Erasmus School of Economics

Thesis

The Role of Line Portfolio Characteristics on Stock Reaction to New Product Announcements

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Abstract

Globalization and mass customization strategies are influencing product lines so that more products are introduced every day in the market to cover different needs of people with different preferences and culture. Extending a product line can bring positive outcomes, such as higher total market share and higher price-setting power. Nevertheless, extending a product line is not always profitable. It may have drawbacks, such as sales cannibalization within the portfolio. Because of this, I argue that advantages and disadvantages of extending a product line vary depending on how the product line portfolio is configured.

Stock price reflects investors' evaluation about the future financial performance of a company. Therefore, stock market acts as a judge to the strategies and performance of a company; share prices go up in the face of good news and go down when bad news are released. Being aware of the importance of the financial performance of a company, my purpose in this thesis is to study how stock price reacts to line extension announcements, depending on the product line portfolio characteristics.

To meet my goal, I analyse six brands from the smartphone industry by using event study methodology. After the analysis, I conclude that line scope and intra-line competition may influence (as a moderators) investors' reaction to line extension announcements. Last, based on the results, financial and marketing applications are discussed.

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Last but not least, I would like to dedicate this thesis to my grandmother Isabel.

Table of Contents

List of Figures

List of Tables

List of Appendix Tables

1. Introduction

1.1. Context of the research, problem definition and research questions.

According to Wong (2010), approximately 250,000 new products are introduced globally per year. However, statistically between 85% and 95% of them are destined to fail. While highly innovative products can cause a high innovation resistance and a slow product adoption (Heidenreich & Kraemer, 2015), less innovative products which are similar to the current ones in the company's portfolio can cause a negative effect on total profits because of cannibalization (Roberts & McEvily, 2005). However, globalization pushes even more the number of new introductions, as products sometimes must be modified in order to meet legal and cultural standards from different countries (Sahling, 2006). Furthermore, a "mass customization" trend –consumers ask for personalized or tailored affordable products- dominates many companies' strategy.

Developing new products can have several advantages which may signal positive information to investors, such as the introduction of a differentiated product in the market and the increase of sales. However, innovation and new product introduction also have drawbacks. Given these contradictory effects, it is unclear how investors react to the announcement of a new innovation. My goal, in this paper, is to examine this issue. Previous research has been developed in this stream, although looking at the company as a whole. My purpose in this paper is to complement these prior studies by focusing on the product line as my unit of analysis. In other words, in this research I try to unveil under which circumstances new product announcements of *line extensions* are more or less welcomed by shareholders.

Given that the scope of the analysis is a specific product line within the company, not the firm as a whole, throughout the paper I refer to new products as line extensions. Most line extensions consist in products which are a modification of a previous one. Moreover, they are usually not the product of a highly innovative process, unless the new product is meant to start a new product generation. Therefore, this similarity between products may worsen the disadvantages of introducing a new product and put the profitability of the new project at risk.

As mentioned by Quelch & Kenny (1994), managers are inclined to carry out proliferation strategies - defined as a market strategy carried by a firm when it markets several variations of the same base product - due to the fact that they are sometimes considered as low-cost and low-risk investments. However, overextending a line and oversegmenting the market can cause cannibalization and, usually, they do not enlarge the overall category demand. Furthermore, it also affects costs. According to the authors "the unit costs for multi-item lines can be 25% to 45% higher than the theoretical cost of producing only the most popular item in the line". Summing up, investing only in line extensions is a short-run focus that may have consequences for a brand's value in the long-run (Quelch & Kenny, 1994).

Therefore, we cannot say that introducing new products and having a large line portfolio always leads to a better company performance. Sometimes "less is more." For instance, the bulk of Nestlé benefits only comes from a 2.5% of its portfolio (Kumar, 2013). And this is far from being an exception. Kumar (2013) defends that many companies obtain between 80% and 90% of their profits from only 20% of the brands in their portfolio. That is to say, many companies are innovating and introducing new products and brands while losing efficiency.

Firms also seem to adopt very different views about the optimal size of their product portfolio. Take the example of the smartphone industry. In the period 2004-2014, Apple launched nine new products to the market, thus exhibiting a preference for a focused portfolio concentrated in a small number of phone models. In contrast to this strategy, one of Apple's biggest competitors, Samsung, launched – in the same period - products under 2000 different names[1]. Given that, one could think that the impact of each of the portfolio strategies of these companies have different effects on sales and market valuation. In fact, both Apple and Samsung have been hugely successful in recent years, which suggests that the effects of product portfolio decisions on sales and profits and, therefore, on investors' reactions to such portfolio decisions are complex and possibly contingent on other characteristics of the mother brand or firm. Due to this fact, in order to measure the effects of portfolio decisions, instead of analysing the impact of the introduction of a new product in isolation, one should try to see the big picture and analyse the portfolio characteristics before and after repeated new product launches and estimate how such launch events influence share prices.

[1] This information has been obtained from an IDC dataset. Detailed information about this dataset is developed in 'Data and measurement' chapter.

In order to examine the effect of new product introductions - specifically, line extensions - on a firm's performance, I examine the effect of new product announcements on stock price. New product announcements are ubiquitous as marketing and management executives are increasingly encouraged to communicate their actions to shareholders (Srinivasan et al, 2009). Although there is an existing and important literature focused on the relationship between innovation or new product introduction and stock performance (Chaney et al, 1991; Eddy & Saunders, 1980; Lane & Jacobson, 1995; Lee & Chen, 2009; Sood & Tellis, 2009; Sorescu et al, 2007; Srinivasan et al, 2009; Wies & Moorman, 2015), no previous paper has focused on line chararacteristics as moderators in the relationship between new product –line extension- and stock performance. Previous research has mainly focused on studying new product introductions in isolation with the rest of the products of the company.

Morgan & Rego (2009) aims to link company's brand portfolio strategy to firm financial performance by taking into account three company's brand portfolio dimensions: (1) scope, which refers to the company's market coverage[2], (2) intra-competition, which refers to the extent to which brands within the company's portfolio compete for meeting the same needs of the same customers and (3) positioning, which refers to the price and quality image of the company's brands in customers' mind. As a consequence of the focus of my analysis – product line – instead of using as unit of analysis *company* and *brands*, I use *product line* and *products*. Hence, I establish, inspired by Morgan & Rego (2009), three dimensions which define the product line portfolio: (1) scope, which refers to the product line market coverage, (2) intra-competition, which refers to the extent to which products within the product line portfolio compete for meeting the same needs of the same customers and (3) positioning, which refers to the price and quality image of the product line in customers' mind.

Therefore, the present paper attempts to address the following research questions:

- Does line scope influence the stock market reaction to a new product announcement?
- Does intra-line competition influence the stock market reaction to a new product announcement?

[2] Market coverage refers to the degree to which the company/brand/line covers the needs of consumers. It includes two sub-dimensions: number of products and number of segments in which the products are marketed.

- Does line positioning influence the stock market reaction to a new product announcement?

For this analysis, we focus our attention in the smartphone industry; specifically in six brands (Apple, HTC, LG, Motorola, Nokia and Samsung). This industry, led by the provider Samsung, has been experiencing a continuous growth over the years. However, IDC states that in 2016 this growth will suffer a slowdown, therefore increasing the already existing competition. Additionally, it is this competition and industry innovativeness what makes appropriate our analysis in this industry, given the fact that smartphone vendors frequently introduce new products to the market.

1.2. Academic relevance.

Previous research has unveiled the relationship between new product introductions and stock performance (Chaney et al, 1991; Lane & Jacobson, 1995; Pauwels et al, 2004; Srinivasan & Hanssens, 2009; Srinivasan et al, 2009; Sood & Tellis, 2009; Wies & Moorman, 2015). The present thesis follows this tradition and attempts to contribute to this literature by studying how product line characteristics of the company affect the investors' judgement about new product introductions. Due to the fact that product launching modifies the company's product portfolio and sales distribution, I consider that neither decisions nor analysis about new product introductions should be addressed in an isolated approach. This approach aims to enrich and complete previous literature in different ways.

First, this paper studies stock price reaction to new product announcements in a unit of analysis –line extension- that, to the best of my knowledge, has been almost unexplored. Second, it aims to clarify under which circumstances line extensions are considered profitable for a company, enlarging therefore the scarce and existing literature about product lines. Previous papers highlight positive (Kekre & Srinivasan, 1990; Lancaster, 1990; Putsis, 1997; Kadiyali et al, 1998; Barroso & Giarratana, 2013) and negative outcomes (Lancaster, 1990; Bayus & Putsis, 1999; Hui, 2004) from line extensions, but generally they fail to explain when the combination of advantages and disadvantages of a line extension affects positively or negatively the whole product line portfolio. Third, another academic contribution is the calculation of intra-line competition by means of a sales concentration index, commonly used to measure industry competition – the Herfindahl index.

1.3. Managerial relevance.

Regarding managerial relevance, stock price is one of the most important performance measures for big firms' managers -some managers indeed have retributions linked to stock performance. Proof of this is that the mere fact of going public changes the innovation behaviour of companies (Wies & Moorman, 2015). Consequently, finding the linkages between product portfolio and innovation can provide managers the right knowledge in order to be able to manage the long-term innovation and portfolio strategy, so that they can enhance the market response to introductions and create a more efficient portfolio in terms of financial equity. Furthermore, the current analysis provides investors' valuation about different types of portfolio, therefore gaining insights about how line scope, line positioning and intra-line competition affect financial value. The insights gained in this analysis do not only improve line portfolio management in the company, but they can also help to design new communicative strategies to maximize the positive repercussion of line extension announcements.

2. Literature review and hypothesis.

2.1. Marketing and stock price.

The relationship between market valuation and managerial decisions it is undeniable. Investors' financial decisions and positions in the stock market are the result of their calculation of the difference between the share price and the objective or intrinsic price (which includes future expectations and future cash flows), estimated by the individual investor. Following this rationale, generally, an investor will buy stock when the share price is considered cheap, while the investor will sell stock when the share price is considered expensive. Due to the fact that investors' forecasts differ, the offer and demand for the stock determines the share price.

In all probability, managerial decisions (e.g. new product announcements) signal valuable information for the financial market and affect investors' forecast, provoking movements in the market rates and abnormal returns (Srinivasan & Hanssens, 2009). Abnormal return is the difference between the actual stock or portfolio return and the expected return, based on the market movements and therefore calculated by using a reference portfolio (Barber & Lyon, 1997). Being aware of the importance of this relationship, an important research stream has been developed around the convergence of marketing and finance, specifically, the stock market performance. There are four key streams of research in this tradition.

First, in the study of the effect of branding in market valuation, it has been found that stronger brands lead to a better stock performance (higher returns and lower risk), due to the fact that investors usually prefer holding stocks from highly recognized products (Frieder & Subrahmanyam, 2005; Madden et al, 2006). Another interesting finding is that corporate brand strategy is related to higher values of Tobin's q, while firms which hold a mixed brand strategy show lower values of Tobin's q (Rao & Agarwal, 2004).

Second, studies have been developed about the relationship between customer satisfaction and firm stock price. Indeed, research from Fornell et al (2006) proposes that higher customer satisfaction leads to higher returns and lower risk. A recent study corroborrates this conclusion and states that customer satisfaction is beneficial, also in the long term for the financial performance (Singh & Pattanayak, 2014). In addition, customer satisfaction has been favorably tested as a partial mediator in the relationship between CSR and stock performance (Luo & Bhattacharya, 2006).

Third, regarding the effect of marketing expenditures on stock market, Fischer (2015) suggests in his research that consistent marketing expenditures cause a low financial performance and volatility, while volatile marketing expenditures are reflected in the financial markets in a better performance and higher volatility. Joshi & Hanssens (2009) found that in the motion picture industry, movies which become hits with the backrest of an expensive advertising campaign show lower returns than those with lower investments in advertising.

Fourth, an important research stream has examined the relationship between innovation and firm value (Pauwels et al., 2004; Sood and Tellis, 2009; Srinivasan et al., 2009). This research stream concludes that new product introductions lead to higher returns as a response to such introductions, and to a healthier financial performance in the long run. Furthermore, such effects are not only instantaneous, but the investor response to new product launches is growing over a period of approximately two months, on average (Pauwels et al, 2004). The same authors studied -in a different paper- the characteristics of the innovations which provoke stronger positive reactions from investors. They propose that products which are new-to-the-world, high-quality, supported by large advertising expenditures and correspond to big categories in a expansion stage yield greater returns (Srinivasan et al, 2009).

2.2. New product announcements.

New product announcement (NPA) is "an announcement or move that precedes an actual new product introduction" (Robertson et al, 1995). In a more generalistic meaning, Eliashberg & Robertson (1988) define announcement as "a formal, deliberated communication before a firm actually undertakes a particular marketing action such as a price change, a new advertising campaign, or a product line change".

Previous literature has mainly used terms "new product announcement" (NPA) and "new product preannouncement" (NPP) in an undifferentiated way. However, authors such as Su & Rao (2010) enfasize that NPA is closer to the launching time and provides more specific information than NPP.

One reason brands announce their new products ahead of product introduction and commercialization is to send signals to shareholders (and/or customers or competitors). The signalling function of new product announcement may trigger both positive and negative consequences (Eliashberg & Robertson, 1988). One positive repercussion is that announcing may accelerate the new product diffusion because of the generated word of mouth. Furthermore, the level of awareness produced by the announcement predicts optimal time introduction (Kalish & Lilien, 1986). Other desirable consequences are the communication of being pioneer in the market, the creation of entry barriers, the possibility to test different designs and prices, reducing customers' switching costs and sending information to the stock market (Eliashberg & Robertson, 1988; Wu et al, 2004; Su & Rao, 2010).

Contrarily, signalling a new product launching may cue competitors and encourage them to take competitive actions, hurt firm's reputation in case it is not able to deliver what it was promised, and cannibalize current products (Robertson et al, 1995; Eliashberg & Robertson, 1988; Sorescu et al, 2007). Eliashberg & Robertson (1988) report that companies with lower market dominance, lower company size and higher customer switching costs are more willing to preannounce new products. Su & Rao (2010) also highlight that announcements are common in highly competitive environments.

New product announcements also provoke the creation of expectations, which may influence at the same time the penetration rate (Le Nagard-Assayag & Manceau, 2001). According to their research, generally high consumers' expectations leads to a faster penetration rate. However, the authors also specify that when complimentary product providers have lower expectations (even if they are still high) than consumers have, penetration rate may be affected negatively.

Last, some papers have partially unveiled the relationship between new product announcement and stock performance (Eddy & Saunders, 1980; Chaney et al, 1991; Lane & Jacobson, 1995; Sorescu et al, 2007; Lee & Chen, 2009; Sood & Tellis, 2009). First, Eddy and Saunders (1980), did not find a significant effect of product announcements on stock price. Contrarily, Chaney et al (1991) found significant small excess returns for different time windows of product announcements (0.25% daily excess for a three-days window and 0.11%-0.12% daily excess for a seven-days window). They also detected a significant difference between single product announcement (0.20% daily excess) and multiple product announcement (0.31% daily excess), and between updated new products (0.14% daily excess) and original new products (0.25% daily excess). Lane & Jacobson, (1995), studied the variables brand attitude and brand familiarity as moderators is the relationship between brand extension announcement and stock price. They conclude that both brand attitude and brand familiarity moderates nonmonotically the stock market reaction to brand extension announcements.

Meanwhile, Sorescu et al (2007) reported four interesting findings: (1) new product announcements provoke positive financial returns in the long term, (2) new product announcements which provide specific information cause positive financial returns in the short term, (3) positive long term financial returns from new product announcements are enhanced when the firm continues updating and (4) reliability is a positive moderator in the relationship between new product announcements and short and long term abnormal returns. Regarding resources and size implications in the relationship between new product announcements and abnormal returns, Lee & Chen (2009) argued and tested that low levels of R&D expending affects negatively –due to the fact that inverstors see it as expenses reducing profits- and significant high levels of R&D expending affects positively stock price -a high spending may signal important potential benefits. With respect to the company size, a negative effect is reported– in other words, when the company is bigger the stock reaction to announcements is smaller. This finding is also corroborated by Sood & Tellis (2009).

2.3. Product line extensions.

A product line is composed by different products which belong to the same group -commonly referred as category- and are offered by the same company. Product proliferation, commonly mentioned in literature, is closely related to product line extensions[3] and refers to the strategy of having multiple products, or models, targeting the same or closely related needs. For instance, according to Connor (1981) and Bayus & Putsis (1999), product proliferation results in generous product introductions, broad product variety and deep product lines.

Previous literature has mainly focused on explaining what are the structural and strategic causes of product proliferation decisions and the consequences of this type of strategy. Regarding the determinants of product proliferation, Putsis & Bayus (2001) posit that companies enlarge their product lines when entry barriers are low and expected profits are high. Also, firms with high market position and firms with high prices or narrow lines

[3] Product proliferation is the name of the strategy which consists on introducing multiple line extensions in the market.

-compared to competition- are more prone to launch new products in their lines. Additionally, large demands for firm's products increase the marginal profitability of extending the line (Putsis & Bayus, 2001) and heterogenous customers increase the incentives to hold a broad product line (Brander & Eaton, 1984). On the other hand, Stavins (1995) states that the longer a company has been in the market and the more products it has introduced in the past, the more prone it is to introduce new products with the aim of enlarging the variety of quality within the portfolio. Last, product proliferation is common in industries with high levels of sales concentration and advertising expending (Connor, 1981).

Regarding product proliferation consequences, previous research has pointed out both positive (Table 2) and negative outcomes (Table 3) of extending product lines (Table 1). Product proliferation can increase the overall demand by meeting better the needs of heterogeneous customers (Lancaster, 1990), although there is a risk of cannibalization (Hui, 2004). It may also increase design and inventory holding extra costs (Bayus & Putsis, 1984) and the unit production costs when economies of scale exist (Bayus & Putsis, 1999). However, Barroso & Giarratana (2013) do defend the existence of management synergies as a consequence of proliferation strategies. Other advantage of proliferation is that it can build up an entry barrier for competitors (Lancaster, 1990). Additionally, proliferation may lead to a higher price-setting power, as reported by Kadiyali et al (1998). As a consequence, there is no agreement on whether product proliferation increases or decreases the overall profit. Due to this fact, it is unclear if extending product lines affects positively or negatively stock price.

As mentioned in Table 1 and Table 3, one of the main disadvantages of having many products in the same line is the potential cannibalization risk and product rivalry between products. This rivalry is positively correlated with the similarity between products (Brander & Eaton, 1984). However, Kim et al (2013) argue that previous research had been based on a dominating preference structure - when it is considered that in all product attributes quality valuation is superior in one segment than in another. But, when considering a nondominant preference structure, results of commonality are diverse and commonality may lead to even lower levels of cannibalization.

Table 1. Positive and negative outcomes of product proliferation (literature summary).

Summary of literature on product proliferation outcomes			
Positive outcome	**Literature**	**Negative outcome**	**Literature**
Higher market share, profitability and prices.	Kekre & Srinivasan (1990)	Increase of inventory and design costs.	Lancaster (1990)
Meeting heterogeneous needs.	Lancaster (1990)	Increase of unit costs.	Bayus & Putsis (1999)
Entry barrier for competitors.	Putsis (1997)	Cannibalization.	Hui (2004)
Higher price-setting power.	Putsis (1997) Kadiyali et al (1998)		
Management synergies.	Barroso & Giarratana (2013)		

Own elaboration.

Table 2. Positive outcomes of product proliferation (literature summary).

Positive outcomes of product proliferation	
Paper	**Description**
Kekre & Srinivasan (1990)	Firms with broader lines show higher market shares, higher profitability and higher prices as significant cost increases when broadening the line were not found in the research.
Lancaster (1990)	Customers are heterogeneous and therefore they seek for diversity. However, companies do not achieve to meet all the different needs because of the existence of economies of scale.
Putsis (1997)	Product proliferation allows national brands to increase prices. The success of the proliferation strategy depends on the intra-brand sales concentration. The higher concentration, the lower price-setting power for national brands.
Kadiyali et al (1998)	Firms which extend their product line gain price-setting power and grow combined sales.
Barroso & Giarratana (2013)	Product proliferation can lead to management synergies and joint use of resources.

Own elaboration.

Table 3. Negative outcomes of product proliferation (literature summary).

Negative outcomes of product proliferation	
Paper	**Description**
Lancaster (1990)	Product proliferation may affect negatively supply side by increasing design and inventory costs of the multiple products.
Bayus & Putsis (1999)	When economies of scale exist, a product proliferation strategy can increase unit costs. Empirical results show that the impact of product proliferation on market share is negative.
Hui (2004)	Due to competition, a new product introduction is not always translated to a higher market share. Instead of that, the new introduction may cannibalize other products sales and cause a redistribution of sales within the portfolio.

Own elaboration.

Nevertheless, looking at cannibalization is not the only factor to be aware of when getting into proliferation strategies; there are competitive considerations that may force a company to be exposed to product rivalry and cannibalization risk. A paper by Brander & Eaton (1984) clarifies this issue with a simple example:

> *"If firm A produces product 1 and product 2 is a close substitute, then production of product 2 is likely to appear more attractive to firm B than to firm A because B will not be concerned about the consequent reduction in demand for product 1. However, one wonders, might not firm A recognize that if it doesn't produce product 2, firm B will, and therefore try to preempt B. Strategic preemption requires a two-stage (or more) decision process."*

Cannibalization and product rivalry have been studied under two different approaches: considering a monopoly (Spence, 1976) and an oligopoly (Desai, 2001). With a monopolistic approach, literature comes to the conclusion that lower-quality products may have the potential to cannibalize products with higher quality. According to Desai (2001), in case there is high competition in the low-end segment, high-end customers have incentives to buy the low-end product and the potential cannibalization increases. On the other way around, when there is low competition in the low-end segment, incentives for high-end segment to buy the low-end product are disminished and thus, potential cannibalization decreases.

On the other hand, Moorthy & PNG (1992) posits that when a producer launches more than one product at the same time (simultaneous introduction), the product with lower quality will cannibalize the product with superior quality. Additionally, sequential introduction is considered more appropiated in case there is a high risk of cannibalization and customers are impatient. Last, Chandy & Tellis (1998) tested that companies with a higher willingness to cannibalize are more prone to produce radical innovations.

While the previous studies analyse advantages and disadvantages of product proliferation in general, some research has unveiled the outcomes of specifics ways of proliferation (e.g. vertical product proliferation, across vs within niche proliferation and versioning vs tailoring strategy). Vertical differentiation of products refers to products in the same line of the company which represent different quality-price tiers. Kim & Chhajed (2001) studied the effect of commonality on vertical product line extensions. Their results show that, in many cases, introducing commonality in line extensions -including in the new product similar characteristics to the original one- increases the valuation of the novel product when it is a low-end one, and decreases the valuation of the novel product when it is a high-end one. Bertini et al (2012) hypothesized and tested that a broad assortment causes the customers to become more discriminant and to show significant different willingness to pay for different qualities.

Meanwhile, Barroso & Giarratana (2013) studied across-niche product proliferation and within-niche product proliferation. While the first one refers to new products introduced in various sub-market niches, the second refers to new products introductions in a single submarket (associated with product versioning). The authors argue that companies which adopt across-niche proliferation strategies should adopt routines to take advantage of economies of scale and scope, while companies using within-niche proliferation should make use of learning effects and customers' feedback from the different versions of the product in order to increase profitability. Interestingly, authors find positive synergies and learning curves in the within-niche strategy, which decrease at some point due to cannibalization.

Last but not least, Boulding & Christen (2009) verify that, in a broad line, a versioning strategy (anticipating customer demand by creating variety from a stardard product) does not create a cost disadvantage, leading therefore to overall profits. Contrarily, a tailoring strategy (defined as "creating variety by customizing a product to actual customer demand") causes a cost disadvantage which can reduce overall profits.

3. Conceptual framework and hypothesis development.

I have previously mentioned some advantages and disadvantages from line extensions. Investors may react positively to a line extension announcement in case they interpret that it would yield positive benefits, such as higher price-setting power (Kadiyali et al, 1998), creation of barriers to new competition (Lancaster, 1990) and higher overall demand (Putsis & Bayus, 2001). Nevertheless, investors may react negatively to a line extension announcement when they interpret that it is not a investment but an expense, there is a high risk of cannibalization (Hui, 2004) or it may increase company costs due to lose of efficiency in the production structure (Bayus & Putsis, 1999). Although Eddy & Saunders (1980) did not find significant effects between product announcement and abnormal returns, posterior works have reported a significant and positive relationship (Chaney et al, 1991; Lane & Jacobson, 1995; Lee & Chen, 2009; Srinivasan & Hanssens, 2009; Srinivasan et al, 2009). I argue that the effect of a line extension announcement on stock price may depend on the characteristics of the line portfolio itself, due to the fact that they possibly determine if a new product in the line will bring more advantages or disadvantages.

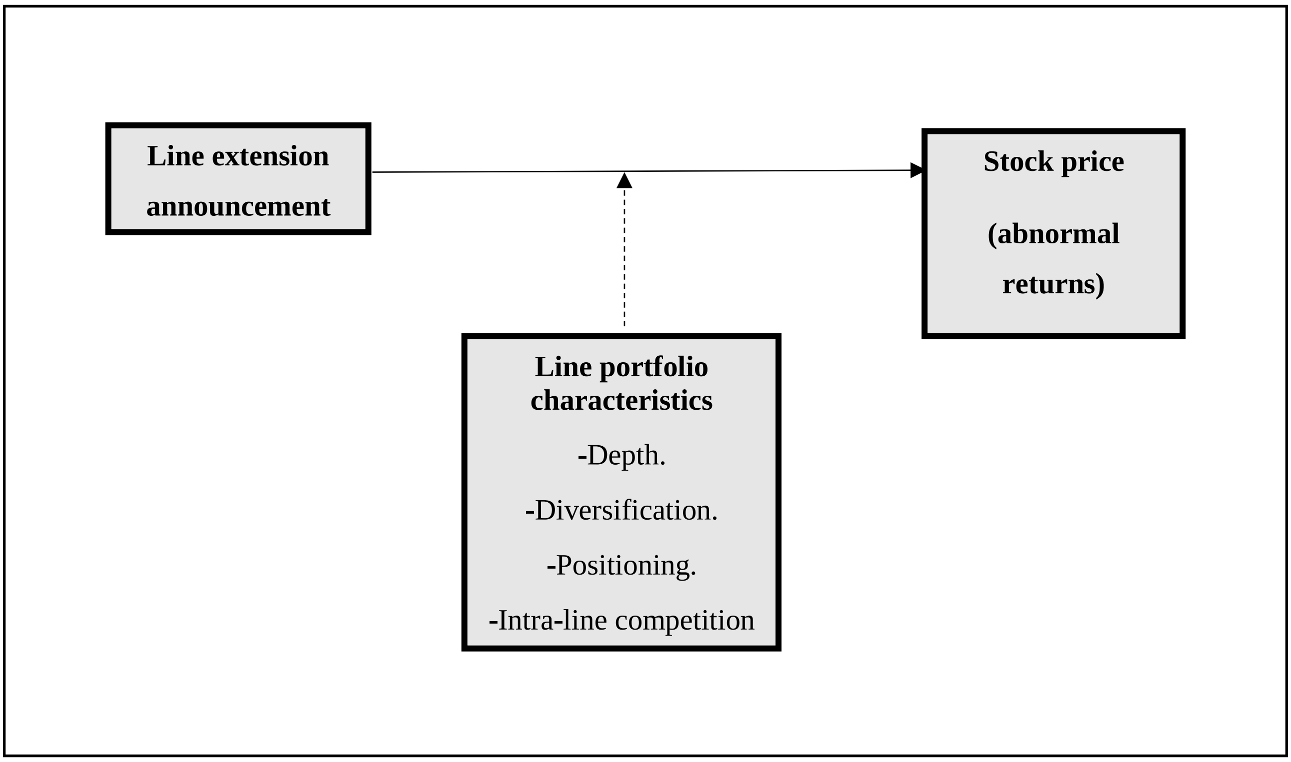
To the best of my knowledge, there is no relevant previous study which unveils the relationship between product line composition, line extension and market value. Closely-related research has been developed, but in the branding dimension. An example is the research conducted by Morgan & Rego (2009), which studies the firm financial performance depending on the brand portfolio strategy.

Previous papers have proposed several dimensions which can define a company's brand portfolio strategy (Aaker, 2004; Chintagunta, 1994). Briefly, these dimensions are (1) scope, which refers to the number of brands and segments, (2) competition, which refers to the extent to which brands compete with each other within the same company and (3) positioning, represented by the consumers' price and quality perceptions. In fact, the analysis performed by Morgan & Rego (2009) is based on these dimensions.

Inspired by the previous authors, I applied these dimensions to the product line approach, which is the unit of analysis of the present research, although with slight differences. First, in order to deeply analyze the dimension *line scope*, I divided it in two subdimensions: *line depth* and *line diversification*. Second, while intra-portfolio competition is measured in the paper of Morgan & Rego in a 'market' approach (the extent to which brands are targetting the same segments), I adopted a sales distribution approach, which is discussed in the next pages. Therefore, I chose *line depth*, *line diversification*, *line positioning* and *intra-line competition* as the main determinants of the product line portfolio composition. Line depth refers to the number of products within the product line. Line diversification refers to the extent to which the line targets different segments. Line positioning refers to the consumers' perceptions about the quality and price of the line. Last, intra-line competition refers to the extent to which products within the line compete with each other.

Companies usually hold numerous and different types of line portfolios (e.g. a company may have a deep line of smartphones but a shallow line of laptops), so this analysis is only focused in a part of the company. I make use of new products announcements (line extension announcements) to study how line portfolio characteristics affect the stock reaction to that event. Figure 1 summarizes the conceptual framework and the hypothesis which will be developed later on.

Figure 1. Conceptual framework.



Own elaboration.

Effect of line depth on stock reaction to announcement

A key line portfolio characteristic that may moderate the effect of a line extension announcement on a firm's stock price is the *line depth.* Line depth refers to the number of products that the firm has in the market and which belong to the same product line.

As stated before, line extensions have both advantages and disadvantages for the overall profit of the company. In general, if we look at the disadvantages of product proliferation (e.g. increase in unit costs and cannibalization), one may think that these will increase as the number of products in the line increases. On the one hand, with a larger number of products in the market, sales will tend to be more spread and the wastage of economies of scale will rise unit costs. On the other hand, as the number of products increases there will be more chances that two or more products are targetting the same segment and, therefore, cannibalizing their sales.

Regarding the advantages of extending a line, while some of them may also increase as number of products arises (e.g. entry barrier), some of them may increase at a lower rate or even decrease as product line depth increases. An example of that is the increase of market share and overall profits as a consequence of meeting heterogeneous needs. As an extreme illustrative explanation, a company which decides to hold a very deep line has two options: either having all differentiated and diversified products, or having similar products in the line portfolio. In the first case, the company would be exposed to oversegmentation, therefore targetting small segments which are not profitable. In the second case, due to the high similarity between products, the company will be exposed to a cannibalization risk (Brander & Eaton, 1984). Given that an extreme deep line disminish some of the value added by product proliferation, I argue that stock price will react stronger to product announcements in shallow product lines.

Supporting the previous statement, I also make use of the overreaction hypothesis suggested by De Bondt & Thaler (1985). They support that stock market overreacts to unexpected and new events. Thus, a product announcement in a shallow portfolio would be more unexpected than in a deep portfolio and consequently, the stock reaction is expected to be bigger in the first case.

> *H_1. The number of current products in a company's product line (i.e. line depth) has a negative effect on the stock market reaction to a line extension (new product) announcement.*

In other words, the effect of a line extension announcement on a firm's stock price is more positive for firms with few products in the line portfolio than for firms with a large number of products in the portfolio.

It is important to highlight that although intra-competition and number or products (line depth) are intuitively related (ρ=-0.461 in my own data), and one may influence the other, they constitute different concepts. For instance, a company may have a deep portfolio with equally-spread sales, while another one may hold a deep portfolio with a flagship product which owns most of the sales volume and small products which play a minor role.

Effect of line diversification on stock reaction to announcement

A second key line portfolio characteristic that may moderate the effect of a line extension announcement on a firm's stock price is the *line diversification.* Line diversification is the extent to which a line covers different segments in the market. The price standard deviation of the products contained in a company's line may be an indicator of the scope of its diversification, as it is an indicator of the degree to which the company markets products in different price-quality tiers.

Extending a brand portfolio to new segments may reduce the risk of cannibalization, increase the generation of economies of scope and even increase profits because of the explotation of previously untargetted consumer segments (Morgan & Rego, 2009). However, marketing literature has pointed out that extending a brand across different segments can make the brand weaker (Aaker & Keller, 1990) and less valuable (John et al, 1998). This is due to the negative consumer perceptions about of the fit within the portfolio (Aaker & Keller, 1990). Indeed, Morgan & Rego's (2009) results suggest that the number of different segments covered by the brand is negatively related to financial performance (measured by Tobin's q). Furthermore, Dacin & Smith (1994) support that as portfolio quality variance boosts, consumers' confidence in their inferrences about the quality of the extended product declines. I argue that these last statements are also applicable to the product line dimension. Additionally, in diversified product lines with different price-quality tiers, low-end products may hurt high-end products image and performance (Desai et al, 2001; Kim and Chhajed, 2001). Therefore, I expect that shareholders will react more negatively to line extensions in brands that already possess a diversified product line as they may deem such extension unnecessary given the diversity of products the brand already possesses in the marketplace. Thus, I hypothesize that:

> *H_2. Price standard deviation within the product line (i.e., product line diversification) affects negatively the stock market reaction to a line extension (new product) announcement.*

That is to say, the effect of a line extension announcement on a firm's stock price is more positive for firms whose product line price standard deviation is lower.

Effect of line positioning on stock price

A third key line portfolio characteristic that may moderate the effect of a line extension announcement on a firm's stock price is the *line positioning.* Line positioning (in terms of price and quality) of a firm's products is determined by customers' product price perceptions, as stated by research in price-quality inferrences (e.g. Kirmani & Rao, 2000). That is to say, as quality is not always observable or clear, consumers often rely on price perceptions to try to guess the quality of a product. For instance, some brands may be clearly positioned as 'premium' brands, while others may adopt a 'value for money' positioning. Therefore, I propose the average price of a product line portfolio as a measure of the product line positioning[4].

According to the statistical evidence from Randall et al (1998), brands with high-end models have higher brand equity, especially when they do not include low-end products in their portfolio. Companies which are perceived as high-quality are perceived as less risky (Aaker & Keller, 1990; Smith & Park, 1992) and generally lead to higher financial returns (Aaker & Jacobson, 1994). Therefore, I hypothesize that companies with higher prices are seen as more capable to produce good quality new products which can succeed in the market and thus, they enjoy a better new product acceptance from investors.

[4] However, this implies assuming a measurement error. The main reason is that this measure takes into account the level of prices of the line, but not the price and quality perceived by consumers.

> *H_3. Average price in a product line affects positively the stock market reaction to a line extension (new product) announcement (i.e. stock market reaction to a line extension is more beneficial for firms with a premium positioning).*

In other words, the effect of a line extension announcement on firm's stock price is more positive for firms with higher prices in their product line than for firms with lower prices.

Effect of intra-line competition on stock price

Finally, a fourth key line portfolio characteristic that may moderate the effect of a line extension announcement on a firm's stock price is the *intra-line competition.* Intra-line competition refers to the extent to which products within the product line compete with each other (Morgan & Rego, 2009). Consequently, it is closely related to product rivalry and risk of cannibalization. The higher intra-line competition, the higher product rivalry and the higher potential cannibalization.

There are drawbacks as a consequence of intra-line competition. In fact, intra-line competition may reduce price premiums, increase cannibalization and lower the efficiency of advertising and administrative expenditures (Morgan & Rego, 2009). In addition, when a new introduction is likely to cannibalize the sales –this likelihood to cannibalize is theoretically higher when a high competition exists in the portfolio- of an existing product and its launching is announced, customers may delay the purchase and wait for the new product (Wu et al, 2004). Morever, Putsis (1997) states that brands with higher intra-competition have a lower price-setting power. This may indicate that line extension announcements in portfolios with high intra-competition are less welcomed by investors.

Industry competition has been commonly calculated by using a sales concentration index (Rhoades, 1993), which indicates how sales are distributed between the different companies in the industry. Sales concentration can range from a monopolistic situation, in which one company owns all the market, to a market with equally distributed market share between the different firms. Assuming that these statements are held in the product line dimension, I propose to use a sales concentration index, specifically the Herfindahl index, to measure the degree of intra-line competition.

Considering that a low concentration in sales within the product line is an indicator of a high intra-line competition and the other way around, I expect a positive relationship between sales concentration in the line portfolio and stock reaction to line extension.

Moreover, when a market is concentrated it is also less competitive (Aboulnasr et al, 2008). The authors argue that a highly concentrated market may signal that only few solutions have been developed to meet a consumers' need and therefore, there is room for improvement. By applying the same rationale to the product line focus, I argue that concentrated sales signal investors that there is still space for a different solution (a new product) which can solve the consumers' problem and therefore yield positive results. Consequently, following this argument, I also hypothesize that new product announcements in concentrated product lines are related to higher stock returns.

> *H_4. Intra-line sales concentration (competition) affects positively (negatively) the stock market reaction to a line extension (new product) announcement.*

In other words, the effect of a line extension announcement on a firm's stock price is more positive for firms with a high sales concentration in the product line (a low intra-line competition) than for firms with a low sales concentration (a high intra-line competition).

Table 4. Summary of hypothesis.

Hypothesis	Portfolio dimension	Independent variable	Dependent variable	Directionality
H_1	Line depth	Number of products	Abnormal returns	Negative
H_2	Line diversification	Price standard deviation	Abnormal returns	Negative
H_3	Line positioning	Average price	Abnormal returns	Positive
H_4	Intra-line competition	Sales concentration	Abnormal returns	Positive

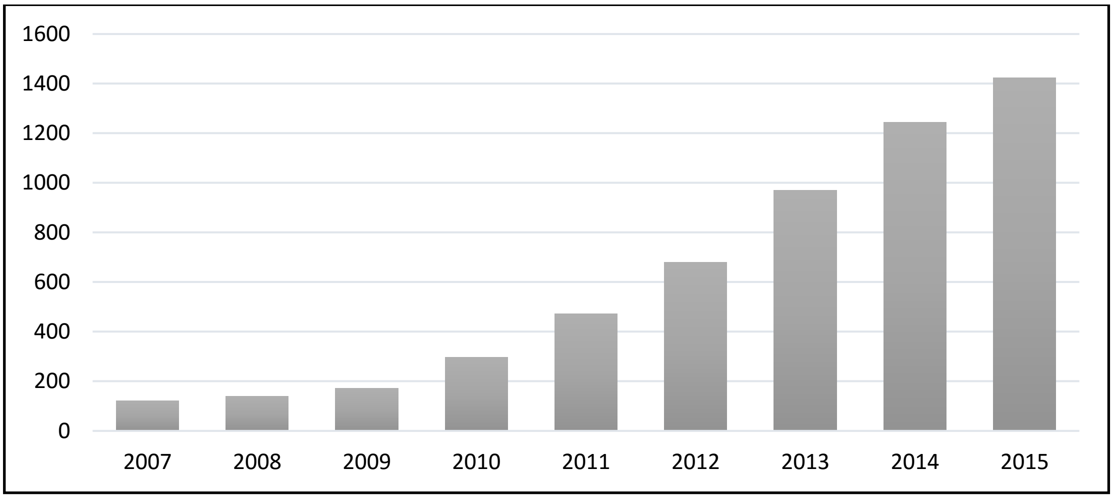
Own elaboration.

4. Data and measurement.

4.1. Analysis scope.

The current paper focuses its attention in the smartphone industry. A smartphone is a mobile phone which includes both personal computer and communication features in a handheld device. The smartphone industry took off between 2006 and 2007 and has experienced a continuous growth, as shown in Figure 2.

Figure 2. Global smartphone sales (in million units).



Source: Statista.

This industry is characterized by its huge consumer base (number of expected smartphone users in 2016 is over two billion, according to Statista) and high innovation, proliferation and concentration (Cecere et al, 2015), where almost 40% sales are owned by Samsung and Apple (Table 5). However, this supremacy is being reduced by Asian companies such as Xiaomi and consequently, competitiveness is growing within the industry.

Table 5. Market share of the main players in the smartphone industry.

Period	Samsung	Apple	Huawei	Xiaomi	Lenovo*	Others
2015Q2	21.40%	13.90%	8.70%	5.60%	4.70%	45.70%
2014Q2	24.80%	11.60%	6.70%	4.60%	8.00%	44.30%
2013Q2	31.90%	12.90%	4.30%	1.70%	5.70%	43.60%

**Motorola is included in Lenovo's data. Source: IDC (Aug 2015).*

Geographically, only data about announcements and portfolio characteristics in US market will be included in the analysis, with the aim of reducing data computing effort. I expect that, given the size of the US, results will be generalized to other countries.

Regarding the time window, I analyse smartphone and stock price data from 2007 (turning point of smartphone industry) until mid-2014[5].

Our sample of smartphone vendors is formed by six brands: Apple, HTC, LG, Motorola, Nokia and Samsung. They all meet the requirements of being listed in the stock market at least from 2007 until 2014 and being top performers in the smartphone industry. Interestingly, they follow different strategies in their smartphone portfolios, as shown in Table 6[6]. The first column in Table 6 lists all the brands in my data. The second column depicts portfolio concentration for each brand. Portfolio concentration is measured with the normalized Herfindahl Index (HHI). Its calculation is specified in the next chapter. For now, it suffices to note that this score ranges from 0 to 1 and that higher values indicate a higher sales concentration. The third column depicts the average price of the smartphone products of each brand. The fourth column depicts the price standard deviation of the products contained in the smartphone line portfolio for each firm. Last, the fifth column indicates the number of products of the smartphone line for each firm.

Apple follows a flagship product strategy and a premium positioning with low concentration, low number of products and high average prices with low standard deviation. LG shows the lowest concentration and average price (so a diversified portfolio with a value-for-money positioning). Nokia stands out due to a high standard deviation in their prices, which may indicate a price-quality vertical strategy in its portfolio (in other words, Nokia holds products in different price-quality tiers). HTC's portfolio is low concentrated and offers moderate prices and a deep quantity of products. Motorola shows the lowest price standard deviation, while maintaining a portfolio with a low concentration and a moderate number of products in the market. Last, Samsung is the vendor who has in average more products in the market (15) and its portfolio is low concentrated.

[5] Note that data includes only announcements, sales, etc. of products which are marketed in US; however, this data may come from companies which have their origin in a different country if they also market their products in the US market. This is the case of HTC, LG, Nokia and Samsung.
[6]The descriptive statistics of Table 6 refer to quarterly data from 2007 to 2014, not only to the announcement dates.

Table 6. Average product line portfolio characteristics from 2007 to 2014.

Vendor	HHI	Average price	Price standard deviation	Number of products
Apple	0.425	595.444	86.320	2.069
HTC	0.197	468.290	103.437	10.104
LG	0.083	358.442	100.497	9.953
Motorola	0.239	433.049	88.252	7.432
Nokia	0.262	377.332	137.091	7.034
Samsung	0.209	418.869	115.217	14.859

Source: Calculated from IDC Data

4.2. Variables.

In this part all variables specification and data gathering procedures are explained. It is important to note that variables are converted to daily frequency (I provide details below in the 'product line portfolio' subsection in the next section) with the aim of being able of studying short windows in the stock price effects of an announcement.

Abnormal returns

Daily stock prices of the previous companies, as well as prices of the reference composites of the markets in which they are listed, have been collected from Yahoo Finance. Calculation of abnormal returns is developed according to state-of-the-art practices in the marketing and finance literatures. I elaborate on these in the Methodology part of this paper.

Product announcement

New smartphone announcements from 2007 until mid-2014 by vendors Apple, HTC, LG, Motorola, Nokia and Samsung in the US have been manually collected by using database Factiva[7]. In order to eliminate as much noise in the data as possible, only launchings which meet the following requirements are included: (1) the launching or device specifications had not been leaked before the announcement and (2) the announcement has been reported in at least three American newspapers included in Factiva database.

[7] Factiva is a business news and economic information provider, commonly used in research. https://global.factiva.com/

Product line portfolio characteristics

Product line portfolio characteristics of the different brands have been calculated from an IDC dataset. The latter includes data of unit sales, value sales, price and device specifications (e.g. screen size, SIM, processor speed, etc.) of every smartphone model, grouped by quarter and country. This dataset includes data from 2004 until mid-2014, from about 18128 smartphone models from 317 vendors in 65 different countries.

As mentioned before, the analysis performed in this paper uses daily data. For that purpose, quarterly data have been converted into daily data with the help of R software and following well-accepted procedures. It is important to note that in order to transform data to a daily frequency, I had to obtain introduction dates for every model so as to have a starting date to count the sales of the first quarter of every smartphone model. This introduction date in the US is not straightforward to obtain. Because of that, I used a three-step method to obtain them: (1) in case the first week in which the product (i.e., a specific smartphone model) is sold is known, I took as introduction date the first working day of the launch week (Monday), (2) in case the exact launch week is not available, I took the first month in which a specific model was sold and assigned the first day of that month as the model introduction date, (3) in case the launch month is also not available, then I took as the introduction date the first day of the first quarter in which a specific smartphone model had non-zero sales in IDC data. However, for models in which we have an announcement date and the application of these three rules causes the introduction date to take place before the announcement date, I took as the introduction date the next Monday after the announcement.

After having daily data of sales and price per model and company, a dataset has been built which includes daily number of products, price standard deviation, average price and sales concentration of each company's smartphone product line.

Intra-line competition

Although intra-line competition is included in the product line portfolio characteristics, it needs further attention in order to detail and explain its calculation. As proposed in the Conceptual Framework and Hypothesis Development part in this paper, sales concentration is used as a measure of intra-line competition.

In order to calculate the sales concentration within the product line portfolio, the Herfindahl index (HHI) has been used[8]. Herfindahl index (aka Herfindal-Hirschman index) is a statistical measure of market concentration (Rhoades, 1993), commonly used by economists and policy-makers when studying market or industry concentration (Kwoka, 1985). Due to this fact, it can be found in some research as a measure of industry competitiveness; examples are the works of Srinivasan et al (2009) and Morgan & Rego (2009). Few studies use Herfindahl index for other purposes. One exception is the paper of Lang & Stulz (1994), which uses HHI as a measure of segment diversification within a company. In this paper, I introduce a novel metric to measure sales concentration within a product portfolio. More precisely, I adapt the Herfindahl index and use it as a measure of sales concentration -and therefore, competiveness- within the product line portfolio. The index is calculated as the summation of the squared market shares of each of the products (see Equation 1).

$$H_{i,t} = \sum_{j=1}^{N} MS_{ij,t}^{2} = \sum_{j=1}^{N} \left(\frac{Sales_{ij,t}}{\sum_{1}^{N} Sales_{ij,t}} \right)^{2} \tag{1}$$

Where $Sales_{ij,t}$ stands for the total sales of product j from firm i at time t. Following the previous expression, the value of the Herfindahl index will range from 1/N to 1. Given that we need a value which can be interpreted equally across different number of products, I calculate a normalized version of the Herfindahl index (see Equation 2). After this transformation, Herfindahl index will range from 0 to 1.

$$H^{*}{}_{i,t} = \frac{H_{i,t} - 1/N_{i,t}}{1 - 1/N_{i,t}} \tag{2}$$

Where $N_{i,t}$ is the total number of products that firm i has on the market at time t.

Last, an example is used with the aim of illustrating the interpretation of this index. Consider two product lines (A and B) with two products each of them. In the case of product line A, both products have the same market share (50% each), while in the case of product line B, product B1 owns 20% of the market while product B2 owns the remaining 80% (product line B has a higher sales concentration).

[8] HHI has been calculated with both units and sales value. However, I chose the sales value HHI as it is the standard method and it shows slightly lower correlations with other variables than the unit sales HHI.

$$H_A = 0.5^2 + 0.5^2 = 0.5 \quad ; \quad H^*{}_A = \frac{0.5 - \frac{1}{2}}{1 - \frac{1}{2}} = 0$$

$$H_B = 0.2^2 + 0.8^2 = 0.68 \quad ; \quad H^*{}_A = \frac{0.68 - \frac{1}{2}}{1 - \frac{1}{2}} = 0.36$$

As illustrated by the example, the more concentrated the sales are, the higher the Herfindahl index is (with the maximum being 1, which occurs when all sales are concentrated on a single product). At the same time, the higher the Herfindahl index, the lower intra-line competition and the lower risk of cannibalization. Last, higher values of Herfindahl index are related to the existence of flagship products.

Control variables

With the aim of trying to eliminate as much noise as possible in the models I make use of control variables, which are related to announcement, line and company characteristics. Table 7, below, summarizes all variables I analyse, including their sources. Announcement-related, I included multiple announcement and local product as control variables. Regarding line performance, I included the value of smartphone sales in US per company. Last, in order to control for company size and performance, I included the total revenue and assets. For these two latter and for companies whose origin is not US, I used official exchange rates from US Federal Reserve.

Table 7. Summary of variables included in the analysis.

Variable	Variable Name	Definition	Source
Dependent variable			
Abnormal returns ($e_{i,t}$)	AR	$R_{i,t} - E(R_{i,t})$	Yahoo Finance
Main independent variables			
Number or products	NUM_PROD	Number of products in the product line portfolio of company *i* in day *t*.	IDC
Price standard deviation	STD_PRICE	Price standard deviation of the product line portfolio of company *i* in day *t*.	IDC
Average price	AVG_PRICE	Average price of the product line portfolio of company *i* in day *t*.	IDC
Sales concentration/ Intra-line competition	CONCENTRATION	Normalized Herfindahl index for day *t* and company *i* applied to the product line portfolio.	IDC
Control variables			
Local product	LOCAL	Dummy variable. Value 1 when the announced product is mean to be sold only in the US. Otherwise 0.	IDC
Multiple announcement	MULTIPLE	Dummy variable. Value 1 when a multiple announcement takes place in day *t* and company *i*. Otherwise 0.	Factiva
Value of smartphone sales	SUM_VALUE	Smartphone sales in the US in day *t* of company *i*	IDC
Assets	ASSETS	Total assets in day *t* of company *i*	COMPUTSTAT
Revenue	REVENUE	Total revenue in day *t* of company *i*	COMPUTSTAT

**Data is only collected and analysed for days in which a product announcement is produced.*

5. Methodology and model specification.

5.1. Event study.

In order to test the effect of a new product announcement in financial short-term value, we need to make use of a stock response model. The event-study model (Brown & Warner, 1995) has been widely and commonly used in the marketing and finance literatures (Lane & Jacobson, 1995; Agrawal & Kamakura, 1995; Sorescu et al, 2007; Srinivasan et al, 2009; Joshi & Hanssens, 2009). This model aims to assess the effect of unexpected events on the stock performance of a company (Agrawal & Kamakura, 1995). Event-study models rely on the theory of market efficiency by Fama et al (1969). This theory posits that the stock price is the present value of the future expected cash flows from a company's assets and it reflects all the available information about the present and future state of the firm (Fama, 1970). Therefore, if an event unveils valuable new information for investors, it will be translated to the stock price as positive or negative abnormal returns. At the same time, the amount of abnormal returns is considered an indicator of the economic value of the event (Brown & Warner, 1995).

The stock return is measured as the percentage change in the stock price:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{3}$$

Where $P_{i,t}$ is the stock price in *t* of the company *i*. Consequently, the return in *t* reflects the change of information and expectations about future cash flows from *t-1* to *t*.

To assess the effect of an event on the stock performance, abnormal returns need to be calculated by comparing the return $R_{i,t}$ in the time containing the event and the expected return $E(R_{i,t})$. The latter is the return which would have been expected if the event had not taken place. It can be obtained by using the market model (Brown & Warner, 1995), which proposes a linear relationship between the general market performance (represented by a benchmark composite[9] of marketable assets, e.g. NASDAQ COMPOSITE) and the expected return:

$$E(R_{i,t}) = \alpha_i + \beta_i \cdot RM_{i,t} \tag{4}$$

[9] See Appendix for information about the benchmark composites of the markets where companies are listed.

Where α_i and β_i are the parameters obtained as the results of an OLS regression of $R_{i,t}$ on $RM_{i,t}$ (return of benchmark portfolio of the market in which the company i is listed). According to this expression, abnormal returns are the prediction error or difference between the real and estimated value:

$$e_{i,t} = R_{i,t} - E(R_{i,t}) = R_{i,t} - (\alpha_i + \beta_i \cdot RM_{i,t}) \qquad (5)$$

Previous literature in event studies in marketing commonly uses cumulative returns (i.e. CAR) in short windows to run their analysis; examples are the papers of Lane & Jacobson (1995) and Joshi & Hanssens (2009). However, by only using cumulative results it is not possible to trace back the stock reactions in specific dates. Thus, I consider that it is also essential to analyze abnormal returns (i.e. AR) day by day.

Following the research methodology of Lane & Jacobson (1995), I focus my analysis in short event windows, between t_0 (announcement date) and t_1, although I also check results from t_2 to t_4. That is to say, I focus my attention on three different dependent variables:

$$AR1_{i,t} = e_{i,t} = R_{i,t} - (\alpha_i + \beta_i \cdot RM_{i,t}) \qquad (6)$$

$$AR2_{i,t} = e_{i,t+1} = R_{i,t+1} - (\alpha_i + \beta_i \cdot RM_{i,t+1}) \qquad (7)$$

$$CAR2_{i,t} = AR1 + AR2 = e_{i,t} + e_{i,t+1} \qquad (8)$$

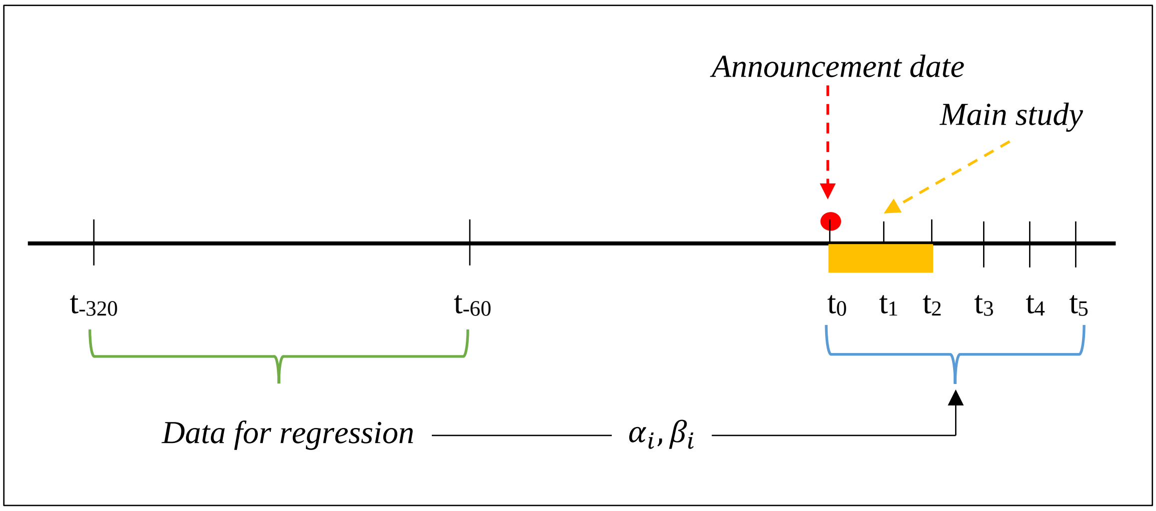
According to this, AR1 measures the stock reaction in the announcement date, AR2 measures the stock reaction to the announcement in the following day and CAR2 represents the cummulative stock reaction from the annoucement date to the following day.

In order to obtain abnormal returns, for each announcement date, I regress stock returns data[10] (Equation 4) starting 320 days before the announcement (t_{-320}) and ending 60 days before the announcement (t_{-60})[11]. As the output of that regression, I obtain α_i and β_i, which are needed to apply the market model (Equation 4). By applying these coefficients to stock returns from t_0 to t_4, I collect the expected returns for those days (Figure 3). Last, by taking the first difference between the actual returns and the expected returns, abnormal returns are obtained (Equation 5) from t_0 to t_4. These abnormal returns will

[10] In total, 95 regressions have been conducted, as each announcement date needs its own regression.
[11] As performed by Lane and Jacobson (1995).

reflect the investors' expectations about the current value of the future cash flows generated by the announcement (Lane and Jacobson, 1995).[12]

Figure 3. Expected returns obtainment in event study methodology.



Own elaboration.

Last, it is important to note that while stock data reflect information about the entire company, the focus of the study is a small part of it: the smartphone portfolio. This fact makes more difficult to aisle and detect the stock reaction to line extension announcements. In fact, according to Lane & Jacobson (1995), if an event affects only a limited part of a firm, it will have also a small effect on the stock price, as information from other parts of the company may also influence security price movements. Due to this fact, the dependent variable contains measurement error; however, it is still possible to estimate unbiased coefficients and standard errors, although the latter may be considerably large and reduce the capability of the tests (Lane & Jacobson, 1995).

5.2. Model specification.

Having defined and obtained abnormal returns according to Equation 5, I then regress these abnormal returns on our independent and control variables, so that my theory-derived hypotheses can be directly tested. That is to say, variables which reflect characteristics about the product line previous to the announcement are included, as well

[12] Event study methodology has also been applied from t_2 to t_4, in order to check for later and wider windows.

as control variables related to the specifications of the product announcement, line performance and company characteristics.

$$AR1_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \beta_5 LOCAL_{i,t} + \beta_6 MULTIPLE_{i,t} + \beta_7 SUM\_VALUE_{i,t} + \beta_8 ASSETS_{i,t} + \beta_9 REVENUE_{i,t} + \varepsilon_{i,t} \quad (9)$$

$$AR2_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \beta_5 LOCAL_{i,t} + \beta_6 MULTIPLE_{i,t} + \beta_7 SUM\_VALUE_{i,t} + \beta_8 ASSETS_{i,t} + \beta_9 REVENUE_{i,t} + \varepsilon_{i,t} \quad (10)$$

$$CAR2_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \beta_5 LOCAL_{i,t} + \beta_6 MULTIPLE_{i,t} + \beta_7 SUM\_VALUE_{i,t} + \beta_8 ASSETS_{i,t} + \beta_9 REVENUE_{i,t} + \varepsilon_{i,t} \quad (11)$$

Line depth ($NUM\_PROD_{i,t}$), line diversification ($STD\_PRICE_{i,t}$), line positioning ($AVG\_PRICE_{i,t}$) and intra-line competition ($CONCENTRATION_{i,t}$) are included as independent variables and they are the main focus of the analysis. However, with the aim of eliminating some external factor which can cause noise in the data, five control variables are included. $MULTIPLE_{i,t}$ is a dummy variable which takes value 1 in case more than a product announcement from the company *i* has taken place in week *t*. $LOCAL_{i,t}$ is a dummy variable which takes value 1 in case the announced product is meant to be sold only in the US market. $MULTIPLE_{i,t}$ is included as a control variable due to the fact that a firm announcement for multiple products may provoke a stronger stock price reaction than a single new product announcement, as suggested by the results of Chaney et al (1991). Additionally, stock price may react less to announcements of products meant to be sold only in one country than to announcements of multi-country products. As line specific control variable, $SUM\_VALUE_{i,t}$ is included. It measures the total smartphone sales in the US of company *i* in *t*. Last, I include the control variables $ASSETS_{i,t}$ -to take into account the size of each company- and $REVENUE_{i,t}$ -as a measure of their performance. Both variables refer to each company as a whole, not to the size and performance of the smartphone portfolio.

6. Empirical results.

6.1. General considerations.

First, it is important to note that results are divided in Study 1 and Study 2 in order to come to stronger conclusions and robust results. From the six brands which are the focus of the analysis, three of them (Apple, Motorola and Nokia) are listed in the US, while three of them (HTC, LG and Samsung) are listed in oriental markets (Korea and Taiwan). In Study 1, for all companies the date of announcement is related with the abnormal return of the same day (AR1) and the four following days. Given the time difference[13] between the country in which a company is listed and the country in which the announcement is produced (mainly US), this study may measure in AR1 a pre-reaction in companies listed in oriental markets -due to the fact that by the time the stock market is open, the announcement may have not taken place yet. However, this study is considered still valid because sometimes agents or investors anticipate the company's actions (e.g. whispering, call for a press conference) or the announcement could have been released before in other countries. In fact, some authors have already and succesfully explored windows which include days before the event which is the focus of the analysis (e.g. Chaney et al, 1991). On the other hand, in Study 2 I have corrected the data taking this difference into account and thus, it serves as a robustness check of the Study 1 results. That is to say, this second study has been performed by using one day lagged data from oriental markets, with the aim of ensuring that the stock prices I am using are produced after the announcement.

In order to model the data I make use of OLS regression, which requires making some assumptions. Table 8 shows the correlation matrix of the variables implicated in the analysis. Regarding the variables which are the main focus of this analysis (*NUM_PROD, STD_PRICE, AVG_PRICE, CONCENTRATION*) some significant correlations are found, which may indicate a potential problem of multicollineality when regressing with a OLS method. Due to the fact that all these correlations are below 0.5, I assume moderate multicollineality in the analysis. With regards to control variables, we find some correlations above 0.5 and 0.6. We find a severe and high correlation between *ASSETS* and *REVENUE* (ρ=0.968); due to this fact, I also run separate regressions for these variables to ensure the reliability of standard errors.

[13] See Appendix for time differences information.

Table 8. Correlation matrix.

			1	2	3	4	5	6	7	8	9
1	**NUM_PROD**	Pearson	1								
		Sig. (2-tailed)									
2	**STD_PRICE**	Pearson	**0.269****	1							
		Sig. (2-tailed)	0.008								
3	**AVG_PRICE**	Pearson	**-0.407****	**0.152**	1						
		Sig. (2-tailed)	0.000	0.140							
4	**CONCENTRATION**	Pearson	**-0.461****	**0.283****	**0.468****	1					
		Sig. (2-tailed)	0.000	0.006	0.000						
5	**LOCAL**	Pearson	**0.285****	**-0.086**	**-0.217***	**-0.314****	1				
		Sig. (2-tailed)	0.005	0.405	0.035	0.002					
6	**MULTIPLE**	Pearson	**-0.160**	**0.006**	**0.090**	**-0.038**	**0.020**	1			
		Sig. (2-tailed)	0.121	0.952	0.384	0.714	0.845				
7	**SUM_VALUE**	Pearson	**0.604****	**0.253***	**-0.013**	**-0.006**	**0.015**	**-0.239***	1		
		Sig. (2-tailed)	0.000	0.013	0.900	0.955	0.886	0.020			
8	**ASSETS**	Pearson	**0.467****	**0.392****	**-0.094**	**0.073**	**-0.039**	**-0.140**	**0.701****	1	
		Sig. (2-tailed)	0.000	0.000	0.363	0.480	0.711	0.176	0.000		
9	**REVENUE**	Pearson	**0.527****	**0.419****	**-0.179**	**0.020**	**0.011**	**-0.125**	**0.649****	**0.968****	1
		Sig. (2-tailed)	0.000	0.000	0.082	0.848	0.918	0.227	0.000	0.000	
	N		95	95	95	95	95	95	95	95	95

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

On the other hand, I have run Breusch-Pagan tests in all models to test for residual heteroskedasticity, with the aim of ensuring the robustness of standard errors. In all cases, the null hypothesis of residuals homoskedasticity cannot be rejected at a significance level of 0.05.

Durbin-Watson null hypothesis –residual autocorrelation equals to 0- is rejected at a significance level of 0.05 in some equations in Study 1 which include control variables; however in Study 2 we do find evidence of residual autocorrelation in equations without control variables, specifically when AR1 and CAR2 are the dependent variables. Serial correlation does not bias or affect the consistency of parameter estimates. Yet, severe autocorrelation may deflate standard errors and inflate t-tests, leading to invalid statistical inferences (i.e., false significant results). Given that the significance of the Durbin-Watson statistic depends on the inclusion or exclusion of control variables, and that I fail to reject the null of residual correlation equal to zero in Study 2, I deem the risk that autocorrelation seriously affect my inferences as sufficiently low to proceed without further corrections.

In addition, residual normality (Shapiro-Wilk test) is rejected in all equations at a significance level of 0.05 and even 0.01. Again, non-normality of the residuals does not bias my parameter estimates but may invalidate statistical inference, as hypothesis testing assumes that the t-statistics are asymptotically normally distributed. It is well-known that formal normality tests such as the Shapiro-Wilk test are sensitive to sample size (see e.g. Royston, 1982). In this case, residual non-normality may be related with the methodology applied[14]. Furthermore, Henderson (1990) mentions that non-normality is commonly found in event studies using daily data.

Regarding time windows, as stated in the previous chapter, the event study methodology has been applied to short windows, following the example of Lane & Jacobson (1995). I have modelled the data using as time windows t_0 (day of the announcement), t_1 (day after the analysis) and the cumulative effect of both days. Due to this fact, main results and conclusions are based on the variables AR1, AR2 and CAR2. However, following Lane

[14] Attempts to fix non-normality of residuals have been performed by eliminating outliers and performing transformations on the dependent variable (y); e.g. 1/y and log(y+a) so that y+a>0.
However, these attempts have been unsuccessful as residuals kept being non-normally distributed.

& Jacobson's (1995) paper, I do check results in wider windows (AR3, AR4, AR5, CAR3, CAR4 and CAR5).

The multiple equations -all of them available in Appendix section- which have been modelled indicate that control variables do not help to eliminate noise in the data, as none of them is statistically significant across the models performed. These control variables are adding noise to the analysis and decreasing adjusted R^2. This suggests they should not be included in the models. Consequently, the main results and conclusions will be based on the following equations.

$$AR1_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \varepsilon_{i,t} \quad (12)$$

$$AR2_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \varepsilon_{i,t} \quad (13)$$

$$CAR2_{i,t} = \beta_0 + \beta_1 NUM\_PROD_{i,t} + \beta_2 STD\_PRICE_{i,t} + \beta_3 AVG\_PRICE_{i,t} + \beta_4 CONCENTRATION_{i,t} + \varepsilon_{i,t} \quad (14)$$

As declared before, the main focus of the analysis are the time windows t_0 (announcement day) and t_1 (day after the announcement). Wider windows (t_2, t_3 and t_4) have been checked, but noise dominates those days, so there are no significant results to report[15].

6.2. Data analysis descriptives.

The data of analysis include 95 announcement dates. In case in one announcement date more than one product has been unveiled by the same company, only one observation is included in the analysis. The variable *MULTIPLE* reflects this multiple announcement[16].

As shown in Table 9, in Study 1 AR1 shows a positive mean (0.0016) which matches the positive reactions to announcements reported by Chaney et al (1991). When taking AR2 average (0.0003) we can see that this positive reaction is still positive but smaller.

On the other hand, in Study 2 AR1 still shows a positive mean (0.0022) while the average reaction reported by AR2 is negative (-0.0002).

[15] See Appendix.

[16] Due to this fact, the number of observations (95) differs from the number of announced products contained in Appendix Table 1.

Table 9. Descriptive statistics of analysis data.

Descriptive Statistics				
	Minimum	Maximum	Mean	Std. Deviation
NUM_PROD	2	33	11.71	8.272
STD_PRICE	7.071	274.357	112.150	48.791
AVG_PRICE (US$)	251.667	616.500	416.288	67.598
CONCENTRATION	0.021	0.920	0.203	0.214
Study 1				
AR1	-0.027	0.084	0.0015	0.011
AR2	-0.027	0.031	0.0003	0.008
CAR2	-0.034	0.070	0.0019	0.012
Study 2				
AR1	-0.017	0.084	0.0022	0.012
AR2	-0.027	0.034	-0.0002	0.008
CAR2	-0.034	0.070	0.0020	0.014

Table 10. Average variable values and number of announcement dates from analysis data.

	Apple	HTC	LG	Motorola	Nokia	Samsung
AR1	0.0008	0.0002	0.0002	-0.0019	0.0103	-0.0002
AR2	0.0033	0.0023	0.0017	-0.0004	-0.0027	-0.0001
CAR2	0.0042	0.0025	0.0019	-0.0023	0.0076	-0.0002
NUM_PROD	2.025	12.044	11.016	7.39	7.41	20.62
STD_PRICE	110.601	79.550	99.481	100.765	139.856	136.075
AVG_PRICE (US$)	556.583	466.347	356.500	436.567	408.249	394.644
CONCENTRATION	0.631	0.148	0.110	0.250	0.298	0.130
LOCAL	0	0.5	0.79	0.61	0.06	0.67
MULTIPLE	0	0.43	0.26	0.39	0.47	0.33
SUM_VALUE (US$)	34,396,186	13,249,782	7,406,505	7,925,139	1,088,442	26,635,464
ASSETS (US$)	133,225,000,000	6,957,161,519	30,504,424,620	20,722,222,222	48,026,950,128	136,887,226,020
REVENUE (US$)	314,008,241	31,499,327	135,561,054	29,576,233	162,780,360	433,495,761
Total number of announcement dates	4	16	19	18	17	21

When looking at the descriptive statistics per company (Table 10), we see that stock reactions differ from one firm to another. While Apple, HTC, LG and Nokia report positive reactions in average, Motorola and Samsung show negative ones. These descriptive statistics of the analysis data are quite similar to the descriptive statistics of continuous data from 2007 to 2014 (as reported in Table 6); nevertheless, results slightly differ as Table 10 only refers to the line portfolio characteristics in dates in which a new product announcement has been produced.

6.3. Study 1.

Table 11. Study 1 Output.

STUDY 1	AR1		AR2		CAR2	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.00067	0.9419	0.0056	0.353	0.006303	0.526
NUM_PROD	-0.00037*	0.0621	0.000096	0.455	-0.00027	0.199
STD_PRICE	0.00006*	0.0613	-0.00003	0.186	0.00003	0.348
AVG_PRICE	0.000004	0.8523	-0.000014	0.320	-0.00001	0.664
CONCENTRATION	-0.0134*	0.0740	0.0109**	0.028	-0.00251	0.755
R^2	0.05925		0.05935		0.02184	

Number of products

In this study a significant coefficient (significance level of 0.10) is found when regressing AR1 (-0.0004, $p<0.10$). However, results become statistically insignificant when exploring wider windows such as AR2 (0.0001, $p>0.10$) and CAR2 (-0.0003, $p>0.10$).

Therefore, we cannot reject H_1 at a significance level of 0.10, although in a short window (0,+1). Then, we can state that empirical results hint that investors value more positively line extensions when the line depth is shorter.

Price standard deviation

Price standard deviation attempts to measure the diversification within the product line. In Study 1 we find a positive and significant effect (significance level of 0.10) on AR1 (0.00006, $p<0.10$). However, the coefficient sign is not the one that was predicted. According to the empirical results, price standard deviation may influence positively stock market reaction to announcements. That is to say, the more diversified a product line portfolio is, the more positive the reaction will be. I find two possible explanations for this sign. First, a more diversified portfolio markets products to different segments, and therefore risk of cannibalization between products may be lower. Following this rationale, when a line extension announcement in produced in a diversified portfolio, investors interpret that, following the previous line diversification strategy, the new product will be designed to target a different segment and there is low risk of cannibalizing other products. Second, following a financial rationale, in the same way that investors aim to diversify their investment portfolio in order to reduce risk (Markowitz, 1968), investors may reward companies' diversified product portfolios.

Results when regressing wider windows are statistically insignificant: AR2 (-0.00003, p>0.10) and CAR2 (0.00003, p>0.10). Thus, we must reject H_2.

Average price

The role of average price in the investors' reaction is not significant across all models and event windows. Consequently, we must reject H_3 and state that price positioning of the product line portfolio does not influence the investors' judgement towards the new product (line extension) announcement.

Concentration

We find a significant (significance level of 0.10) and negative coefficient for the moderating effect of the sales concentration index in the investors' reaction to an announcement when AR1 (-0.013, p<0.10) is the dependent variable. Contrarily, when studying the announcement effect on the day after, a positive and significant effect is found (0.01, p<0.05). As a potential explanation, these inconsistent results might be a consequence of investors' fear. It could happen that the first investors to react are risk averse and they are afraid that a company with a highly concentrated portfolio may hurt its flagship product with the new introduction; however, in the day after, more information about the new product is spread and more bold investors may start seeing the positive aspects of the new introduction. The opposite signs in AR1 and AR2 cause the result obtained in CAR2 (-0.0025, p>0.10) to be insignificant. Given the previous results, in the only case we cannot reject H_4 is in time window t_1.

Goodness of fit

Goodness of fit, measured by R^2 measure, is quite low across all models (Table 11). In the case of AR1, the model achieves to explain 5.926% of the variance of the abnormal returns produced in the same day in which a new product (line extension) is announced. Very similar to the previous one, when regressing AR2, the model explains 5.935% of the variance of abnormal returns in the day after the announcement. Last, when the dependent variable is CAR2, the goodness of fit is the lowest – as reported in Table 11. Despite the fact that previous literature usually models cumulative abnormal returns instead of daily ones, in this study looking at daily abnormal returns is more informative.

There are several reasons which can justify these results. First, a product line is only a part of the company, while the stock price reflects the whole company's situation. Due to this fact, the performance or events from other parts of the company may be influencing the stock price of the company too. Second, variables may not reflect all the characteristics to consider in a product line portfolio. Third, even if the chosen variables reflect all dimensions of a product line portfolio, they may in fact have a minor role moderating the stock reaction to line extension announcements. In addition, the fact that the dependent variables are estimated previously with a market model may influence the low R^2. In fact, previous papers which use a similar methodology report low R^2. Lane and Jacobson (1995) explain 8% of the variance of the cumulative abnormal returns in their first model. Chaney et al (1991) even report lower R^2 (between 3% and 9%).

6.4. Study 2.

Table 12. Study 2 Output.

STUDY 2	**AR1**		**AR2**		**CAR2**	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.00501	0.5840	0.0053	0.3742	0.01032	0.3388
NUM_PROD	-0.000439**	0.0264	0.00005	0.6754	-0.00038*	0.0955
STDPRICE	0.00006**	0.0363	-0.00002	0.2841	0.00004	0.2301
AVGPRICE	-0.000007	0.7392	-0.00001	0.3195	-0.00002	0.4041
CONCENTRATION	-0.0087	0.2408	0.009*	0.0646	0.00029	0.9732
R^2	0.06955		0.04544		0.04465	

Number of products

We find significant results when regessing AR1 (-0.0004, *p*<0.05) and CAR2 (-0.0004, *p*<0.10), being the latter influenced by the results of AR1. These results indicate that we cannot reject H_1, which states that number of products affects negatively the stock reaction to a line extension announcement, in t_0. This conclusion is consistent with the results of Study 1.

Price standard deviation

If we take into consideration time differences between financial markets (aka Study 2), we still find a positive and significant coefficient when we model the dependent variable AR1 (0.00006, *p*<0.05). In line with Study 1 results, the sign is the opposite to the one that was hypothesized. As proposed before, this may be explained by the investors' preference for diversification and the possibly lower perceived risk of cannibalization.

When modelling AR2 (-0.00002, *p*>0.10) and CAR2 (0.00004, *p*>0.10) statistically significant results are not found. For this reason, H_2 is rejected in all models, consistent with Study 1 results.

Average price

Same with Study 1, due to insignificant results (*p*>0.10) with AR1, AR2 and CAR2 as dependent variables, we must reject H_3, which proposed that price positioning of the product line portfolio affects positively stock reaction to line extension announcements.

Concentration

We only find a significant (significance level of 0.10) coefficient when the dependent variable is AR2 (0.009, *p*<0.10), hence we cannot reject H_4 in the time window t_1, which stated that sales concentration in the line affects positively stock reaction to line extension announcements. Interestingly, this conclusion in consistent with Study 1 output when modelling AR2.

Goodness of fit

In Study 2, goodness of fit is also low, and the same reasons are argued. When regressing AR1, the model explains 6.955% of the variance of the abnormal returns produced in the same day in which the line extension is announced, which is higher than the R^2 reported in Study 1. With AR2 as dependent variable, the model explains 5.935% of the variance of abnormal returns in the day after the announcement. Last, when modelling CAR2, 4.465% of its variance is explained by the model.

6.5. Robustness check.

As reported in Table 10, Apple's characteristics differ significantly from the rest of brands. Due to the supremacy of Apple in the industry and given its brand power, a robustness check is needed to check if it is influencing the results. After this analysis, it is proved that results[17] remain stable when excluding Apple from the data, hence corroborating previous conclusions.

6.6. Empirical conclusions.

In the previous pages, significance levels of 0.05 and 0.10 have been used. In the process of obtaning, gathering and calculating announcements and line characteristics data[18], some assumptions have been needed, which makes difficult to get to accurate results. Because of that I consider that a significance level of 0.10 should be enough to report significant results in the moderating role of product line characteristics on the stock reaction to line extensions. However, given the results of the tests of residual normality and autocorrelation, it could be advisable to use a significance level of 0.05 and disminish the probability of obtaining false significant results.

Two studies and one robustness check have been performed so as to check the reliability of the results. By focusing on the consistent results from the studies, we can come to quite robust conclusions.

[17] Results from robustness check are available in Appendix.
[18] See Chapter 4.

1. In the announcement date, number of products (which represents *line depth*) influences negatively the stock reaction to a line extension announcement. This implies not rejecting H_1 in t_0.
2. In the announcement date, price standard deviation of the product line portfolio (which represents *line diversification*) influences positively the stock reaction to a line extension announcement. This implies rejecting H_2 (the sign is the opposite to the one that was hypothesized).
3. Average price (which represents line *positioning*) does not have any effect on the stock reaction to a line extension announcement. This implies rejecting H_3.
4. In the day after the announcement, sales concentration (which represents *intra-line competition*) influences positively the stock reaction to a line extension announcement. This implies not rejecting H_4 in t_1.

The previous conclusions are based on results which are significant at a significance level of 0.10 in both studies (Study 1 and 2) and which are significant at a significance level of 0.05 in one of the studies.

7. Discussion.

7.1. Summary of findings.

In this paper the main goal is to unveil the moderating role played by the product line characteristics in the investors' reaction to a line extension (new product) announcement. For that, I make use of six different brands from the smartphone industry and the event study methodology to try to aisle the effects of product line characteristics on the stock reaction to announcements.

After two studies, one of them (the second one) which controls for time differences between the US and Asian stock markets, I detected statistically significant effects in two of the three dimensions proposed by Morgan & Rego -scope, positioning and intra-competition.

Regarding the line scope, it includes the sub-dimensions line depth (number of products) and line diversification (portfolio price standard deviation). The results of my empirical analyses show that the more products a firm has in its product line portfolio (high line depth), the more negative is the stock reaction when this portfolio is extended. Additionally, stock reaction is more positive when the product line portfolio in which the new product is introduced is more diversified (i.e., contains products with several different price levels, leading to a high price standard deviation). This shows that investors value more positively product line extensions when portfolios are shallow (with few products) and diversified in terms of pricing options. This may indicate that investors are averse to the *risk of cannibalization*, especially when the firm has little price variation among its models (so a lack of price diversification in its portfolio). On the one hand, the more products in a line, the more likely products overlap in meeting the needs of consumers and cannibalize the sales of each other. On the other hand, if a line is designed in a way that each product targets a different segment, products are less likely to cannibalize each other's sales.

As to line positioning, which has been measured by the line portfolio average price, no significant result has been found. However, when looking at intra-line competition, measured by the Herfindahl sales concentration index, results show that more positive reactions are related to higher levels of sales concentration. This means that investors react more positively when a product is introduced in a line with low intra-competition.

Perhaps, they interpret that the portfolio is not competitive enough and a line extension will bring more profits than losses as there is room for a new product.

Last but not least, these previous effects have been only detected in short windows. Specifically, the effects of line scope are detected in the same day of the announcement, while the effects of intra-line competition are detected in the following day.

7.2. Managerial implications.

Knowledge about how stock price reacts to line extensions provides managers with useful insights about how to design an optimal product line portfolio. Stock price reflects the investors' valuation about the future financial performance of a company, thus right changes in the line are expected to have positive consequences in the firm's financial health. Managers could use the previous results to maximize stock reaction to announcements in the short-term; however, I think this knowledge is not exclusively applicable in a financial field, but it can help to improve product and communication strategies.

Empirical analysis tested that line depth affects negatively stock reaction to a new line extension, while line diversification affects positively. These results show that investors are sensitive to *cannibalization risk*; they prefer shorter product lines which target different segments with different price sensitivities. Based on this, managers which aim to create an optimal product line should carefully segment the market, taking into account willingness-to-pay, and design a product line portfolio in which several segments are covered and each product is clearly differentiated and has a specific role in the portfolio. In relation to communication strategies, so as to ensure that investors' acceptance towards the new product is optimized, managers should clearly communicate (1) the characteristics that differentiate the new product from older ones and (2) the target of the new product. Price strategy could also help to differentiate products within the line.

Investors value more positively new launches in a low competitive line. This means that the markets reward product lines which contain a flagship product. Low intra-competition, as proposed before, may indicate that there is room for a new product. Also, this flagship product may set an example of the company's abilities and signal that the brand is able to market another successful product. Last, regarding communication applications, managers could leverage the fame of the flagship product to enhance the chances of the new product to be accepted and successful.

Definitely, companies in the smartphone industry could draw upon the previous managerial implications. Based on the portfolio characteristics of the six brands from 2007 to 2014 (Table 6), Apple should maintain its small portfolio and keep leveraging the reputation of its flagship product; however, it should introduce a different price-quality tier in its portfolio.

HTC and LG could improve their portfolio by cutting a few products out. In particular, LG's smartphone portfolio shows a very low concentration; due to this fact, it should redefine its smartphone line by differentiating its products in terms of characteristics and target, and start designing a flagship product. Motorola's first priority should be to diversify its portfolio and to establish different price-quality tiers so as to avoid cannibalization.

Nokia, according to the conclusions in this paper, holds a quite adequate portfolio; it could get better by reducing product line depth, but it would probably lose some line diversification. Therefore, Nokia should invest in improving the acceptance of new products by means of the previously mentioned communicative strategies.

Last, Samsung holds a very deep portfolio. It should reduce the quantity of products and transform its portfolio into a more efficient one. With such amount of products, Samsung is probably losing money, because of the failure to take advantage of economies of scale, and confusing consumers. By cutting out products with no strategic role or products which pay a minor role, Samsung could invest more in enhancing and promoting its big players and it could probably fight back more efficiently against new suppliers in the Asian market (e.g. Xiaomi).

7.3. Limitations and further research.

Inevitably, the current analysis carries some limitations with it. First, with regards to data limitations, announcements data have been collected manually, which attains some errors with it; for instance, there might be mistakes in the data collection process and there is a sample bias due to the fact that only announcements which have been found are included in the analysis. Moreover, stock price data have a daily frequency, while the rest of the data have a quarterly frequency. Although this still allows to run the analysis by converting quarterly data to a daily frequency, because of the linear conversion, it is difficult to achieve precise estimations in the models. Due to the same reason, control variables are not able to explain part of the abnormal returns as converted data cannot reflect the specific performance of a company in a certain day. Last, a larger sample with a higher number of companies in it might be able to get to better and more robust results.

Second, regarding methodology limitations, in the event study which has been performed, dependent variables are estimations of previous OLS regressions, which is a drawback. In addition to this, stock price data reflect the state of the whole company, but the smartphone line and its announcements are only a part from it. Although it is still possible to get estimations, we cannot discard that abnormal returns are also influenced by other parts of the companies. Additionally, some models transgress linear regression assumptions, particularly residual normality and no autocorrelation. Therefore, I cannot ensure that t-tests are fully reliable. In order to fix this problem, further research could use different models, different variables or take into account brand heterogeneity.

Third, the analysis has been performed only in the smartphone industry. For this reason, results are expected to be generalizable to industries with similar profiles – with high innovativeness, growing competition and medium product life cycle. Further research could apply this analysis to different industries in order to test the generalizability of the previous conclusions.

On the other hand, due to the fact that this is a quite unexplored topic, further research needs to explore and complete it. Some options may be analysing interactions between line portfolio dimensions, considering new line dimensions or trying to measure them in a different way. For instance, it has already been mentioned that the line positioning variable may have measurement error; hence, research could propose more accurate methods to measure it. In addition, one could deeply explore differences in stock reactions between oriental and occidental markets.

Last, the concept of sales concentration in a product portfolio is an unexplored topic in the literature. Research is needed to assess what are the consequences of having a high or low concentrated portfolio, to determine how it is related to cannibalization risk and to define new ways to measure it.

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Appendix 1: Data Analysed.

Appendix Table 1. New smartphone announcements in US (2007-2014).

Date	Vendor	Model	Date	Vendor	Model
08/01/2007	Nokia	N76	**12/04/2011**	LG	Thrive
28/06/2007	Motorola	Q9	**21/04/2011**	Samsung	Droid Charge
14/11/2007	Nokia	N82	**05/05/2011**	Motorola	Titanium
11/02/2008	Nokia	N78	**05/05/2011**	Motorola	XPRT
11/02/2008	Nokia	N96	**02/06/2011**	Samsung	Gravity Smart
18/02/2008	Samsung	Ace	**30/06/2011**	HTC	Status
16/06/2008	Nokia	E66	**02/09/2011**	HTC	Radar
16/06/2008	Nokia	E71	**09/09/2011**	Samsung	Galaxy Pro
26/08/2008	Nokia	N79	**14/09/2011**	LG	Marquee
26/08/2008	Nokia	N85	**20/09/2011**	HTC	Rhyme
11/11/2008	HTC	Fuze	**21/09/2011**	LG	Enlighten
12/11/2008	Nokia	E63	**28/09/2011**	LG	Esteem
02/12/2008	Nokia	N97	**04/10/2011**	Apple	iPhone 4s
06/01/2009	Motorola	Tundra VA76R	**05/10/2011**	Samsung	Conquer
16/02/2009	HTC	Touch Pro2	**11/10/2011**	Samsung	Transfix
17/02/2009	Nokia	E75	**17/10/2011**	LG	DoublePlay
14/05/2009	Samsung	Jack	**18/10/2011**	Motorola	Droid Razr
25/06/2009	HTC	Ozone	**20/10/2011**	Motorola	Admiral
25/08/2009	Nokia	5230	**03/11/2011**	HTC	Rezound
02/09/2009	Nokia	X6	**09/01/2012**	HTC	Titan II
10/09/2009	Motorola	Cliq	**09/01/2012**	LG	Connect
06/10/2009	Samsung	Intrepid	**09/01/2012**	Samsung	Galaxy Attain
07/10/2009	Samsung	Moment	**10/01/2012**	Samsung	Galaxy S Blaze
07/01/2010	Apple	iPhone 4	**11/01/2012**	Motorola	Droid Razr Maxx
07/01/2010	Motorola	Backflip	**27/02/2012**	Nokia	Pureview 808
22/03/2010	Motorola	I1	**29/02/2012**	HTC	One X
13/04/2010	Nokia	E5	**29/02/2012**	HTC	One V
13/04/2010	Nokia	C6	**29/02/2012**	HTC	One S
24/05/2010	LG	Fathom	**17/04/2012**	LG	Optimus Elite
14/06/2010	HTC	Aria	**24/05/2012**	Samsung	Galaxy Appeal
23/06/2010	Motorola	Droid X	**01/08/2012**	Motorola	Electrify 2
24/06/2010	Samsung	Acclaim	**03/08/2012**	Samsung	Galaxy S Lightray
07/07/2010	Motorola	Charm	**05/09/2012**	Nokia	Lumia 820
02/09/2010	Motorola	Defy	**06/09/2012**	Samsung	Galaxy S Relay
14/09/2010	Nokia	E7	**12/09/2012**	Apple	iPhone 5
05/10/2010	Motorola	Flipside	**18/09/2012**	LG	Optimus G
05/10/2010	Motorola	Bravo	**04/10/2012**	Samsung	Galaxy Stellar
06/10/2010	LG	Optimus S	**08/10/2012**	LG	Optimus L9
06/10/2010	LG	Optimus T	**08/10/2012**	Nokia	Lumia 810
06/10/2010	Motorola	Citrus	**29/10/2012**	Samsung	Galaxy Express

14/10/2010	Nokia	C5-03	**29/10/2012**	Samsung	Galaxy Rugby Pro
15/11/2010	LG	Vortex	**01/11/2012**	Motorola	Electrify M
22/11/2010	LG	Optimus M	**05/12/2012**	Nokia	Lumia 620
07/12/2010	Samsung	Nexus S	**13/02/2013**	LG	Optimus G Pro
05/01/2011	Motorola	Atrix	**21/02/2013**	LG	Optimus F7
05/01/2011	Motorola	Cliq 2	**07/06/2013**	LG	Optimus F3
06/01/2011	HTC	Thunderbolt	**26/06/2013**	HTC	8XT
06/01/2011	HTC	Inspire 4G	**18/07/2013**	Samsung	Galaxy Discover
06/01/2011	LG	Revolution	**24/07/2013**	Motorola	Droid Mini
15/02/2011	HTC	Wildfire S	**03/09/2013**	HTC	Desire 601
25/02/2011	HTC	Merge	**10/09/2013**	Apple	iPhone 5c
11/03/2011	Samsung	Galaxy Fit	**10/09/2013**	Apple	iPhone 5s
24/03/2011	LG	Thrill 4G	**23/10/2013**	LG	Enact
12/04/2011	HTC	Sensation	**23/10/2013**	Samsung	Galaxy S4 Mini

Appendix Table 2. Financial and geographic information of the companies included in the analysis.

	Apple	HTC	LG	Motorola	Nokia	Samsung
Financial market	Nasdaq	TW	KSE	NYSE	NYSE	KSE
Country of financial market	EEUU	Taiwan	South Korea	EEUU	EEUU	South Korea
Benchmark composite	NASDAQ COMPOSITE	TSEC	KOSPI	NYSE COMPOSITE (DJ)	NYSE COMPOSITE (DJ)	KOSPI
Currency	U.S. Dollar	Taiwan New Dollar	South Korean Won	U.S. Dollar	U.S. Dollar	South Korean Won
Time difference	GMT – 4	GMT + 8	GMT + 9	GMT – 4	GMT – 4	GMT + 9
Country of origin (COO)	EEUU	Taiwan	South Korea	EEUU	Finland	South Korea

Appendix Table 3. Descriptive statistics of abnormal and cumulative abnormal returns.

Apple					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	4	-0.002351	0.006364	0.000864	0.003815
AR2	4	-0.001574	0.012725	0.003315	0.006394
AR3	4	-0.002989	-0.000067	-0.000973	0.001355
AR4	4	-0.003222	0.005099	-0.000036	0.003664
AR5	4	-0.001481	0.008174	0.002459	0.004543
CAR2	4	-0.003925	0.019089	0.004180	0.010193
CAR3	4	-0.006915	0.018739	0.003207	0.010945
CAR4	4	-0.010137	0.023838	0.003171	0.014573
CAR5	4	-0.011030	0.032013	0.005630	0.018467

HTC					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	16	-0.027284	0.027713	0.000160	0.013347
AR2	16	-0.016960	0.030922	0.002332	0.012674
AR3	16	-0.016686	0.033535	0.000772	0.013346
AR4	16	-0.037213	0.026937	-0.001170	0.014197
AR5	16	-0.022606	0.038343	0.001834	0.017626
CAR2	16	-0.019859	0.035519	0.002492	0.017710
CAR3	16	-0.031691	0.054227	0.003265	0.021902
CAR4	16	-0.037431	0.055565	0.002095	0.026852
CAR5	16	-0.050949	0.091100	0.003929	0.041589

LG					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	19	-0.005228	0.005344	0.000214	0.002373
AR2	19	-0.007438	0.020009	0.001690	0.005068
AR3	19	-0.006252	0.007765	0.000354	0.002862
AR4	19	-0.004456	0.002235	0.000314	0.001898
AR5	19	-0.001650	0.014065	0.002288	0.003897
CAR2	19	-0.006062	0.025353	0.001904	0.006420
CAR3	19	-0.012314	0.026740	0.002258	0.007522
CAR4	19	-0.010079	0.028617	0.002572	0.008236
CAR5	19	-0.007792	0.030492	0.004860	0.008900

Motorola					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	18	-0.007531	0.006926	-0.001883	0.003516
AR2	18	-0.022365	0.010319	-0.000380	0.007038
AR3	18	-0.004650	0.001884	-0.000472	0.001932
AR4	18	-0.012401	0.007322	-0.000394	0.004328
AR5	18	-0.008160	0.008080	-0.000071	0.003385
CAR2	18	-0.027403	0.006552	-0.002263	0.007864
CAR3	18	-0.031827	0.006133	-0.002735	0.008719
CAR4	18	-0.044228	0.011332	-0.003129	0.012344
CAR5	18	-0.044656	0.011090	-0.003201	0.012699

Nokia					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	17	-0.008160	0.084216	0.010287	0.022548
AR2	17	-0.027405	0.007080	-0.002654	0.008936
AR3	17	-0.034873	0.026030	0.001419	0.012428
AR4	17	-0.017090	0.013341	0.002128	0.006842
AR5	17	-0.028547	0.008326	-0.002223	0.008993
CAR2	17	-0.015486	0.069633	0.007633	0.019749
CAR3	17	-0.020810	0.043599	0.009052	0.016730
CAR4	17	-0.015248	0.045063	0.011180	0.016508
CAR5	17	-0.016837	0.051477	0.008957	0.017659

Samsung					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AR1	21	-0.003898	0.010693	-0.000106	0.003390
AR2	21	-0.007461	0.007123	-0.000100	0.003362
AR3	21	-0.007207	0.007850	-0.000185	0.002891
AR4	21	-0.015601	0.005591	-0.001564	0.004955
AR5	21	-0.006094	0.002527	-0.001302	0.001972
CAR2	21	-0.006499	0.017816	-0.000207	0.005295
CAR3	21	-0.007409	0.016870	-0.000391	0.005531
CAR4	21	-0.012907	0.007830	-0.001956	0.005213
CAR5	21	-0.016572	0.009826	-0.003257	0.005956

Appendix Table 4. Descriptive variables of line portfolio characteristics.

Apple					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
NUM_PROD	4	2	3	2.025	0.500
STD_PRICE	4	70.711	145.418	110.601	33.869
AVG_PRICE	4	499.000	616.500	556.583	56.310
CONCENTRATION	4	0.374	0.920	0.631	0.227

HTC					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
NUM_PROD	16	7	20	12.044	4.366
STD_PRICE	16	49.444	158.676	79.550	31.585
AVG_PRICE	16	442.000	522.429	466.347	23.445
CONCENTRATION	16	0.028	0.675	0.148	0.193

LG					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
NUM_PROD	19	2	19	11.016	6.021
STD_PRICE	19	70.71	153.857	99.481	34.137
AVG_PRICE	19	288.947	416.667	356.500	34.056
CONCENTRATION	19	0.042	0.681	0.110	0.143

Motorola					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
NUM_PROD	18	2	12	7.39	3.381
STD_PRICE	18	35.178	150.438	100.765	34.896
AVG_PRICE	18	357.500	499.000	436.567	42.373
CONCENTRATION	18	0.034	0.642	0.250	0.167

Nokia					
	N	Minimum	Maximum	Mean	Std. Deviation
NUM_PROD	17	2	14	7.41	4.784
STD_PRICE	17	35.355	274.357	139.856	76.218
AVG_PRICE	17	251.667	544.000	408.249	90.713
CONCENTRATION	17	0.058	0.835	0.298	0.294

Samsung					
	N	Minimum	Maximum	Mean	Std. Deviation
NUM_PROD	21	4	33	20.62	10.590
STD_PRICE	21	81.343	201.813	136.075	34.116
AVG_PRICE	21	356.903	475.000	394.644	34.381
CONCENTRATION	21	0.021	0.300	0.130	0.078

Appendix Table 5. Descriptive statistics of continuous control variables.

Apple					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	4	14,636,537	57,189,668	34,396,186	21,029,025
ASSETS	4	53,900,000,000	200,000,000,000	133,225,000,000	63,072,993,428
REVENUE	4	172,340,659	388,164,835	314,008,241	100,997,101

HTC					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	16	3,133,227	27,061,632	13,249,782	8,409,497
ASSETS	16	3,340,726,178	9,035,322,850	6,957,161,519	2,049,552,284
REVENUE	16	11,006,418	51,148,203	31,499,327	14,052,284

LG					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	19	740,260	13,896,766	7,406,505	4,254,431
ASSETS	19	27,871,785,190	34,218,586,600	30,504,424,620	2,108,348,014
REVENUE	19	118,942,131	154,478,718	135,561,054	9,889,765

Motorola					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	18	341,525	16,704,721	7,925,139	5,061,520
ASSETS	18	12,000,000,000	34,600,000,000	20,722,222,222	6,931,475,996
REVENUE	18	16,670,330	95,956,044	29,576,233	20,004,955

Nokia					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	17	141,261	3,329,172	1,088,442	707,948
ASSETS	17	29,921,363,040	60,395,881,210	48,026,950,128	7,776,014,466
REVENUE	17	99,573,727	250,238,026	162,780,360	41,237,850

Samsung					
	N	Minimum	Maximum	Mean	Std. Deviation
SUM_VALUE	21	820,885	64,981,332	26,635,464	20,494,447
ASSETS	21	95,631,746,430	202,000,000,000	136,887,226,020	28,000,058,327
REVENUE	21	303,931,573	613,931,434	433,495,761	89,619,806

Appendix Table 6. Descriptive statistics of discrete control variables.

		Apple	HTC	LG	Motorola	Nokia	Samsung	
LOCAL	0	4	8	4	7	16	7	46
	1	0	8	15	11	1	14	49
MULTIPLE	0	4	9	14	11	9	14	61
	1	0	7	5	7	8	7	34
Total		4	16	19	18	17	21	95

Appendix Table 7. Correlation matrix.

			1	2	3	4	5	6	7	8	9	10	11
1	NUM_PROD	Pearson	1	0.269**	-0.407**	-0.487**	-0.461**	0.285**	-0.160	0.698**	0.604**	0.467**	0.527**
		Sig. (2-tailed)		0.008	0.000	0.000	0.000	0.005	0.121	0.000	0.000	0.000	0.000
2	STD_PRICE	Pearson	0.269**	1	0.152	0.291**	0.283**	-0.086	0.006	0.243*	0.253*	0.392**	0.419**
		Sig. (2-tailed)	0.008		0.140	0.004	0.006	0.405	0.952	0.018	0.013	0.000	0.000
3	AVG_PRICE	Pearson	-0.407**	0.152	1	0.479**	0.468**	-0.217*	0.090	-0.123	-0.013	-0.094	-0.179
		Sig. (2-tailed)	0.000	0.140		0.000	0.000	0.035	0.384	0.237	0.900	0.363	0.082
4	CONCENTRATION_ UNITS	Pearson	-0.487**	0.291**	0.479**	1	0.977**	-0.331**	0.017	-0.185	-0.089	0.026	-0.002
		Sig. (2-tailed)	0.000	0.004	0.000		0.000	0.001	0.867	0.073	0.393	0.800	0.988
5	CONCENTRATION_ VALUE	Pearson	-0.461**	0.283**	0.468**	0.977**	1	-0.314**	-0.038	-0.109	-0.006	0.073	0.020
		Sig. (2-tailed)	0.000	0.006	0.000	0.000		0.002	0.714	0.291	0.955	0.480	0.848
6	LOCAL	Pearson	0.285**	-0.086	-0.217*	-0.331**	-0.314**	1	0.020	0.073	0.015	-0.039	0.011
		Sig. (2-tailed)	0.005	0.405	0.035	0.001	0.002		0.845	0.485	0.886	0.711	0.918
7	MULTIPLE	Pearson	-0.160	0.006	0.090	0.017	-0.038	0.020	1	-0.240*	-0.239*	-0.140	-0.125
		Sig. (2-tailed)	0.121	0.952	0.384	0.867	0.714	0.845		0.019	0.020	0.176	0.227
8	SUM_UNITS	Pearson	0.698**	0.243*	-0.123	-0.185	-0.109	0.073	-0.240*	1	0.982**	0.667**	0.644**
		Sig. (2-tailed)	0.000	0.018	0.237	0.073	0.291	0.485	0.019		0.000	0.000	0.000
9	SUM_VALUE	Pearson	0.604**	0.253*	-0.013	-0.089	-0.006	0.015	-0.239*	0.982**	1	0.701**	0.649**
		Sig. (2-tailed)	0.000	0.013	0.900	0.393	0.955	0.886	0.020	0.000		0.000	0.000
10	ASSETS	Pearson	0.467**	0.392**	-0.094	0.026	0.073	-0.039	-0.140	0.667**	0.701**	1	0.968**
		Sig. (2-tailed)	0.000	0.000	0.363	0.800	0.480	0.711	0.176	0.000	0.000		0.000
11	REVENUE	Pearson	0.527**	0.419**	-0.179	-0.002	0.020	0.011	-0.125	0.644**	0.649**	0.968**	1
		Sig. (2-tailed)	0.000	0.000	0.082	0.988	0.848	0.918	0.227	0.000	0.000	0.000	
	N		95	95	95	95	95	95	95	95	95	95	95

***. Correlation is significant at the 0.01 level (2-tailed).*

**. Correlation is significant at the 0.05 level (2-tailed).*

Appendix 2: Study 1 output.

Main results

Appendix Table 8. Study 1 output with AR1 as dependent variable.

DEPENDENT VARIABLE: Abnormal returns of window t_0 (AR1)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.000670017	0.9419	0.003448417	0.7122	0.001693085	0.8582	0.001670895	0.8612	0.004309188	0.6693
NUM_PROD	-0.000366098*	0.0621	-0.000322896	0.1118	-0.000461455	0.1008	-0.000408390*	0.0682	-0.000375059	0.1894
STD_PRICE	0.000055888*	0.0613	0.000052937*	0.0784	0.000057621*	0.0567	0.000055574*	0.0761	0.000053534*	0.0976
AVG_PRICE	0.000003930	0.8523	0.000003182	0.8801	0.000002222	0.9177	0.000001930	0.9309	0.000001205	0.9584
CONCENTRATION	-0.013406755*	0.0740	-0.01531547**	0.0464	-0.014516300*	0.0660	-0.014586388*	0.0633	-0.01619595**	0.0485
LOCAL			-0.003982643	0.1244					-0.003794242	0.1547
MULTIPLE			-0.000559105	0.8285					-0.000421707	0.8739
SUM_VALUE					0.000000031	0.6328			2.107e-11	0.8878
ASSETS							5.142e-14	0.6014	2.542e-14	0.8194
REVENUE							-1.283e-11	0.7052	-6.500e-12	0.8559
R^2	0.05925		0.08525		0.06325		0.0641		0.08741	
ADJUSTED R^2	0.01744		0.02288		0.01062		0.00029		-0.009218	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.1373		0.2583		0.2179		0.2958		0.494	
Durbin-Watson (p-value)	0.0524		0.05118		0.04569		0.03978		0.02876	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Abnormal returns of window t_0 (AR1)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.0008024	0.9307	0.0004863	0.9580
NUM_PROD	-0.0004209*	0.0563	-0.0004102*	0.0659
STD_PRICE	0.00005299*	0.0813	0.00005294*	0.0853
AVG_PRICE	0.000004384	0.8362	0.000005053	0.8131
CONCENTRATION	-0.01455*	0.0627	-0.01423*	0.0677
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	1.577e-14	0.5760		
REVENUE			4.141e-12	0.6701
R^2	0.06257		0.06118	
ADJUSTED R^2	0.009904		0.008435	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.2119		0.1993	
Durbin-Watson (p-value)	0.05071		0.04942	
METHOD	OLS		OLS	

Appendix Table 9. Study 1 output with AR2 as dependent variable.

DEPENDENT VARIABLE: Abnormal returns of window t_1 (AR2)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.005633	0.353	0.005846	0.3493	0.006588	0.3012	0.006900	0.2729	0.008032	0.2318
NUM_PROD	0.00009562	0.455	0.0001056	0.4329	0.00003609	0.8352	0.0001298	0.3740	0.00007898	0.6756
STD_PRICE	-0.00002587	0.186	-0.00002663	0.1826	-0.00002468	0.2117	-0.00002117	0.3004	-0.00001966	0.3563
AVG_PRICE	-0.00001384	0.320	-0.00001407	0.3185	-0.00001553	0.2800	-0.00001765	0.2292	-0.00001994	0.1951
CONCENTRATION	0.01090**	0.028	0.01085**	0.0346	0.01003*	0.0564	0.01116*	0.0311	0.01061*	0.0512
LOCAL			-0.0004456	0.7953					-0.0003188	0.8561
MULTIPLE			0.0002552	0.8821					0.0004807	0.7851
SUM_VALUE					3.840e-11	0.6098			5.639e-11	0.5697
ASSETS							4.914e-14	0.4475	3.010e-14	0.6838
REVENUE							-1.927e-11	0.3876	-1.536e-11	0.5180
R^2	0.05935		0.06027		0.06211		0.06794		0.07239	
ADJUSTED R^2	0.01754		-0.003807		0.009425		0.004389		-0.02582	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.8007		0.8615		0.8743		0.5597		0.7198	
Durbin-Watson (p-value)	0.9561		0.941		0.9397		0.9382		0.9145	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Abnormal returns of window t_1 (AR2)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.005596	0.359	0.005768	0.312
NUM_PROD	0.000111	0.441	0.0001281	0.379
STD_PRICE	-0.00002506	0.209	-0.00002369	0.240
AVG_PRICE	-0.00001397	0.319	-0.00001467	0.298
CONCENTRATION	0.01122*	0.030	0.01150	0.0254
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	-4.417e-15	0.812		
REVENUE			-3.054e-12	0.633
R^2	0.05995		0.06177	
ADJUSTED R^2	0.007141		0.009063	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.4918		0.4284	
Durbin-Watson (p-value)	0.9517		0.9543	
METHOD	OLS		OLS	

Appendix Table 10. Study 1 output with AR2 as dependent variable.

DEPENDENT VARIABLE: Cumulative abnormal returns of window t_0- t_1 (CAR2)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.006303	0.526	0.009295	0.358	0.009005	0.387	0.008571	0.406	0.01234	0.257
NUM_PROD	-0.0002705	0.199	-0.0002173	0.319	-0.0004388	0.124	-0.0002786	0.245	-0.0002961	0.334
STD_PRICE	0.00003002	0.348	0.00002630	0.414	0.00003338	0.301	0.00003440	0.305	0.00003387	0.327
AVG_PRICE	-0.00000991	0.664	-0.00001089	0.632	-0.0000147	0.531	-0.00001572	0.513	-0.00001873	0.451
CONCENRATION	-0.002510	0.755	-0.004463	0.587	-0.004970	0.559	-0.003426	0.683	-0.005583	0.523
LOCAL			-0.004428	0.113					-0.004113	0.151
MULTIPLE			-0.0003039	0.913					0.00005897	0.984
SUM_VALUE					1.086e-10	0.379			7.746e-11	0.630
ASSETS							1.006e-13	0.344	5.552e-14	0.643
REVENUE							-3.210e-11	0.380	-2.186e-11	0.570
R^2	0.02184		0.04988		0.03038		0.03194		0.05883	
ADJUSTED R^2	-0.02163		-0.0149		-0.0241		-0.03407		-0.04083	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.1573		0.2493		0.304		0.2423		0.4134	
Durbin-Watson (p-value)	0.1063		0.4231		0.08571		0.0624		0.01774	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Cumulative abnormal returns of window t_0- t_1 (CAR2)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.006398	0.522	0.006255	0.532
NUM_PROD	-0.0003099	0.191	-0.000282	0.239
STD_PRICE	0.00002793	0.392	0.00002924	0.376
AVG_PRICE	-0.000009583	0.676	-0.000009615	0.677
CONCENTRATION	-0.003332	0.690	-0.002726	0.744
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	1.135e-14	0.709		
REVENUE			1.087e-12	0.918
R^2	0.02338		0.02196	
ADJUSTED R^2	-0.03149		-0.03298	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.204		0.164	
Durbin-Watson (p-value)	0.09103		0.09008	
METHOD	OLS		OLS	

Results with wider time windows

Appendix Table 11. Study 1 output with AR3, AR4 and AR5 as dependent variables.

	AR3		AR4		AR5	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.008984	0.144	0.0009412	0.868	0.00984	0.146
NUM_PROD	-0.00004457	0.730	-0.0001068	0.374	-0.00002731	0.848
STD_PRICE	-0.000007603	0.699	0.00002063	0.260	-0.00001633	0.452
AVG_PRICE	-0.0000198	0.160	-0.000006394	0.624	-0.00002161	0.165
CONCENTRATION	0.00452	0.361	0.002369	0.606	0.007276	0.184
R^2	0.02934		0.03523		0.0401	
ADJUSTED R^2	-0.0138		-0.007648		-0.002557	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.2731		0.7026		0.6385	
Durbin-Watson (p-value)	0.9641		0.8027		0.319	
METHOD	OLS		OLS		OLS	

Appendix Table 12. Study 1 output with AR3, AR4 and AR5 as dependent variables.

	CAR3		CAR4		CAR5	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.01529	0.145	0.01623	0.182	0.02607	0.105
NUM_PROD	-0.000315	0.155	-0.0004218	0.101	-0.0004491	0.185
STD_PRICE	0.00002241	0.505	0.00004305	0.270	0.00002672	0.603
AVG_PRICE	-0.00002971	0.217	-0.00003611	0.195	-0.00005772	0.118
CONCENTRATION	0.002010	0.812	0.004379	0.655	0.01165	0.368
R^2	0.03586		0.05445		0.05374	
ADJUSTED R^2	-0.006993		0.01242		0.01168	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.4567		0.5267		0.6536	
Durbin-Watson (p-value)	0.03906		0.01158		0.02841	
METHOD	OLS		OLS		OLS	

Appendix 3: Study 2 output.

Main results

Appendix Table 13. Study 2 output with AR1 as dependent variable.

DEPENDENT VARIABLE: Abnormal returns of window t_0 (AR1)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.00500786	0.5840	0.006740740	0.4710	0.004679288	0.6267	0.005568070	0.5589	0.006726684	0.5052
NUM_PROD	-0.00043509**	0.0264	-0.000377669*	0.0634	-0.000414617	0.1167	-0.000412996*	0.0643	-0.000319474	0.2629
STDPRICE	0.000062336**	0.0363	0.000058048**	0.0539	0.000061927**	0.0399	0.000064818**	0.0385	0.000059743*	0.0650
AVGPRICE	-0.00000699	0.7392	-0.000008261	0.6953	-0.000006406	0.7678	-0.000008775	0.6926	-0.000008874	0.7007
CONCENTRATION	-0.00870711	0.2408	-0.009430734	0.2166	-0.008407928	0.2869	-0.008450564	0.2771	-0.008669721	0.2869
LOCAL			-0.003120103	0.2272					-0.003189120	0.2308
MULTIPLE			0.001010970	0.6953					0.000964329	0.7167
SUMVALUE					-1.320e-11	0.9076			-2.242e-11	0.8807
ASSETS							2.045e-14	0.8348	1.692e-14	0.8793
REVENUE							-8.760e-12	0.7954	-7.719e-12	0.8292
R^2	0.06955		0.086		0.06969		0.07047		0.08738	
ADJUSTED R^2	0.0282		0.02368		0.01743		0.007093		-0.009249	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.06744		0.09324		0.1137		0.1625		0.2486	
Durbin-Watson (p-value)	0.01182		0.003269		0.00974		0.006436		0.001192	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Abnormal returns of window t_0 (AR1)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.004975	0.589	0.005097	0.5798
NUM_PROD	-0.0004215*	0.055	-0.0004137	0.0624
STD_PRICE	0.00006305**	0.038	0.00006377	0.0380
AVG_PRICE	-0.0000071	0.737	-0.000007533	0.7232
CONCENTRATION	-0.008425	0.276	-0.008308	0.2808
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	-3.894e-15	0.890		
REVENUE			-2.011e-12	0.8353
R^2	0.06976		0.07001	
ADJUSTED R^2	0.01749		0.01776	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.1073		0.1026	
Durbin-Watson (p-value)	0.008937		0.00851	
METHOD	OLS		OLS	

Appendix Table 14. Study 2 output with AR2 as dependent variable.

DEPENDENT VARIABLE: Abnormal returns of window t_1 (AR2)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.005309	0.3742	0.005807	0.3455	0.006754	0.282	0.007272	0.2390	0.008125	0.218
NUM_PROD	0.00005282	0.6754	0.00005518	0.6772	-0.00003725	0.827	0.00006147	0.6671	0.00002716	0.883
STD_PRICE	-0.00002061	0.2841	-0.00002071	0.2921	-0.000018881	0.332	-0.00001591	0.4269	-0.00001465	0.483
AVG_PRICE	-0.00001367	0.3195	-0.00001366	0.3258	-0.00001623	0.252	-0.00001893	0.1890	-0.00002008	0.184
CONCENTRATION	0.009000*	0.0646	0.008574*	0.0888	0.007683	0.136	0.008521*	0.0915	0.007964	0.134
LOCAL			-0.0006022	0.7220					-0.0003343	0.846
MULTIPLE			-0.0003411	0.8402					-0.00007803	0.964
SUM_VALUE					5.809e-11	0.433			3.435e-11	0.724
ASSETS							8.417e-14	0.1860	7.064e-14	0.332
REVENUE							-2.832e-11	0.1965	-2.539e-11	0.278
R^2	0.04544		0.04735		0.05204		0.0644		0.0664	
ADJUSTED R^2	0.00301		-0.0176		-0.001217		0.0006129		-0.03245	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.5709		0.3196		0.7172		0.523		0.3427	
Durbin-Watson (p-value)	0.9526		0.9558		0.9454		0.9526		0.9298	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Abnormal returns of window t_1 (AR2)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.005354	0.3727	0.005333	0.3753
NUM_PROD	0.00003382	0.8115	0.00005859	0.6831
STD_PRICE	-0.00002162	0.2710	-0.00002023	0.3086
AVG_PRICE	-0.00001351	0.3279	-0.00001381	0.3207
CONCENTRATION	0.008604*	0.0896	0.009107	0.0717
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	5.465e-15	0.7652		
REVENUE			-5.423e-13	0.9315
R^2	0.0464		0.04552	
ADJUSTED R^2	-0.007176		-0.008108	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.433		0.3943	
Durbin-Watson (p-value)	0.9428		0.9425	
METHOD	OLS		OLS	

Appendix Table 15. Study 2 output with CAR2 as dependent variable.

DEPENDENT VARIABLE: Cumulative abnormal returns of window t_0- t_1 (CAR2)										
	EQUATION 1.1.		EQUATION 1.2.		EQUATION 1.3.		EQUATION 1.4.		EQUATION 1.5.	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.01032	0.3388	0.01255	0.256	0.01143	0.314	0.01284	0.252	0.01485	0.211
NUM_PROD	-0.0003823*	0.0955	-0.0003225	0.176	-0.0004519	0.146	-0.0003515	0.177	-0.0002923	0.382
STD_PRICE	0.00004172	0.2301	0.00003734	0.289	0.00004311	0.221	0.00004891	0.180	0.00004509	0.233
AVG_PRICE	-0.00002065	0.4041	-0.00002192	0.378	-0.00002263	0.376	-0.0000277	0.288	-0.000002896	0.287
CONCENTRATION	0.0002924	0.9732	-0.0008565	0.924	-0.0007248	0.938	0.00007044	0.994	-0.0007058	0.941
LOCAL			-0.003722	0.221					-0.003523	0.259
MULTIPLE			0.0006699	0.826					0.0008863	0.776
SUM_VALUE					4.489e-11	0.738			1.193e-11	0.946
ASSETS							1.046e-13	0.364	8.755e-14	0.503
REVENUE							-3.708e-11	0.350	-3.311e-11	0.431
R^2	0.04465		0.06109		0.04586		0.05416		0.06906	
ADJUSTED R^2	0.002193		-0.002929		-0.007739		-0.01033		-0.02951	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.2687		0.2012		0.4166		0.2299		0.1917	
Durbin-Watson (p-value)	0.01599		0.003163		0.01195		0.008119		0.001003	
METHOD	OLS		OLS		OLS		OLS		OLS	

DEPENDENT VARIABLE: Cumulative abnormal returns of window t_0- t_1 (CAR2)				
	EQUATION 1.6.		EQUATION 1.7.	
	Coefficient	p-value	Coefficient	p-value
C	0.01033	0.341	0.01043	0.337
NUM_PROD	-0.0003877	0.132	-0.0003551	0.172
STD_PRICE	0.00004143	0.243	0.00004354	0.225
AVG_PRICE	-0.00002061	0.408	-0.00002135	0.395
CONCENTRATION	0.0001787	0.984	0.0007989	0.930
LOCAL				
MULTIPLE				
SUM_VALUE				
ASSETS	1.570e-15	0.962		
REVENUE			-2.553e-12	0.823
R^2	0.04468		0.0452	
ADJUSTED R^2	-0.008993		-0.008445	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.1658		0.1375	
Durbin-Watson (p-value)	0.01261		0.01183	
METHOD	OLS		OLS	

Results with wider time windows

Appendix Table 16. Study 2 output with AR3 and AR4 as dependent variables.

	AR3		AR4	
	Coefficient	p-value	Coefficient	p-value
C	0.008607	0.182	0.004899	0.4438
NUM_PROD	-0.000001911	0.989	-0.0001827	0.1783
STD_PRICE	-0.00002335	0.260	0.00003528*	0.0886
AVG_PRICE	-0.00001798	0.225	-0.00001569	0.2861
CONCENTRATION	0.005731	0.272	0.002953	0.5680
R^2	0.03823		0.06508	
ADJUSTED R^2	-0.004515		0.02353	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.4541		0.5767	
Durbin-Watson (p-value)	0.8998		0.457	
METHOD	OLS		OLS	

Appendix Table 17. Study 2 output with CAR3 and CAR4 as dependent variables.

	CAR3		CAR4	
	Coefficient	p-value	Coefficient	p-value
C	0.01892	0.129	0.02382	0.168
NUM_PROD	-0.0003842	0.145	-0.0005669	0.121
STD_PRICE	0.00001837	0.645	0.00005365	0.333
AVG_PRICE	-0.00003864	0.177	-0.00005433	0.171
CONCENTRATION	0.006024	0.548	0.008977	0.519
R^2	0.04697		0.05599	
ADJUSTED R^2	0.004617		0.01403	
Saphiro-Wilk (p-value)	0.0000		0.0000	
Breusch-Pagan (p-value)	0.7686		0.6913	
Durbin-Watson (p-value)	0.03584		0.05248	
METHOD	OLS		OLS	

Appendix 4: Robustness check.

Appendix Table 18. Study 1 output with AR1, AR2 and CAR2 as dependent variables and Apple exclusion.

	AR1		AR2		CAR2	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.001583	0.8738	0.005198	0.4227	0.006781	0.526
NUM_PROD	-0.000381*	0.0630	0.0001144	0.3864	-0.0002666	0.222
STD_PRICE	0.00005827*	0.0657	-0.00002931	0.1524	0.00002895	0.389
AVG_PRICE	0.000001942	0.9329	-0.00001271	0.3971	-0.00001077	0.663
CONCENTRATION	-0.01467*	0.0778	0.01133*	0.0367	-0.003342	0.705
R^2	0.06046		0.06081		0.01973	
ADJUSTED R^2	0.01676		0.01713		-0.02586	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.1464		0.6504		0.169	
Durbin-Watson (p-value)	0.0518		0.9377		0.08323	
METHOD	OLS		OLS		OLS	

Appendix Table 19. Study 2 output with AR1, AR2 and CAR2 as dependent variables and Apple exclusion.

	AR1		AR2		CAR2	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
C	0.004689	0.6364	0.005559	0.3843	0.01025	0.378
NUM_PROD	-0.0004380**	0.0323	0.0000642	0.6211	-0.0003739	0.116
STD_PRICE	0.00006216**	0.0488	-0.0000225	0.2645	0.0000397	0.278
AVG_PRICE	-0.00005955	0.7952	-0.00001423	0.3361	-0.0000202	0.453
CONCENTRATION	-0.008815	0.2841	0.008774*	0.0989	-0.00004186	0.997
R^2	0.06898		0.04445		0.04146	
ADJUSTED R^2	0.02567		0.000003		-0.003123	
Saphiro-Wilk (p-value)	0.0000		0.0000		0.0000	
Breusch-Pagan (p-value)	0.06601		0.479		0.2003	
Durbin-Watson (p-value)	0.01087		0.9626		0.01859	
METHOD	OLS		OLS		OLS	