypothesis: cross-sectional dependence
```

Serial correlation

```
 Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  (Price) ~ Launch + Launch2
chisq = 386.43, df = 27, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Testing for roots/stationarity

```
              Augmented Dickey-Fuller Test

data:  PMdata$Price
Dickey-Fuller = -4.7425, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Heteroskedasticity

```
           Breusch-Pagan test

data:  randommodel
BP = 50.164, df = 2, p-value = 1.28e-11
```

Accounting for serial correlation and heteroskedasticity

Out of the tests conducted in the regression diagnostics of the iPhone 7 Plus 128GB, we can conclude that we have to account for serial correlation and heteroskedasticity. We will use the 'Arellano' method because it controls for both the serial correlation and the heteroskedasticity. The resulting launch coefficient and standard error are presented below.

```
t test of coefficients:

            Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 993.9311     7.9326 125.2974 < 2.2e-16 ***
Launch      -38.0686     9.4506  -4.0282 6.322e-05 ***
Launch2     -17.5093     6.3967  -2.7372  0.006374 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```