International Bachelor Economics and Business Economics (IBEB)

Bachelor Thesis

Do New Product Launches Matter for Smartphone Firm Stock Returns? An Event Study Taking Advantage of Google Trends

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Contents

1 Introduction

In *Capitalism, Socialism, and Democracy* (1942), Schumpeter writes on the concept of creative destruction, that “[it] incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one.” (p. 83). This mechanism of product and process innovation has been recognized by economists to be one of the most important drivers of growth for firms, the transformation of markets, and intense competition between global leaders. Product innovation is an important indicator of the innovativeness of the firm and its ability to maintain a competitive advantage.

This is especially true for firms participating in the touchscreen smartphone segment of the ICT industry, where consumers and investors highly value innovative, cutting-edge products. There is intense competition between incumbent firms, best exemplified by the ‘patent wars’, where major players sue and countersue for intellectual property infringement. One of the most prominent cases was the decade-long legal battle between Apple Inc. and Samsung Electronics Co., ending with Samsung ordered to pay the largest jury award for patent infringement in history, at over $1 billion (Zohni, 2018). With every new product launch, consumers expect unprecedented levels of innovation from firms, and thus firms are forced to ‘out-innovate’ their competitors with every new release cycle. Firms are also under intense public scrutiny during all stages of the product development cycle, as consumers yearn to obtain information on the next release. As a result, there exist a considerable number of smartphone bloggers, reviewers, news outlets, and industry experts. For this reason, any information on new products in this industry is quickly disseminated through social media to customers. These characteristics paint the smartphone segment as one of the most innovative and competitive in the ICT industry.

Manufacturers of smartphones are also some of the most important players in the financial markets. For example, Apple Inc. is the world’s largest company by market capitalization, with a value of around $1.5 trillion in 2020, and Samsung is 18th in the world at $301.6 billion (Woo-hyun, 2020). Apple’s shares constitute 4.7% of the Dow Jones industrial average and have a correlation of 0.78 to the S&P 500. For these reasons, investors pay close attention to the success of Apple and related companies, as they play an important role in the movements of financial markets.

However, the connection between the market value of a firm and its level of innovation is not always so clear. Firms often underinvest in R&D due to high uncertainty in the amount and timing of returns on innovation (Sood & Tellis, 2009). Furthermore, research on this relation is plagued by the difficulty of measuring firm performance and innovation. Most research uses the stock market's valuation of firms, while some literature uses accounting measures of firm value (Hall, 1999), or even evaluations by credit ratings agencies (Kraft & Czarnitzki, 2002). This results in the difficulty of establishing a causal relationship between innovation and the firm's performance.

For this reason, the present paper will use the event study methodology to directly relate an innovation – the launch of a new product – to a firm's abnormal returns on the stock market. The advantage of the event study lies with its assumption of efficient markets. If a market is efficient, it will react immediately to any new information, such as the launch of a new product. Given that the information contained in the launch is new and bears implications for future cash flows of the firm, the market will adjust the firm's share price, resulting in abnormal returns, or returns in excess of the normal returns estimated for the firm. This leads to the following research question:

To what extent do new product launches by smartphone companies affect their abnormal returns?

One drawback of the event study, as noted by Sprenger et al. (2014), occurs when there is ambiguity of the event date. Using news, for example T*he Wall Street Journal,* is a common method for data collection in this field (Chaney et al, 1991; Sood & Tellis, 2009). However, a news story covering an event may not be published on the date of the event itself. Additionally, this method often implies searching through thousands of articles and categorizing events manually. Thus, it is cumbersome and may even be misleading to construct an event study using news releases as indicators of events. A solution to this drawback, only made possible recently, is the usage of aggregated data from online social media platforms, such as Google and Twitter. Due to their widespread usage, social networks provide plentiful data on the attention and sentiment of investors and consumers on almost every firm. Some literature has begun using this source of vast data to aid in research, This study will follow Da et al. (2011) in using the Google Search Volume Index (SVI) to enhance and avoid some constraints of event studies. This results in the following sub-question:

Does the Google Search Volume Index bear a relationship with product launches and abnormal returns for firms?

The answers to these research questions bear both societal and scientific implications. From a managerial perspective, it may be valuable to have deeper insights into the effect of product launches on the abnormal returns of the firm. Positive abnormal returns following events are associated with a good outlook on the firm by investors. Given that managers generally aim to increase shareholder value, and if product launches do indeed have a significant effect on abnormal returns, managers should pay more care to how these products are launched in order to ensure positive, rather than negative abnormal returns. Furthermore, a manager can employ an event study ex-post to analyze the effect of a product launch on their firm's value.

From a scientific standpoint, most event studies have focused on events such as earnings releases, mergers and acquisitions, and macroeconomic announcements. There has been research on other events, for example lawsuits (Muoghalu et al, 1990) and collections of events (Antweiler & Frank, 2006), however research focusing on product launches has been limited to a few studies (Sood & Tellis, 2009, Chaney et al, 1991). The results of this paper will also provide evidence for whether the efficient market hypothesis is applicable in this sphere. Finally, this paper will add to the recent but ever-increasing wealth of literature which utilizes data obtained from social media platforms to aid in analysis.

To answer the research question, an event study is conducted on product launches by smartphone companies. 229 product launches from the top 6 publicly traded smartphone companies by market share are investigated. These 6 companies make up around 50% of global smartphone market share and include Apple, Samsung, and Xiaomi.

In brief, this study first utilized Google Trends Search Volume Index data to identify event dates based on peaks in search frequency for products. When comparing these identified peaks to real event dates, which are available for some firms, an almost exact match was found. This alleviates a common limitation of event studies of finding precise dates of events. Next, this study found that (cumulative) abnormal returns were generally insignificant, meaning that new product launches do not result in abnormal effects on the firm's stock prices. An explanation for this result is that 'leakages' of information regarding the new product prior to the event occur frequently in this industry, and thus firms do not experience abnormal returns on the date of the event itself. To test this explanation, a measure of abnormal attention to a product was constructed as a proxy for information leakage, again using the Google Trends Search Volume Index. It was found that this measure, the Abnormal Search Volume Index, is positive and significant before events, implying there is leakage of information about products prior to their release.

The rest of the paper will be organized as follows. Section 2 will build a theoretical framework utilizing relevant literature on the topics of financial markets and event studies, as well as on the use of social media platforms in research on financial markets. Section 3 will give a detailed explanation of the data sources and methods used, namely the event study methodology. Section 4 will give the results, and Section 5 will discuss these results and present a conclusion.

2 Theoretical Framework

There is a wealth of literature concerning the study of financial markets, and the relation of social media platforms to financial markets. The relevant literature on finance will be split into literature on the efficient market hypothesis and its relation to event studies, and behavioral finance literature on investor attention and information release.

2.1 Efficient Market Hypothesis and Event Studies

The Efficient Market Hypothesis (EMH) states that share prices reflect all current information in the market, and are unrelated to prices from other time periods, effectively following a random walk. The efficient market hypothesis has not been proven or disproven, and there is strong support on both sides. Supporters of the hypothesis claim neither technical nor fundamental analysis can allow an investor to build a portfolio that performs better overall than a randomly selected market portfolio with the same amount of risk. Opponents of the theory claim that it is in fact possible to use analysis techniques to predict market movements or to find stocks that are valued incorrectly.

The most common tool used to study the efficient market hypothesis and accordingly the effect of new information releases on firm share prices, is the event study. The present-day methodology for event studies largely stems from Fama et al. (1969), who considered the effect of stock splits, and Ball and Brown (1968) who investigated information contained in earnings reports. These studies introduced the present-day methodology of the event study. Since then, event studies have been performed on all manner of events pertaining to financial and managerial aspects of firms, for example layoffs, plant closures, investment decisions, and even deaths of CEOs (McWilliams & Siegel, 1997).

Event studies work under some main methodological assumptions which relate to capital market efficiency. Event studies assume that markets are efficient in the semi-strong form of the Efficient Market Hypothesis, namely that security prices reflect all publicly available information. New information, such as an earnings release, should have an immediate effect on the security price (Born et al., 2017). If markets are instead slow in reacting to new information, then they may be inefficient. If the markets do not react at all, then this information may be incorporated into the price already and the release contains no new information. This can be summarized into three main methodological assumptions, namely that the stock returns in the event window accurately reflect the economic impact of the event, that the event is unexpected and its effect has not yet been factored into the share price, and that there are no other events in the window which could also be responsible for a change in stock price.

The type of event that this study focuses on is a new product launch, which is inherently a marketing event as it is connected to the commercialization of products. Due to the relative disconnect between finance and marketing literature, literature on the relation between new product launches and firm value is somewhat sparse. However, it is fairly simple to connect the launch of new products to a firm's value: A firm introduces a new product because it expects that the incremental benefits of that project are greater than not undertaking the project (Eddy & Saunders, 1980). By introducing the product, funds are increased for equity interests, increasing discounted cash flow, and in turn affecting the stock price. Thus, it is reasonable to expect a relation between new product launches and changes in stock prices. While there is literature which focuses on this relation, it delivers contradicting results.

Eddy and Saunders (1980) found no effect of new product announcements on stock returns in a sample of 66 announcements over a nine-year period, concluding that markets are efficient in pricing new product developments. They were limited however, in using monthly data as opposed to daily data. Chaney et al. (1991), on the other hand, found aggregate impact of +0.75% on a firm's stock price in a 3-day period around a new product announcement. They also found that the market reaction is negatively related to the number of new product announcements from the firm within a 10-year period, and that the largest market reaction is towards simultaneous announcements of multiple original products. Pauwels et al. (2004) investigate new product introductions in the American automobile industry using variance decomposition analysis and find significant impact of new product introductions on firm value in the short run and especially long run. Sood and Tellis (2009) perform event studies on various types of innovation projects undertaken by firms, one of which is the launch of a new product. They find positive significant market returns of 0.2% ($t = 2.5$) to positive new product announcements, and significant negative market returns to negative product launch announcements such as cancellations or delays (-4.7%, $t = -7.2$). Talay et al. (2019) take an alternative approach and assess the role of moderating variables in stock market reactions to new products, in international markets. They show that CARs are positive (0.31%) around the launch of new products in the packaged foods industry, and that more innovative products lead to more positive abnormal returns. Reasons for negative returns given by literature are summarized as: Disappointing products relative to expectations, high costs of launch, and lack of new competitive advantages from the product. Reasons for positive returns can be signals of competitiveness from the firm, expansion of product lines, and successful innovation. Overall, the direction and significance of returns is highly dependent on the context of the industry and country under study.

This study focuses on the global smartphone industry. As mentioned in Section 1, this industry is highly innovative and competitive. Touchscreen smartphones are released at least yearly by firms such as Apple and Samsung, and feature the latest in processors, storage, displays, and camera technology. Smartphones are released often, for example the major players such as Apple follow a schedule of one flagship device released yearly, with multiple devices released simultaneously at varying price points. Samsung also releases a flagship 'Galaxy S' model phone yearly, with other budget options released around half a year after the flagship. The results of Chaney et al. (1991) give varying indications as to whether smartphone launches influence returns. The frequency of product launches is found to be negatively related to the magnitude of abnormal returns, thus potentially returns will be lower in this study. On the other hand, Chaney et al. (1991) find that CARs in a one-day window around the event are greatest for firms in technologically intensive industries, such as computers and chemicals. Additionally, products regarded as original or innovative receive higher returns than refreshed or repositioned products. Finally, multiple simultaneous product launches give rise to higher abnormal returns (Chaney et al., 1991). Based on this previous literature, it can be expected that smartphone product launches may experience significant abnormal returns. This leads to the first hypothesis:

H1: Smartphone product launches result in significant cumulative abnormal returns for firms.

Event studies often measure abnormal returns, which are the actual ex-post returns of the firm, minus the normal returns of the firm. The cumulative abnormal returns (CARs) over the event window are then used for significance tests (MacKinlay, 1997). If the CARs are significant, this indicates that the security experienced abnormal returns during the event window. The event study methodology used in this study will be explained in greater detail in Section 3.

2.2 Attention and Information Release

This section will discuss the behavioral finance concept of attention and its applications to the event study methodology. Kahneman (1973) wrote that attention is a limited cognitive resource, and thus security prices are affected by the degree of attention they are provided by investors. If a certain stock lacks investor attention, it may be that information is not instantaneously incorporated into the price, contradicting the efficient market hypothesis.

A drawback of studying investor attention is that it is not easily measurable. Previous literature used proxies for investor attention such as extreme trading volume (Barber and Odean, 2008), news articles and headlines (Barber and Odean, 2008; Yuan, 2015), with the assumption that since trading volume was extreme, or news articles were published, then there was investor attention towards that particular stock. This is, however, a strong assumption, as trading volume may change for any number of other reasons, and news articles only imply attention but do not guarantee it.

More recently, studies have used more direct measures of attention obtained from social media platforms. For example, Da et al. (2011) use Google Trends Search Volume as a proxy for investor attention, finding that it is correlated to other proxies of attention and reveals attention of retail investors rather than institutional investors. Peaks in Yahoo! Search traffic volume for certain queries have also been shown to predict peaks in trading volume, with up to 3 days lead (Bordino et al., 2012). Ben-Rephael et al. (2017) focus on institutional investor attention by obtaining search volume data from Bloomberg terminals, which are predominantly used by financial professionals. They find that institutional attention leads retail attention and results in permanent price adjustments, whereas retail attention price adjustments are typically reversed after a year.

Being able to measure attention directly has implications for event studies. The event study methodology assumes that capital markets are efficient, and when information is made public, markets immediately react by adjusting firm stock prices. The existence of abnormal returns is therefore dependent on whether the information released during an event was truly new, or already priced in. This results in an issue when not all the information is released simultaneously, but is instead 'leaked' early, or has delays in becoming public after the event. In this case, there will be abnormal returns at each point where there is a leak of new information, rather than only at the event itself. For this reason, past research often uses longer event windows to capture leaks of information directly before and after the event to be included in the CARs. However, long event windows reduce the power of the test statistic, leading to false inferences on the event's significance (Brown & Warner, 1980, 1985). Another approach to account for leakage of information is to identify all leakage events and estimate abnormal returns for these events as well. Cumulating all the abnormal returns from the event and leakage events will give the total abnormal returns (McWilliams et al., 1999). Examples of leakage events include shareholder meetings or press releases.

In the context of this study, it is reasonable to assume that leakage events in smartphone launches are quite prevalent. The number of people who work on designing and manufacturing smartphones is large, and it is certain that they are not all able to keep the next big release a secret. Moreover, firms affiliated with smartphones, such as case manufacturers, are sent the dimensions and details of the next release in advance so they may prepare accessories. Controlling for these leakages using the method of extending event windows is not feasible. Leakages may occur on all steps of the phone's design and production process, and thus it would be impossible to set the event window long enough to include all of these. However, using the Google Trends Search Volume Index, it may in fact be possible to identify these leaks.

The variable introduced to identify leaks is the Abnormal Search Volume Index (ASVI) (Da et al., 2011). ASVI has a novel use in that it can detect periods in which there is abnormal attention to a product. Da et al. (2011) write that SVI is a measure of revealed attention – an individual who searches for a product is undoubtedly paying attention to it. If the product has not been released, it means that this individual has become aware of some information regarding that product and is seeking more. In the context of this study, abnormal attention is assumed to be a proxy for releases of information. An abnormal number of individuals searching for a certain unreleased product likely indicates that there is some new information available on this product. Thus, ASVI can be used to identify and investigate information leaks. In a perfect scenario, with no leakage prior to an event, ASVIs would equal zero until the day of the event. A significant and positive ASVI on the other hand, indicates that individuals are paying attention to a product at an abnormal level. This measure allows one to statistically check one of the main assumptions in an event study – whether the information released in the event is new or has been leaked prior to the event.

3 Method

Section 3.1 will describe the event study methodology, including the calculations and testing procedures for (cumulative) abnormal returns. Section 3.2 will focus on the usage of the Google Trends Search Volume Index in this study. Both sections will also explain their respective data and sample selection.

3.1 Event Study

To perform an event study, abnormal returns need to be calculated by taking the difference of actual returns and normal returns. Actual return data for all firms and market indices was obtained from the historical price data section on Yahoo! Finance. Closing price data for each firm was obtained from January 2006 until July 2020. To obtain daily actual returns, the following formula was used:

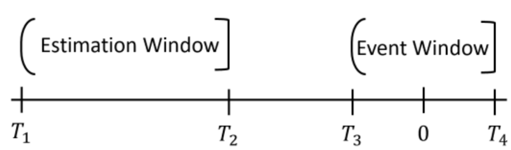
$$R_{i,t} = \ln\left(closing\ price_t - closing\ price_{t-1}\right)$$

The returns data was compared to that given by Compustat and found to be identical. Non-trading days were dropped from the dataset, defined as any day on which either the firm or market returns were missing.

Calculating abnormal returns involves proper selection of an event window and estimation window. An event window needs to be defined around the event date, which usually consists of several days before and after the event. This allows to capture all abnormal returns related to the event, which may occur shortly before or after the event date. A shorter event window is more robust against confounding events, for example another product release occurring within the same timeframe. On the other hand, information may be slow to reach investors, and thus a longer event window may be more effective in capturing the market's entire reaction to an event. An estimation window is also defined, which is used to estimate normal returns. The estimation window typically does not overlap the event window, is set before the event window, and runs for at least 70 days in most studies. Figure 1 shows the timeline of an event study.

Figure 1.

Event Study Timeline



Consider an event occurring at $t = 0$. Let $T_3 = -5$, the beginning of the event window, and $T_4 = 5$, the end of the event window. The length of this event window is:

$$L_2 = (T_4 - T_3) + 1 = 11 \text{ days.}$$

This study will employ several different event windows, shown in Table 1.

Table 1.

Lengths of Event Windows for (Cumulative) Abnormal Returns

	T_3	T_4	L_2
Estimation Window 1	-5	+5	11
Estimation Window 2	-3	+3	7
Estimation Window 3	-1	+1	3

Several different estimation windows will also be defined, for robustness checks. These are summarized in Table 2.

Table 2.

Lengths of Estimation Windows for Estimating Normal Returns

	T_1	T_2	L_1
Estimation Window 1	-100	-30	70
Estimation Window 2	-130	-30	100
Estimation Window 3	-160	-30	130

All estimation windows end 30 days before the event itself. This is to ensure that no information relating to the event confounds the estimation of normal returns. For example, it is possible in the smartphone industry that there is a leak of information on a new product by an insider source. These 'leaks' are often widely publicized, especially for highly anticipated products. The length of estimation windows typically ranges from 90 to 200 days. A longer estimation window is recommended to diminish sampling error (MacKinlay 1997). The lengths chosen in this study are 70, 100, and 130 days, which are on the lower end of the range. The reason for this choice is that smartphone companies operate in a highly dynamic sector, experiencing rapid growth and changes. Furthermore, these companies release products at a rapid pace, often several a year. Thus, choosing a longer estimation period may have two disadvantages: The performance of the firm during a longer estimation window may no longer be relevant to the performance of the firm during the event window, and there may be products released or other events occurring during the estimation window which affect the estimate of normal returns.

With the estimation and event windows defined, it is possible to begin constructing the abnormal returns. Abnormal returns are represented by the following general formula:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

where the three terms are abnormal, actual, and normal returns respectively, for firm i in period t. X_t refers to the conditioning information that determines the normal returns (MacKinlay, 1997). The present paper uses the market model for estimating X_t, which considers each firm's CAPM β factor, and thus assumes a linear relation between the firm's return and market return. Notably, this results in the assumption that the relation between the firm's returns and the market's returns are stable throughout the estimation and event window. The market model for any firm i is:

$$R_{i,t} = \alpha_i + \beta_i R_{mkt} + \varepsilon_{i,t}$$

$$E(\varepsilon_{i,t}) = 0$$

$$var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon_t}$$

where R_{mkt} is the return on the market portfolio in period t. $\varepsilon_{i,t}$ is the error term. For market return, the daily return on the NASDAQ Equal-Weighted index is used. The NASDAQ is used specifically because it is weighted towards the type of technology firms that are the focus of this paper, and thus will form a more accurate baseline than a more general index used in other event studies such as the S&P 500 index or CRSP Value-Weighted index. Additionally, one of the assumptions for obtaining test statistics in event studies is the normality of abnormal return measures. According to Campbell and Wesley (1993), the NASDAQ Value-Weighted index suffers from non-normality of daily returns, and thus recommend using the NASDAQ Equal-Weighted instead. Consequently, in addition to the NASDAQ Equal-Weighted index, this paper will perform robustness checks with the NASDAQ Value-Weighted index, and the CRSP Value-Weighted index. In any case, these indexes are all highly correlated, as shown in Table 2.

Table 2.

Correlations of Returns between Various Market Indexes

	NASDAQ Value-Weighted	NASDAQ Equal-Weighted	CRSP Value-Weighted
NASDAQ Value-Weighted	1.0000		
NASDAQ Equal-Weighted	0.9143	1.0000	
CRSP Value-Weighted	0.9609	0.9202	1.0000

The abnormal returns formula specific to the market model is:

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{mkt}$$

Note that $AR_{i,t}$ is the error term from the market model formula after rearranging.

To draw overall inferences for an event it is necessary to cumulate abnormal returns across time, obtaining the cumulative abnormal returns (CARs). This is achieved in the following formula:

$$CAR_i(T_{3,}T_{4,}) = \sum_{t=T_{3,}}^{T_{4,}} AR_{i,t}$$

Abnormal returns may be aggregated to give average abnormal returns by firm. For example, a firm which releases three products has three sets of abnormal returns. Taking the cross-sectional average gives average abnormal returns by firm.

$$AAR_{i,t} = \frac{\sum AAR_{i,t}}{N}$$

AARs can be cumulated over time, or CARs can be averaged cross-sectionally, to create ACARs. ACARs show the stock market reaction to an average new product launch for each firm:

$$ACAR_i(T_{3,}T_{4,}) = \frac{\sum CAR_i(T_{3,}T_{4,})}{N}$$

The sign, magnitude, and significance of the ACARs and AARs will be used to test whether firms experience abnormal returns within the event windows, or on any day around the launch of new products. Selection of products and event dates is detailed in section 3.2.

3.2 Google Trends

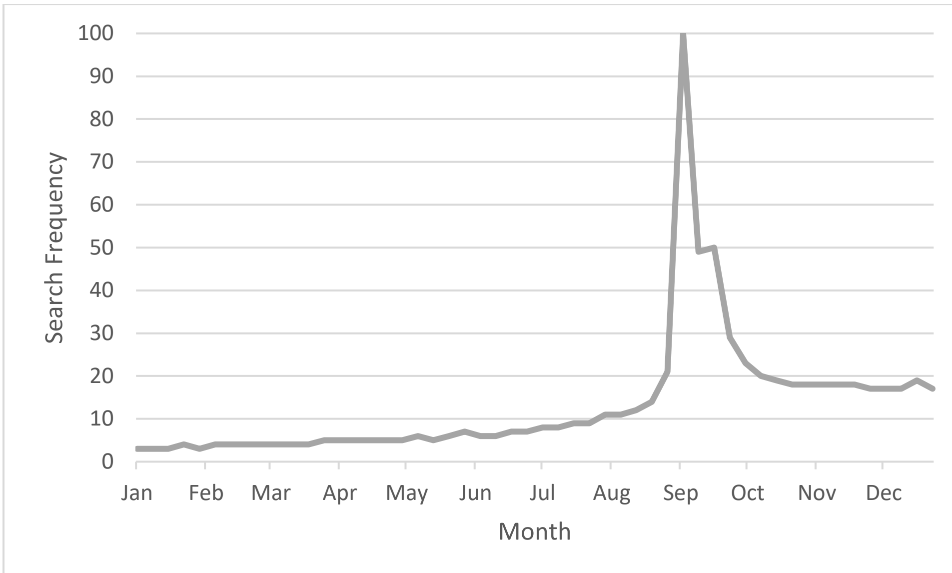
This section will outline the method used to detect product launches to be used in the event study, as well as the construction of the Abnormal Search Volume Index (ASVI) used to identify information leakage. The Trends feature, offered by Google (trends.google.com), is used for both processes.

Recall that one of the limitations of event studies is often the selection of the event date, which may be unclear and labor-intensive to determine. This study will utilize a novel means of detecting event dates by identifying peaks in search frequency for a certain term using Google Trends. Other literature which utilizes similar methods includes Sprenger et al. (2014), Ranco et al. (2015), and Tumarkin and Whitelaw (2001).

The main feature of Google Trends is the Search Volume Index (SVI). This data source provides the frequency of Google searches for any term, scaled by the time series average. The timeframe to be queried is chosen by the user. Google Trends adjusts the granularity of the data based on timeframe chosen. For timeframes under approximately six months long, Trends shows daily search frequency data, and for timeframes longer than six months, Trends gives weekly data. For each product in the sample, the year of the launch was determined, and Google Trends was queried for the name of the product with timeframe set as the year of the launch. For example, a basic search shows that the Apple iPhone 6 was released in 2014. Inputting the search term ‘iPhone 6’ into Google Trends with 2014 as the timeframe gives the output shown in Figure 2.

Figure 2.

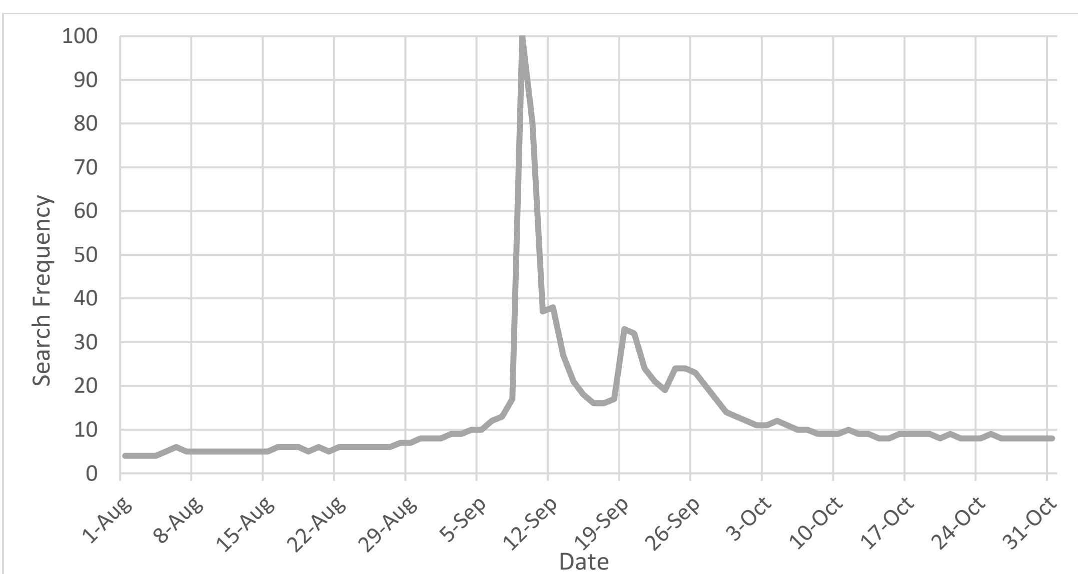
Google Search Frequency for the Apple iPhone 6 in 2014



There is a peak in searches for the Apple iPhone 6 in the beginning of September. To retrieve an exact date for this peak, the timeframe is shortened to 3 months: August, September and October, as shown in Figure 3. From this it is determined that the peak occurs on the 9th of September, which is the date of the press event where Apple unveiled the iPhone 6.

Figure 3.

Google Search Frequency for the Apple iPhone 6 from 1 August to 31 October, 2014



Event dates were determined by selecting the day following the largest single-day increase in search frequency within the timeframe. In Figure 3, the largest single-day increase occurs between the 8th and 9th of September. Thus, the 9th is chosen as the event date. To ensure the accuracy of the chosen dates, the real release dates for Apple and Samsung products within this study (61 products) were identified using traditional methods such as news articles and databases, for example 'GSMArena.com'. Henceforth, Real Event Date refers to a product's event date as determined manually, and Trends Event Date refers to events detected via the Google Trends process. It was found that 60% of the Trends Event Dates exactly match the Real Event Date, and 38% are one day off. Notably, these 38% have a Trends Event Date which is one day after the Real Event Date, and most of the Real Event Dates fall on a weekend or public holiday. Event studies assume that when news is released on a non-trading day, the markets react on the closest following trading day. Thus, within an event study, non-trading days and the trading day immediately following non-trading days are equivalent. The exact choice of date in this case will have no effect on the results. For the firms in this study, the largest single-day increase method of detecting events returns the highest percentage of correct dates relative to other methods such as simply choosing the date of the peak in search frequency, or the 5-day approach used by Tumarkin and Whitelaw (2001).

The data collection results in a sample of 229 product launches from the top 6 publicly traded smartphone companies by market share, which together make up around 50% of the smartphone market (Counterpoint, 2020). Table 3 shows the number of products, or events, per firm.

Table 3.

Number of Touchscreen Smartphone Product Launches Between 2007-2019

Firm	Number of Product Launches
Apple	25
LG	15
Lenovo	38
Samsung	38
Sony	93
Xiaomi	20
Total	229

Note. A product launch is classified as any initial official announcement of a new touchscreen smartphone product by the firm, excluding region-specific releases, for example those only intended for the mainland Chinese market.

The oldest product launch in this dataset is the Apple iPhone, launched on the 9th of January 2007, and the last launch was the Lenovo Motorola One Hyper, on the 5th of December 2019. The full list of product names and Trends Event Dates is available in Appendix 1.

The second part of this section concerns the construction of the Abnormal Search Volume Index (ASVI). Using Search Volume data exported from Google Trends, this variable is constructed by taking the different of log SVI in the current period and the log median SVI during the previous four weeks. Since this variable intends to track SVI over a longer period, the ASVI uses weekly SVI data, as opposed to daily SVI data as when detecting event dates.

ASVI is represented by the following formula:

$$ASVI_t = \log(SVI_t) - \log[Median(SVI_{t-1}, \dots, SVI_{t-4})],$$

where *t* represents the current week.

Using the log median SVI over the previous four weeks captures the median level of search frequency, or attention, that a product receives. This ensures robustness to sudden jumps in search frequency. Logarithms are taken to bring in the high values of SVI which occur with spikes in search frequency. ASVI also removes time trends and seasonality in search frequency. It is important to remove seasonality, as searches for new products, such as the latest iPhone, are highly seasonal. Individuals know that the products are released annually, and thus searches for the next generation increase as the year goes on, regardless of whether any information on the iPhone has been released. Thus, this measure captures abnormal and sudden attention towards a certain search term and can be compared across different search terms. If a product receives a constant level of searches, it will have an ASVI of zero. An ASVI of zero can be interpreted as no abnormal search frequency for a product.

In the present paper, weekly SVI data is extracted from Google Trends for the 300 calendar days before a product release (or approximately 43 weeks). This timeframe was chosen such that there are no confounding effects from other smartphone releases from the same firm, such as the previous-generation smartphone.

4 Results

This section will present all results obtained from the analysis, in two main components. Section 4.1 will present the results of the event study and Section 4.2 will analytically examine an explanation for the results of the event study.

4.1 Event Study

This section will present the results of the event studies. Results are aggregated across events by firm, and across all firms. Table 5 presents Average Cumulative Abnormal Returns (ACARs) for the three different event windows and Abnormal Average Returns (AARs) for each day five days before and after the event. This table uses dates of events as detected by Google Trends. T-statistics test whether the abnormal returns significantly differ from zero with the expectation that AARs are positive and significant on the date of the event and ACARs positive and significant across the event window. Table 5 shows only Lenovo experiences negative and significant (at the 5% level) AARs on the date of the event, however they are quite small (−0.44%). Lenovo experiences negative and significant (at the 10% level) ACARs over the 11-day event window of −2.13%. The 7 and 3-day ACARS are also negative but are insignificant. None of the other firms experience significant ACARs with any length of event window. Notably, the direction of ACARs reverses between the 3-day event window and other windows for Apple and Samsung, indicating abnormal returns may be positive just around the event, but negative when considering more days. In any case, they are insignificant and thus may not be different from zero. None of the firms appear to follow any pattern in the direction of AARs, apart from Lenovo for which all are negative. Apple experiences significant (at the 10% level) positive abnormal returns of 0.65% the day before the event, which are followed by negative but insignificant abnormal returns the next day. This may indicate that investors push the stock price up in anticipation of the event.

The results shown in Table 5 use abnormal returns generated from the 70-day estimation window. Using the alternative windows (as described in Table 1, Section 3) with lengths of 100 days and 130 days do not change the size or direction of the results but do bring the T-statistics closer to zero. ACARs from these alternative estimations with different estimation windows and market return indexes can be found in Appendix 2. Event study literature advocates for longer estimation windows, which reduce sampling error and ensure that the abnormal returns are independent through time (MacKinlay, 1997). However, shorter estimation windows were chosen due to the dynamic nature of these firms. They frequently experience confounding events, such as releases of other products, that could bias normal returns upward, or downward for a disappointing release. It is therefore unclear if the reduced significance of the results in longer estimation windows occurs due to lower sampling error, or existence of confounding factors that bias the estimated normal returns. Regarding the choice of market index when estimating normal returns using the market model, the NASDAQ Equal-Weighted and CRSP Value-Weighted did not give different results. The only significant result when using either index being the positive ACARs for Lenovo using a 70-day estimation window. However, the NASDAQ Value-Weighted market index gives no significant results at all for any firm or estimation window. This follows Campbell and Wesley (1993), who showed that using the NASDAQ Value-Weighted index may result in incorrect inference about significance of mean abnormal returns. Regardless, these robustness checks do not give very different results. Given the previous literature regarding the effect of new product launches on firm value, it is somewhat surprising that no significant abnormal returns were found at all. To test the extent to which using Trends Event Dates influences the results of the event studies, they were repeated for Apple and Samsung using the Real Event Dates obtained from manual research. Table 6 presents the results of the event studies using Real Event Dates and Trends Event Dates side by side for Apple and Samsung.

Table 5.

Market Reaction to New Product Launches in Touchscreen Smartphone Segment, by Firm, using Google Trends to Determine Event Dates

	Apple		LG		Lenovo		Samsung		Sony		Xiaomi	
Event Window	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**
(-5, +5)	-0.4098	-0.25	0.4905	0.38	-2.1335*	-2.07	-0.0722	-0.04	1.0880	1.08	1.5528	0.59
(-3, +3)	-0.7929	-0.49	1.1500	0.88	-1.1588	-1.16	-0.0427	-0.05	0.7124	0.75	1.0008	0.38
(-1, +1)	1.1928	0.73	0.3246	0.25	-0.4674	-0.50	0.0767	0.07	0.1214	0.12	0.2220	0.08
Day Relative to Event	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**
-5	-0.2113	-0.41	-0.2459	-0.93	-0.3730	-1.13	0.0432	0.10	0.2427	1.06	0.0410	0.06
-4	0.7030	1.10	-0.2973	-0.87	-0.0073	-0.03	-0.0005	0.00	-0.0415	-0.16	0.4150	0.45
-3	-0.1957	-0.47	0.5280	1.54	-0.2702	-0.89	0.4697	1.46	0.3889	1.36	1.0672*	1.93
-2	-0.3897	-1.00	0.5853**	2.80	-0.2003	-0.55	-0.5647	-1.29	0.2307	0.79	0.5298	0.56
-1	0.6480*	1.86	-0.0222	-0.06	-0.0226	-0.07	0.0076	0.02	-0.1078	-0.32	1.4058	1.48
0	-0.0686	-0.10	-0.2423	-0.47	-0.4366**	-2.03	0.4672	1.11	-0.0408	-0.16	-0.5125	-0.65
1	0.6134	0.98	0.5890*	2.04	-0.0082	-0.03	-0.3982	-1.21	0.2700	0.82	-0.6713	-0.84
2	-0.5791	-1.56	0.3694	0.64	-0.1228	-0.38	-0.4846*	-1.93	-0.0085	-0.03	0.6448	1.07
3	-0.8212*	-1.84	-0.6572	-1.50	-0.0982	-0.23	0.4603	1.33	-0.0201	-0.08	-1.4630**	-2.41
4	-0.1516	-0.39	-0.4686	-0.96	-0.3805	-1.62	0.0380	0.11	0.3012	1.08	0.1237	0.13
5	0.0429	0.14	0.3522	0.89	-0.2140	-0.77	-0.1103	-0.42	-0.1268	-0.52	-0.0277	-0.07

Note: The first section shows Average Cumulative Abnormal Returns (ACARs) for the three different event windows, and the second section shows Average Abnormal Returns (AARs) by relative day. Days indicated according to the Google Trends date of the events.

***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. Significance levels are derived from two-sided *t*-tests.

Table 6.

Market Reaction to New Product Launches in Touchscreen Smartphone Segment

	Real Event Dates				Trends Event Dates			
	Apple		Samsung		Apple		Samsung	
Event Window	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**	**ACAR**	**T-Stat**
(-5, +5)	-0.9127	-0.57	-0.1417	-0.12	-0.4098	-0.25	-0.0722	-0.04
(-3, +3)	-1.6870	-1.05	-0.0767	-0.07	-0.7929	-0.49	-0.0427	-0.05
(-1, +1)	0.6261	0.39	0.0385	0.03	1.1928	0.73	0.0767	0.07
Day Relative to Event	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**	**AAR**	**T-Stat**
-5	-0.0607	-0.12	-0.1139	-0.26	-0.2113	-0.41	0.0432	0.10
-4	0.5198	0.81	0.1693	0.51	0.7030	1.10	-0.0005	0.00
-3	-0.3805	-1.18	0.3550	1.07	-0.1957	-0.47	0.4697	1.46
-2	-0.5349*	-1.92	-0.4559	-0.99	-0.3897	-1.00	-0.5647	-1.29
-1	0.4768	1.55	-0.0549	-0.17	0.6480*	1.86	0.0076	0.02
0	-0.1771	-0.25	0.4385	1.05	-0.0686	-0.10	0.4672	1.11
1	0.3264	0.48	-0.3452	-1.03	0.6134	0.98	-0.3982	-1.21
2	-0.5626	-1.56	-0.4908*	-1.96	-0.5791	-1.56	-0.4846*	-1.93
3	-0.8352	-1.76	0.4765	1.39	-0.8212*	-1.84	0.4603	1.33
4	-0.1099	-0.22	0.0440	0.13	-0.1516	-0.39	0.0380	0.11
5	0.4251	1.11	-0.1645	-0.63	0.0429	0.14	-0.1103	-0.42

Note: The first set of rows shows Average Cumulative Abnormal Returns (ACARs) for the three different event windows, and the second set shows Average Abnormal Returns (AARs) by relative day. Left columns give show results using Real Event Dates, right columns using Trends Event Dates, to allow for comparison.

***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. Significance levels are derived from two-sided *t*-tests.

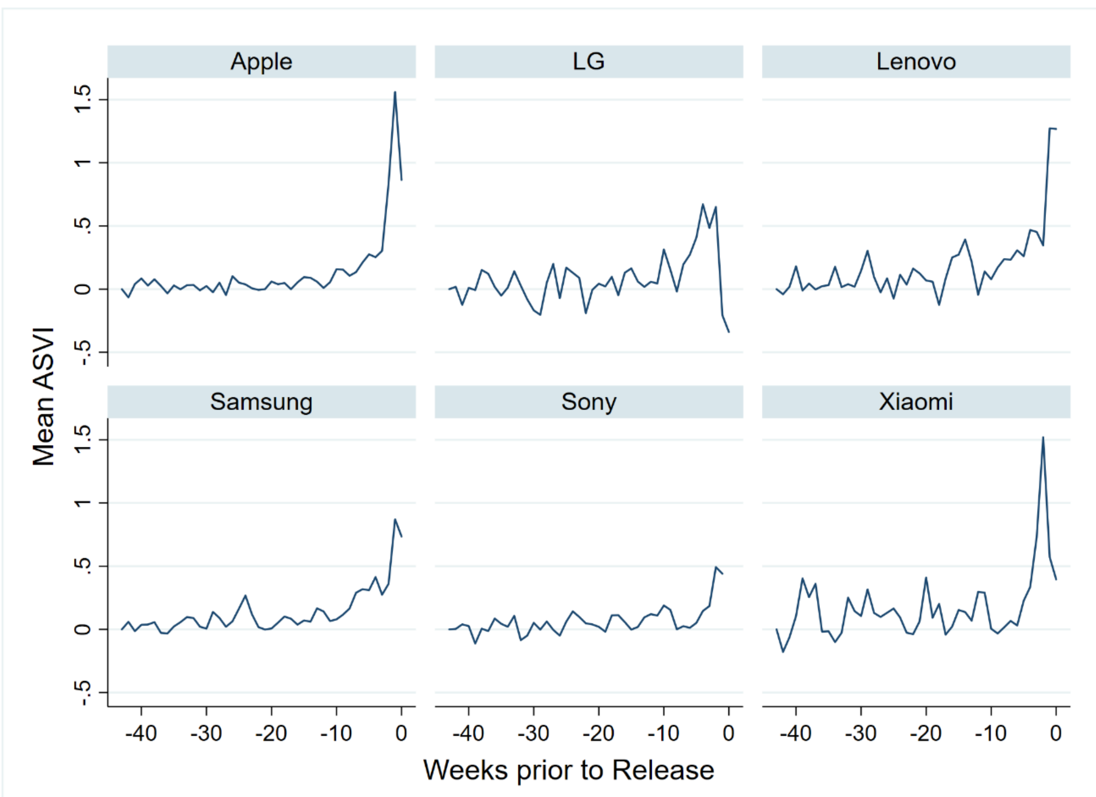
Table 6 shows that ACARs maintain the same sign and significance regardless of which dates are used. The ACARs for Apple are approximately twice as large using Real Event Dates as opposed to Trends Event Dates. Regardless, the T-Statistics indicate that the result is not significant. All AARs for Apple also maintain the same sign, and without major differences in magnitude. Before the event date, the AARs for Samsung differ between Real Dates and Trends Dates, however all these results are insignificant and thus may not differ from zero. Apple experiences significant (at the 10% level) negative AARs on day −2 using Real Dates, however when using Trends Dates, day −1 is significant instead. Samsung experiences a negative and significance AAR on day +2, regardless of how event dates are identified. Overall, Table 6 shows that using Trends Dates gives fairly similar results as using Real Dates. While specific AARs may have difference signs, magnitudes, or significances, the ACARs do not change. In any case, Tables 5 and 6 show that new product launches by smartphone firms do not appear to generate significant abnormal returns. Since this is a somewhat surprising result, the next section will provide additional analysis into one of the assumptions of the event study – that the information contained in the event was not publicly available prior to the event.

4.3 Abnormal Search Volume Index

Figure 3 shows aggregated Abnormal Search Volume Indexes (ASVIs) for all products released by the 6 firms in this study. As with AARs, ASVIs are aggregated across all product launches by firm to give a mean ASVI for each day leading up to the product launch.

Figure 3.

Cross-Sectional Average ASVI before New Product Launch, by Firm



It can be seen from Figure 3 that ASVIs for the firms tend to be positive and increasing up until the product launch. There is a spike just before the launch of the product which likely occurs due to announcements or invitations for the official launch event. Expectations and speculation on the details of the event increase search frequency for terms related to the products to be released. Table 6 presents the results of running a linear regression of ASVI on dummy variables for the week relative to the launch. This allows to view the significance of the ASVIs across time. Almost all coefficients are positive and significant, meaning that ASVIs for these products are non-zero leading up to the event. In the All Firms columns of Table 6, the most positive coefficients are 2 and 1 weeks before the event, with values of 0.696 and 0.646 (p-value < 0.01), respectively. The largest increase relative to the reference category occurs for Apple products, with a highly significant coefficient of 1.531 (*t*-statistic = 189.64) the week before the event. On the other hand, weeks -9 to -12 are insignificant in the Apple column, moreover the constant is only significant with 90% confidence. LG notably has an insignificant constant, meaning the ASVIs more than 12 weeks before the release of the product are not different from zero. Furthermore, the coefficient in weeks -9 to -12 is only significant at the 10% level, and the coefficient in weeks -5 to -8 at the 5% level. This means that LG begins to experience ASVIs only as the date of the event draws closer. The same can be said for Lenovo and Xiaomi, where ASVIs are insignificant in weeks -9 to -12 for both and weeks -5 to -8 for Xiaomi. As these firms both have a highly significant constant, it seems that ASVIs remain constant until closer to the event date.

Figure 3 and Table 6 clearly show that all firms experience ASVIs for their products prior to their release. This demonstrates that new product launches are especially susceptible to leakages of information, especially as the official announcement date draws nearer.

Table 6.

Linear Regression Results of Google Trends Abnormal Search Volume Index on Week Relative to Product Launch

Week Relative to Event	All	Apple	LG	Lenovo	Samsung	Sony	Xiaomi
-9 to -12	0.0626*** (0.021)	0.0656* (0.036)	0.119* (0.063)	-0.000166 (0.051)	0.0407* (0.021)	0.114*** (0.021)	0.0365 (0.090)
-5 to -8	0.117*** (0.026)	0.153*** (0.038)	0.191** (0.088)	0.173*** (0.028)	0.210*** (0.036)	-0.00717 (0.016)	-0.0183 (0.054)
-4	0.326*** (0.070)	0.225*** (0.0081)	0.648*** (0.021)	0.381*** (0.023)	0.354*** (0.013)	0.116*** (0.011)	0.233*** (0.028)
-3	0.350*** (0.074)	0.275*** (0.0081)	0.461*** (0.021)	0.366*** (0.023)	0.214*** (0.013)	0.155*** (0.011)	0.627*** (0.028)
-2	0.646*** (0.17)	0.808*** (0.0081)	0.627*** (0.021)	0.259*** (0.023)	0.300*** (0.013)	0.463*** (0.011)	1.417*** (0.028)
-1	0.696*** (0.24)	1.531*** (0.0081)	-0.230*** (0.021)	1.186*** (0.023)	0.810*** (0.013)	0.411*** (0.011)	0.468*** (0.028)
0	0.502** (0.21)	0.836*** (0.0081)	-0.363*** (0.021)	1.181*** (0.023)	0.674*** (0.013)	0.391*** (0.011)	0.292*** (0.028)
Constant	0.0552*** (0.0074)	0.0285*** (0.0081)	0.0234 (0.021)	0.0866*** (0.023)	0.0603*** (0.013)	0.0295** (0.011)	0.103*** (0.028)
N	264	44	44	44	44	44	44

Note: This table gives coefficients from linear regressions of ASVI on dummy variables for week relative to event, where week 0 indicates the week starting 5 days before the (Trends Date) event occurred. The reference category is weeks -44 to -13. The first column presents ASVI for all firms, while the others display each firm individually. Standard errors in parentheses.

* indicates p < .1, ** indicates p < .05, *** indicates p < .01

In a final step to this analysis, ASVI data was matched to CARs by product. For each product, the average ASVI was calculated over the 43-week period. Based on the Efficient Markets Hypothesis, it is expected that products which receive more attention prior to their launch, or those for which more information is leaked, will experience lower abnormal returns during the event window. This is because the new information will have been priced in already. Table 7 shows the correlation of mean ASVI to the AR, CAR and T-Statistics for the CARs of each product. While the correlations themselves are weak, they are all negative. As ASVIs increase, ARs, CARs, and T-Statistics appear to decrease, and vice-versa.

Table 7.

Correlation of ASVI to AR, CAR, and the T-Stat by Product

	ASVI
AR	-0.0151
CAR	-0.0146
T-Stat	-0.343

Note: Since the returns data is by firm, and ASVI data by product, the ASVI data was collapsed. For example, if two products were released by Apple on the same day, the average of their ASVIs was taken to be comparable to abnormal returns for Apple on that date.

The next section will discuss all the results obtained in Section 4, as well as present limitations and areas for further research.

5 Discussion and Conclusion

The purpose of this study was to investigate the research question:

To what extent do new product launches by smartphone companies affect their abnormal returns?

The method of analysis was the event study, which is most used to study the effect of certain events on the market value of firms. 229 products from the top six (by market share) touchscreen smartphone companies were analyzed. It was expected that there would be price pressure on the firm's share price. However, it was found that (cumulative) abnormal returns were generally insignificant, meaning that new product launches do not result in abnormal effects on the firm's stock prices. This result agrees with Eddy and Saunders (1980). The magnitude of these abnormal returns is also much closer to zero than other studies assessing the effect of new product launches on stock returns (Chaney et al., 1991; Sood & Tellis, 2009; Talay et al., 2019; Pauwels et al., 2004). The explanation given by this paper for this result is that leakages of information regarding the new product launch occur in this industry, and thus firms do not experience abnormal returns on the date of the event itself. This is further supported by the negative correlation between the level of Abnormal Search Volume (used as a proxy for information leaks) and abnormal returns. Based on these results, the first hypothesis is rejected: Smartphone product launches do not result in significant (cumulative) abnormal returns. No effect of new product launches can be ascertained in an 11, 7, or 3-day event window around the event date.

However, due to limitations of this study, there is a possibility of Type II error, when a false hypothesis is incorrectly not rejected. These limitations are primarily present in the choice of sample and resulting potential violation of event study assumptions.

The firms sampled in this study were chosen based on those with highest global market share. This means that there may be some selection bias, as the firms in this study may experience a different effect of new product launches on their value. However, this choice was justified in that the six firms in this study make up around 50 percent of the global market share, meaning they are the most important players in the market. It may be that other smaller public firms, such as Nokia and HTC, experience a different effect from new product launches, however no inferences for those firms can be made based on the results of this study. Additionally, the firms in this study constitute most of the publicly traded firms in this industry segment. A method other than the event study would be required to examine the effect of new product launches on privately held firms such as Huawei and BBK Electronics, which make up another 32% of the global market share (Counterpoint, 2020). While other methods of assessing firm value may be able to include these privately held firms, such as book value or discounted cash flows, none of them allow for the daily level of granularity required for an event study.

Next, event studies rely on several assumptions for estimating abnormal returns. One of these is that there are no confounding effects within the event window which may also affect returns. In this study, many events occurred on similar dates, both within firms and between firms. For example, firms often released multiple phones at once, or many firms released new phones at the same conference and on the same date. Both could possibly affect abnormal returns and confound the true value of the effect of one event on firm value. This highlights an important limitation of this study. For example, a firm could release a highly praised device and disappointing device on the same day. Since returns are on a firm level, they will represent the sum of the negative and positive reactions to these devices. Overall returns may stay neutral, leading to an incorrect non-rejection of a false null hypothesis. To solve this problem, many studies employing the event study methodology simply drop events when they share event windows (McWilliams & Siegel, 1997). This would be unfeasible in the present study, as removing events which occur within another events window would necessitate removing 31% of the products in this study.

Finally, relating to the problem of shared event windows, this study makes the strong assumption that Google search frequency is a proxy for investor attention and information leakage. While search frequency certainly is a proxy for general consumer attention, it is unclear whether this also captures the attention of investors. Other studies avoid this issue by only using stock tickers (Such as AAPL) as keywords (Da et al., 2011), however this makes it impossible to capture the levels of attention towards specific products, only to an entire firm. The most optimal solution is to analyze data sources which contain more contextual information than just a Google search, such as Twitter Tweets (Ranco et al., 2015; Sprenger et al., 2014; Tumarkin & Whitelaw, 2001). These tweets may include stock tickers, as well as specific product names, and even information on sentiment towards these products or firms, allowing for a deep level of analysis.

In conclusion, this study makes several contributions to literature in the fields of finance and marketing. Firstly, this study adds to the small but growing literature on using event studies to assess the relation between new product launches and firm value. The results of this study show that there appears to be no effect of new product launches, on the date of the launch, on firm returns. For investors, this means that it is not possible to develop a trading strategy to take advantage of excess returns based on new product launches. Additionally, managers of firms may choose to measure the direct effect of new product launches through alternative methods, rather than using event studies. Managers seeking to improve the market value of their firm through innovation may choose other methods of communicating innovativeness. This study also showed the value of data obtained from social media platforms in analysis. The main methodological contribution of this study is the use of Google Trends to identify event dates. Google Trends is but one resource which allows future researchers to directly measure variables such as attention, which previously were much less straightforward to obtain. Future research may take advantage of these sources of data for further investigation of the effects of innovation on firm value. For example, through applying social media sentiment analysis to new product launches, it may be possible to analyze whether the direction of abnormal returns is linked to consumer sentiment towards new products.

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7 Appendix

Appendix 1.

List of Products, Corresponding Firm and Event Date

Firm	Product	Event Date	Firm	Product	Event Date	Firm	Product	Event Date
Apple	iPhone 2G	09-01-07	**Lenovo**	K800	10-01-12	**Sony**	Xperia X1	12-02-08
Apple	iPhone 3G	09-06-08	**Lenovo**	K900	08-01-13	**Sony**	Xperia X2	03-09-09
Apple	iPhone 3GS	19-06-09	**Lenovo**	A820	06-03-13	**Sony**	Xperia X10	03-11-09
Apple	iPhone 4	07-06-10	**Lenovo**	Vibe X	05-09-13	**Sony**	Xperia X10 Mini	14-02-10
Apple	iPhone 4S	04-10-11	**Lenovo**	Vibe Z	02-01-14	**Sony**	Xperia X10 Mini pro	14-02-10
Apple	iPhone 5	12-09-12	**Lenovo**	Vibe Z2	04-09-14	**Sony**	Xperia X8	16-06-10
Apple	iPhone 5c	10-09-13	**Lenovo**	A7000	01-03-15	**Sony**	Xperia arc	06-01-11
Apple	iPhone 5s	10-09-13	**Lenovo**	Vibe Shot	02-03-15	**Sony**	Xperia Play	13-02-11
Apple	iPhone 6	09-09-14	**Lenovo**	K3 Note	23-03-15	**Sony**	Xperia neo	13-02-11
Apple	iPhone 6 Plus	09-09-14	**Lenovo**	Smart Cast	28-05-15	**Sony**	Xperia Mini Pro	05-05-11
Apple	iPhone 6s	09-09-15	**Lenovo**	Z1	21-08-15	**Sony**	Xperia mini	05-05-11
Apple	iPhone 6s Plus	09-09-15	**Lenovo**	Vibe S1	02-09-15	**Sony**	Xperia ray	22-06-11
Apple	iPhone SE	21-03-16	**Lenovo**	Vibe B	04-01-16	**Sony**	Live with Walkman	22-08-11
Apple	iPhone 7	16-09-16	**Lenovo**	K4 Note	05-01-16	**Sony**	Xperia neo V	25-08-11
Apple	iPhone 7 Plus	16-09-16	**Lenovo**	Lemon 3	13-01-16	**Sony**	Xperia arc S	31-08-11
Apple	iPhone 8	12-09-17	**Lenovo**	Vibe K5	21-02-16	**Sony**	Xperia S	09-01-12
Apple	iPhone 8 Plus	12-09-17	**Lenovo**	Z2	31-05-16	**Sony**	Xperia P	28-02-12
Apple	iPhone X	12-09-17	**Lenovo**	Moto Z	09-06-16	**Sony**	Xperia U	28-02-12
Apple	iPhone XR	12-09-18	**Lenovo**	Moto Z Play	31-08-16	**Sony**	Xperia sola	13-03-12
Apple	iPhone XS Max	12-09-18	**Lenovo**	K6 Note	02-09-16	**Sony**	Xperia neo L	20-03-12
Apple	iPhone XS	12-09-18	**Lenovo**	Moto M	08-11-16	**Sony**	Xperia SX	09-05-12
Apple	iPhone 11	10-09-19	**Lenovo**	ZUK Edge	20-12-16	**Sony**	Xperia acro S	30-05-12

Apple	iPhone 11 Pro	10-09-19	**Lenovo**	Moto Z2 Play	01-06-17	**Sony**	Xperia advance	30-05-12
Apple	iPhone 11 Pro Max	10-09-19	**Lenovo**	Moto C	20-06-17	**Sony**	Xperia tipo	13-06-12
Apple	iPhone SE 2020	15-04-20	**Lenovo**	Moto Z2 Force	25-07-17	**Sony**	Xperia SL	19-08-12
LG	Optimus GT540	23-04-10	**Lenovo**	K8 Note	20-08-17	**Sony**	Xperia J	29-08-12
LG	Optimus G	19-09-12	**Lenovo**	Moto X4	31-08-17	**Sony**	Xperia T	29-08-12
LG	Optimus G Pro	25-02-13	**Lenovo**	Moto Z3 Play	06-06-18	**Sony**	Xperia TX	29-08-12
LG	G2	07-08-13	**Lenovo**	Moto Z3	01-08-18	**Sony**	Xperia V	29-08-12
LG	G Pad 8.3	04-09-13	**Lenovo**	Motorola One	31-08-18	**Sony**	Xperia E	05-12-12
LG	G Flex	27-10-13	**Lenovo**	Motorola One Power	31-08-18	**Sony**	Xperia Z	08-01-13
LG	G Pro 2	13-02-14	**Lenovo**	Motorola One Vision	16-05-19	**Sony**	Xperia ZL	08-01-13
LG	G3	27-05-14	**Lenovo**	Moto Z4	30-05-19	**Sony**	Xperia L	18-03-13
LG	G3 Stylus	15-09-14	**Lenovo**	Motorola One Action	16-08-19	**Sony**	Xperia SP	18-03-13
LG	G4	28-04-15	**Lenovo**	Motorola One Zoom	05-09-19	**Sony**	Xperia ZR	13-05-13
LG	G4 Stylus	18-05-15	**Lenovo**	Motorola One Macro	09-10-19	**Sony**	Xperia M	04-06-13
LG	G5	21-02-16	**Lenovo**	Motorola Razr	13-11-19	**Sony**	Xperia C	25-06-13
LG	G6	26-02-17	**Lenovo**	Motorola One Hyper	05-12-19	**Sony**	Xperia Z Ultra	25-06-13
LG	G7	02-05-18	**Samsung**	Galaxy S	24-03-10	**Sony**	Xperia Z1	04-09-13
LG	G8	24-02-19	**Samsung**	Galaxy S2	13-02-11	**Sony**	Xperia Z1 Compact	06-01-14
Firm	Product	Event Date	**Samsung**	Galaxy Note	01-09-11	**Sony**	Xperia E1	14-01-14
Xiaomi	Mi Play	24-12-18	**Samsung**	Galaxy S3	03-05-12	**Sony**	Xperia T2 Ultra	14-01-14
Xiaomi	Mi 9	20-02-19	**Samsung**	Galaxy Note 2	29-08-12	**Sony**	Xperia M2	24-02-14
Xiaomi	Mi 9 EE	20-02-19	**Samsung**	Galaxy S4	14-03-13	**Sony**	Xperia Z2	24-02-14
Xiaomi	Mi 9 SE	20-02-19	**Samsung**	Galaxy Note 3	04-09-13	**Sony**	Xperia ZL2	08-05-14
Xiaomi	Mi MIX 3 5G	24-02-19	**Samsung**	Galaxy Note 3 Neo	03-02-14	**Sony**	Xperia A2	14-05-14
Xiaomi	Mi 9T	12-06-19	**Samsung**	Galaxy S5	24-02-14	**Sony**	Xperia C3	07-07-14
Xiaomi	Mi CC9	02-07-19	**Samsung**	Galaxy Note 4	03-09-14	**Sony**	Xperia E3	03-09-14

Xiaomi	Mi CC9e	02-07-19	**Samsung**	Galaxy Note Edge	03-09-14	**Sony**	Xperia Z3	03-09-14
Xiaomi	Mi A3	17-07-19	**Samsung**	Galaxy S6	01-03-15	**Sony**	Xperia Z3 Compact	03-09-14
Xiaomi	Mi 9T Pro	21-08-19	**Samsung**	Galaxy S6 Edge	01-03-15	**Sony**	Xperia E4	10-02-15
Xiaomi	Mi 9 Pro	24-09-19	**Samsung**	Galaxy S6 Active	09-06-15	**Sony**	Xperia E4g	24-02-15
Xiaomi	Mi MIX Alpha	24-09-19	**Samsung**	Galaxy Note 5	13-08-15	**Sony**	Xperia M4 Aqua	01-03-15
Xiaomi	Mi Note 10	06-11-19	**Samsung**	Galaxy S6 Edge Plus	13-08-15	**Sony**	Xperia Z4	20-04-15
Xiaomi	Mi Note 10 Pro	06-11-19	**Samsung**	Galaxy S7	21-02-16	**Sony**	Xperia C4	06-05-15
Xiaomi	Mi 10	13-02-20	**Samsung**	Galaxy S7 active	21-02-16	**Sony**	Xperia A4	13-05-15
Xiaomi	Mi 10 Pro	13-02-20	**Samsung**	Galaxy S7 edge	21-02-16	**Sony**	Xperia C5 Ultra	03-08-15
Xiaomi	Mi 10 Lite	27-03-20	**Samsung**	Galaxy Note 7	02-08-16	**Sony**	Xperia M5	03-08-15
Xiaomi	Mi 10 Lite Zoom Edition	27-04-20	**Samsung**	Galaxy S8	29-03-17	**Sony**	Xperia Z5	02-09-15
Xiaomi	Mi 10 Youth	27-04-20	**Samsung**	Galaxy S8 Plus	29-03-17	**Sony**	Xperia Z5 Compact	02-09-15
Xiaomi	Mi Note 10 Lite	04-05-20	**Samsung**	Galaxy Note FE	03-07-17	**Sony**	Xperia Z5 Premium	02-09-15
			Samsung	Galaxy Note 8	23-08-17	**Sony**	Xperia X	22-02-16
			Samsung	Galaxy S9	25-02-18	**Sony**	Xperia X Performance	22-02-16
			Samsung	Galaxy S9 Plus	25-02-18	**Sony**	Xperia XA	22-02-16
			Samsung	Galaxy Note 9	09-08-18	**Sony**	Xperia XA Ultra	16-05-16
			Samsung	Galaxy S10	20-02-19	**Sony**	Xperia E5	31-05-16
			Samsung	Galaxy S10 5G	20-02-19	**Sony**	Xperia X Compact	01-09-16
			Samsung	Galaxy S10 Plus	20-02-19	**Sony**	Xperia XZ	01-09-16
			Samsung	Galaxy S10e	20-02-19	**Sony**	Xperia XA1	26-02-17
			Samsung	Galaxy Note 10	07-08-19	**Sony**	Xperia XZ Premium	26-02-17
			Samsung	Galaxy Note 10 Plus	07-08-19	**Sony**	Xperia XZs	26-02-17
			Samsung	Galaxy Note 10 Lite	03-01-20	**Sony**	Xperia L1	20-03-17
			Samsung	Galaxy S10 Lite	03-01-20	**Sony**	Xperia XA1 Plus	31-08-17
			Samsung	Galaxy S20	11-02-20	**Sony**	Xperia XZ1	31-08-17

Samsung	Galaxy S20 Plus	11-02-20	**Sony**	Xperia XZ1 Compact	31-08-17
Samsung	Galaxy S20 Ultra	11-02-20	**Sony**	Xperia L2	08-01-18
			Sony	Xperia XA2	08-01-18
			Sony	Xperia XA2 Ultra	08-01-18
			Sony	Xperia XZ 2 Compact	26-02-18
			Sony	Xperia XZ2	26-02-18
			Sony	Xperia XZ 2 Premium	16-04-18
			Sony	Xperia XZ3	30-08-18
			Sony	Xperia 1	24-02-19
			Sony	Xperia 10	24-02-19
			Sony	Xperia 10 Plus	24-02-19
			Sony	Xperia L3	25-02-19
			Sony	Xperia Ace	16-05-19
			Sony	Xperia 5	05-09-19
			Sony	Xperia 8	07-10-19
			Sony	Xperia 1 II	24-02-20
			Sony	Xperia 10 II	24-02-20
			Sony	Xperia L4	24-02-20
			Sony	Xperia PRO	24-02-20

Appendix 2.

Average Cumulative Abnormal Returns for New Product Launches over 11-Day Event Window

		NASDAQ Value-Weighted	CRSP Value-Weighted	NASDAQ Equal-Weighted
	Firm	**ACAR**	**ACAR**	**ACAR**
70 Days Estimation Window	Apple	0.114984	0.131228	-0.004098
	LG	-0.003566	-0.006523	0.004905
	Lenovo	0.095585	0.104135*	-0.021103**
	Samsung	0.063170	0.063590	-0.000573
	Sony	0.043063	0.037678	0.010229
	Xiaomi	0.018015	0.031123	0.015528
100 Days Estimation Window	Apple	0.104983	0.120112	0.108801
	LG	0.001520	-0.000265	-0.002790
	Lenovo	0.082417	0.091446	0.067392
	Samsung	0.070924	0.071667	0.071961
	Sony	0.048979	0.045703	0.046992
	Xiaomi	0.018015	0.031123	0.012241
130 Days Estimation Window	Apple	0.119578	0.137389	0.124542
	LG	0.014831	0.012133	0.009830
	Lenovo	0.079114	0.087796	0.064074
	Samsung	0.060864	0.061678	0.062670
	Sony	0.058168	0.055116	0.057234
	Xiaomi	0.018015	0.031123	0.012241

Note: This table shows Average Cumulative Abnormal Returns over the 11-day event window for various estimation windows and market return indexes. Event dates detected using Google Trends.

* indicates p < .1, ** indicates p < .05, *** indicates p < .01