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HOW EARNINGS ANNOUNCEMENT IMPACT FAANG STOCK PRICES?

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Abstract

Beginning in the late '30s, stock market event studies intend to provide more information about market movements and behavior, around the major events during the year, allowing market players to make better and more sustained investment decisions.

This paper analyzes how the FAANG stocks behave when quarterly earnings announcement results are reported. To answer this question, we compare the performance of 7 different announcements for each firm, by the calculation of the abnormal returns, using 3 different normal models with 2 different extensions, and test the statistical robustness with 4 different statistical tests. Our results showed different price reactions around events, but consistent high abnormal returns on an individual event and period analysis on the day after the announcement.

Results also revealed that on a multi-period analysis, the stocks are not consistently positive or negative, leading to symmetric high abnormal returns and a low percentage of abnormal performance. At the same time, on a multi-event analysis, results, by type of news, show significant under and overreactions on the stock market price movements.

However, the efficient market hypothesis is not consistent when the news, resulting from the announcement, incorporate the stock price. From a safety perspective, this study emphasizes on the necessity to consider the impact of quarterly earnings announcement reports, on FAANG stock prices, and consequently on market players' investment decisions.

Keywords: Abnormal returns; Stock Price; Earnings announcement; Efficient market hypothesis; News sentiment; Price reaction; Market behavior

JEL Classification: C, G

Sumário

Com início no final dos anos 30, os estudos sobre eventos nos mercados de capitais surgem com o intuito de proporcionar mais informação sobre os movimentos e o comportamento do mercado, em torno dos maiores eventos anuais, permitindo aos *players* de mercado tomar decisões de investimento mais sustentadas.

Esta tese analisa como é que as ações FAANG reagem, quando é anunciado o relatório dos resultados trimestrais das empresas. Para conduzir a análise, iremos comparar a performance de 7 anúncios, diferentes para cada empresa, através do cálculo dos abnormal returns, utilizando 3 modelos normais com 2 extensões diferentes, e testar a robustez estatística através de 4 testes. Os resultados demonstram diferentes reações dos preços em torno dos eventos. Mais precisamente, abnormal returns elevados e consistentes, no dia após o anúncio, numa análise individual.

Os resultados também revelaram que, numa análise de vários períodos, as ações não apresentam consistência positiva ou negativa, levando a abnormal returns simétricos e uma percentagem reduzida de abnormal performance. Ao mesmo tempo, numa análise multi-eventos, os resultados, de acordo com o tipo de notícias, são significativamente baixos e demonstram reações exageradas nos movimentos de preço no mercado acionista.

No entanto, a Hipótese de Mercado Eficiente não é consistente quando as notícias relacionadas com os anúncios trimestrais incorporam o preço da ação. De forma geral, o estudo enfatiza a necessidade de considerar o anúncio dos resultados trimestrais nos preços das ações FAANG e, consequentemente, nas decisões de investimento dos players de mercado.

Keywords: Abnormal returns; Stock Price; Earnings announcement; Efficient market hypothesis; News sentiment; Price reaction; Market behavior

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List of Abbreviations

AR – Abnormal Returns

CAR – Cumulative Abnormal Returns

AAR – Average Abnormal Returns

CAAR – Cumulative Average Abnormal Returns

EPS – Earnings per Share

VIX – CBOE Volatility Index

$\boldsymbol{R_{IND}}$ – Average Return Industry Proxy

SMB – Small Minus Big

HML – High Minus Low

RMW- Robust Minus Weak

CMA- Conservative minus Aggressive

FF - Fama French

EMH – Efficient Market Hypothesis

FAANG – Facebook, Amazon, Apple, Netflix, Google

P/E – Price-to-Earnings Ratio

M&A – Mergers and Acquisitions

CAPM – Capital Asset Pricing Model

MM – Market Model

BHAR - Buy and Hold Abnormal Return

1.Introduction

The market behavior after an earnings announcement is considered to be one of the most effective ways to prove that asset's price do not adjust all public information available immediately, and often investors profit based on public information. Several researches have empirically found that stock prices after earnings announcements do not adjust as quickly as expected by the efficient market hypothesis (EMH), allowing investors to profit on the margin generated in between market adjustments. Findings have also shown that earnings announcement expectancy is largely affected by tone and type of information of press releases near the event, causing what's referred to as "Post earnings announcement drift". Other variables impact the direction and the amplitude of the stock price movement after the event, such as post earnings surprise and private information.

These findings have been supported by a variety of theoretical explanations, on articles of the main authors working in event studies, Patell and Wolfson (1981), Boehmer, Musumeci and Poulsen (1991), Fama and French (1992), Kothari and Warner (2006) and Kolari and Pynnonen (2010), Our main focus is to comprehend and study the behavior of FAANG stock prices (Facebook, Apple, Amazon, Netflix and Google) after earnings announcement. We investigate abnormal returns performance of 35 different earnings events, 7 for each FAANG stocks.

On this study we make three contributions to existing literature. First, as mentioned above, we focus on market abnormal return movements after the earnings announcements on the FAANG stocks, specifically, 10 days before and 10 days after the event day using a 750 days estimation window. We study the abnormal performance behavior, statistical significance and possible linear correlation between FAANG stocks events, what is the impact among events from each company. Second, much like existing literature, our study also focuses on behavioral effects around the event base, most precisely after the announcement. In order to test another type of variables, we run a linear regression model to understand how market earnings surprise value influence the abnormal returns scale. Third, we perform a joint study of FAANG average abnormal returns and average cumulative abnormal returns through a series of parametric tests, in order to properly conclude about the significance of results. Also, and consequently, infer to the investor's perspective, practical material to increase the quality of the investment decisions towards the FAANG stocks after the earnings announcement report.

Our empirical analysis uses the earnings announcement dates of FAANG stocks, from the second quarter of 2017 until the last quarter of 2018. We will analyze 35 earnings announcements, 7 per firm, in terms of abnormal returns activity. Every earnings announcement will be treated as an event and conducted by the following empirical strategy. For each stock, the event window used will be from 10 days before the event date to 10 days after. As estimation window we will consider 750 days before the first day of the event window. Daily data will be used in order to catch the presence of abnormal returns on a short-term analysis.

Abnormal returns are the difference from the estimated return through a specific model and the return that was registered. To estimate the returns in order to calculate the abnormal returns, single factor and multi-factor models were used. Inside the single factor, the most common model, the Market Model, was used with two extensions on the error term, GARCH and EGARCH to account for time-varying volatility effects and shocks. On the multi-factor side, the Fama-French (FF hereinafter) three factors plus the VIX Index, and another model with a proxy for the tech industry and the VIX were chosen in order to mitigate risks.

The market proxy used is the S&P 500 Index for all the models. To investigate the presence of significant abnormal return, we will test the abnormal returns performance, through the estimation models, by calculating the abnormal returns, average abnormal returns, cumulative abnormal returns and cumulative average abnormal return and test the statistical robustness through the parametric tests, t-test, adjusted Patell test, adjusted cross-sectional test and skewness corrected test. All tests will be done under specific conditions and assumptions that will be shown and explained during the study. The null hypothesis, (non-presence of abnormal returns performance) will be rejected at 5% and 1% significance level for the abnormal returns, and at 10% and 5% for the parametric tests.

FAANG stocks show evidence of a not stable and constant behavior with large speculation and expectancy from the market players due to the small percentage (21.74%) of statistically significant CAR values. Regarding the sensitivity to news, the correlation coefficient, between abnormal returns and type of news, is on average, 0.176 and 0.36 in absolute value which represents weak linear correlation. Also, we see that 60% of the firms present abnormal performance ($AAR > 0$) with positive AAR with good news and only 25% when bad news appears.

The parametric tests displayed a rejection of the null (abnormal returns equal to 0) at 5% on day 1 after the announcement on, 80% for the Patell test, 20% for the BMP test and 20% for the skewness correct $t\ test$. Thus, the results support the true rejection of the null only in 20% of the firms. For the CAAR values, we do not have sufficient evidence to reject the null hypothesis and conclude about the presence of statistically significant abnormal returns on a multi event and multi day analysis.

From all the event we conclude that, individually, events impact stock prices. on the day after the announcement, presenting a good profit margin basis for investor to trade on public news. The magnitude of the impact derives from a lot of variables, some studies on this thesis, others to be approached on future works, but taking out of the equation private news and *insider trading* pressure, in a cumulative analysis, all stocks show different bearish and bullish patterns of abnormal performance, leading investors to be able to better understand the stock price tendency around and after the earnings announcement reports.

Following the thesis structure, in the next section we discuss the Literature Review about the event studies and its contribution to test the EMH and to the finance literature in general. After, we approach the general methodology on event studies and propose the methodology used to address our analysis. Data gathering and empirical evidence are focused on the last sections before the conclusion and in the end, we suggest some points to consider on future researches.

2. Literature Review

In the following subsections, the theory behind event studies, the impact of information in the markets as well as the anomalies of the market and the way that event studies test the EMH will be addressed.

2.1. Introduction to EMH

Can information be used to improve our investing performance?

Efficient Market Hypothesis suggests that we cannot profit based on new information. EMH supports Fama (1970:383) definition that "*A market in which prices always "fully reflect" all available information"*. In other words, the asset´s market price reflects the true price as the asset reflects all available value-relevant information. This theory expands into three different forms (Fama, 1970), weak form, semi-strong form and strong form of efficiency.

Many studies were conducted in this field, from the theory construction in the 1960s, Fama (1965a, 1965b) and Samuelson (1965) to the establishment of empirical corroboration on the 1970´s Fama (1970, 1976a). After that, the theory becomes challenged by Behavioral Finance, Thaler (1999) and Shiller (2003), Adaptive Market Hypothesis, Lo (2004) and many other authors.

2.1.2. Where does information come from?

Information can be distinguished into three types according to its provenience. The exchanges, SEC filings[1] and news. This type of information matches the three different forms of market efficiency since one is based on technical indicators, the other on fundamentals and public news and the last on private news.

As previous studies suggest, the information does affect asset prices (Easley et al., 2002). In the current study, the aim is on event studies, which is based on the effect of mostly public information and the sentiment about that information on stock prices after earnings announcements. As previously studied, event studies showed significant results on asset price responsiveness to new information (Mackinlay, 1997), which opens the window of opportunity to test the possible delays in the price adjustment (Busse and Green, 2002).

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[1] Securities and Exchange Commission (SEC) maintains company's public and non-public records. Many records, such as registration statements, reports, public comments and other information filed by regulated companies and individuals can be viewed on SEC online search.

2.1.3. Market Efficiency Anomalies

Though reasonably supported in early empirical work, reported in Fama (1970, 1991), anomalies have been documented in later work that contradicts the efficient market hypothesis. EMH is violated in the field of event studies as asset prices show that new information has a significant impact on returns. If the semi-strong form of market efficiency was correct, P/E ratio over time should not demonstrate a linear relationship with returns, although Shiller (2005) suggests that the lower the P/E ratio the higher the return, which indicates that this fundamental indicator is a good predictor of returns.

Furthermore, Henry (2008), showed that abnormal market returns tend to be higher or lower based on press releases' tone, suggesting a correlation between time of the press release and the impact of unexpected earnings. To challenge the strong market efficiency, many authors studied the field of insider trading, suggesting relevant profit bases in comparison to investors based only on public information (Macey and Haddock, 1987). Literature is reviewed very briefly on this topic since the paper does not focus on these types of anomalies.

2.2. Event Studies

In EMH theory it is assumed that capital markets reflect all available information about a firm in the stock prices and event studies appear as a tool to test and verify the validation of this theory. Event studies movement started in the 1930s, on a study conducted by Dolley (1933). Further and more recent studies appear in Breinlich et al. (2018), but during the years, many researchers have developed the event study methodology to perform this type of analysis (Ball and Brown, 1968; Armitage, 1995; Corrado, 2011) and all the others previously mentioned in the study.

The analysis is in its most common form, focused on stock returns, and less used, with a focus on trading volumes and volatilities. McWilliams and Siegel (1997: 626) state that an event study methodology*, "determines whether there is an ´abnormal` stock price effect associated with an unanticipated event. From this analysis the researcher can infer the significance of the event".*
Return event studies quantify an event's economic impact calculating abnormal returns by deducting the normal returns that would have been realized if the analyzed event would not have taken place. While the actual returns can be empirically observed, the normal returns need to be estimated. For this, the event study methodology uses expected return models. In earlier empirical work, an event study is referred to as a semi-strong-form test of market efficiency (Fama, 1970).

Over the years, numerous researchers have performed event studies, whether the topic of interest was stock splits, dividend announcements or quarterly earnings. Kothari and Warner (2006) state that there were over 550 published event studies. In sum, in the event study methodology, the researcher hypothesizes that markets adjust to new information immediately assuming EHM as null hypothesis (Kothari, 2001).

2.2.1 Long vs Short

On event studies, the event window can be short or long and can be considered in days, months or years. On one hand, concerning longer-term effects, the related methodology that has been developed captures if an event has had a persistent impact on stock prices over long periods [2]. On the other hand, by Kothari (2001) definition, short term event studies can be characterized as studies estimating the abnormal returns up until one year from the event date. This paper will focus on short term event studies, considering a 21 days event window.

In the long term, many studies show that abnormal returns spread over long horizons. The main literature on this subject is present on Fama (1998), Kothari and Warner (1997), Schwert (2001), and Kothari (2001). More detailed discussions appear in (Barber and Lyon (1997), Kothari and Warner (1997), Lyon, Barber, and Tsai (1999), Fama (1998), Brav (2000), Jegadeesh and Karceski (2004), Viswanathan and Wei (2004), Eckbo, Masulis, and Norli (2006).

2.2.2 Event Study Methodology

Every event study is calculated based on an expected return model which has some methodological assumptions behind (Brown and Warner, 1980).

The following three are the most important:

1. Event window stock returns of a particular event study accurately reflect the economic impact of the event;
2. Event is unexpected and has not yet been factored into the stock price;
3. There are no other events during the event window, which could be responsible for the stock price change.

[2] On event studies, long periods by default, are considered more than 1 month after the event.

Depending on the expected return model used, more assumptions need to be met. For the most common model, the Market Model, which is being used in this paper, the relationship between the stock and the market needs to remain stable throughout the estimation and event window. Only then, the alpha and beta factors, which are established with a regression analysis during the estimation window, can be used to predict expected returns for the event window (Schimmer, Levchenko, and Müller, 2015)

When testing for market efficiency, the researcher must always use a returns' normal model, where the tests are jointly testing market efficiency and the asset-pricing model. This creates a joint-hypothesis problem and, conclusions about market inefficiency cannot be accepted naively without acknowledging a potential model misspecification's effect on the results (Fama, 1991). Fama states in the same article that one way to possibly minimize this problem is to use daily data in event studies, allowing a precise measure of how quickly the stock price responds. Event study methodology will be reviewed later in this paper.

The next section will review some of the earlier research on earnings announcements applied to event study methodology.

2.2.3. Earnings Announcement

The semi-strong form of market efficiency states that stock market prices reflect all publicly available information and therefore, trading on this basis is not profitable. If it were true, investors couldn't outperform the market by trading on public information. Is the hypothesis valid? A few studies supported the EMH by observing zero abnormal returns while, on the other hand, studies observed abnormal returns and empirically proved market inefficiency. This mixed evidence gives further scope for empirical investigation of EMH on the capital market, Bernard and Thomas (1989 and 1990) and Freeman and Tse (1989) argue that stock markets do not adjust instantly to new information flow, therefore investors can make abnormal profits by trading based on earnings data. Ball and Kothari (1991) concluded that earnings announcement usually include information which is not available to the market and excess returns are generated after the announcement day.

All this evidence demonstrate that earnings announcements contain information which is not available to markets and stock prices fail to reflect all the information released to the public.

2.2.4. Post-Earnings Announcement

Post earnings announcement drift referred by Shivakumar (2007: 434) as the "*longest standing anomaly in the finance and accounting literature*", represents a contradiction to the efficient market hypothesis. The drift implies market under-reaction to earnings news. which means that information does not immediately adjust to prices. It was first documented by Ball and Brown (1968) and after, more detailed studies were conducted by Watts (1978) and Ball and Bartov (1996). Ball and Brown (1968) established that asset prices do not always immediately reflect the new earnings information and firms, experiencing positive or negative earnings surprises, have been documented to encounter drifts in estimated cumulative abnormal returns, upward or downward for some time after the event day.

Bernard and Thomas (1989) propose two hypotheses for the post-earnings announcement drift. First, there is the possibility that part of the price´s response to new information is delayed, due to failure in assimilating available information. Second, when the drift has been observed, in research where the normal returns are estimated with the CAPM, studies have shown that the model fails to properly adjust the securities for risk (Foster, Olsen, and Shevlin, 1984; Ball, Kothari and Watts, 1993).

In previous sections, some documented anomalies in contradiction to the efficient market hypothesis were briefly introduced. Questions have been raised about whether the post-earnings announcement drift exists, independently of other anomalies, but what are the implications of the post-earnings announcement drift for securities trading? Kothari (2001:196) states that "*the post earnings announcement drift appears to be incremental to a long list of anomalies that are inconsistent with the joint hypothesis of market efficiency and an equilibrium asset-pricing model*". A few years later, Shivakumar (2007) pointed out that, a trading strategy using the post-earnings announcement drift is still profitable, nearly forty years after its first realization.

2.2.5. Earnings Surprise

Investors are not able to fully recognize the market shocks created by earnings announcement hence, they misestimate future expected earnings. In the next quarters, when earnings are announced, stock prices adjust to different results instead of the predicted based on past time series of announcements, causing a surprise shock in the market. Research by Liu and Thomas (2000) shows that a significant portion of the market reaction surrounding earnings announcements is attributable to other information, released around the announcement date, rather than the earnings information itself. Prior research has predominantly focused on earnings surprise and very little attention has been directed towards non-earnings information released around the earnings announcement date. Information presented on press releases and the way that the information is written is a major factor when it comes to influencing market price movements. Press releases “construct” investors’ sentiment towards the earnings report of that quarter (Henry, 2008).

Experts predict the next quarterly earnings EPS and compare their estimations to the real value when the report comes out. The difference between the predicted and the reported EPS value generates a percentage of surprise. Could this surprise be correlated with the abnormal return movements? In the results section, we will discuss the possible existing correlation in more detail.

2.3. Research Goals

<u>Research question:</u>

How earnings announcements impact in stock price movements?
(FAANG stocks event study analysis)

<u>Goals of the paper:</u>

• Test whether FAANG stocks follow a semi-strong form of EMH or not.
• Test if FAANG stocks market reactions to quarterly earnings announcement through 35 different events generate abnormal returns and if they are statistically significant.
• Test if the difference, between predicted and reported EPS related to an earnings announcement, is somehow correlated with FAANG stock price movements

<u>Hypothesis that will be tested:</u>

• If Abnormal Return (AR), Cumulative Abnormal Returns (CAR), Average Abnormal Returns (AAR) and Cumulative Average Abnormal Return (CAAR) are approximately equal to zero.
• If there is randomness in the occurrence of AARs.
• If AAR are sensitive to the type of news (“Good”, “Bad”, “No news”)
• If parametric tests corroborate with the possible rejection of the null on AARs and CAARs.
• If exists a correlation between earnings surprise and abnormal returns on the day after the announcement date.

3. Methodology

In this section, the methodology used is described. The first subsection presents the overall framework, in other words, the research paradigm. The second and third subsections present the research processes, more specifically, the choice of window, models, and variables applied in the study. The fourth and fifth subsections explain the test statistics used and hypothesis tested, as well as the market expectations and surprises.

3.1 Event Studies

From the literature review section, it was possible to conclude that post-earnings announcement drift tends to violate the semi-strong form efficiency market hypothesis. So, it is important to introduce an event study approach to test the performance of capital markets. The underlying assumption of this approach is that capital markets follow a semi-strong form of efficiency. For that, it is necessary to measure the valuation effects of earnings announcements, as well as, examine the response of stock price around the event's earnings announcement, by treating and process data in MS Excel and Event Study Tools ARC [3].

The event study framework has not changed drastically since the late 1960s when Ball and Brown (1968) and Fama et al. (1969) introduced their methodology concerning the estimation of abnormal returns (AR) as an important measure to test the market's efficiency in response to announcement events. Moreover (Fama, 1991:1602) states that event studies are an important part of finance and states that "*event studies are the cleanest evidence we have on efficiency".*

There are short (< 1 year) and long-horizon (> 1 year up to 5 years) event studies. As in Kothari and Warner (2006), long-horizon event studies have been improved in recent years, but short-term horizon remains more reliable. In line with this conclusion, we will conduct our event study in a short-term paradigm. To construct an event study, it is necessary to design the event study timeline. For this, we will follow the first two steps of the standard event study technique (Brown and Warner 1985).

[3] EventStudyTools website (https://eventstudytools.com/) helps perform event studies dedicated research apps as the Event Study ARC (Abnormal Returns Calculator)

Firstly, based on data from the estimation window, also known as control period, the market model is estimated through a regression model, which is used to determine the normal behavior of a stock's return in comparison with the market or industry Index. Secondly, the event window is centered on the announcement day and encompasses a set number of days around the event day. This length in short-term events is normally between 1 and 20 days excluding the event date. Abnormal returns are calculated on this window, based on the predicted and observed returns. In this period, we will calculate the abnormal returns to understand the abnormal performance and gather information to conclude on the stock price response to new information, generated by the earnings announcement.

For the present event study, we will focus on FAANG stock's quarterly earnings announcements. More precisely, for each firm, we will analyze 7 quarterly reports between the 2^{nd} quarter of 2017 and the 4^{th} quarter of 2018. Trading data is collected daily and the study window is based on short term horizon. Although, there are challenges regarding the use of daily data for event studies (Brown and Warner, 1985), as Kothari and Warner (2006: 8) state, daily data *"permits more precise measurements of abnormal returns and more informative studies of announcement effects"*.

The estimation window should be chosen in a way that the returns are not compromised with their performance within the event. Armitage (1995) suggests that results are not sensitive to varying estimation window lengths as long as the window exceeds 100 days. Moreover, Holler (2014) on his meta-research analysis concluded that the main window length spreads out between 30 and 750 days. The event windows typically range in their lengths between 1 and 11 days and center symmetrically around the event day. The most common choice of event length in a recent paper by Oler, Harrison, and Allen (2007) is 5 days.

We decide that the estimation window length will have 750 trading days, the event window 21 trading days, including 10 days before the event date and 10 days after, to capture early and late market adjustments (Figure 1). Considering that the estimation window will count in descending order, 750 days starting before the first day of the event window, the estimation window will be adjusted for every event.

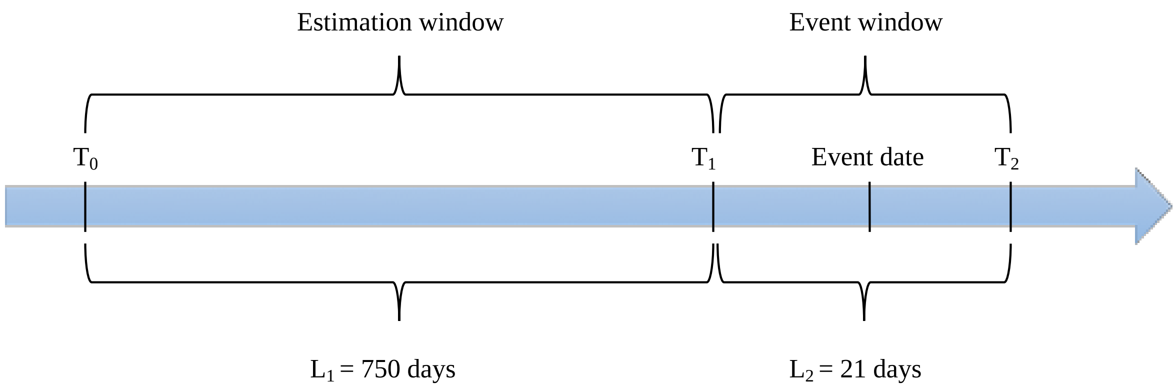

Figure 1- Event study timeline

From previous literature, many event studies have been performed and the methodology has become fairly standardized over time. In this thesis we adopt the below summarized methodology:

1. Identify the stocks to analyze.
2. Select the frequency of data to use (daily, weekly, monthly or annually).
3. Identify the announcement day and define the event type (short or long term).
4. Identify the estimation and event window length.
5. Choose the market proxy, normal returns model and exogenous variables for the multi-factor.
6. Compute the abnormal returns, average abnormal returns, cumulative abnormal returns, cumulative average abnormal returns.
7. Compute the 4 main statistical tests, $t\ test$, $Adjusted\ Standardize\ Cross\ Sectional\ test$, $Adjusted\ Pattel\ test$ and $Skewness\ Corrected\ test$.
8. Test the hypothesis and evaluate the results.

3.2 Normal Performance Models

Event studies are used to measure the impact of a specific event on a firm's value and prices. To accurately conclude on the results, it is necessary to appropriately choose the normal return model. To estimate the normal returns, there are two types of models, statistical and economic (MacKinlay, 1997). The author affirms that statistical models follow (MacKinlay, 1997: 7) "*the assumption that asset returns are jointly multivariate normal and independently and identically distributed through time is imposed*". However, in general, these assumptions lead to analysis´s problems, therefore we will use statistical tests to minimize their impact.

3.2.1 Statistical Models

Statistical models are separated into two categories, single factor and multi-factor models. The most popular model according to financial literature, for an event study, is the Market Model, which includes a single factor model. Supported by Holler (2004) meta-research, almost 80% of papers elaborated throughout the years used the MM as estimation model and only 4% used multi-factor models.

As the estimation model, we will use a combination of single and multi-factor models to compare and conclude with more accuracy about the significance of the event results. As single factor model, we will use the MM with two different extensions on the error term and for multi-factor, two models with different types and numbers of variables, are used.

3.2.1.1 Single Factor Statistical Models

The MM is the most common approach to calculate expected returns. This model overcomes the impact of general market movements in a rudimentary way by assuming a constant and linear relation between individual asset returns and the return of a market Index.
Although the type of estimation model used, represent a huge factor in the quality of the results, the market proxy Index choice is also a main aspect to obtain accurate results. In general, the Index that is considered the most capable to portrait the American market is S&P500, which is the one used to calculate abnormal returns on this study. Market Model general equation assumes the following form:

$$\mathrm{r}_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{1}$$

Where r_{it} is the return of the stock of asset i on day t, r_{mt} is the return of the reference market on day t, αi is the intercept of the value of r_i when r_m equals to zero, β_i is the regression coefficient (estimation of the systematic risk for asset i) and a measure of the sensitivity of r_{it} on the reference market. The ε_{it} is zero mean error term on the asset i on the period t.

It is assumed that ε_{it} is uncorrelated to the market return r_{mt} and firm return r_{jt} with $i \not\equiv j$ not autocorrelated, and homoscedastic. Moreover, the variance ($\sigma^2_{\varepsilon_i}$), beta (β_i), alpha (α_i) are the parameters of the model. The estimation results are displayed on Table 27, Table 28, Table 29, Table 30 and Table 31 (Appendix B).

Although the MM is widely accepted as a standard model for event studies, it has also some limitations. The model assumes that risk-free interest rate, included in the α factor, is constant, which conflicts with the assumption that market returns vary over time and assume homoscedasticity on the error term. To diminishing the homoscedasticity impacts on results, we expand the MM using a GARCH model to deal with conditional heteroskedasticity of error term; see equation (4). As in Corhay and Tourani (1996) and Wang et al (2002), MM with GARCH expansion is used to account for time-varying volatility effects to obtain more efficient results.

The GARCH (q,p) model is defined as:

$$\mathrm{r}_{it} = \mu_t + u_{it} \tag{2}$$

$$u_{it} = \sigma_t z_t \tag{3}$$

And the conditional variance (Bollerslev, 1986) may be written as:

$$\sigma_t^2 = w + \sum_{i=1}^{q} u_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \tag{4}$$

Where r_{it} represents the log return of an asset at time , u_{it} is the mean-corrected return of an asset at time t, μ_t is the conditional mean of r_{it} , σ_t^2 is the conditional variance at time t conditioned on the history, u and β the parameters of the model and z the sequence of independent and identically distributed standardized random variables (i.e. E[$r|\Psi$] = 0, VAR [$r|\Psi$] = σ_t^2).

By handling the MM with GARCH expansion (2), the general feature of conditional heteroscedasticity is added to the equation allowing the MM to successfully capture time-varying volatility. GARCH application's main problem is the non-distinction of positive and negative market movements, failing to explain the "leverage effects", which are observed in the financial time series (Matei, 2009). First observed by Black (1976), leverage effects represent a tendency of variation in stock prices to be negatively correlated with changes in stock volatility. The effect of a shock upon the volatility is asymmetric, meaning that the impacts of good news and bad news are distinct (Matei, 2009). For this reason, we will also estimate the MM with EGARCH expansion (5), assuming non-symmetric effect events on the stocks and volatility, to obtain better results.

The equation of conditional variance (Nelson, 1991) is written as:

$$\ln \sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} \gamma_i \frac{|u_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} \beta_i \, ln \, \sigma_{t-i}^2 \qquad (5)$$

Where the asymmetry coefficient, γ_i allows the leverage effect to be accounted for. Hence, positive and negative values of u_{t-i} have a different impact on volatility at time t."*Unlike the GARCH model, the logarithmic transformation of the conditional variance implies no restrictions on the parameters are required to ensure that* $\sigma_t > 0$" (Curto, 2018: 32).

In the present study, single factor model used for expected normal returns calculations is the MM without any extension and, with GARCH and EGARCH extension (4), (5).

3.2.1.2 Multi-factor Statistical Models

Multifactor models are used to construct portfolios with certain risk characteristics with the final goal of mitigating issues in relation to CAPM model (Equation (37), Appendix A) and thus, provide better estimates for benchmarked returns in event studies. The literature around multi-factor model is limited but suggests that multi models produce only marginal benefits over a standard MM in predicting event day normal returns. However, they generate less skewed abnormal returns, which are better suited for statistical tests (Ahern, 2009).

The most known multi-factor model is the Fama and French three-factor model, (Equation (38), Appendix A). This model has three factors: size of firms, book-to-market values and excess return on the market. In other words, SMB, HML and portfolio's return less the risk-free rate of return, are the three factors used (Fama and French, 1993). Behind the multi-factor models remain the idea that a model with more variables can explain better the market behavior. In comparison to single models, multi-factor, despite their several limitations, offer increased explanatory power and flexibility.

In the event study field, the use of multifactor models does not decrease the forecast error bias, in comparison to more simple methods. Instead, only the characteristic-based benchmark approach exhibits no mean bias in any sample grouping. Power can also be improved slightly on test statistics (Ahern, 2009).

In the present study we will use 2 multi-factor models, a model with 2 variables and another one with 3 variables. More precisely, on the first one, industry proxy is one of the variables, calculated through the average of SP NA Tech Index and IGM Index, and as second variable the VIX Index (6). These variables will be used to catch investor sentiment towards the market and, industry performance to better explain stock performance.

$$\mathrm{r}_{it} = \alpha_i + \beta_i(r_{mt}) + \beta_j(r_{Ind}) + \beta_l(r_{VIX}) + \varepsilon_{it} \tag{6}$$

The second multi-factor model used is an extension of FF three-factor model, adding volatility risk adjustment, through VIX Index to the equation (7). This will be an adaptation of the FF 4 factor model presented by Carhart (1997), (Equation (39), Appendix A).

$$\mathrm{r}_{it} = \alpha_i + \beta_i\left(r_{mt} - r_f\right) + \beta_j(SMB) + \beta_l(HML) + \ \beta_l(r_{VIX}) + \varepsilon_{it} \tag{7}$$

Further research was conducted by Fama and French (2015) with the introduction of other risk factors. Along with the original three factors, the new model adds two more factors, profitability and investment. Few studies have been conducted with these multi-factor models leaving space to new and further research in this area (Equation (40), Appendix A).

What differs among these models are the assumptions about the expected return and risk for the stock. In practice, gains from using more sophisticated models are limited because the variance of abnormal returns is not reduced significantly by choosing these models (Brown and Warner, 1985; MacKinlay, 1997).

33.3 Estimation of Model

Through the MM choice and parameters presented in the previous sub-section, the respective choice of methods and calculations will be explained in the following sub-sections, considering S&P500 Index as a proxy of the market.

3.3.1 Abnormal Returns

Abnormal returns are the difference between the actual return and expected return from the normal model calculation, making them an essential measure to evaluate the impact of an event. More precisely, abnormal returns are essential in determining the asset's risk-adjusted performance when compared to the overall market or benchmark Index.

An abnormal return is referred to as, either a positive or a negative abnormal return, depending on where the actual return falls in comparison to the normal return.

Abnormal returns on are calculated as follows:

$$AR_{it} = r_{it} - (\hat{\alpha} + \beta_i r_{mt}) \tag{8}$$

Where AR_{it} the abnormal return, which is the disturbance term ε_{it} on the event window of the MM for firm i at the period t. The actual return for firm i at the period t, r_{it}, and $\hat{\alpha} - \beta_i(r_{mt})$ is the expected return.

As in Corrado and Truong (2008), daily stock returns calculated with a logarithmic function, perform better test specifications in event studies. There are two different measures to aggregate abnormal returns that are normally used in the finance literature for an event study, BHAR (Buy-and-Hold Abnormal Returns) and CAR (Cumulative Abnormal Returns). As in Loughran and Ritter (1995) and Fama (1998), BHAR method provides best returns when the focus is on long-horizon event studies. While it is true for long-term studies, it is also true that CARs perform better for short-term studies. The focus of the study relies on short term and CARs will be used as the comparison method.

3.3.2 Cumulative Abnormal Returns

A hierarchy of abnormal returns calculated is compounded to cumulative abnormal returns (CARs), which can be averaged to cumulative average abnormal returns (CAARs) in cross-sectional studies. The cumulative abnormal return method is normally used to determine how accurate the model is. More often, it is used to investigate the impact of any extraneous events affecting stock prices. Additionally, the authors, Kothari and Warner (2008), suggest that this measure should be used to see how fast the market reacts to new information and consequently test the semi-strong form of EMH.

CARs method is the sum of the abnormal returns of the stock i at the period t (9).

$$CAR_i = \sum_{t=T_1+1}^{T_2} AR_{it} \tag{9}$$

Performance analysis of abnormal returns for multiple events may give typical stock market response patterns. So, the standard abnormal returns associated with a specific period, N days before and after the event day, gives us the following formula for average abnormal returns:

$$AAR_i = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{10}$$

After calculating the cumulative and average abnormal returns, we perform the CAARs (11). This measure is known to have significant statistical importance in addition to the AAR because it adds the cumulative effect on abnormal returns.:

$$\text{CAAR} = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{11}$$

The statistical tests considering these measures will be approached in the following section.

3.4 Test Statistics

The literature on event study test statistics is very rich, as is the range of significance tests. Generally, significance tests can be grouped in parametric and nonparametric tests. Parametric tests assume that an individual firm's abnormal returns are normally distributed, whereas nonparametric tests do not rely on such assumptions. In research, scholars commonly complement a parametric test with a nonparametric test to verify research findings (Schipper and Smith,1983). Table 1 – Description of hypothesis and parametric tests used on different levels of provides an overview of the hypothesis and test statistics that will be used in the study.

Null Hypothesis	Parametric tests	Test level
$H_0: AR = 0$ *Hypothesis 1*	$AR\ t\ test$	Individual Event
$H_0: CAR = 0$ *Hypothesis 2*	$CAR\ t\ test$	Multi-period Event
$H_0: AAR = 0$ *Hypothesis 3*	$AAR\ t\ test$ $Adjusted\ Cross\ sectional\ test$ $Adjusted\ Patell\ test$ $Skewness\ corrected\ test$	Multi-Event
$H_0: CAAR = 0$ *Hypothesis 4*	$Adjusted\ Cross\ sectional\ test$ $Adjusted\ Patell\ test$ $Skewness\ corrected\ test$	Multi-Period and Multi-Event

Table 1 – Description of hypothesis and parametric tests used on different levels of analyze

Parametric test statistics ground on the classic $t - test$. On the other hand, further research on the area developed tests to correct the t-test's prediction error where the most widely used tests are the ones developed by Patell (1976) and Boehmer, Musumeci, and Poulsen (1991). As shown in Table 1, to accurately conclude on our model results and the sample significance, we will test, not only the AR and CAR t-test for each event but also, AAR and CAAR t tests. We are searching for market anomalies, thus the rejection of H_0 confirms the presence of anomalies in the market. A rejection of the alternative hypothesis confirms otherwise. On the next subsection, all tests and hypotheses will be explained in detail.

The power of using test statistics is being able to accurately capture abnormal returns that differ from zero with some statistical validity. An informed choice of test statistic should be based on the research setting and the statistical issues that analyzed data holds. Specifically, event-date clustering poses a problem leading to cross-sectional correlation of abnormal returns, and distortions from event-induced volatility changes. Cross-sectional correlation arises when sample studies focus on events that happened for multiple firms at the same day(s). Therefore, these issues introduce a downward bias in the standard error of regression and thus overstates the t-statistic, leading to an over-rejection of the null hypothesis. To overcome this issue, several authors introduce new statistics parametric tests that will be reviewed on the next subsection.

3.4.1 Parametric Tests

Parametric tests assume that individual firm's abnormal returns are normally distributed as in Campbell and Wasley (1993). The normality of abnormal returns is a key assumption underlying to use parametric tests for event studies. The parametric test used for this event study are the adjusted Patell (21), adjusted cross sectional test (28) and, skewness corrected test (31). As previously presented, to overcome the downward bias generated by the statistical issues that analyzed data holds, we decided to use the most known and used parametric test on the event study literature to correctly analyze the results.

Patell (1976) and Patell and Wolfson (1981) tried to overcome the t-test's proneness to event-induced volatility by standardizing the event window's ARs. The author used the dispersion of the estimation interval's ARs to limit the impact of stocks with high return standard deviations. However, the test too often rejects the true null hypothesis, particularly when samples are characterized by non-normal returns, low prices or little liquidity.

Moreover, the test has been found to still be affected by event-induced volatility changes, (Campbell and Wasley, 1993; Cowan, and Sergeant, 1996; and Kolari and Pynnone, 2010). Boehmer, Musumeci and Poulsen (1991) resolved this issue by developing a test statistic robust against volatility-changing events. Furthermore, the simulation study of Kolari and Pynnönen (2010) indicates an over-rejection of the null hypothesis, if cross-sectional correlation is ignored. Also. Kolari and Pynnonen (2010) developed an adjusted version for both test statistics that accounts for cross-sectional correlation. Details about these parametric tests can be found in the following descriptions.

$\boldsymbol{T_1}$**:** $\boldsymbol{T\ test}$

Introduced by Gosset (1908), $t\ test$ (12) is the most used test on event study literature. In this test statistic, the mean excess return is divided by its estimated standard error of regression, which is estimated from the time-series of mean excess returns.

$$t_{AR_{it}} = \frac{AR_{it}}{S_{AR_{it}}}, \tag{12}$$

$AR\ t\ test$ is calculated under the null (Hypothesis 1).
where $S_{AR_{it}}$ (13) is the standard error of regression.[4]

$$S_{AR_i}^2 = \frac{1}{M_i - 2} \sum_{t=T_0}^{T_1} (AR_{it})^2 \tag{13}$$

Second, we provide t statistics of the cumulative abnormal returns for each firm.

$$t_{CAR_{it}} = \frac{CAR_{it}}{S_{CAR_{it}}} \tag{14}$$

$CAR\ t\ test$ is calculated under the null (Hypothesis 2)
where $S_{CAR_{it}}$ (15) is the standard error of regression.[5]

$$S_{CAR_i}^2 = L_2\, S_{AR_i}^2 \tag{15}$$

[4] M_i refers to the number of non-missing returns.
[5] L_2 represents the event window, see Figure 1.

For the AARs, we calculate the $t\ test$ as below.

$$t_{AAR_{it}} = \frac{AAR_{it}}{S_{AAR_{it}}} \tag{16}$$

$AAR\ t\ test$ is calculated under the null (Hypothesis 3)
where $S_{AAR_{it}}$ (17) is the standard error of regression across firms at time t.

$$S^2_{AAR_i} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAr_t)^2 \tag{17}$$

CAARs $t\ test$ is calculated on equation (18).

$$t_{CAAR_{it}} = \frac{CAAR_{it}}{S_{CAAR_{it}}} \tag{18}$$

where $S_{CAAR_{it}}$ (19) is the standard error of regression of the cumulative abnormal returns across the sample.

$$S^2_{CAAR_i} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAr_t)^2 \tag{19}$$

The $t\ test$ has a major advantage, which is the simplicity of the calculations. However, it is prone to cross-sectional correlation and volatility changes (Brown and Warner, 1985). For this reason, further statistical test has to be added to the study to achieve accurate conclusions.

$\boldsymbol{T_2}$: ***Adjusted Standardized Residual test*** (***Adjusted Pattel***)

The standardized residual test also as known as Patell test, developed by Patell (1976), is one of the cross-sectional independence tests. The standardization (20) reduces the effect of stocks with large returns but assumes abnormal returns' cross sectional and no event induced change in the variance, across the event period of abnormal returns.

$$\text{SAR}_{it} = \frac{AR_{it}}{S_{AR_{it}}} \tag{20}$$

SAR_{it} are Student's t distributed with $M_i - 2$ degrees of freedom [6] under Hypothesis 3.

[6] Degrees of freedom of an estimate is the number of independent pieces of information that went into calculating the estimate. In this case we will use 2, $M_i - 2$.

Boehmer et al. (1991) found that, under the absence of an event induced variance, this test is well specified and has appropriate power. Patell has been known to be immune to how ARs are distributed across the (cumulated) event window but has limitations that prone to cross-sectional correlation and event-induced volatility. Kolari and Pynnönen (2010) propose a modification to the Patell test to account for cross-correlation of the abnormal returns.

Using the standardized abnormal returns (20), the forecast-error corrected standard error of regression (25), and defining as the average of the sample cross-correlation of the estimation period abnormal returns, the adjusted Patell test for Hypothesis 3 is:

$$z_{Patell,t} = z_{Patell,t}\sqrt{\frac{1}{1+(N-1)\bar{r}}} \tag{21}$$

Where $ASAR_t$ (22) is the sum over the sample of the standardized abnormal returns with standard error of regression (23), on Pattel test (24) .

$$ASAR_t = \sum_{i=1}^{N} \mathrm{SAR}_{it} \tag{22}$$

$$S^2_{ASAR_t} = \sum_{i=1}^{N} \frac{M_i - 2}{M_i - 4} \tag{23}$$

$$z_{Patell,t} = \frac{ASAR_t}{S_{ASAR_t}} \tag{24}$$

As event-window abnormal returns are an out-of-sample forecasts, $S^2_{AR_{it}}$ is the adjusted standard error of regression by the forecast error:

$$S^2_{AR_{it}} = S^2_{AR_t}\left(1 + \frac{1}{M_i} + \frac{(r_{mt} - \bar{r}_m)^2}{\sum_{t=T_0}^{T_1}(r_{mt} - \bar{r}_m)^2}\right) \tag{25}$$

For Hypothesis 4, see equations (41) to (44) (Appendix A).

In sum, adjusted Patell test improves Patell test by its immunity to cross sectional correlation.

$\boldsymbol{T_3}$: ***Adjusted Standardized Cross Sectional test*** (***Adjusted BMP test***)

Harrington and Shrider (2007) found that, in a short horizon, we should always use tests that are robust against cross-sectional variation. They found that standardized cross-sectional test, for AAR (26) and CAAR (Equations (45) to (48), Appendix A) a good candidate for a robust parametric test in conventional event studies.

$$z_{BMP,t} = \frac{ASAR_t}{\sqrt{N}S_{ASAR_t}} \tag{26}$$

With $ASAR_t$ defined as in equation (22) and with standard error of regression:

$$S_{ASAR_t}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(SAR_{i,t} - \frac{1}{N}SAR_{i,t}\right)^2 \tag{27}$$

As for strengths, it presents immunity to the how ARs are distributed across the (cumulated) event window and accounts for event-induced volatility and serial correlation. As limitations, the test is prone to cross-sectional correlation. Kolari and Pynnönen (2010) propose a modification to the BMP test to account for cross-correlation of the abnormal returns. Using the standardized abnormal returns ($SAR_{i,t}$) and defining $\bar{r}$ as the average of the sample cross-correlation for the estimation period abnormal returns, the adjusted BMP-test statistic for Hypothesis 3 is:

$$z_{BMP,t} = z_{BMP,t}\sqrt{\frac{1-\bar{r}}{1+(N-1)\,\bar{r}}} \tag{28}$$

As for strengths, the test is immune to how AR are distributed across the event window and it accounts for event induced volatility, serial correlation, and cross-correlation.

$\boldsymbol{T_4}$: ***Skewness Corrected Test***

The skewness-adjusted t-test, introduced by Hall (1992), corrects the cross-sectional $t\ test$ for skewed abnormal return distribution. This test is applicable for averaged abnormal return (Hypothesis 3) and the cumulative averaged abnormal return (Hypothesis 4). The cross-sectional standard error of regression (unbiased by sample size) for the CAARs follow:

$$S_{CAAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2 \tag{29}$$

And the skewness estimation (unbiased by sample size) is given by:

$$\gamma = \frac{N}{(N-2)(N-1)}\sum_{i=1}^{N}(CAR_i - CAAR)^3 S_{CAAR}^{-3} \tag{30}$$

Then, the skewness adjusted test statistic for CAAR is given by

$$t_{skew} = \sqrt{n}\left(S + \frac{1}{3}\gamma S^2 + \frac{1}{27}\gamma^2 S^3 + \frac{1}{6N}\gamma\right) \tag{31}$$

Where S is equal to $\frac{CAAR}{S_{CAAR}}$, which is asymptotically standard normal distributed.

The literature on skewness correct-test is presented by Hall (1992), Cramer (1961) and Rimoldini (2013). The aim in using this test is to correct-test statistics for skewed distributions. All tests will be analyzed at 5% and 10% levels of significance. Results related to the test statistics presented in this subsection will be shown and analyzed in the next section.

3.5 Market Expectations and Earnings Surprise

To what concerns the importance of market expectations, Fried and Givoly (1982) measured the performance of an alternative, knowing from their previous study that analysts' forecasts results are not accurate. Prediction errors are more associated with the price asset movement and, consequently, Fired and Givoly (1982: 85) were able to conclude that "*analysts' forecasts provide a better surrogate for market expectations than forecasts generated by time-series models*".

The main reason for time series models to be presented as an alternative to market expectations is not reliable, because it is further impaired by the underlying assumptions that earnings-generating processes are stationary alongside stable parameters. Also, the model characteristics are applied to all firms involved. In the literature, there are distinguishable views to apply EPS surprises methods, some are used for time series models while others used for analysts' forecasts.

We will rely and follow the methods provided by Yan and Zhao (2011) based on the analyst forecasts. The formula they used can be translated as the difference between the reported EPS and expected EPS, divided by the absolute value of the expected EPS:

$$\text{Earnings Surpise}_{iq} = \frac{Reported\ EPS_{iq} - Expected\ EPS_{iq}}{\left|Expected\ EPS_{iq}\right|} \tag{32}$$

Where, $Reported\ EPS_{iq}$ is the actual EPS announced on the earnings announcement date for firms i in quarter q, and the $Expected\ EPS_{iq}$ is the mean analyst forecast of EPS. All divided by the absolute value of the $Expected\ EPS_{iq}$.

To analyze if the results are somehow correlated with market surprise towards the announcement report, we will calculate the AAR assuming three scenarios (33), (34) and (35).
Data will be collected on Yahoo Finance and equations for calculations will be as follows:

1) $$\frac{Reported\ EPS_{iq} - Expected\ EPS_{iq}}{\left|Expected\ EPS_{iq}\right|} > 5\% \rightarrow Good\ News \tag{33}$$

2) $$\frac{Reported\ EPS_{iq} - Expected\ EPS_{iq}}{\left|Expected\ EPS_{iq}\right|} < 5\% \rightarrow Bad\ news \tag{34}$$

3) $$-5\% < \frac{Reported\ EPS_{iq} - Expected\ EPS_{iq}}{\left|Expected\ EPS_{iq}\right|} < 5\% \rightarrow No\ news \tag{35}$$

Also, we will test if the ARs are correlated with Earnings surprise by using Pearson correlation coefficient, formula shown below:

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)s_x s_y} \tag{36}$$

Where n is the sample size, x_i and y_i the individual sample points, $\bar{x}$ the sample mean and s_x the sample standard error of regression.

Authors, as Jegadeesh and Livnat (2006) find that the post-earnings drift may not be so strong because it is very difficult to confirm future information to the original earnings surprise. Others, as Kinney et al. (2002) claim that earnings surprise is not a good indicator for market reactions on earnings announcement. In the present study, our goal is test if the AAR are sensible to market surprises and also test whether or not a linear or inverse relationship between Earnings Surprise and AR exists. On section 4, we will explain the results in detail.

3.6. Data Gathering and Collection

As previously presented in section 3.1, the first step to conduct an event study is identifying the stocks to analyze. They will be the five highest-performing technology companies in the market, Apple, Facebook, Amazon, Netflix, and Google.

First, we take into consideration that all firms have at least 7 consecutive quarters reported between 2017 and 2018. Second, daily data will be used, and all stocks' financial information is gathered from Yahoo finance website. The third and fourth steps are related to the window choice, as shown on Figure 1. The fifth step is the choice of market proxy, variables and normal return model to use. On this, and as stated in section 3.2.1.1, the market proxy used is S&P500 and the single normal performance models to calculate abnormal returns are described in (1) with extensions on equation (4) and (5), and the multi-factor presented on equation (6) and (7).

Market data was obtained from Yahoo finance. Model composition and information were gathered from the Event Study Tools [7] website. Variables data was collected from the ETFdb website and Kenneth R-French data library**.** The sixth step is the abnormal returns´ calculations: AR, CAR, AAR, CAAR and Earnings Surprise. Seventh and last step is the computation of all test statistics used in the present study, which were computed through the Event Study ARC API from the Event Study Tools website. All the information received from the API [8] and was prepared in MS Excel. Finally, hypotheses are tested based on the cumulative standard normal distribution and student t distribution tables.

3.6.1. Estimation Model

Estimating the MM, for each of the 7 observation quarters of the 5 firms sample, produces a total of 35 individual observations and 35 calculations for each MMs (Table 47 to Table 56, Appendix B). In the next section, we will finally present the event study results and findings.

[7] EventStudyTools website (https://eventstudytools.com/) is considered one most popular and used websites to calculate and gather information about Event studies.

[8] The calculation engine of EventStudyTools' abnormal return calculators is also accessible through a JSON RPC application programming interface (API).

4. Empirical Evidence

In this section, we will conduct and compare results, statistical analysis and study limitations. In the first section, 4.1 we will analyze the AR and CAR results for each event and firm, evaluating the results and conclude about the t-test values. In section 4.2, we will test the AAR sensitivity to news, CAAR sensitivity to different time periods in the event window and, all the z statistics showed on the methodology. Third and last, we will underly the test assumptions, its statistical power and limitations and, the main causes for the standard hypothesis to be violated.

4.1 AR and CAR Behavior

As previously mentioned, the AR are the main factor to prove the existence of statistical significance on the event, therefore it is crucial to correctly compute them to have accurate results and true findings. For this matter, on the next subsections, we will present and analyze the AR results for the estimation models used.

To properly analyze the sample events, other measures have to be evaluated, more precisely, the cumulative abnormal returns, average abnormal returns, and cumulative average abnormal returns. The CAR focus is to test if the evolution of the market is consistent during the event window or if it shows retracements or extensions. In the present subsection, CAR will also be analyzed. In section 4.2, AAR and CAAR results will be displayed, tested and interpreted.

4.1.1 Sample observations AR

According to AR model calculations, abnormal returns were calculated based on specific estimation models for each event and firm as presented on Table 2. Since we are calculating the AR with 5 different approaches, to ease the results and mitigate outliers on the model calculations, we will calculate the average of the 5 estimation models to calculate all test statistics and the remaining measures (CAR, AAR, and CAAR).

Event	1	2	3	4	5	6	7
AR value *N* + 1							
MM	0.84%	-2.47%	11.43%	5.10%	3.27%	1.14%	2.93%
MM/GARCH	0.65%	-2.50%	11.57%	5.04%	3.22%	1.01%	2.87%
MM/EGARCH	0.81%	-2.47%	11.44%	5.22%	3.28%	1.09%	2.98%
Multi (Industry + Vix)	0.67%	-2.57%	11.59%	5.34%	3.28%	1.04%	2.99%
Multi (Fama + Vix)	0.85%	-2.37%	11.30%	5.02%	3.34%	1.25%	2.94%
Average	0.76%	-2.48%	11.47%	5.14%	3.28%	1.11%	2.94%
T test value N + 1							
MM	0.5030	-1.5535	7.3742	3.3117	2.1946	0.7972	2.1232
MM/GARCH	0.3736	-1.5723	7.4167	3.2727	2.1611	0.7063	2.0797
MM/EGARCH	0.4850	-1.5535	7.3806	3.3896	2.2013	0.7622	2.1594
Multi (Industry + Vix)	0.4012	-1.6062	7.4774	3.4675	2.2013	0.7273	2.1667
Multi (Fama + Vix)	0.5090	-1.4906	7.2903	3.2810	2.2416	0.8803	2.1304
Average	0.4544	-1.5552	**7.3878[a]**	**3.3445[a]**	**2.2000[b]**	0.7747	**2.1319[b]**
Average [9]	**4** Statistically Significant Events			**57.14%** events are Statistically Significant			

Table 2 – Amazon abnormal returns and t-test value per model

As displayed on Table 2, Amazon provides statistically significant results. From the events, 2 of the 7, show abnormal returns statistically significant at 1% and 5%. Individually, the Amazon t-test provides solid evidence of AR presence, 57% of the events are statistically significant.

All Amazon events that are statistically significant have positive abnormal performance, 11.47% (event 3), 5.14% (event 4), 3.28% (event 5) and 2.94% (event 7). In general, 6 of the 7 events exhibit positive returns, which points the question that Amazon´s abnormal returns could be correlated to Earnings surprise (when positive Earnings surprise, the market shows positive abnormal performance). In section 4.2 this matter will be analyzed.

From Figure 2 we have a clear view of the AR evolution from day -10 until day 10 after the event.

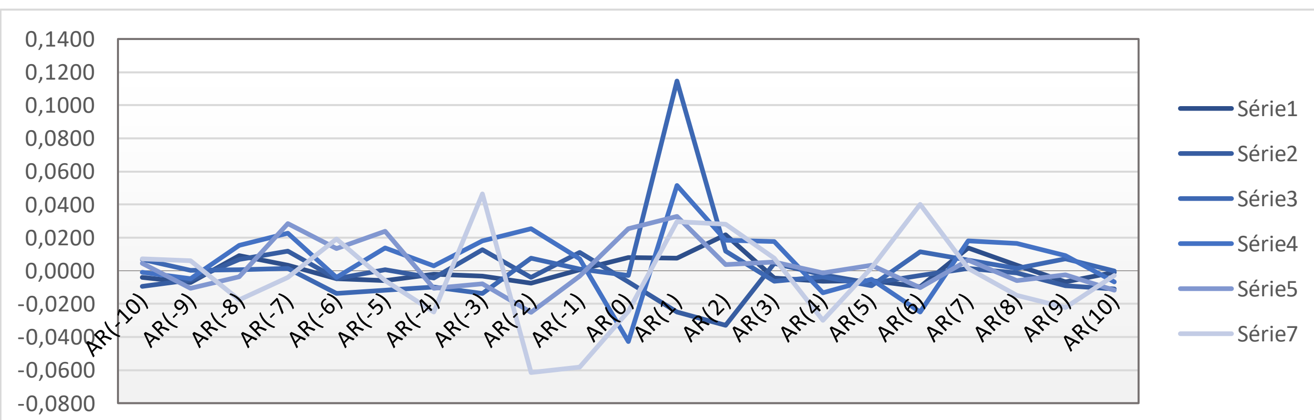

Figure 2 – Amazon abnormal returns during the event window for each event

[9] For the statistically significance, [a] means rejected at 1% ($\pm$ 2.58) and [b] rejection at 5% ($\pm$ 1.96)

Amazon display a significant concentration of AR on the day after the announcement (day 1), but also shows significant negative and positive fluctuations around the announcement which can be related to insider trading positions, anticipated news and press releases.

Event 7 displays a lot of noise up until the event day. From 4.64% abnormal return on day (-3) to -6.15% on the next day, followed by a significant extension to 2.95% on the day 1. Also, following the announcement, it becomes clear that the market tends to adjust after assimilating the news. From event to event, all tend to 0% AR on day 10 but the pace of price adjustments differs from each other. Some, as event 7, still display significant movements six days after the announcement (abnormal return of 4% on day 6). However, others adjust almost immediately, from an AR of 11% on day 1 to 1.18% on day 2 (event 3). In sum, Amazon is a good example of a company that on average, has considerable expectations from investors towards their report results.

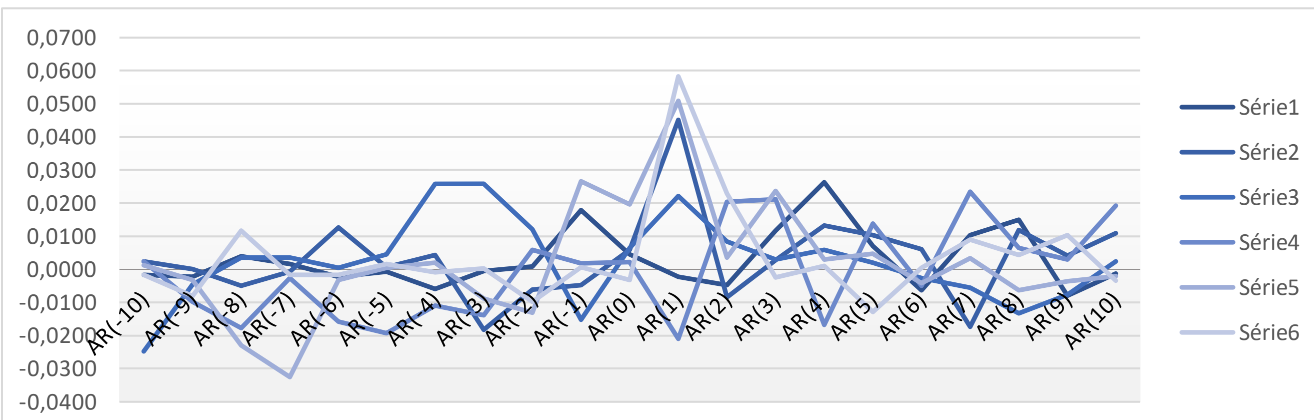

Figure 3 - Apple abnormal returns during the event window for each event

As in Amazon analysis, Apple AR evolution (Figure 3) shows an abnormal return concentration on the day after the announcement and, a precise view of the noise around and after the announcement. This movements, before the announcement, could be related to news that generates feelings of doubt within investors. The market seems to be uncertain about the type of results that the company will announce.

After the announcement, the market tries to adjust its price on day 2 but violates the EMH by not being able to integrate the recent news either on day 2 or during the 10-day window following the event. However, Apple presents an almost perfect AR distribution, 55.1% are positive during the 21 days on the 7 events and 44.9% negative. Also, as per Table 3 results, the null AR=0 is rejected at 1% significance level on 57.14% of the events.

Event	1	2	3	4	5	6	7
AR value $N + 1$							
MM	-0.22%	4.53%	2.21%	-2.08%	5.11%	5.82%	-6.22%
MM/GARCH	-0.24%	4.50%	2.17%	-2.13%	5.11%	5.79%	-6.22%
MM/EGARCH	-0.21%	4.54%	2.21%	-2.10%	5.11%	5.81%	-6.24%
Multi (Industry + Vix)	-0.17%	4.53%	2.17%	-2.15%	5.01%	5.75%	-6.32%
Multi (Fama + Vix)	-0.28%	4.49%	2.27%	-2.03%	5.14%	5.95%	-6.10%
Average	-0.22%	4.52%	2.21%	-2.10%	5.10%	5.82%	-6.22%
T test value N + 1							
MM	-0.1897	3.9391	1.9386	-1.8246	4.6036	5.1964	-5.6545
MM/GARCH	-0.2069	3.9130	1.9035	-1.8684	4.6036	5.1696	-5.6545
MM/EGARCH	-0.1810	3.9478	1.9386	-1.8421	4.6036	5.1875	-5.6727
Multi (Industry + Vix)	-0.1466	3.9052	1.9035	-1.8860	4.5135	5.1339	-5.7455
Multi (Fama + Vix)	-0.2414	3.9043	1.9512	-1.7807	4.6306	5.3125	-5.5455
Average	-0.1931	**3.9219**[a]	1.9271	-1.8404	**4.5910**[a]	**5.2000**[a]	**-5.6545**[a]
Average	**4** Statistically Significant Events				**57.14%** events are Statistically Significant		

Table 3 - Apple abnormal returns and t-test value per model

Similarly, to Amazon and Apple, Facebook's abnormal returns show statistically significant values. More precisely, 57% of the events are statistically significant, 3 at a 1% level and 1 at 5% (Table 4 -Facebook abnormal returns and t-test value per model. Facebook displays 3 significant positive AR (events 2, 3 and 4) and one huge drop from 0.29%, on the announcement day, to (-15.3%) on the day after (event 6).

Event	1	2	3	4	5	6	7
AR value $N + 1$							
MM	-0.78%	2.90%	-2.16%	3.27%	7.42%	-20.73%	2.46%
MM/GARCH	-0.81%	2.85%	-2.22%	3.20%	7.44%	-20.83%	2.46%
MM/EGARCH	-0.75%	2.90%	-2.17%	3.27%	7.45%	-20.76%	2.56%
Multi (Industry + Vix)	-0.76%	2.90%	-2.22%	3.45%	7.61%	-20.72%	2.65%
Multi (Fama + Vix)	-0.71%	2.87%	-2.00%	3.43%	7.45%	-20.80%	2.40%
Average	-0.76%	2.88%	-2.15%	3.32%	7.47%	-20.77%	2.51%
T test value N + 1							
MM	-0.5735	2.2308	-1.7008	2.5952	5.7519	-15.7045	1.6184
MM/GARCH	-0.5956	2.1923	-1.7480	2.5197	5.7674	-15.7803	1.6184
MM/EGARCH	-0.5515	2.2308	-1.7087	2.5952	5.7752	-15.7273	1.6842
Multi (Industry + Vix)	-0.5588	2.2308	-1.7480	2.7381	5.8992	-15.6970	1.7434
Multi (Fama + Vix)	-0.5221	2.2077	-1.5748	2.7222	5.7752	-15.7576	1.5789
Average	-0.5603	**2.2185**[b]	-1.6961	**2.6341**[b]	**5.7938**[a]	**-15.7333**[a]	1.6487
Average	**4** Statistically Significant Events.				**57.14%** events are Statistically Significant		

Table 4 -Facebook abnormal returns and t-test value per model

This fall can be related to negative news reported, causing a high negative earnings surprise percentage or, a large expectancy by investors in a possible drop on the results. In subsection 4.2, we will consider and analyze in greater detail the relation between the average abnormal returns and earnings market surprise by type of news.

On Figure 4, Apple, unlike Facebook, boasts a clear graph with small noise during the event. From day -10 to -1 the average abnormal return is 0.014% and from day 2 to 10 is (-0.02%), proving that Facebook events behave in a much more constant way in comparison to the other firms. This phenomenon could be related to predictive news and smaller or more certain expectations from investors and market players towards the announcements.

In terms of observations distribution, Facebook shows, as well as Amazon and Apple, an almost perfect abnormal return distribution. In fact, out of the 147 abnormal returns calculated, 48.3% are positive and 51.7% are negative. These values are related to small constant fluctuations, where the price only drops or increases with more significance when the announcement happens and, after the announcement, almost immediately adjusts its price on day. This stock, in a way, is very resistant to news and speculation and follow on most of the events, the EMH.

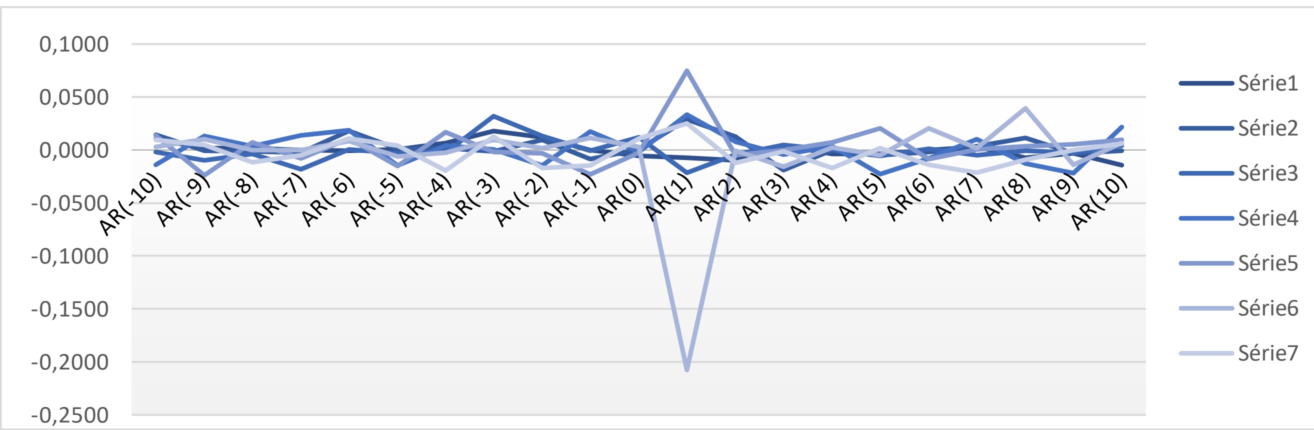

Figure 4 - Facebook abnormal returns during the event window for each event

Netflix AR calculations show solid evidence (Table 5 – Netflix abnormal returns and t-test value per model of abnormal performance after the announcement day. From the 7 events, 5 of them are statistically significant. This evidence seems to be enough, from an individual event analysis point of view, to state that Netflix has a significant tendency to provide higher or lower returns after the earnings announcements. In terms of AR distribution, the firm presents the most symmetric distribution in comparison to all the other firms, 49.7% positive abnormal returns and 50.3% negative AR.

Abnormal statistically significant returns are positively concentrated, showing four of the five significant events positive and, only one negative. The absence of negative news towards the earnings report could be one of the reasons to justify this AR positive concentration.

Event	1	2	3	4	5	6	7
AR value *N* + 1							
MM	-2.39%	12.54%	-1.77%	9.07%	7.15%	-6.11%	5.10%
MM/GARCH	-2.39%	12.60%	-1.75%	9.07%	7.14%	-6.12%	5.07%
MM/EGARCH	-2.33%	12.61%	-1.71%	9.20%	7.20%	-6.03%	5.16%
Multi (Industry + Vix)	-2.49%	12.42%	-1.85%	9.39%	7.03%	-6.49%	4.97%
Multi (Fama + Vix)	-2.59%	12.25%	-1.91%	8.91%	6.82%	-5.76%	5.82%
Average	-2.44%	12.48%	-1.80%	9.13%	7.07%	-6.10%	5.22%
T test value N + 1							
MM	-0.9373	5.0361	-0.6996	3.7950	3.0042	-2.6450	2.3394
MM/GARCH	-0.9409	5.0602	-0.6917	3.7950	3.0127	-2.6494	2.3257
MM/EGARCH	-0.9173	5.0643	-0.6759	3.8494	3.0252	-2.6104	2.3670
Multi (Industry + Vix)	-0.9765	4.9880	-0.7312	3.9289	2.9538	-2.8095	2.2798
Multi (Fama + Vix)	-1.0237	4.9395	-0.7610	3.7280	2.8776	-2.4935	2.6820
Average	-0.9591	**5.0176**[a]	-0.7119	**3.8193**[a]	**2.9747**[a]	**-2.6416**[b]	**2.3988**[b]
Average	5 Statistically Significant Events.			**71.43%** events are Statistically Significant			

Table 5 – Netflix abnormal returns and t-test value per model

Figure 5 helps to understand the AR behavior on the 21-event window run. Although on the day following the announcement the average abnormal return is huge, 8% in absolute values, before the announcement date, fluctuations are very unpredictable, ranging from 5% to -0.04% in two days (event 3) and from -4% to 3.5% in two days (event 7).

After the event date, the stock violates the EMH on 3 of the 5 significant events.

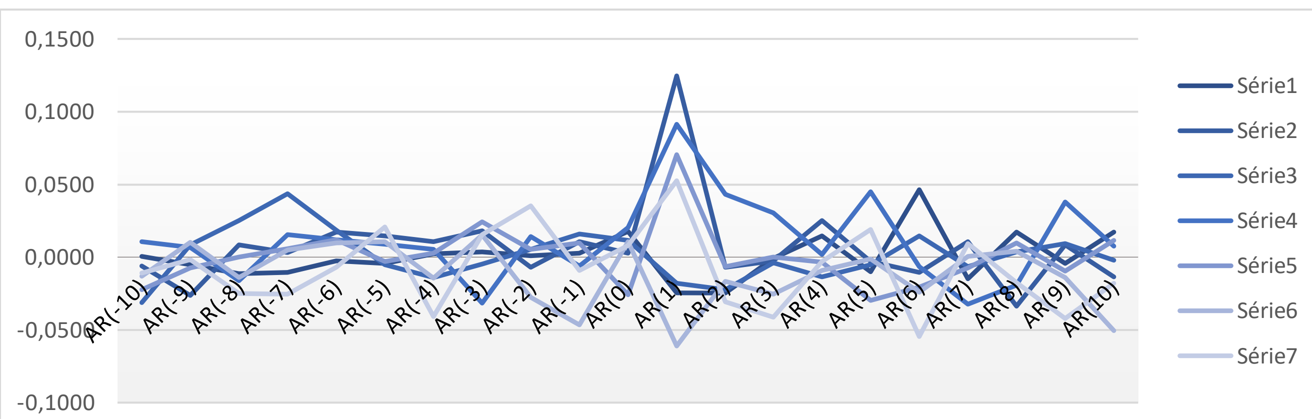

Figure 5 - Netflix abnormal returns during the event window for each event

In sum, the pre and post-earnings announcement drift on Netflix is unstable. The stock only has one moment of lower AR (day -1) which shows, an average AR of ±1.6%. This market "cooldown" can be related to market players "holding" for more concrete news about the way that the market is going to behave (after the announcement) before taking their market positions.

Google, since the 2nd quarter of 2017, from the companies studied, has shown to be, on individual abnormal return analysis, the one that shows more significant events. From the 7 events, 85.71% are statistically significant at the 1% level (Table 6).

Event	1	2	3	4	5	6	7
AR value *N* + 1							
MM	3.82%	-3.31%	3.31%	-3.23%	-3.40%	3.22%	0.25%
MM/GARCH	3.83%	-3.25%	3.45%	-3.27%	-3.39%	3.26%	0.29%
MM/EGARCH	3.84%	-3.31%	3.31%	-2.91%	-3.35%	3.23%	0.32%
Multi (Industry + Vix)	3.71%	-3.43%	3.29%	-3.12%	-3.28%	3.26%	0.34%
Multi (Fama + Vix)	3.78%	-3.42%	3.22%	-3.27%	-3.44%	3.19%	0.36%
Average	3.80%	-3.34%	3.32%	-3.16%	-3.37%	3.23%	0.31%
T test value N + 1							
MM	3.4107	-2.9292	2.9554	-2.9099	-3.1193	2.9009	0.2660
MM/GARCH	3.4196	-2.8761	3.0804	-2.9459	-3.1101	2.9369	0.3085
MM/EGARCH	3.4286	-2.9292	2.9554	-2.6216	-3.0734	2.9099	0.3404
Multi (Industry + Vix)	3.3125	-3.0354	2.9375	-2.8108	-3.0092	2.9369	0.3617
Multi (Fama + Vix)	3.3750	-3.0265	2.8750	-2.9459	-3.1560	2.8739	0.3830
Average	**3.3893**[a]	**-2.9593**[b]	**2.9607**[a]	**-2.8468**[b]	**-3.0936**[a]	**2.9117**[b]	0.3319
Average	**6** Statistically Significant Events.			**85.71%** events are Statistically Significant			

Table 6 – Google abnormal returns and t-test value per model

This high percentage proves the power of news, trough announcements, in the stock market. The only event that does not show statistically significant returns is event 7. Moreover, this event, has an early adjustment on the announcement day and late adjustment on day 2 after the event, showing an AR of 2.15%, on day 0, to an AR of -3.81% on day 2 (Figure 6). On this event, news integrates the market on day 0, which is often associated with insider trading positions. Consequently, AR are reflected on the market one earlier from the expected (day 0) and one day late (day 2) day. Also, Google stock has an AR symmetrical distribution, 50% positive and 50% negative.

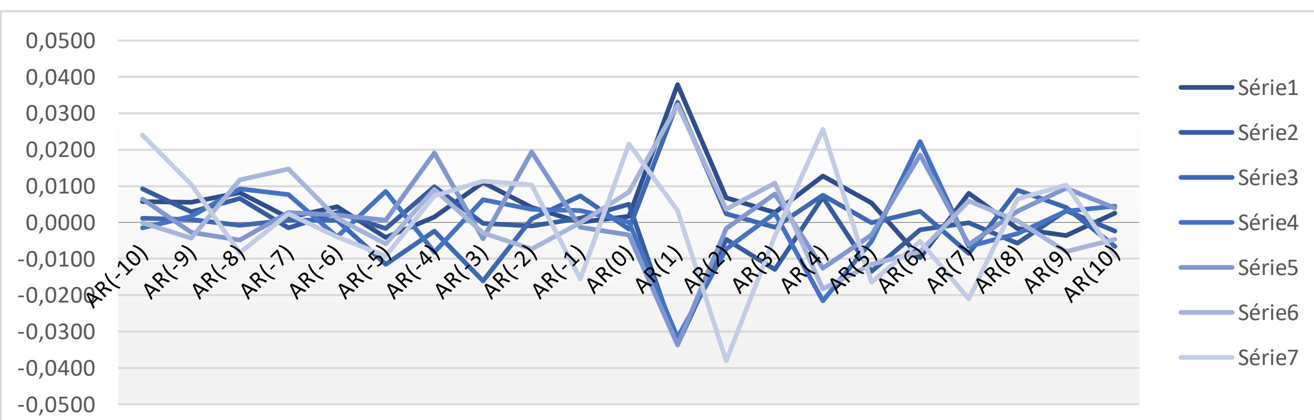

Figure 6 - Google abnormal returns during the event window for each event

As well as Netflix, Apple, and Amazon, Google shows sharp fluctuations during the 21 days of the event window. The market speculation is huge, making the investors' environment very volatile.

However, the returns do not surpass the 1.96 mark on most of the cases. From the 70 returns in-between day -10 to -1 only 2 of them broke the 1.96 mark and after day 1, only 6.3% of the AR showed to be significant. In short, Google seems to be a great company to predict, in terms of AR, after the announcement, by showing consistent and significant results. On the other hand, it is a bad one to predict during the pre and post-announcement (day -10 to -1 and day 2 to 10) due to the presence of high volatility.

In sum, since we are dealing with the major market players in the technology industry (FAANG stocks), it is expected that the public noise is considerably large and significant around the announcement. For that reason, abnormal returns tend to fluctuate before the announcement, increase on the day after the announcement and then, according to the market players' expectations on the reported earnings, adjust almost immediately. In some events, adjust to near 0% on day 2 or, in some cases, bounces back and forward from 5 to 6 days after the announcement and, only afterwards, the market adjusts to the non-presence of AR. On average, 65.7% of the events have abnormal returns statistically significant on day 1 following the day after the announcement. Also, 43.7% of the events showed considerable fluctuations, positive (>2%) or negative (< -2%) before the announcement, 30.4% of the events adjust their market price immediately after day 1 and 21.7 % fluctuates positively (>2%) or negatively (< -2%) after the announcement day and, only start to adjust the market price after the 7thday.

This evidence does not corroborate with the EMH, violating on approximately 70% of the statistically significant events.

4.1.2 Sample observations CAR

As previously stated, the CAR focus is to test if the evolution of the market is consistent during the event window. This measure is necessary to accommodate a multiple-day event window and can be very useful to understand the market reaction towards different events. Due to the arbitrage choice of days inside the event window, the cumulative abnormal is very sensitive. If the window is too long the CAR are biased due to many factors, for instance, late news that does not concern the event in study, could increase or decrease the AR on a large scale and distort the results. If the window is too short, the CAR does not have space to cover the market pre and post reactions to the news, presenting on most of the cases a high CAR.

On average cumulative abnormal returns tend to zero and the stock does not follow the EMH by adjusting its price with delay, which is the case of approximately 70% of the firms studied in the thesis. With the CAR t-test values, we will be able to conclude with more certainty about the violation of the EMH and test the stock's price ability to neutralize the effects of statistically significant AR.

From Table 2 to Table 6, we can conclude about the type of AR drift during the event window. Starting with Amazon, from the statistically significant events, we can derive that no event has a cumulative abnormal return above the 1.96 mark. This evidence shows that Amazon stock price can be inserted into one of the three following scenarios.

Scenario 1

A firm's stock price has a significant high abnormal return on day one after the announcement and, on the other days of the event window, low AR are registered.

Scenario 2

Abnormal returns have higher highs and lower lows and consequently, when the cumulative value is calculated, the higher positive values write off the lower negative values and a small CAR is the final value. Inside this scenario, it is possible to have a predominance of positive higher values or negative lower values and consequently a cumulative statistically significant value.

Scenario 3

Abnormal returns have symmetry of positive and negative lower abnormal returns during the event window, making the cumulative value low.

By analyzing the CAR values in Table 7, regarding events 3, 4, 5 and 7, Amazon represents on average, a predominance of Scenario 2 with 100% of the significant events. This conclusion is obtained by the asymmetric values on "$\mathrm{CAR}-$ and $\mathrm{CAR}+$", violating scenario 3 and the "$-1\% < CAR > 1\%$" values largely different from the final CAR value. When scenario 3 is verified, CAR values will always be low and consequently, CAR t-test will never be significant.

AMAZON								
Event	Window	CAR -	CAR +	CAR [-1%,1%]	-1% < CAR >1%	CAR Value	CAR t-test	AR (1)
1	(-10, 10)	-6.91%	6.76%	-3.71%	3.69%	-0.02%	-0.0030	0.76%
2	(-10, 10)	-12.62%	4.91%	-4.42%	-3.19%	-7.61%	-1.0434	-2.48%
3	**(-10, 10)**	**-7.11%**	**17.05%**	**0.04%**	**9.78%**	**9.82%**	**1.3814**	**11.46%**
4	**(-10, 10)**	**-10.29%**	**23.72%**	**-0.24%**	**13.44%**	**13.20%**	**1.8722**	**5.15%**
5	**(-10, 10)**	**-9.28%**	**14.73%**	**-0.11%**	**5.54%**	**5.43%**	**0.7950**	**3.28%**
6	(-10, 10)	-9.32%	10.77%	3.72%	-2.25%	1.47%	0.2247	1.11%
7	**(-10, 10)**	**-26.73%**	**18.77%**	**1.12%**	**-9.35%**	**-8.22%**	**-1.3004**	**2.95%**

Table 7 – Amazon cumulative abnormal return values per category and t-test value

APPLE								
Event	Window	CAR -	CAR +	CAR [-1%,1%]	CAR >1% / <-1%	CAR Value	CAR t-test	AR (1)
1	(-10, 10)	-3.59%	9.92%	-1.79%	9.21%	7.42%	1.1833	-0.22%
2	**(-10, 10)**	**-6.03%**	**13.06%**	**0.14%**	**6.88%**	**7.02%**	**1.3293**	**4.52%**
3	(-10, 10)	-7.35%	12.60%	1.99%	3.29%	5.28%	1.0103	2.21%
4	(-10, 10)	-13.28%	11.98%	0.43%	-1.64%	-1.21%	-0.2320	-2.10%
5	**(-10, 10)**	**-9.99%**	**13.91%**	**-1.30%**	**5.34%**	**4.04%**	**0.7934**	**5.09%**
6	**(-10, 10)**	**-4.55%**	**12.08%**	**-1.52%**	**9.03%**	**7.51%**	**1.4632**	**5.83%**
7	**(-10, 10)**	**-20.59%**	**7.94%**	**-0.56%**	**-11.99%**	**-12.55%**	**-2.4893[b]**	**-6.22%**

Table 8 – Apple cumulative abnormal return values per category and t-test value

FACEBOOK								
Event	Window	CAR -	CAR +	CAR [-1%,1%]	CAR >1% / <-1%	CAR Value	CAR t-test	AR (1)
1	(-10, 10)	-5.55%	5.80%	-2.35%	2.58%	0.23%	0.0366	-0.76%
2	**(-10, 10)**	**-4.37%**	**10.24%**	**-0.74%**	**6.62%**	**5.87%**	**0.9857**	**2.88%**
3	(-10, 10)	-7.95%	6.79%	-2.90%	1.73%	-1.16%	-0.2000	-2.15%
4	**(-10, 10)**	**-11.48%**	**14.81%**	**0.51%**	**2.52%**	**3.02%**	**0.5235**	**3.34%**
5	**(-10, 10)**	**-9.14%**	**16.93%**	**0.39%**	**7.18%**	**7.56%**	**1.2796**	**7.48%**
6	**(-10, 10)**	**-25.23%**	**11.82%**	**2.15%**	**-15.64%**	**-13.50%**	**-2.2311[b]**	**-20.77%**
7	(-10, 10)	-14.20%	8.55%	1.13%	-7.02%	-5.89%	-0.8459	2.51%

Table 9 – Facebook cumulative abnormal return values per category and t-test value

GOOGLE								
Event	Window	CAR -	CAR +	CAR [-1%,1%]	CAR >1% / <-1%	CAR Value	CAR t-test	AR (1)
1	**(-10, 10)**	**-1.90%**	**11.96%**	**3.89%**	**6.31%**	**10.20%**	**1.9873[b]**	**3.79%**
2	**(-10, 10)**	**-7.92%**	**4.78%**	**2.86%**	**-5.79%**	**-2.93%**	**-0.5658**	**-3.36%**
3	**(-10, 10)**	**-4.93%**	**7.05%**	**1.58%**	**0.66%**	**2.23%**	**0.4353**	**3.31%**
4	**(-10, 10)**	**-8.92%**	**7.25%**	**1.43%**	**-3.18%**	**-1.76%**	**-0.3452**	**-3.17%**
5	**(-10, 10)**	**-7.42%**	**9.29%**	**0.80%**	**0.99%**	**1.79%**	**0.3587**	**-3.37%**
6	**(-10, 10)**	**-7.10%**	**9.78%**	**-1.28%**	**3.92%**	**2.64%**	**0.5194**	**3.23%**
7	(-10, 10)	-13.09%	13.28%	-2.05%	2.03%	-0.02%	-0.0037	0.32%

Table 10 – Google cumulative abnormal return values per category and t-test value

NETFLIX								
Event	Window	CAR -	CAR +	CAR [-1%,1%]	CAR >1% / <-1%	CAR Value	CAR t-test	AR (1)
1	(-10, 10)	-11.34%	12.27%	-0.75%	1.87%	1.11%	0.0956	-2.46%
2	**(-10, 10)**	**-11.01%**	**25.32%**	**-0.34%**	**14.90%**	**14.56%**	**1.2773**	**12.46%**
3	(-10, 10)	-12.65%	15.57%	-0.08%	3.38%	3.30%	0.2846	-1.81%
4	**(-10, 10)**	**-11.16%**	**35.01%**	**1.75%**	**21.89%**	**23.64%**	**2.1586[b]**	**9.13%**
5	**(-10, 10)**	**-13.56%**	**15.17%**	**-0.32%**	**2.13%**	**1.81%**	**0.1658**	**7.04%**
6	**(-10, 10)**	**-31.83%**	**6.63%**	**0.91%**	**-25.78%**	**-24.88%**	**-2.3501[b]**	**-6.11%**
7	**(-10, 10)**	**-32.78%**	**16.07%**	**-0.35%**	**-16.61%**	**-16.95%**	**-1.6979**	**5.25%**

Table 11 – Netflix cumulative abnormal return values per category and t-test value

Apple results (Table 8), differ from Amazon, in fact, 75% of the statistically significant events follow Scenario 1. Symmetry is violated on all significant events, with more than 2% and minus than -2% of the difference between "CAR – and CAR +". Also, only one event follows Scenario 2 conditions.

Apple shows only one event statistically significant, event 7 at 5% level, which is the only one that follows Scenario 2. The reason behind this value is the negative AR after the announcement day. (-6.22%), followed by other lower lows (below -1%) during the event window. The negative predominance is clearly shown by the "CAR – " value of -20.59% in comparison with the 7.94% "CAR + " value. A high AR and a positive or negative predominance on the event window are the main conditions to have a statistically significant cumulative abnormal return.

After analyzing Amazon and Apple, we see that Facebook results (Table 9) follow Scenario 1and Scenario 2. On 50% of the significant events, events 1 and 6, scenario 2 is verified while, on the other hand, events 4 and 5 follow scenario 1. Scenario 3 is violated on all significant events but only one CAR value is statistically significant at 5% significance level (event 6). This event shows the same conditions and characteristics of Apple´s significant CAR value. A huge abnormal return after the announcement day, a discrepancy of 13.41% between "CAR – and CAR +", and a predominance of lower negative values during the event window. Apple´s cumulative statistically significant abnormal return shows a violation of scenario 3, a predominance of negative values on Scenario 2 and validation on Scenario 1.

In contrast to Amazon stock price, Google follows Scenario 1 on 83% of the events that have a statistically significant abnormal return on day 1 and only 1 event (event 1) follows Scenario 2. On a CAR statistically significant level, event 1 is significant at 5 % level and has, much like the remaining of the firm´s CAR significant values, a violation of Scenario 3 on a 10.06% difference from "CAR – and CAR +". Also, we see a predomination of higher AR values on Scenario 2 and a considerably high value on the day 1 abnormal return.

Netflix is the only company that shows more than one CAR significant event at the 5% level. From the 5 significant events after announcement day, 100% of the events follow Scenario 2 and 80% violate the condition of Scenario 1. Also, on day 1 after the announcement, the difference of 23.85% between CAR – and CAR + (event 4) establish the conditions to have a significant CAR value, which is registered with the t-test value of 2.1586. On the other hand, a predominance of lower negative abnormal returns during the event window, a lower negative abnormal return on day 1 and a violation of scenario 3 with a difference value (-25.2%), build a significant CAR value for event 6.

On average, only 21.74% of the CAR values were statistically significant at 5% significance level. This small percentage is related to the balance between negative and positive high abnormal returns during the event window. On 78.26% of the events, the cumulative value is not sufficiently high or low, to be statistically significant, mainly due to peaks and price retracements on the event window. Also, on 13% of the events that show high AR value on the day 1, alongside with a stable low level of AR, between 1% and -1%, do not have enough power to surpass the 1.96 normal level due to the symmetry between "$\text{CAR}-$ and $\text{CAR}+$" positive values.

In sum, evidence shows that CAR statistically significant values, on most cases, are achieved when the following pattern conditions are verified. The event window must have a predominance of positive higher values or negative lower values in line with a positive or negative high abnormal return on the day after the announcement (above 3% or below -3%). Also, an asymmetrical distribution between "$\text{CAR}-$ and $\text{CAR}+$" of more than 10% or (-10%). All the other scenarios that violate the previous conditions have a lower probability of generating a cumulative value statistically significant.

Cumulative abnormal returns are a crucial value to interpret the firm's movements and price adjustments during the event window. On the five firms studied, 78.26% of the events write off the effect of a statistically significant value on the day after the announcement, with movements in the opposite direction. The Scenario 2 in these cases doesn't have a predominance on the positive or negative side and, on average, the large movements on the positive are balanced with large negative movements, and the small AR returns during the event window tend to have the same behavior. FAANG stocks show evidence of unstable behavior with large speculation and expectancy from the market players. The small percentage, 21.74%, of statistically significant CAR values corroborate that evidence.

4.2 From AR and CAR to AAR and CAAR

As mentioned before, AAR and CAAR are fundamental measures to infer on a firm's significance in terms of abnormal returns. On the calculations, the main problem is the cancelation between events. Since we are calculating the average value, the positive ones write off with the negative ones. To surpass this issue and correctly calculate and conclude on the statistical significance of the z statistics, we divided the calculations in "good news", "no news" and "bad news". More precisely, when earnings surprise is above 5%, we consider good news, when below -5%, we consider bad news and in between 5% and -5% we consider no news.

These calculations aim to achieve a clear value of the average abnormal return during the event window and, at the same time, test a possible correlation between earnings surprise and the abnormal values. The importance of AAR and CAAR values are crucial to the interpretation and comprehensiveness of the firm´s stock price movements on all events of the observation sample. In the present subsection, we will analyze in detail AAR and CAAR values and the correspondent z statistic values. In section 4.3 we will display and interpret the results summary and limitations of the study.

4.2.1. AR to AAR

Abnormal returns calculate the impact of an individual event but, to test the firm's sensitivity to the announcement, average abnormal returns must be calculated for the entire 21 days of the event window. On the AAR z statistics, we will calculate, with the AAR total value for each day of the event window, without differentiate by type of news for days 0 and 1.

The following tables (Table 12 to Table 16) show the AAR values for the FAANG stocks calculated per type of news for each day of the event window and the correspondent t-test value. On the sample observations used in the present research, some companies do not have a given type of news, Amazon does not have "no news" and Apple does not show "bad news"

4.2.1.1 Sample observations AAR

Amazon`s average abnormal returns per type of news are displayed on Table 12. On the good and bad news, we have statistically significant values on a specific day of the event window. On one hand, when good news comes out, following the announcement day, a positive AAR value of 3.5311% is registered and consequently, the t-test rejects the null hypothesis at 1% significance level. On the other hand, when bad news happens, AAR value appears with a day delay (day 2) of the event window. This delay is related to uncertainty by market players' decisions towards the price movements.

	AAR			
Window	Good News	t-test	Bad News	t-test
-10	0.3636%	0.2806	-0.1339%	-0.5887
-9	-0.1399%	-0.1080	-0.0789%	-0.3469
-8	0.1174%	0.0906	0.0974%	0.4280
-7	0.8215%	0.6342	0.1708%	0.7509
-6	0.0744%	0.0574	-0.0704%	-0.3093
-5	0.0052%	0.0040	0.0085%	0.0372
-4	-0.6321%	-0.4880	-0.0615%	-0.2705
-3	0.4164%	0.3214	0.1814%	0.7975
-2	-0.7685%	-0.5932	-0.0562%	-0.2470
-1	-0.6382%	-0.4926	0.1567%	0.6886
0	-0.9295%	-0.7175	-0.0948%	-0.4165
1	3.5311%	**2.7257**[a]	-0.3536%	-1.5542
2	0.9781%	0.7550	-0.4708%	-2.0696[b]
3	0.1699%	0.1311	0.0638%	0.2805
4	-0.6202%	-0.4788	-0.0333%	-0.1465
5	-0.0292%	-0.0225	-0.1058%	-0.4652
6	-0.0865%	-0.0668	-0.0401%	-0.1763
7	0.7767%	0.5995	0.0221%	0.0973
8	0.0510%	0.0393	-0.0177%	-0.0780
9	-0.0563%	-0.0435	-0.1305%	-0.5735
10	-0.2402%	-0.1854	-0.1554%	-0.6829

Table 12 – Amazon average abnormal returns and t-test value per type of news

A good percentage of the market take a negative position, causing a drop in the price on day 1 after. However, on day 2 the market seems to be certain of the price tendency and a drop of -34% from the day 1 to day 2 is displayed and, a statistically significant value of (-2.0696) is verified. Amazon stock price movements seem to be very sensitive to news. When good news is present, a positive statistically AAR value is registered and when the market faces bad news a negative significant value is also verified. Although the market, on average, took more time to incorporate the negative news, the linear correlation between the type of news and abnormal returns, on day 1 after the announcement, has a correlation coefficient of 0.86, thus indicating a strong linear correlation.

The event window evolution on the good news side has 12 positive values representing 57.14% of the observations. Nonetheless, on the negative side, 66.67% of the AAR are negative showing on average many AR in favor of the type of news.

Apple´s average abnormal returns, in contrast to Amazon, report a statistically significant value when earnings surprise is above 5% (Table 13). The null is rejected at 1% significance level with a positive AAR value of 1.7933%. On the no news perspective, AAR´s values are not significant during the event window and the market reaction is almost insignificant, which can be related to news reporting low expectations for the incoming earnings report or market players inside information on the report details.

	AAR			
Window	Good News	t-test	No News	t-test
-10	-0.3444%	-0.7065	-0.0964%	-0.0579
-9	-0.1793%	-0.3678	-0.0096%	-0.0058
-8	0.1477%	0.3031	-0.3800%	-0.2281
-7	0.0187%	0.0383	-0.2683%	-0.1611
-6	0.1650%	0.3385	-0.3262%	-0.1958
-5	0.0967%	0.1983	-0.2694%	-0.1617
-4	0.4193%	0.8601	-0.1815%	-0.1090
-3	0.1117%	0.2291	-0.5104%	-0.3064
-2	-0.0546%	-0.1121	-0.2727%	-0.1637
-1	-0.2750%	-0.5641	0.8432%	0.5062
0	0.1298%	0.2662	0.4181%	0.2510
1	1.7933%	**3.6786**[a]	-0.4924%	-0.2956
2	0.3279%	0.6725	-0.2352%	-0.1412
3	0.0487%	0.0999	0.8575%	0.5147
4	0.2868%	0.5883	0.2617%	0.1571
5	-0.0065%	-0.0134	0.3437%	0.2063
6	0.0554%	0.1136	-0.3662%	-0.2198
7	-0.1957%	-0.4015	0.0955%	0.0573
8	0.0451%	0.0926	0.0856%	0.0514
9	0.0963%	0.1976	-0.4254%	-0.2553
10	0.1417%	0.2906	0.3987%	0.2393

Table 13 – Apple average abnormal returns and t-test value per type of news

We consider that the absence of a statistically significant average abnormal return on the no news perspective is the expected market movement. Good news has a 76.2% predominance of positive abnormal returns and no news an almost symmetric distribution, presenting 57.1% positive values and 43.9% negative values. In terms of linear correlation regarding the news, Apple’s abnormal returns have a weak linear correlation with a coefficient correlation value of 0.31.

Market players have different expectations regarding the magnitude of the earnings announcement from firm to firm. Facebook is the first company to have the three categories of news, good, bad and no news.

According to Table 14, AAR rejects the null (AAR=0) with a positive high AAR for good news. For negative news, no rejection is shown, instead, when the market face "no news" instead the null is rejected at 1% significance level. This value for no news is strangely high and could be probably related to some stock price manipulation towards a downfall. Type of reported news on media can be also related but, since we cannot conclude with certainty about the cause of the abnormal returns, we will focus on the significance of this event to the sample.

	AAR					
Window	Good News	t-test	Bad News	t-test	No News	t-test
-10	0.5150%	0.6701	-0.0529%	-0.1412	0.0407%	0.2159
-9	-0.4218%	-0.5488	0.2195%	0.5865	0.1499%	0.7948
-8	-0.1414%	-0.1840	0.0748%	0.1997	-0.0030%	-0.0158
-7	-0.4765%	-0.6200	0.1944%	0.5194	-0.0021%	-0.0114
-6	0.5686%	0.7398	0.2568%	0.6861	0.1168%	0.6193
-5	-0.1863%	-0.2424	-0.2073%	-0.5538	-0.0904%	-0.4792
-4	-0.0426%	-0.0555	0.1551%	0.4144	-0.0350%	-0.1856
-3	0.5933%	0.7720	0.2607%	0.6966	0.1382%	0.7330
-2	0.0365%	0.0476	-0.0336%	-0.0897	0.0251%	0.1332
-1	-0.6671%	-0.8680	0.2461%	0.6574	0.1639%	0.8693
0	0.3017%	0.3925	-0.1133%	-0.3028	0.0410%	0.2172
1	1.5329%	**1.9944**[b]	0.3694%	0.9870	-2.9667%	**-15.7323**[a]
2	-0.1289%	-0.1678	-0.0273%	-0.0728	-0.0129%	-0.0682
3	-0.2221%	-0.2890	0.0056%	0.0149	-0.2245%	-1.1907
4	-0.1401%	-0.1823	0.0012%	0.0032	0.0317%	0.1679
5	0.1700%	0.2212	-0.3743%	-1.0000	-0.0681%	-0.3611
6	-0.3318%	-0.4317	-0.1186%	-0.3168	0.2951%	1.5650
7	-0.3238%	-0.4213	0.1881%	0.5025	0.0271%	0.1439
8	0.0701%	0.0913	-0.2862%	-0.7646	0.5614%	2.9773
9	0.0007%	0.0009	-0.3492%	-0.9329	-0.2019%	-1.0707
10	0.2712%	0.3529	0.1025%	0.2739	0.0974%	0.5164

Table 14- Facebook average abnormal returns and t-test value per type of news

From the AAR results after the announcement day and, with the coefficient correlation of 0.17, we can extract a very weak linear correlation between Facebook stock prices and news.

Also, good symmetry is displayed on good news, with 48% positive values and 52% negative. On the negative side, only 62% of the returns are positive which causes the AAR on day 1 to decrease, and as such, the negative values are canceled by the positive ones.

In sum, Facebook is not very sensitive to news and presents a certain degree of unpredictableness on average abnormal returns on the "no news" and "bad news" scenario.

Regarding Google AAR values (Table 15), in general, we verify the opposite of other firms on the bad news side. When bad news is displayed, the null is rejected with 1% level of significance with a positive abnormal instead of a negative one. This evidence indicates the presence of inverse linear relationship which on a medium scale is confirmed with the Pearson correlation coefficient of -0.46. The correlation is not stronger due to the neutral values on the good news perspective.

	AAR					
Window	Good News	t-test	Bad News	t-test	No News	t-test
-10	0.5845%	0.9560	-0.0011%	-0.0068	0.0599%	0.0269
-9	0.1645%	0.2691	-0.0624%	-0.3934	0.1038%	0.0466
-8	-0.1046%	-0.1711	0.1663%	1.0488	0.2500%	0.1121
-7	0.0608%	0.0995	0.2093%	1.3198	0.1264%	0.0567
-6	0.0180%	0.0294	0.0167%	0.1051	0.0055%	0.0025
-5	-0.3125%	-0.5111	-0.0838%	-0.5285	0.0631%	0.0283
-4	0.4843%	0.7921	0.1294%	0.8161	-0.0955%	-0.0428
-3	-0.1370%	-0.2241	-0.0423%	-0.2665	0.2452%	0.1100
-2	0.4217%	0.6896	-0.1032%	-0.6509	0.1110%	0.0498
-1	-0.1207%	-0.1974	-0.0010%	-0.0060	0.0483%	0.0217
0	0.3040%	0.4973	0.1188%	0.7492	0.0227%	0.0102
1	-0.4433%	-0.7251	0.4615%	**2.9107**[a]	0.0888%	0.0398
2	-0.5999%	-0.9811	0.0519%	0.3273	-0.0090%	-0.0041
3	-0.1432%	-0.2342	0.1544%	0.9737	0.0756%	0.0339
4	0.3911%	0.6396	-0.2612%	-1.6471	-0.1251%	-0.0561
5	-0.4770%	-0.7802	-0.1655%	-1.0435	0.0020%	0.0009
6	0.2050%	0.3353	-0.1142%	-0.7200	0.1790%	0.0803
7	-0.5121%	-0.8376	0.0830%	0.5233	0.0189%	0.0085
8	0.1796%	0.2938	0.0062%	0.0390	-0.0673%	-0.0302
9	0.3871%	0.6332	-0.1148%	-0.7237	-0.0074%	-0.0033
10	-0.2020%	-0.3304	-0.0656%	-0.4137	0.1010%	0.0453

Table 15 -Google average abnormal returns and t-test value per type of news

Although the average abnormal return is negative when earnings surprise is above 5%, with a value of -0.4433%, it is not enough to be statistically significant and inflate the correlation coefficient. On the no news category, the expectancy of low abnormal returns due to low surprise from market players towards the earnings report announcement leads to an expected non-rejection of the null with a very small AAR value of 0.08%,

Concerning the last company, Netflix results (Table 16) displays low sensitiveness to news, showing a correlation coefficient of 0.16. Good news presents a negative AAR value, bad news a small negative value and no news, a very high positive value and consequently statistically significant at 1%. However, when the market faces good news, the distribution of positive is balanced, with 11 negatives to 10 positive which means that the drop from day 0 to day 1 is considerably high, more specifically, almost 1% difference from 0.51% to -0.47%.

This evidence proves that investors took an opposite position from the earnings surprise value. The same happens on the negative news, 11 positives to 10 negative and a significant drop from 0.46 to -0.72 are registered from day 0 to day 1. A pattern could be in place towards the positive and negative earnings surprise by market players. In future research, a larger sample should be analyzed to check the validation of this possible pattern.

	NETFLIX					
	AAR					
Window	Good News	t-test	Bad News	t-test	No News	t-test
-10	-0.3380%	-0.3366	-0.4463%	-1.2373	-0.2596%	-0.2506
-9	0.0468%	0.0466	0.1187%	0.3290	-0.3871%	-0.3736
-8	-0.7248%	-0.7218	0.3563%	0.9878	-0.1092%	-0.1054
-7	-0.4451%	-0.4433	0.6226%	1.7261	0.3465%	0.3344
-6	0.0017%	0.0017	0.2658%	0.7370	0.5856%	0.5651
-5	0.3896%	0.3880	-0.0737%	-0.2043	0.2889%	0.2788
-4	-0.7562%	-0.7531	-0.2014%	-0.5584	0.2663%	0.2570
-3	0.4885%	0.4864	-0.0674%	-0.1868	0.1524%	0.1471
-2	0.1254%	0.1248	0.0745%	0.2066	0.1782%	0.1720
-1	-0.7582%	-0.7551	0.2248%	0.6231	0.2046%	0.1975
0	0.5173%	0.5151	0.1662%	0.4607	-0.0462%	-0.0446
1	-0.4726%	-0.4707	-0.2588%	-0.7175	4.0907%	**3.9478**[a]
2	-1.0288%	-1.0245	-0.3194%	-0.8855	0.4286%	0.4136
3	-0.9712%	-0.9672	-0.0577%	-0.1601	0.4013%	0.3873
4	0.0381%	0.0379	-0.1910%	-0.5294	0.3338%	0.3222
5	0.1130%	0.1125	-0.0717%	-0.1987	0.1727%	0.1667
6	-0.4627%	-0.4608	0.2101%	0.5825	-0.5350%	-0.5163
7	-0.0687%	-0.0684	-0.0908%	-0.2518	-0.4127%	-0.3983
8	0.0530%	0.0528	0.0537%	0.1488	-0.6195%	-0.5979
9	-0.8661%	-0.8625	0.1320%	0.3660	0.5270%	0.5086
10	-0.7350%	-0.7320	-0.0295%	-0.0818	0.0737%	0.0711

Table 16 – Netflix average abnormal returns and t-test value per type of news

Average abnormal returns were analyzed in three parts, being one, the level of sensitiveness to news. The statistical significance on day 1 after the announcement, the second and, the percentage of positive and negative days per type of news as third.

In sum, the sensitivity of the group of firms studied regarding news is on average 0.176 and 0.36 in absolute value, which represents a weak linear correlation. Also, we see that 60% of the firms reject the null at 5% and 1% significance level with positive AAR values on the day after the announcement on "good news". However, when bad news comes out, only 25% of the events on day 1 are statistically significant. Moreover, and not according to the expected, the AAR value that rejects the null is positive instead of negative. For no news, we expect to have low AAR values and consequently a constant non-rejection of the null hypothesis but instead, the null is rejected on 50% of the events with 25% with positive values and 25% with negative values.

This result supports the lack of sensitiveness towards the market earnings surprise. Regarding the distribution of AAR per type of scenario we verify that 53.6% are negative on bad news scenario, 59.5% are positive on the good news scenario. This distribution proves that the firms' AR in between events and during the 21 days of the event window does not have a positive or negative pattern. The market is constantly shifting from negative to positive around the event date and, as seen before, 65.7% of the events present an AR outside the normal range of non-rejection of the null, rejecting at 5% significance level.

Having into consideration all the previously stated assumptions, which will be further analyzed in section 4.3, we can infer that the AAR values for FAANG stocks are consistent and present a significant percentage of null rejection per type of news. On the other hand, stocks display low news sensitiveness towards Earnings surprise. In the next subsection, we will verify the validation of the results by testing the robustness through the adjusted Patell test, adjust standardized cross-sectional and skewness corrected t-test.

4.2.2 AAR Statistical Tests

Z statistics are calculated with r_m as the mean of the market returns in the estimation window and with the standard error of the abnormal returns distributed as a t-distribution with 2 degrees of freedom under the null hypothesis.

Amazon tests (Table 17), reject the null hypothesis at 5% level, after the announcement day, on the adjusted standardized residual tests, that measure the strength of the difference between observed and expected values, under the assumption of cross-sectional independence and event induced volatility. To test the robustness for potential event-date clustering and potential variance increase induced by the event, the adjusted standardized cross-sectional proposed by Kolari and Pynnönen (2010) is conducted and the null is rejected at 10% and 5% significance level. Also, to correct the cross-sectional t-test for skewness abnormal return distribution, the skewness correct t-test (Hall, 1992) is conducted and rejected at 10% significant level.

Z statistics	AAR (0)	AAR (1)
Adjusted Patell Z	-1.8552	**5.5145^{b}**
Adjusted StdCSect Z (BMP)	-1.1868	**1.9649^{c}**
Skewness Corrected T	-1.1253	**2.5159^{c}**

Table 17 – Amazon AAR results for parametric tests

According to test statistic values[10], Amazon presents solid evidence of abnormal return presence on the day after the announcement for the sample observations in the study. On Table 18, Table 19 and 20, Apple, Facebook, and Netflix parametric test results are displayed, and in contrast with Amazon, the test statistics only show rejection of the null at 5% and 10% significant levels on the adjusted standardized residual test on the day after the announcement. These tests, as stated before, reduce the effect of the events with large returns, assuming cross- sectional independence in abnormal returns, and that there is no event induced changes in the variance across the event period of abnormal returns.

Z statistics	AAR (0)	AAR (1)
Adjusted Patell Z	1.2939	**3.0288[b]**
Adjusted StdCSect Z (BMP)	2.0576	0.7699
Skewness Corrected T	3.0650	0.6735

Table 18 – Apple AAR results for parametric tests

Z statistics	AAR (0)	AAR (1)
Adjusted Patell Z	0.4312	**-2.1516[c]**
Adjusted StdCSect Z (BMP)	0.8583	-0.3079
Skewness Corrected T	0.9893	-0.4579

Table 19 – Facebook AAR results for parametric tests

Z statistics	AAR (0)	AAR (1)
Adjusted Patell Z	0.6909	**3.7323[b]**
Adjusted StdCSect Z (BMP)	1.0751	1.3123
Skewness Corrected T	0.7152	1.2579

Table 20- Netflix AAR results for parametric tests

On the robust parametric tests, the null of AAR=0 is not rejected on the announcement day and for the skewness correct t-test the null is also not rejected. Behind the tests used to conclude on the AAR hypothesis, relies the assumption that abnormal returns are contemporaneously uncorrelated. This assumption leads sometimes to biased results. Therefore, we will analyze this in detail in section 4.3.

The average abnormal return values for Apple, Facebook, and Netflix without the categorization by type of news is 1.30%, -1.06% and 3.73% respectively and the tests indicate that the null is only rejected on the Patell test, whilst not rejected on the remaining statistics.

[10] Test statistics will be rejected at 10%, represented by [c] and at 5% represented by [a] according to t student distribution table with 2 degrees of freedom

This evidence does not support the statement that AAR for Apple, Facebook and Netflix are statistically significant on the day after the announcement.

After analyzing AR and AAR significant values, test statistics are important to verify the validation of the null rejection of AAR = 0. Displayed in Table 21, Google shows very low values on all test statistics, therefore we do not reject the null on Patell test, cross-sectional and skewness t-test. Although individual event significance on Google is the highest among the other FAANGs, 86%, in terms of abnormal returns, the evidence does not support the presence of statistical significance on day one after the announcement date on a multi event analysis.

Z statistics	AAR (0)	AAR (1)
Adjusted Patell Z	1.1897	0.2584
Adjusted StdCSect Z (BMP)	1.3433	0.0856
Skewness Corrected T	1.8976	0.0818

Table 21- Google AAR results for parametric tests

These values are related to a low AAR value on day 1 which is caused by the symmetry on the positive and negative statistically significant AR. The positive values write off with the negative ones causing the low average value.

In sum, based on an average correlation of only 0.05, the true rejection probabilities at the nominal 5 percent level on the AAR values on day 1 after the announcement on the 5 firms studied is 80% for the Pattel test, 20% for the BMP test and 20% for the skewness correct t-test. Thus, the results support the true rejection of the null in 20% of the firms.

With large sample sizes, the results were probably be more satisfactory, leaving space for further research to accurately conclude about the statistical results for the FAANG stocks. However, with the sample size in place and taking into consideration that the calculations for the test statistics were based on the AAR values without the categorization by the news, which presents an over not rejection of the null on the t-test, the test statistics are crucial to correctly conclude on the results.

On average, evidence shows that only one firm, representing 20% of the FAANG stocks is correctly rejecting the null on the AAR level.

4.2.3. CAR to CAAR

After analyzing the CAR value during the 7 different events studied for each FAANG stock, the CAAR value is an extension and a crucial value to test if the cumulative returns, on average are significant. Also, this measure is important to properly conclude on the final average cumulative behavior of the stock price towards different announcements with different type of news and earnings surprise values.

To properly evaluate the CAAR values, we will split them by time frame intervals, from day 0 to 1, from 0 to 5, from 0 to 10 and all of the event window ranging from day -10 to 10. We will conduct test statistics taking in consideration these factors with the null being rejected at 10% and 5% for the hypothesis of no abnormal performance (CAAR=0).

4.2.3.1 Sample Observations CAAR

Amazon displays an interesting stable cumulative average abnormal return during the different time frames. Figure 7 provides a clear overview of this behavior, showing a difference between the event window CAAR value and the other time frames, on average -0.22%, which is very low for the analysis.

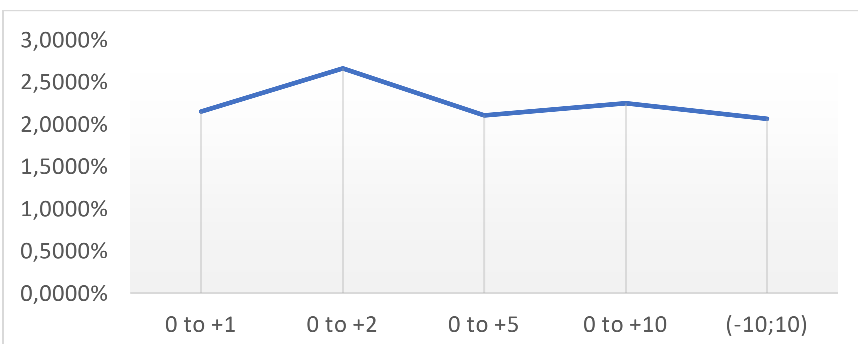

Figure 7 – Amazon multi-period CAAR results

This evidence reinforces the predominance of positive CAR values as seen in subsection 4.1.2 and the tendency of the company to stabilize their cumulative abnormal returns in terms of multi-event analysis. Thus, in order to check if the results are statistically significant, the statistical tests for all companies are conducted and the results are displayed from Table 22 to Table 26 on the next subsection (4.2.3).

Apple CAAR evolution during the different time frames is different from Amazon in the way that it doesn't portray a stable and constant pattern (Figure 8). From day 0 to day 1 the abnormal returns inflate the return to 1.85%, displaying a positive abnormal return predominance. From that mark forward the market suffers late positive adjustments increasing the CAAR value to 3.73% and stabilizing on that mark until the end of the event window.

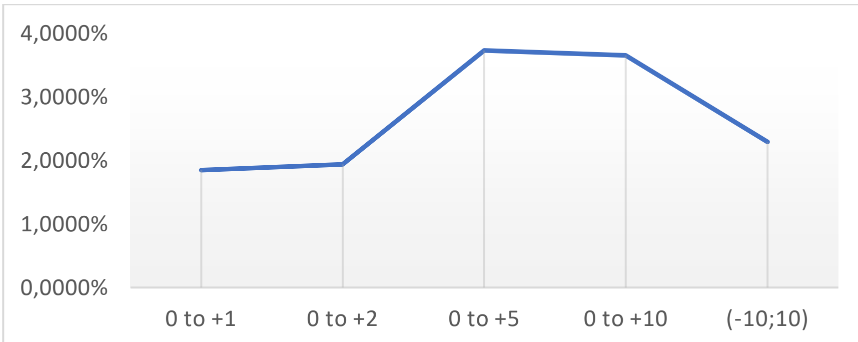

Figure 8 – Apple multi-period CAAR results

However, Apple's abnormal returns confirm the positive predominance, 71.4%, displayed earlier on CAR subsection analysis. In sum, Apple, as well as Amazon, provide solid evidence of positive abnormal returns on a multi-day and multi-event analysis, which is a good performance indicator for market players.

For Facebook stock price returns CAAR values, Figure 9 displays an exact opposite behavior from Apple. Cumulative average values show a drift starting with a small negative of -0.83% value increasing to a low value of -1.83% on day 10 of the event window.

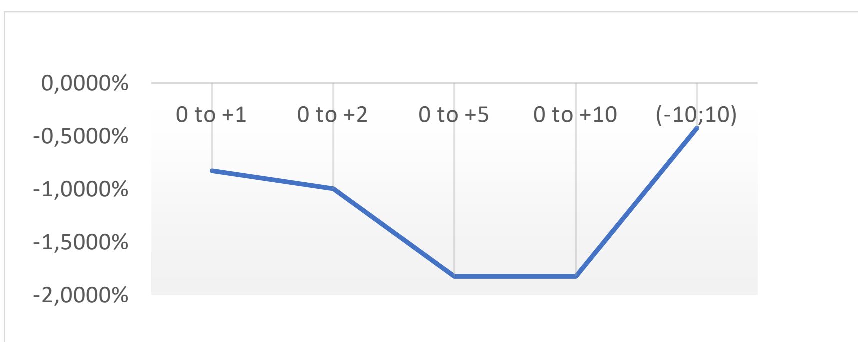

Figure 9 - Facebook multi-period CAAR results

Evidence on this firm provides solid evidence of negative cumulative abnormal returns mostly from day 0 to day 10 which is a solid bearish indicator for investors to short the stock. On average, the cumulative value of the entire event window is very close to 0% which is caused by the negative CAR negative predominance showed on subsection 4.1.2.

After analyzing Amazon, Apple and Facebook we see that Google displays a different CAAR pattern (Figure 10). On the (-10 to 10) days event window range, a positive value of 1.73% is registered. However, from time 0 to day 10 we see a bearish tendency with a decrease from 0.55% to -0.48%.

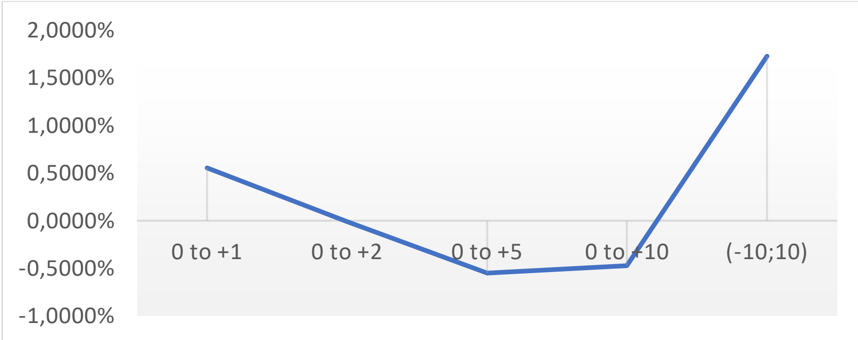

Figure 10 – Google multi-period CAAR results

In sum, this company provides some margin to profit gains on a short position perspective from day 0 forward but, presents an unstable behavior with an unclear price tendency based on speculative peaks and positive highs.

Netflix is the most bearish firm from all the FAANG stocks, displaying a CAAR value from 4% to 0.07% on day 10 (Figure 11). This difference opens margin to profit gains and, it is related to the predominance of high positive returns on the day after the announcement, with a slow decrease in the following days. Also, clear evidence of the EMH violation is displayed by the CAAR value late adjustment.

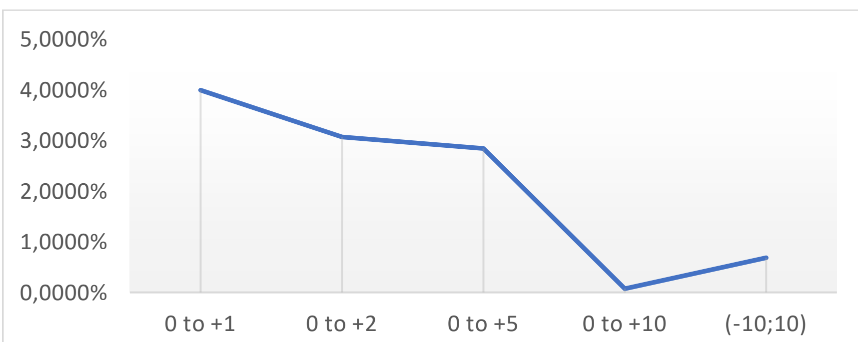

Figure 11 – Netflix multi-period CAAR results

Moreover, when the CAAR values are aggregated on the entire event window, a value close to zero is registered which is caused by early (before the announcement) and late (after day 2) negative abnormal returns.

In sum, Netflix as well as Facebook and Google, present margin to profit gains on short positions after the market incorporates the new price (on the day after the announcement) representing 60% of the sample. Apple, on the other hand, is the only company that provides a long signal. Thus, the margin to scale in the long run is low. Amazon is the only company that does not assume any long or short tendency, being quite stable during the late 10 days after the announcement day, leaving margin, on average, to profit after the price adjustment on the day 1.

FAANG stocks provide different type of tendencies and results, creating a margin to profit with a portfolio of the stocks, as well as opening opportunity to test and further analyze, on future studies, the impact of the abnormal returns, using a portfolio with FAANG stocks instead of analyzing them on an individual level.

In the next subsection, we will analyze in detail the CAAR values of statistical significance.

4.2.3 CAAR Statistical Tests

The results from Table 22 to Table 26 approve the non-rejection of the null hypothesis (CAAR = 0) in all test statistics, therefore the cumulative abnormal returns from all FAANG stocks are not statistically significant, leaving us unable to conclude on the real presence of CAAR values.

These results do not necessarily mean that the FAANG stocks do not have significant abnormal returns related to the earnings announcement report, instead it means that for the sample size of 7 events studied in the present thesis, and during the 21 days event window chosen, the abnormal returns behaves in such a way that the cumulative effects, on average, do not provide sufficient statistical power to prove a direct and clear link, between the earnings announcements and abnormal performance on a multi-event analysis.

AMAZON		Z statistics		
Event Interval	CAAR	Adjusted Patell Z	Adjusted StdCSect Z	Skewness Corrected T
0 to +1	2.1517%	0.9056	0.7424	0.6898
0 to +2	2.6600%	1.1196	0.9178	0.8528
0 to +5	2.1042%	0.8856	0.7260	0.6746
0 to +10	2.2442%	0.9446	0.7743	0.7195
(-10;10)	2.0633%	0.8684	0.7119	0.6615

Table 22 - Amazon CAAR parametric tests results

APPLE		Z statistics		
Event Interval	CAAR	Adjusted Patell Z	Adjusted StdCSect Z	Skewness Corrected T
0 to +1	1.8492%	0.9039	0.6277	0.4550
0 to +2	1.9417%	0.9491	0.6591	0.4777
0 to +5	3.7342%	1.8253	1.2676	0.9188
0 to +10	3.6600%	1.7891	1.2424	0.9005
(-10;10)	2.2975%	1.1231	0.7799	0.5653

Table 23- Apple CAAR parametric tests results

FACEBOOK		Z statistics		
Event Interval	CAAR	Adjusted Patell Z	Adjusted StdCSect Z	Skewness Corrected T
0 to +1	-0.8333%	-0.2243	-0.1168	-0.4585
0 to +2	-1.0017%	-0.2697	-0.1404	-0.5511
0 to +5	-1.8267%	-0.4918	-0.2560	-1.0050
0 to +10	-1.8283%	-0.4922	-0.2563	-1.0059
(-10;10)	-0.4267%	-0.1149	-0.0598	-0.2347

Table 24 - Facebook CAAR parametric tests results

NETFLIX		Z statistics		
Event Interval	CAAR	Adjusted Patell Z	Adjusted StdCSect Z	Skewness Corrected T
0 to +1	3.9933%	0.4045	0.0335	0.5581
0 to +2	3.0725%	0.3112	0.0258	0.4294
0 to +5	2.8417%	0.2878	0.0238	0.3971
0 to +10	0.0725%	0.0073	0.0006	0.0101
(-10;10)	0.6817%	0.0691	0.0057	0.0953

Table 25 - Netflix CAAR parametric tests results

GOOGLE		Z statistics		
Event Interval	CAAR	Adjusted Patell Z	Adjusted StdCSect Z	Skewness Corrected T
0 to +1	0.5533%	0.3157	0.3802	0.4375
0 to +2	-0.0067%	-0.0038	-0.0046	-0.0053
0 to +5	-0.5500%	-0.3138	-0.3780	-0.4349
0 to +10	-0.4750%	-0.2710	-0.3264	-0.3756
(-10;10)	1.7275%	0.9857	1.1871	1.3660

Table 26 - Google CAAR parametric tests results

One of the biggest problems in event studies is the sample and event window size. These two factors can dictate a big part of the quality of the results. Thus, it is important to take into consideration the limitations of the present study, specified in subsection 4.3, to understand and comprehend the factors in which AR, CAR, AAR, and CAAR behave in terms of statistical significance.

In sum, CAAR values from all the firms do not provide enough evidence to reject the null hypothesis and conclude about the presence of statistically significant abnormal returns on a multi-event and multi-day analysis.

4.3 Results Summary and Limitations

As stated before, event studies are based on a certain type of assumptions, which generate limitations that need to be approached in order to obtain better and more accurate results and also to avoid some of the main problems faced in these types of studies. First, we will nominate the most common conditions to properly conduct an event study, then we will present the main violations to the standard hypothesis for abnormal returns equal to zero, and on subsection 4.3.1 we will conduct a brief analysis to the statistical power and test errors.

On short-term window lengths and small sample sizes, which is the case of this research, the t statistic for the t-test Z^D cannot be expected to follow a standard normal distribution. However, to surpass this issue the sample size would have to be bigger.

We will assume the same conditions for an event study with a short length and large sample, which states that Z^D will require the following conditions for standard normality (Kramer, 1991)

I. *The MM is well specified;*
II. *The ti are independent across firms;*
III. *The denominator of Z^D is appropriately defined as the square root of the summed variances of the individual ti.*

Also, it is important to take into consideration the below questions before conducting any event study (Schimmer et al., 2015).

1. *Is the stock of the analyzed firm frequently traded, and the capital market represented by the reference Index liquid and shows sufficient trading volume?*
2. *Are the time series of prices between the stock and the reference matching?*
3. *Has information leakage taken place prior to the event?*
4. *Have there been other events during the event window that could be responsible for the analyzed firm's stock price changes?*
5. *Does the chosen reference Index correlate the best to the firm's stock price?*
6. *Has the relationship between the reference Index and the firm's stock price changed over the estimation period?*

These questions are very important when approaching an event study research to avoid biased results, lack of statistical power and consequently wrong conclusions about the results.

Infrequent trading of the firm's stock may lead to problems in deriving the estimation parameters α and β of the MM. Further, infrequent trading suggests that the capital market might not be efficient, questioning the validity of the stock price. Mismatches in the time series estimation window may lead to shorter estimation periods and potentially biased parameters. When markets leak information prior to the event window, CAR value will not be correct since a certain part or the totality of the event has already been priced into the stock during the estimation window. For smaller sample studies, Schimmer et al. states that "*event studies with a single firm/event combination, confounding events may void the validity of results*" and "*in large sample studies, the adverse effects of confounding events may be sufficiently 'corrected' by creating mean values over large numbers of observations"*.

However, it is very difficult to follow the script and accommodate all the conditions, therefore we present below the most common violations to the standard hypothesis used on the event study and the assumptions considered.

1) Non-Normality

There is considerable evidence that returns data is not normally distributed, violating the condition that states that disturbances are independent and normally distributed, with constant variance over time.

2) Autoregressive conditional heteroscedasticity

Time-varying conditional heteroscedasticity is a well-documented empirical regularity of stock returns data, as evidenced on the ARCH family by Bollerslev, Chou, and Kroner (1992). Neglecting the time-varying aspect of variance may lead to a violation of the requirement of constant variance implicit in the following condition: disturbances are independent and normally distributed with constant variance over time.

3) Changes in variance around the event (Event induced variance)

So far, the test statistics studied lean on the estimation of the abnormal return variance. As the event is expected to increase uncertainty, variance is most likely to increase on the event window. This will bias the tests towards a higher rejection of the null hypothesis. In order to correct this bias, we need to eliminate reliance on past returns. For this purpose, test statistic proposed by Boehmer, Musumeci and Poulsen (1991) and later improved by Kolari and Pynnonen (2010**)** to the adjusted standardized cross-sectional test are used on the present study.

4) Changes in MM coefficients during the event period

Several researchers have established that MM parameters can experience changes around the time of the event. Donaldson and Hathaway (1994) demonstrate the importance of account for changes in the intercept and market return coefficients at the event time. Failure to model such effects violates the condition that the MM be well specified.

5) Partially anticipated events

When investors partially anticipate an event, the event´s timing becomes unclear, therefore, the announcement effect only reflects the changes in firm´s value, derivable from the uncertainty. In sum, the announcement significance undervalues the actual economic impact of the event.

In sum, many conditions must be integrated in the analysis of an event study, and the assumptions considered have to be correctly interpreted in order to best choose the most capable test statistics, so as to accommodate main issues faced when conducting an event study research.

However, due to the large dimension of conditions and violations on the assumptions, the present thesis does not incorporate all the factors previously stated. Nonetheless, the test statistics, firms, models, estimation factors, window length and event dates were carefully chosen in order to obtain the best possible results.

4.3.1 Statistical Power

By using test statistics, errors appear in two types. Type 1 error occurs when the null hypothesis is falsely rejected, and type 2 error occurs when the null hypothesis is falsely accepted. Accordingly, two properties of event study tests are investigated, the first is whether the test statistic is correctly specified. A correctly specified test concedes a type 1 error probability equal to the size of the test. The second concern is power, the test's ability to detect abnormal performance when present. When comparing tests that are well specified, those with higher power are preferred.

While the specification and power of a test can be statistically determined, economic interpretation is not as straightforward because all tests are joint tests. To address this issue, different event study methods are conducted by repeated application of each method, to samples that have been constructed over a random selection of securities and event dates. If abnormal returns are measured correctly, these samples should, on average, show absence of abnormal performance.

Further, various levels of abnormal performance are introduced. This technique also allows to study the behavior of the test in presence of abnormal variance.

For every event study, regardless of the horizon length, several basic issues must be approached, the risk adjustment and estimation models, the aggregation of abnormal returns, and the scale of statistical significance of abnormal returns.

In sum, regarding short event studies, the specification is good. Power increases with sample size and is high when abnormal performance is concentrated in the event window and low otherwise. Also, if abnormal returns do not crucially depend on the return-generating model, results lack statistical significance. However, some models are better in addressing the issue of cross-sectional and time-series dependence as well as the variance of abnormal returns.

5. Future Research

To better evaluate future event studies, we see 4 factors as most important to consider in future researches. First, a large sample size is required in order to increases the statistical power and capture a more accurate and precise overview of the announcement effect on the firm or portfolio studied. Second, the choice of event window time frame is crucial in order to avoid biased CAR and CAAR results. We suggest considering a smaller event window instead of 21 days, 11 days should be a good number to test on future works. Third, instead of studying individual firms, different portfolio analysis, as an example the NYSE FANG + Index, which is an aggregation of FAANG stocks, would have a higher analysis reach and ability to mitigate sample outliers.

In sum, the field of event studies has had a lot of improvements by many different authors in different areas, giving the opportunity to achieve the most trustworthy results. In fourth, and last, the use of non-parametric tests can improve the results obtained by parametric tests. Parametric tests can analyze only continuous data and the findings can be overly affected by outliers. Conversely, nonparametric tests can also analyze ordinal and ranked data, and not be tripped up by outliers.

Furthermore, non-parametric tests are valid when the sample size is small, and the data is potentially non-normal. On the event studies field the margin to improvements is considerably high, leaving researchers in a good position for new findings and allowing the development of stronger tools and better approaches.

6. Conclusion

In this study, we challenge FAANG stocks´ ability to adjust new information and consequently test the EMH. More precisely, we investigate the presence and behavior of abnormal returns after earnings announcement report. First, to calculate the abnormal returns, we use two different types of estimation models, single factor with S&P 500 as market proxy and multi-factor with Fama and French, CBOE volatility Index and the average of SP NA Tech Index and IGM Index as industry proxy. Moreover, in order to increase the accuracy of the estimation returns results, we treat the error term on the market model with GARCH and EGARCH processes. Secondly, we checked the existence of a linear relationship between type of news, by the value of Earning surprise, and the magnitude of abnormal returns.

We found that on a firm individual analysis, event by event, abnormal returns tend to fluctuate before the announcement, increasing on the day after the announcement and then, according to the market players' expectations on earnings reported, adjust almost immediately. In some events, adjustments are near to 0% on day 2. Also, on average, irregular movements, fluctuating from positive to negative, are present after day 2 until 5 to 6 days after the announcement. Only after, the market adjusts to the non-presence of AR.

We see that the null hypothesis (AR=0) at 5% and 1% level of significance is rejected on 65.7% of events after the announcement. Approximately, 70% of significant events do not corroborate with EMH, showing late price adjustment by the magnitude of the abnormal returns registered after two days of the event date. Cumulative abnormal returns show an interesting value, 78.26% of events write off the effect of a statistically significant value on the day after the announcement with movements in the opposite direction. Large movements on the positive side are balanced with large negative movements and the small AR returns during the event window tend to have the same constant behavior. FAANG stocks show evidence of unstable behavior with large speculation and expectancy from the market players due to the small percentage, 21.74%, of statistically significant CAR values.

On a multi-event analysis, the sensitivity of the group of firms studied regarding news, is on average, 0.176 and 0.36 in absolute value, which represents weak linear correlation. Also, we see that 60% of firms reject the null at 5% and 1% with positive AAR values on the day after the announcement when good news is registered. However, when the market face bad news, only 25%

of the events on day 1 are statistically significant with a positive AAR, instead of negative. For no news, we expected to have low AAR values, hence a constant non-rejection of the null hypothesis. Instead, the null is rejected on 50% of the events, 25% of those with positive values and 25% with negative values. This result supports the lack of sensitiveness towards the market earnings surprise.

After calculating the parametric tests, based on the average correlation of 0.05, the true rejection probabilities at 5% on the AAR value on day 1 is 80% for the Patell test, 20% for the BMP test and 20% for the skewness correct t-test. Thus, the results support the true rejection of the null in 20% of firms. Cumulative average abnormal results follow a non-rejection of the null hypothesis, (CAAR=0) in all test statistics, therefore, cumulative average abnormal returns from all FAANG stocks are not statistically significant and we cannot conclude about the real presence of CAAR values. These results do not necessarily mean that FAANG stocks do not have significant abnormal returns related to earnings announcement news. Instead, it means that, for the sample size of 7 events studied on the present thesis and during the 21 days event window chosen, abnormal returns behaves in such a way that, cumulative effects, on average, do not stand sufficient statistical power to prove a direct link between the earnings announcements and abnormal returns, on a multi event analysis.

Our findings corroborate, on an individual event analysis, with a violation of EMH on 70% of the events. For a multi-period, analysis, CAR values show evidence of unstable behavior, partly with large speculation and expectancy from market players, present only 21.74% statistically significant values. On a multi-event analysis, AAR values have low statistical significance, with only 20% rejection of the null hypothesis through the parametric tests. Lastly, on a multi-period and multi events scope, results do not have enough statistical power to prove the true existence of significant cumulative average abnormal returns.

The study has some limitations imposed by the assumptions and conditions that are considered. Some of the most common violations of standard hypothesis are the following: non-normality, autoregressive conditional heteroscedasticity, event induced variance, changes in MM coefficients during the event period, event date uncertainty and partially anticipated events. To overcome some of these issues we used the adjusted Patell test and adjusted cross sectional test that accounts for induced volatility, serial correlation and cross-correlation.

This study has significant contributions to the literature, because, to best of our knowledge, there is a lack of investigation in this field regarding the FAANG stocks and, we fill this gap by studying, individually, each company that build the FAANG stocks.

For further research, a larger sample and a shorter post-event window could be applied in order to generate more powerful results, as some authors suggest. Also, instead of analyzing individual stocks, portfolios´ behavior, would have a higher analysis reach and ability to mitigate sample outliers. As an example, we have the NYSE FANG + Index, which is an FAANG stocks´ aggregation. To conclude, as previously stated, the usage of non-parametric tests can improve the results, obtained by parametric tests, due to ability to analyze ordinal and ranked data, and not be tripped up by outliers, as well as having capacity to handle small samples were data is potentially non-normal.

From an investor perspective, FAANG stocks, after the announcement day, present a variety of results that allows any investor to profit. Also, on the pre and post-earnings announcement, the margin to take profit positions on the short or long side is available to those who correctly understand the abnormal performance signals.

In sum, on individual analysis, Google is the best company for market players to profit. On the other hand, on a multi-event analysis, Amazon is the firm that shows more correlation to the type of news hence, it provides a good margin basis to invest based on the market sentiment. On a multi-event and multi-period analysis, Netflix displays the most solid price tendency of all firms, a dominant bearish trend from day 0 to day 10 after the announcement, leaving opportunity for investors to profit by short selling the stock.

7. Bibliography

Ahern, K. 2009. Sample selection and event study estimation, ***Journal of Empirical Finance***,16 (3): 466-482.

Aktas, N., De Bodt E. and Cousin, Jean-Gabriel. 2007. Event studies with a contaminated estimation period, ***Journal of Corporate Finance***, Elsevier, 13(1): 129-145.

Amihud Y. 2002. Illiquidity and stock returns: cross-section and time-series effects, Journal of Financial Markets, 5: 31-56.

Armitage, S. 1995. Event study methods and evidence on their performance, ***Journal of Economic Surveys***, 8 (4): 25-52.

Ball, R. and Brown, P. 1968. An Empirical Evaluation of Accounting Income Numbers, Journal of Accounting Research, 6 (2):159-178.

Ball, R., and Bartov E. 1996. How naive is the stock market's use of earnings information?, ***Journal of Accounting and Economics,*** 21(3): 319-337.

Ball, R., S. P. Kothari and Ross L. Watts. 1993. Economic Determinants of the Relation between Earnings Changes and Stock Returns, ***Accounting Review***, 68(3): 622-638.

Basu, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, ***Journal of Finance***, 32: 663-682.

Barber, B., and J. Lyon. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics, ***Journal of Financial Economics***, 43: 341-372.

Bernard, V. L., & Thomas, J. K. 1989. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? ***Journal of Accounting Research***, 27:1-36.

———. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. ***Journal of Accounting and Economics***, 13(4): 305-340.

Brav, A. 2000. Inference in long-horizon event studies: A Bayesian approach with application to initial public offerings, ***Journal of Finance***, 55: 1979-2016.

Boehmer, E., Musumeci, J. and Poulsen, B. A. 1991. Event-study methodology under conditions of event-induced variance, ***Journal of Financial Economics***, 30 (2): 253-273.

Bollerslev, Tim. 1986. Generalized Autoregressive Conditional Heteroskedasticity, ***Journal of Econometrics,*** **31** (3): 307–327.

Bollerslev, T., R.Y. Chou, and K.F. Kroner, 1992. ARCH modeling in finance, ***Journal of Econometrics,*** 52:5-59.

Black, F. 1976. ***Studies of Stock Price Volatility Changes***, Proceedings of the Business and Economics Section of the American Statistical Association, 177–181.

Brockett, P.L, H.M. Chen, and J.R. Garven. 1994. Event study methodology: A new and stochastically flexible approach, University of Texas manuscript.

Breinlich, H., E. Leromain, D. Novy, T. Sampson and A. Usman. 2018. The Economic Effects of Brexit: Evidence from the Stock Market. ***Journal of Applied Public Economics***, 39(4): 581-623.

Brown, S., and Warner J. 1980. Measuring security price performance, ***Journal of Financial Economics*** 8: 205-258.

Brown, S.J., Warner, J.B. 1985. Using Daily Stock Returns: The Case of Event Studies, ***Journal of Financial Economics***, 14(1): 3-31.

Campbell, John Y., Andrew Wen-Chuan Lo. And Archie Craig MacKinlay. 1997. ***The econometrics of financial markets***, Princeton, NJ: Princeton Univ. Press.

Campbell, C. J. and C. E. Wasley. 1993. Measuring Security Price Performance Using Daily Nasdaq Returns, ***Journal of Financial Economics***, 33(1): 73-92.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance, ***Journal of Finance***, 52 (1): 57–82.

Clifford A. Ball and Walter N. Torous.1988. Investigating security-price performance in the presence of event-date uncertainty, ***Journal of Financial Economics***, 22 (1): 123-153.

Corrado, Charles J. (2011), Event Studies: A Methodology Review, ***Accounting and Finance***, 51: 207-234.

Corrado, C. and Truong, C. 2008. Conducting event studies with Asia-Pacific security market data, ***Pacific-Basis Finance Journal,*** *16(5): 493-521.*

Curto, J.J.D. 2016. ***Forecasting Methods Handouts***, Class Handouts, ISCTE-IUL, Lisbon.

Curto, J.J.D. 2016. ***Quantitative Methods for Finance Handouts***, Class Handouts, ISCTE-IUL, Lisbon.

Corhay, A. and Rad, A.Tourani. 1996. Conditional Heteroskedasticity Adjusted Market Model and an Event Study, ***Quarterly Review of Economics and Finance***. 36: 529-538.

Cowan, R. A. and Segeant, M.A. Anne. 1996. Trading frequency and event study test specification, ***Journal of Banking and Finance***, 20 (1): 1731-1775.

Cramer, H. 1961. ***Mathematical Methods of Statistics***, Princeton University Press.

Dolley, James C. 1933. Characteristics and Procedure of Common Stock Split-Ups, ***Harvard Business Review***,11: 316–26.

Eckbo, B., R. Masulis, and O. Norli. 2006. Seasoned public offerings: Resolution of the ‘New Issues Puzzle’, ***Journal of Financial Economics***, 56: 251-291.

Easley, D., Hvidkjaer, S. and O’hara, M. 2002. Is information risk a determinant of asset returns?, ***Journal of Finance***, 57(5): 2185–2221.

Fama, Eugene F. 1965a.The Behavior of Stock-Market Prices., ***The Journal of Business***, 38 (1): 34-105.

———. 1965b. Random Walks in Stock Market Prices, ***Selected Papers of the Graduate School of Business***, University of Chicago, reprinted in the ***Financial Analysts Journal*** (September - October 1965), ***The Analysts Journal***, London (1966), ***The Institutional Investor***,1968., October, 55-59.

———. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work, ***Journal of Finance***, 25 (2): 383-417.

———. 1976a. ***Foundations of finance: portfolio decisions and securities prices***, New York: Basic Books.

———. 1998. Market efficiency, long-term returns, and behavioral finance, **Journal of Financial Economics,** 49: 283-306.

———. 1991. Efficient Capital Markets II, ***Journal of Finance***, 46 (5): 1575- 1617.

Fama, E. F. and French, K. R. 1992. The Cross-Section of Expected Stock Returns, ***Journal of Finance***, 47:427-465.

———. 1993. Common Risk Factors in The Returns on Stocks and Bonds, ***Journal of Financial Economics,*** 33:3-56.

———. 2015. A five-factor asset pricing model, ***Journal of Financial Economics,*** 116 (1): 1-22.

Fama, Eugene F., Lawrence Fisher, Michael C. Jensen, and Richard Roll. 1969. The Adjustment of Stock Prices to New Information, ***International Economic Review***, 10(1): 1-21.

Foster, G., Olsen, C. and Shevlin, T. 1984. Earnings Releases, Anomalies, and the Behavior of Security Returns. ***Accounting Review***, 59: 574-603.

Fried, D. and D. Givoly. 1982. Financial Analysts of Earnings - A Better Surrogate for Market Expectations, ***Journal of Accounting & Economics***, 4(2): 85-107.

Gibbons M. R., Ross, S. A. and Shanken. J. 1989. A Test of the Efficiency of a Given Portfolio, ***Econometrica***, 57(5): 1121-1152.

Haddock, D.D. and J.R. Macey. 1987. Regulation on demand: A private interest model, with an application to insider trading regulation, ***Journal of Law and Economics***, 30: 311-352.

Hall, P.1992. On the Removal of Skewness by Transformation, ***Journal of the Royal Statistical Society***, 54 (1): 221-228.

Henry, E. 2008. Are investors influenced by how earnings press releases are written?, ***Journal of Business Communication*** 45 (4): 363-407.

Holler, J. 2014. ***Event Study-Methodik und statistische Signifikanz,*** Book, O|WIR, Oldenburg.

Jeffrey A. Busse and T. Clifton Green. 2002. Market Efficiency in Real Time, ***Journal of Financial Economics***, 65 (3): 415-437.

Jegadeesh, N., and Karceski, J. 2004. ***Long-run performance evaluation: Correlation and heteroskedasticity-consistent-tests***, Working Paper, Emory University.

Jegadeesh, N. and Livnat, J.. 2006. Post-Earnings-Announcement Drift: The Role of Revenue Surprises, ***Financial Analysts Journal***, 62(2): 22-34.

Kinney, W., Burstahler, D., and Martiny, R. 2002. Earnings Surprise "Materiality" as Measured by Stock Returns, ***Journal of Accounting Research***, 40(5): 1297-1329.

Kolari, W.J. and Pynnönen, S. 2010. Event Study Testing with Cross-sectional Correlation of Abnormal Returns, ***Review of Financial Studies***, 23 (11): 3996-4025.

Kothari, S. P. and Warner, J. B. 1997. Measuring long-horizon security price performance, ***Journal of Financial Economics***, 43 (3):301-339.

———. 2006. Econometrics of Event *Studies*, ***Handbook of Corporate Finance***: **Empirical Corporate Finance,** B. Espen Eckbo.

———. 2008. Econometrics of event studies, Book, ***Handbook of Corporate Finance: Empirical Corporate Finance***.

Kothari, S. 2001. Capital markets research in accounting, ***Journal of Accounting & Economics***, 31: 105-231.

Liu, J., Thomas, J. 2000. Stock returns and accounting earnings, ***Journal of Accounting Research***, 38: 71–101.

Lo, Andrew W. 2004. ***The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective***, SSRN Scholarly Paper ID 602222. Rochester, NY: Social Science Research Network.

Loughran, T. and Ritter, R. J. 1995. The New Issues Puzzle, ***Journal of Finance***, 50 (1): 23-51

Lyon, J., B. Barber and C. Tsai. 1999. Improved methods of tests of long-horizon abnormal stock returns, ***Journal of Finance,*** 54: 165-201.

Malatesta, P. and Thompson, R. 1985. Partially anticipated events: A model of stock price reactions with an application to corporate acquisitions, ***Journal of Financial Economics***, 14 (2): 237-250.

Matei, Marius. 2009. Assessing Volatility Forecasting Models: Why GARCH Models Take the Lead. *Journal for Economic Forecasting.* 4.: 42-65.

McWilliams, A. and Donald S. Siegel. 1997. Event Studies in Management Research: Theoretical and Empirical Issues, ***Academy of Management Journal***, 40 (3):626-657.

Nelson, D. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach, ***Econometrica***, 59: 347-370.

Oler, D., Harrison, S.J. and Allen, R.M. 2007. ***Over-Interpretation of Short-Window Event Study Findings in Management Research: An Empirical Illustration***, web article, SSRN Electronic Journal.

Patell, J.A. 1976. Corporate forecasts of earnings per share and stock price behavior: Empirical test, ***Journal of Accounting and Finance***, 14 (2): 246-276.

Patell, M. J. and Wolfson, A. M. 1981. The Ex Ante and Ex Post Price Effects of Quarterly Earnings Announcements Reflected in Option and Stock Prices, ***Journal of Accounting Research***, 19 (2): 434-458.

Rimoldini, L. 2013. Weighted skewness and kurtosis unbiased by sample size, ***Astronomy and Computing***, 5: 1-8.

Robert N. Freeman and Senyo Tse. 1989. The Multiperiod Information Content of Accounting Earnings: Confirmations and Contradictions of Previous Earnings Reports, ***Journal of Accounting Research***, 27: 49-79.

Samuelson, Paul A. 1965. Rational Theory of Warrant Pricing, ***Industrial Management Review***, 6 (2): 13-39.

Shiller, Robert J. 2003. From efficient markets theory to behavioral finance, ***Journal of Economic Perspectives***, 17 (1): 83-104.

Schimmer, M., Levchenko, A., and Müller, S. (2014). ***EventStudyTools*** (Research Apps), St.Gallen. Available on: http://www.eventstudytools.com.

———. 2005. ***Irrational exuberance***, Princeton, N.J: Princeton University Press.
Schwert, W. 2001. Anomalies and Market Efficiency, ***Handbook of the Economics Finance***, Elsevier Science Publisher, 2: 939-974.

Student.1908a."The Probable Error of a Mean," Biometrika, 6, 1–25

Schipper, K. and Smith, A. 1983, Effects of recontracting on shareholder wealth: The case of voluntary spin-offs, ***Journal of Financial Economics***, 12 (4): 437-467.

Shivakumar L. 2007. Discussion of Information Uncertainty and Post-Earnings-Announcement-Drift, ***Journal of Business Finance and Accounting***, 34 (3): 434-438.

Thaler, Richard H. 1999. The End of Behavioral Finance, ***Financial Analysts Journal***, 55 (6): 12-17.

Viswanathan, S., and B. Wei. 2004. ***Endogenous event and long run returns***, Working Paper, Duke University.

Wang, S. 2002. A Universal Framework for Pricing Financial and Insurance Risks. ***Journal of the IAA***.

Yan, Z. P. and Y. Zhao. 2011. When Two Anomalies Meet: The Post-Earnings Announcement Drift and the Value-Glamour Anomaly, ***Financial Analysts Journal***, 67(6): 46-60.

Watts, R.L. 1978. Systematic "Abnormal" Returns after Quarterly Earnings Announcements. ***Journal of Financial Economics***, 6: 127-150.

8. Appendix

8.1 Appendix A – Equations

CAPM:

$$\mathrm{E}_{r_i} = r_f + \beta_i(\mathrm{E}_{r_i} - r_f \qquad (37)$$

FF 3 factor:

$$\mathrm{E}_{r_i} = r_f + \beta_1\left(\mathrm{E}_{r_i} - r_f\right) + \beta_2(SMB) + \beta_3(HML) + \varepsilon_{it} \qquad (38)$$

Carhart 4 factor:

$$\mathrm{Xr}_t = \alpha^c + \beta_{mkt} EXMKT_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_{it} \qquad (39)$$

Where *UMD* represents the monthly premium on winners minus losers

FF 5 factor:

$$\begin{aligned}\mathrm{E}_{r_i} = r_{f,t} + \alpha_{(5\,factor)} + \beta_{i,MKT}\left(\mathrm{E}_{r_{m,t}} - r_{f,t}\right) + \beta_{i,SM}(SMB) \\ + \beta_{i,HML}(HML) + \beta_{i,RMW}(RMW) + \beta_{i,CMA}(CMA) + \varepsilon_{it}\end{aligned} \qquad (40)$$

RMW: relates the concept that companies reporting higher future earnings have higher returns in the stock market.
CMA: relates the concept of internal investment and returns, suggesting that companies directing profit towards major growth projects are likely to experience losses in stock market.

Pattel test for Hypothesis 4:

$$z_{Pattel} = \frac{1}{\sqrt{N}} + \sum_{i=1}^{N} \frac{CSAR_i}{S_{CSAR_i}} \qquad (41)$$

With CSAR as the cumulative standardized abnormal returns

$$CSAR_i = \sum_{t=T_1+1}^{T_2} SAR_{i,t} \qquad (42)$$

With expectancy zero and variance:

$$S^2_{CSAR_i} = L_2 \frac{M_i - 2}{M_i - 4} \tag{43}$$

Finally, the Adjusted Pattel for Hypothesis 4:

$$z_{Patell,t} = z_{Patell,t} \sqrt{\frac{1}{1 + (N-1)\bar{r}}} \tag{44}$$

Cross-Sectional Test (BMP) for Hypothesis 4

$$z_{BMP} = \sqrt{N} \frac{\overline{SCAR}}{S_{\overline{SCAR}}} \tag{45}$$

Where $\overline{SCAR}$ is the average standardized cumulated abnormal returts across N firms with standard error of regression:

$$S^2_{\overline{SCAR}} = \frac{1}{N-1} \sum_{i=1}^{N} (SCAR_I - \overline{SCAR}^2) \tag{46}$$

$$\overline{SCAR} = \frac{1}{N} \sum_{i=1}^{N} SCAR_i \tag{47}$$

And $SCAR_I = \frac{CAR_i}{S_{CAR_i}} * S_{CAR_i}$ is the forecast error corrected standard error of regression Mikkelson and Partch (1988).

Finaly the Adjusted Cross-Sectional Test for Hypothesis 4:

$$z_{BMP} = z_{BMP} \sqrt{\frac{1 - \bar{r}}{1 + (N-1)\,\bar{r}}} \tag{48}$$

8.2 Appendix B – Results Explanation

Section 4.1.1 - Abnormal Returns (AR)

Netflix – 4 events statistically significant at 1% and 1 event at 5%. Total of 5 events, 5/7 = 71.43%

Google – 6 events statistically significant at 1%. Total of 6 events, 6/7 = 85.71%

Facebook – 2 events statistically significant at 1% and 2 at 5%. Total of 4 events, 4/7 = 57.14%

Apple - 4 events statistically significant at 1%. Total of 4 events, 4/7 = 57.14%

Amazon - 2 events statistically significant at 1% and 2 at 5%. Total of 4 events, 4/7 = 57.14%

FAANG – 18 events statistically significant at 1% and 5 at 5%. **Total of 23**, 23/35 = 65.7%

3/7 = 43% AMAZON	2/7 = 29% APPLE
2/7 = 29% FB	0/7 = 0% GOOGLE
2/7 = 29% NETFLIX	
TOTAL [Window (-6 to -1)] = 9/23 = 43.7%	

Considering:

- AR (day 1 after event statistically significant);
- AR >2% and <-2% on event window (1 to 6);
- AR <1.5% and >-1.5% on window (7 to 10).

Netflix: event 5 fluctuates after the day 1and adjusts after day 6

Apple: event 5 fluctuates after the day 1 and adjusts after day 6

Amazon event 6 fluctuates after the day 1 and adjusts after day 6

Facebook: event 2 fluctuates after the day 1 and adjusts after day 6

Google: event 2 fluctuates after the day 1 and adjusts after day 6

Total: 5, 5/23= 21.7%

Considering:

- AR of day 1 after event statistically significant
- AR <1.5% and >-1.5% on day 2
- AR <1.5% and >-1.5% on window (3 to 10)

Netflix: event 3 adjusts immediately after day 1

Apple: event 6 adjusts immediately after day 1

Amazon: event 2 and 5 adjusts immediately after day 1

Facebook: event 3 adjusts immediately after day 1

Google: event 1 and 3 adjusts immediately after day 1

Total: 7, 7/23 = 30.4%

EMH: 100% - (30.4% events that price adjust immediately) = 69.6%

8.3. Appendix C - Tables

Event	Firm	Reference Market	Event Date	Estimation Window Length	End of Estimation Window	First Date Estimation Window	Last Date Estimation Window	Actual Stock Return	Actual Market Return	Alpha	Beta	Standard Error of Regression	Expected Market Return
1	Apple	SP500	2017-05-02	750	-11	2014-04-25	2017-04-17	0.0063	0.0012	0.0016	1.0633	0.0116	1.7224
2	Apple	SP500	2017-08-01	750	-11	2014-07-25	2017-07-17	0.0088	0.0024	0.0006	1.0833	0.0115	2.5596
3	Apple	SP500	2017-11-02	750	-11	2014-10-28	2017-10-18	0.0073	0.0002	0.0000	1.1186	0.0114	2.4629
4	Apple	SP500	2018-02-01	750	-11	2015-01-27	2018-01-17	0.0021	-0.0006	-0.0003	1.1069	0.0114	3.2471
5	Apple	SP500	2018-05-01	750	-11	2015-04-24	2018-04-16	0.0230	0.0025	-0.0010	1.1137	0.0111	1.6179
6	Apple	SP500	2018-07-31	750	-11	2015-07-24	2018-07-16	0.0020	0.0049	-0.0007	1.0953	0.0112	1.0038
7	Apple	SP500	2018-11-01	750	-11	2015-10-27	2018-10-17	0.0152	0.0105	-0.0003	1.0990	0.0110	3.3702

Table 27- Apple estimation parameters description

Event	Firm	Reference Market	Event Date	Estimation Window Length	End of Estimation Window	First Date Estimation Window	Last Date Estimation Window	Actual Stock Return	Actual Market Return	Alpha	Beta	Standard Error of Regression	Expected Market Return
1	Amazon	SP500	2017-04-27	750	-11	2014-04-22	2017-04-11	0.0099	0.0006	0.0005	1.0357	0.0168	2.2590
2	Amazon	SP500	2017-07-27	750	-11	2014-07-22	2017-07-12	-0.0065	-0.0010	0.0012	1.0984	0.0159	1.8182
3	Amazon	SP500	2017-10-26	750	-11	2014-10-21	2017-10-11	-0.0005	0.0013	0.0036	1.0551	0.0155	1.7363
4	Amazon	SP500	2018-02-01	750	-11	2015-01-27	2018-01-17	-0.0429	-0.0006	0.0035	1.1238	0.0154	1.7343
5	Amazon	SP500	2018-04-26	750	-11	2015-04-21	2018-04-11	0.0388	0.0104	0.0023	1.1416	0.0149	4.1967
6	Amazon	SP500	2018-07-26	750	-11	2015-07-21	2018-07-11	-0.0303	-0.0030	0.0017	1.1230	0.0143	3.0197
7	Amazon	SP500	2018-10-30	750	-11	2015-10-23	2018-10-15	-0.0055	0.0155	0.0020	1.1790	0.0138	3.7955

Table 28 – Amazon estimation parameters description

Event	Firm	Reference Market	Event Date	Estimation Window Length	End of Estimation Window	First Date Estimation Window	Last Date Estimation Window	Actual Stock Return	Actual Market Return	Alpha	Beta	Standard Error of Regression	Expected Market Return
1	Facebook	SP500	2017-05-03	750	-11	2014-04-28	2017-04-18	-0.0064	-0.0013	0.0019	1.0891	0.0136	2.6411
2	Facebook	SP500	2017-07-26	750	-11	2014-07-21	2017-07-11	0.0020	0.0003	0.0016	1.0544	0.0130	1.7996
3	Facebook	SP500	2017-11-01	750	-11	2014-10-27	2017-10-17	0.0143	0.0016	0.0008	1.0659	0.0127	2.2014
4	Facebook	SP500	2018-01-31	750	-11	2015-01-26	2018-01-16	-0.0012	0.0005	0.0021	1.0617	0.0126	1.8702
5	Facebook	SP500	2018-04-25	750	-11	2015-04-20	2018-04-10	0.0100	0.0018	0.0021	1.1296	0.0129	3.6370
6	Facebook	SP500	2018-07-25	750	-11	2015-07-20	2018-07-10	0.0131	0.0091	0.0011	1.1330	0.0132	2.1102
7	Facebook	SP500	2018-10-30	750	-11	2015-10-23	2018-10-15	0.0287	0.0155	0.0015	1.1557	0.0152	4.7601

Table 29 - Facebook estimation parameters description

Event	Firm	Reference Market	Event Date	Estimation Window Length	End of Estimation Window	First Date Estimation Window	Last Date Estimation Window	Actual Stock Return	Actual Market Return	Alpha	Beta	Standard Error of Regression	Expected Market Return
1	Google	SP500	2017-04-27	750	-11	2014-04-22	2017-04-11	0.0026	0.0006	0.0012	1.0537	0.0112	1.5720
2	Google	SP500	2017-07-24	750	-11	2014-07-17	2017-07-07	0.0045	-0.0011	0.0006	1.0348	0.0113	1.4320
3	Google	SP500	2017-10-26	750	-11	2014-10-21	2017-10-11	0.0030	0.0013	0.0010	1.0122	0.0112	2.4256
4	Google	SP500	2018-02-01	750	-11	2015-01-27	2018-01-17	-0.0005	-0.0006	0.0017	1.0619	0.0111	3.3598
5	Google	SP500	2018-04-23	750	-11	2015-04-16	2018-04-06	-0.0033	0.0001	0.0016	1.1299	0.0109	3.4466
6	Google	SP500	2018-07-23	750	-11	2015-07-16	2018-07-06	0.0109	0.0018	0.0012	1.1519	0.0111	2.7587
7	Google	SP500	2018-10-25	750	-11	2015-10-20	2018-10-10	0.0430	0.0185	0.0010	1.1946	0.0094	4.1718

Table 30 – Google estimation parameters description

Event	Firm	Reference Market	Event Date	Estimation Window Length	End of Estimation Window	First Date Estimation Window	Last Date Estimation Window	Actual Stock Return	Actual Market Return	Alpha	Beta	Standard Error of Regression	Expected Market Return
1	Netflix	SP500	2017-04-17	750	-11	2014-04-09	2017-03-30	0.0298	0.0086	0.0034	1.3436	0.0254	2.6053
2	Netflix	SP500	2017-07-17	750	-11	2014-07-10	2017-06-29	0.0036	-0.0001	0.0037	1.3065	0.0249	1.9155
3	Netflix	SP500	2017-10-16	750	-11	2014-10-09	2017-09-29	0.0159	0.0017	0.0047	1.3476	0.0253	1.6171
4	Netflix	SP500	2018-01-22	750	-11	2015-01-14	2018-01-04	0.0318	0.0080	0.0056	1.3470	0.0239	2.2012
5	Netflix	SP500	2018-04-16	750	-11	2015-04-09	2018-03-29	-0.0125	0.0081	0.0022	1.4017	0.0238	3.9248
6	Netflix	SP500	2018-07-16	750	-11	2015-07-09	2018-06-28	0.0118	-0.0010	0.0007	1.4750	0.0231	2.8358
7	Netflix	SP500	2018-10-16	750	-11	2015-10-09	2018-10-01	0.0391	0.0213	0.0014	1.4418	0.0218	3.8556

Table 31- Netflix estimation parameters description

SINGLE FACTOR MODELS			
MM			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.061	1.1475
2	(-10, 10)	0.0718	1.3624
3	(-10, 10)	0.0566	1.0834
4	(-10, 10)	-0.0068	-0.1302
5	(-10, 10)	0.046	0.9043
6	(-10, 10)	0.0769	1.4983
7	(-10, 10)	-0.12	-2.3806
MM w/GARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0582	1.0949
2	(-10, 10)	0.0644	1.222
3	(-10, 10)	0.048	0.9188
4	(-10, 10)	-0.0108	-0.2067
5	(-10, 10)	0.0443	0.8709
6	(-10, 10)	0.0707	1.3775
7	(-10, 10)	-0.12	-2.3806
MM w/EGARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0642	1.2077
2	(-10, 10)	0.0736	1.3966
3	(-10, 10)	0.0571	1.093
4	(-10, 10)	-0.0072	-0.1378
5	(-10, 10)	0.045	0.8847
6	(-10, 10)	0.0761	1.4827
7	(-10, 10)	-0.1239	-2.4579

Table 32 – Apple single factor CAR values per event

MULTI- FACTOR MODELS			
3 FACTORS (INDUSTRY + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0738	1.3883
2	(-10, 10)	0.0722	1.3582
3	(-10, 10)	0.048	0.9188
4	(-10, 10)	-0.0249	-0.4766
5	(-10, 10)	0.0216	0.4246
6	(-10, 10)	0.0627	1.2216
7	(-10, 10)	-0.1448	-2.8725
4 FACTORS (FAMA + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0573	1.0779
2	(-10, 10)	0.0689	1.3074
3	(-10, 10)	0.0542	1.0375
4	(-10, 10)	-0.0109	-0.2086
5	(-10, 10)	0.0449	0.8827
6	(-10, 10)	0.0891	1.736
7	(-10, 10)	-0.1187	-2.3548

Table 33 - Apple multi-factor CAR values per event

SINGLE FACTOR MODELS			
MM			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0088	0.115
2	(-10, 10)	-0.0706	-0.9689
3	(-10, 10)	0.0901	1.2685
4	(-10, 10)	0.12	1.7004
5	(-10, 10)	0.0564	0.826
6	(-10, 10)	0.0188	0.2869
7	(-10, 10)	-0.0864	-1.3662
MM w/GARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0042	0.0527
2	(-10, 10)	-0.0749	-1.028
3	(-10, 10)	0.0931	1.3023
4	(-10, 10)	0.115	1.6295
5	(-10, 10)	0.0457	0.6693
6	(-10, 10)	0.0039	0.0595
7	(-10, 10)	-0.1028	-1.6256
MM w/EGARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0024	0.0314
2	(-10, 10)	-0.0707	-0.9703
3	(-10, 10)	0.0968	1.3628
4	(-10, 10)	0.133	1.8846
5	(-10, 10)	0.0584	0.8553
6	(-10, 10)	0.0231	0.3525
7	(-10, 10)	-0.087	-1.3757

Table 34 – Amazon single factor CAR values per event

MULTI- FACTOR MODELS			
3 FACTORS (INDUSTRY + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	-0.0241	-0.3149
2	(-10, 10)	-0.0909	-1.2398
3	(-10, 10)	0.1213	1.7077
4	(-10, 10)	0.1823	2.5832
5	(-10, 10)	0.0592	0.867
6	(-10, 10)	-0.0017	-0.0259
7	(-10, 10)	-0.0805	-1.2729
4 FACTORS (FAMA + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0077	0.1006
2	(-10, 10)	-0.0736	-1.0101
3	(-10, 10)	0.0899	1.2657
4	(-10, 10)	0.1096	1.5632
5	(-10, 10)	0.0517	0.7572
6	(-10, 10)	0.0293	0.4503
7	(-10, 10)	-0.0545	-0.8618

Table 35 – Amazon multi-factor CAR values per event

SINGLE FACTOR MODELS			
MM			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0022	0.0353
2	(-10, 10)	0.0594	0.9971
3	(-10, 10)	-0.0058	-0.0997
4	(-10, 10)	0.0238	0.4122
5	(-10, 10)	0.0716	1.2112
6	(-10, 10)	-0.1333	-2.2037
7	(-10, 10)	-0.0666	-0.9561
MM w/GARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	-0.0058	-0.0931
2	(-10, 10)	0.0539	0.9048
3	(-10, 10)	-0.0192	-0.3299
4	(-10, 10)	0.0074	0.1272
5	(-10, 10)	0.0588	0.9947
6	(-10, 10)	-0.1471	-2.4318
7	(-10, 10)	-0.0671	-0.9633
MM w/EGARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0078	0.1252
2	(-10, 10)	0.0633	1.0626
3	(-10, 10)	-0.0099	-0.1701
4	(-10, 10)	0.0226	0.3914
5	(-10, 10)	0.0697	1.1791
6	(-10, 10)	-0.1349	-2.2301
7	(-10, 10)	-0.0721	-1.0351

Table 36 – Facebook single factor CAR values per event

MULTI- FACTOR MODELS			
3 FACTORS (INDUSTRY + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0069	0.1107
2	(-10, 10)	0.0585	0.982
3	(-10, 10)	-0.019	-0.3265
4	(-10, 10)	0.0716	1.24
5	(-10, 10)	0.1097	1.8557
6	(-10, 10)	-0.1306	-2.159
7	(-10, 10)	-0.0314	-0.4508
4 FACTORS (FAMA + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0003	0.0048
2	(-10, 10)	0.0585	0.982
3	(-10, 10)	-0.0043	-0.0739
4	(-10, 10)	0.0258	0.4468
5	(-10, 10)	0.0684	1.1571
6	(-10, 10)	-0.1289	-2.1309
7	(-10, 10)	-0.0574	-0.8241

Table 37 – Facebook multi-factor CAR values per event

SINGLE FACTOR MODELS			
MM			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.1059	2.0633
2	(-10, 10)	-0.0257	-0.4963
3	(-10, 10)	0.0199	0.3877
4	(-10, 10)	-0.0278	-0.5465
5	(-10, 10)	0.0079	0.1582
6	(-10, 10)	0.0215	0.4227
7	(-10, 10)	-0.009	-0.2089
MM w/GARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.1083	2.1101
2	(-10, 10)	-0.0141	-0.2723
3	(-10, 10)	0.0355	0.6917
4	(-10, 10)	-0.0182	-0.3578
5	(-10, 10)	0.0225	0.4504
6	(-10, 10)	0.0289	0.5682
7	(-10, 10)	-0.0092	-0.2136
MM w/EGARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.1082	2.1081
2	(-10, 10)	-0.022	-0.4248
3	(-10, 10)	0.0259	0.5046
4	(-10, 10)	-0.0168	-0.3303
5	(-10, 10)	0.0156	0.3123
6	(-10, 10)	0.0245	0.4817
7	(-10, 10)	-0.0077	-0.1788

Table 38 – Google single factor CAR values per event

MULTI- FACTOR MODELS			
3 FACTORS (INDUSTRY + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0874	1.7029
2	(-10, 10)	-0.0493	-0.952
3	(-10, 10)	0.0158	0.3078
4	(-10, 10)	0.0041	0.0806
5	(-10, 10)	0.0364	0.7287
6	(-10, 10)	0.0282	0.5544
7	(-10, 10)	0.0097	0.2252
4 FACTORS (FAMA + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.1002	1.9523
2	(-10, 10)	-0.0354	-0.6836
3	(-10, 10)	0.0146	0.2845
4	(-10, 10)	-0.0291	-0.5721
5	(-10, 10)	0.0072	0.1441
6	(-10, 10)	0.029	0.5701
7	(-10, 10)	0.0154	0.3575

Table 39 – Google multi-factor CAR values per event

SINGLE FACTOR MODELS			
MM			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0152	0.1301
2	(-10, 10)	0.147	1.2883
3	(-10, 10)	0.0428	0.3692
4	(-10, 10)	0.2203	2.0114
5	(-10, 10)	0.0185	0.1696
6	(-10, 10)	-0.2408	-2.2748
7	(-10, 10)	-0.1832	-1.8338
MM w/GARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0152	0.1306
2	(-10, 10)	0.1593	1.3961
3	(-10, 10)	0.0465	0.4011
4	(-10, 10)	0.2204	2.0124
5	(-10, 10)	0.0178	0.1639
6	(-10, 10)	-0.2433	-2.2984
7	(-10, 10)	-0.1855	-1.8569
MM w/EGARCH			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.025	0.2148
2	(-10, 10)	0.1606	1.4075
3	(-10, 10)	0.0554	0.4778
4	(-10, 10)	0.2439	2.2269
5	(-10, 10)	0.0419	0.3842
6	(-10, 10)	-0.2242	-2.1179
7	(-10, 10)	-0.1686	-1.6877

Table 40 – Netflix single factor CAR values per event

MULTI- FACTOR MODELS			
3 FACTORS (INDUSTRY + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	-0.0152	-0.1301
2	(-10, 10)	0.125	1.0955
3	(-10, 10)	0.0248	0.2139
4	(-10, 10)	0.2949	2.6926
5	(-10, 10)	0.001	0.0092
6	(-10, 10)	-0.3152	-2.9776
7	(-10, 10)	-0.204	-2.042
4 FACTORS (FAMA + VIX)			
Event	Window	CAR Value	CAR t-test
1	(-10, 10)	0.0154	0.1328
2	(-10, 10)	0.1363	1.1993
3	(-10, 10)	-0.0045	-0.0391
4	(-10, 10)	0.2026	1.8498
5	(-10, 10)	0.0111	0.1022
6	(-10, 10)	-0.2204	-2.082
7	(-10, 10)	-0.1063	-1.069

Table 41 – Netflix multi-factor CAR values per event

MM MM w/GARCH MM w/EGARCH	-0.68% -0.98% -0.70%
Industry + VIX FAMA+ VIX	-1.45% 4.59%
AVERAGE	0.16%

Table 42 – Netflix correlation between AR (1) and Earnings Surprise

MM MM w/GARCH MM w/EGARCH	-0.4589 -0.4542 -0.4665
Industry + VIX FAMA+ VIX	-0.4593 -0.4549
AVERAGE	-46%

Table 43 – Google correlation between AR (1) and Earnings Surprise

MM MM w/GARCH MM w/EGARCH	0.1684 0.1710 0.1691
Industry + VIX FAMA+ VIX	0.1651 0.1641
AVERAGE	17%

Table 44 – Facebook correlation between AR (1) and Earnings Surprise

MM MM w/GARCH MM w/EGARCH	0.8584 0.8611 0.8535
Industry + VIX FAMA+ VIX	0.8509 0.8585
AVERAGE	86%

Table 45 – Amazon correlation between AR (1) and Earnings Surprise

MM MM w/GARCH MM w/EGARCH	0.3103 0.3095 0.3106
Industry + VIX FAMA+ VIX	0.3120 0.3143
AVERAGE	31%

Table 46- Apple correlation between AR (1) and Earnings Sur

Event	AR(10)	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
1	-0.1742%	-0.2317%	0.3950%	0.1558%	-0.2300%	-0.0600%	-0.5967%	-0.0433%	0.0908%	1.7850%	0.4550%
2	0.2325%	0.0067%	-0.5008%	-0.0600%	1.2733%	0.0683%	0.4358%	-1.8233%	-0.6033%	-0.4750%	0.5817%
3	-2.4758%	-0.4492%	0.3558%	0.3583%	0.0533%	0.4508%	2.5833%	2.5858%	1.2050%	-1.5192%	0.6400%
4	0.2325%	-0.9800%	-1.7783%	-0.2658%	-1.5767%	-1.9208%	-1.1033%	-1.3892%	0.5858%	0.1792%	0.2167%
5	0.1275%	-0.3267%	-2.2958%	-3.2508%	-0.3292%	0.0442%	0.1992%	-0.8725%	-1.3142%	2.6542%	1.9608%
6	-0.1675%	-0.8125%	1.1792%	-0.1675%	-0.1717%	0.1575%	-0.0842%	0.0192%	-0.9842%	0.0692%	-0.3133%
7	-0.8608%	1.4708%	1.0192%	1.4825%	-0.1475%	0.0508%	0.2300%	-1.2675%	-1.2717%	1.2842%	0.2942%

Table 47- Apple model´s average AR evolution from day -10 to event day

Event	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
1	-0.2242%	-0.4808%	1.1742%	2.6317%	0.7000%	-0.6292%	1.0408%	1.4908%	-0.7933%	-0.1217%
2	4.5167%	-0.8425%	0.2800%	1.3167%	1.0433%	0.6083%	-1.7258%	1.1992%	0.4075%	1.0875%
3	2.2083%	0.8425%	0.2983%	0.5833%	0.1958%	-0.2708%	-0.5450%	-1.3242%	-0.7617%	0.2350%
4	-2.0967%	2.0417%	2.1100%	-1.6775%	1.3750%	-0.4958%	2.3467%	0.6475%	0.3092%	1.9317%
5	5.0925%	0.3592%	2.3733%	0.2950%	0.4642%	-0.4192%	0.3383%	-0.6208%	-0.3608%	-0.2008%
6	5.8283%	2.2950%	-0.2375%	0.1075%	-1.2850%	0.0500%	0.9008%	0.4408%	1.0283%	-0.3308%
7	-6.2183%	-3.5667%	0.3450%	0.5825%	-0.1333%	-1.0192%	-3.0575%	-0.9183%	-2.1325%	1.1817%

Table 48 – Apple model´s average AR evolution from day 1 after the announcement to day 10

Event	AR(-10)	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
1	-0.4125%	-0.6983%	0.9067%	0.3350%	-0.4900%	-0.6000%	-0.2242%	-0.3200%	-0.7700%	0.0658%	0.7983%
2	-0.9375%	-0.5525%	0.6817%	1.1958%	-0.4925%	0.0592%	-0.4308%	1.2700%	-0.3933%	1.0967%	-0.6633%
3	0.6783%	0.0133%	0.0567%	0.1283%	-1.3683%	-1.1642%	-0.9892%	-1.3742%	0.7475%	0.1133%	-0.2850%
4	-0.0850%	-0.4808%	1.5425%	2.2717%	-0.4208%	1.3792%	0.3067%	1.8200%	2.5233%	0.7275%	-4.2783%
5	0.4667%	-1.0608%	-0.3558%	2.8367%	1.3483%	2.3717%	-1.0433%	-0.8042%	-2.5142%	-0.3092%	2.5408%
6	1.1675%	0.6333%	0.4425%	0.5975%	-0.4717%	-1.3683%	0.0300%	-1.0492%	0.7842%	0.7625%	-2.8350%
7	0.7300%	0.6142%	-1.7708%	-0.4183%	1.9233%	-0.5817%	-2.5050%	4.6425%	-6.1500%	-5.8275%	-2.4475%

Table 49 - Amazon model´s average AR evolution from day -10 to event day

Event	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
1	0.7633%	2.1708%	-0.4325%	-0.6508%	-0.5850%	-0.9667%	1.3858%	0.3325%	-0.6592%	-0.1025%
2	-2.4750%	-3.2958%	0.4467%	-0.2333%	-0.7408%	-0.2808%	0.1550%	-0.1242%	-0.9133%	-1.0875%
3	11.4625%	1.1758%	-0.6442%	-0.3475%	-0.9217%	1.1608%	0.6300%	0.1575%	0.7250%	-0.0200%
4	5.1500%	1.8358%	1.7658%	-1.3133%	-0.5233%	-2.4967%	1.8092%	1.6617%	0.9283%	-0.6925%
5	3.2833%	0.3625%	0.5450%	-0.1275%	0.3467%	-1.0325%	0.6250%	-0.5958%	-0.2667%	-1.1692%
6	1.1125%	-1.5217%	-0.7900%	1.1083%	1.3017%	-1.2833%	0.8317%	0.2975%	1.1033%	0.6000%
7	2.9458%	2.8233%	0.7450%	-3.0108%	0.1775%	4.0125%	0.1550%	-1.4967%	-2.2250%	-0.2975%

Table 50- Amazon model´s average AR evolution from day 1 after the announcement to day 10

Event	AR(-10)	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
1	1.0408%	0.1850%	0.1833%	-0.0333%	-0.0708%	0.0275%	0.6533%	1.7917%	1.1958%	-0.0033%	-0.5775%
2	1.4592%	-0.0742%	-0.1508%	-0.2450%	1.7942%	0.1350%	0.1900%	-0.1150%	0.9892%	-0.8375%	0.0700%
3	-0.2158%	-0.9633%	-0.3883%	-1.8292%	0.0558%	-0.3125%	-0.2250%	3.1933%	1.3142%	-0.0508%	1.2025%
4	-1.4108%	1.3517%	0.3400%	1.3942%	1.8683%	-1.4783%	0.4325%	0.0333%	-1.4308%	1.7258%	-0.2158%
5	1.3892%	-2.3942%	0.6892%	-0.7742%	1.0617%	-1.5417%	1.6667%	-0.1650%	-0.3333%	-2.2967%	-0.2458%
6	0.2850%	1.0492%	-0.0209%	-0.0150%	0.8175%	-0.6325%	-0.2450%	0.9675%	0.1758%	1.1475%	0.2867%
7	0.9725%	0.4792%	-1.1400%	-0.4875%	1.0683%	0.4150%	-1.9300%	1.2400%	-1.7142%	-1.4850%	1.0850%

Table 51- Facebook model´s average AR evolution from day -10 to event day

Event	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
1	-0.7575%	-0.9558%	0.4425%	-0.3633%	-0.3433%	-0.0150%	0.2775%	-0.7125%	-0.2867%	-1.4283%
2	2.8842%	1.2475%	-1.8958%	0.0167%	-0.4675%	-0.2083%	0.3258%	1.1233%	-0.2875%	-0.0850%
3	-2.1467%	-0.4508%	0.4575%	-0.0351%	-0.5700%	0.1317%	-0.4850%	-0.0465%	-0.2308%	0.4308%
4	3.3433%	0.7650%	-0.4033%	0.3717%	-2.2767%	-0.8150%	1.0392%	-1.2908%	-2.1575%	2.1458%
5	7.4833%	-0.4992%	-0.0175%	0.7433%	2.0342%	-0.8717%	0.0283%	0.3283%	0.5400%	0.9625%
6	-20.7667%	-0.0900%	-1.5717%	0.2217%	-0.4767%	2.0658%	0.1900%	3.9300%	-1.4133%	0.6817%
7	2.5092%	-1.2000%	-0.0992%	-1.7058%	0.1933%	-1.3742%	-2.1358%	-0.9142%	-0.0167%	0.5900%

Table 52 – Facebook model´s average AR evolution from day 1 after the announcement to day 10

Event	AR(-10)	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
1	0.5692%	0.5583%	0.8258%	0.1233%	0.4325%	-0.4067%	0.1542%	1.0967%	0.4175%	0.0133%	0.1592%
2	0.9300%	0.2883%	0.6633%	-0.1417%	0.2708%	-0.1617%	0.9817%	-0.0275%	-0.1042%	0.1192%	0.4975%
3	0.1208%	0.0825%	-0.0800%	0.0558%	0.0558%	-1.1583%	-0.2367%	-1.6092%	0.0967%	0.7333%	-0.1867%
4	-0.1500%	0.1683%	0.9242%	0.7617%	-0.3942%	0.8483%	-0.8225%	0.6200%	0.3592%	0.3250%	0.0000%
5	0.6333%	-0.2725%	-0.4767%	0.2767%	0.2025%	0.0550%	1.9158%	-0.4575%	1.9375%	-0.1375%	-0.3358%
6	-0.0075%	-0.4367%	1.1642%	1.4650%	0.1167%	-0.5867%	0.9058%	-0.2958%	-0.7225%	-0.0067%	0.8317%
7	2.4075%	1.0533%	-0.8392%	0.2350%	-0.4033%	-0.9225%	0.7292%	1.1350%	1.0217%	-1.5600%	2.1533%

Table 53 Google model´s average AR evolution from day -10 to event day

Event	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
1	3.7875%	0.6717%	0.2658%	1.2825%	0.5408%	-0.9683%	0.7950%	-0.1658%	-0.3617%	0.2625%
2	-3.3575%	-0.4658%	-1.2883%	0.7017%	-1.3517%	-0.2042%	-0.0058%	-0.5725%	0.3233%	-0.2367%
3	3.3058%	0.2333%	-0.1292%	0.7400%	-0.0075%	0.3075%	-0.8558%	0.8967%	0.4167%	-0.6658%
4	-3.1658%	-0.7350%	0.2633%	-2.1583%	-0.5267%	2.2217%	-0.6625%	-0.3050%	0.3100%	0.4442%
5	-3.3700%	-0.1600%	0.7858%	-1.2642%	-0.3367%	1.8500%	-0.6117%	0.2992%	0.9358%	0.3983%
6	3.2308%	0.3633%	1.0808%	-1.8283%	-1.1583%	-0.7992%	0.5808%	0.0433%	-0.8033%	-0.4592%
7	0.3183%	-3.8067%	-0.3708%	2.5600%	-1.6433%	-0.5183%	-2.1117%	0.6342%	1.0342%	-0.9100%

Table 54 - Google model´s average AR evolution from day 1 after the announcement to day 10

Event	AR(-10)	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
1	0.0600%	-0.5142%	-1.1392%	-1.0650%	-0.2758%	-0.4117%	0.2408%	0.3433%	0.0742%	0.2633%	1.7542%
2	-0.6217%	-2.6442%	0.8267%	0.2950%	1.7042%	1.4417%	1.0508%	1.8008%	-0.6958%	1.0633%	0.2525%
3	-3.1242%	0.8308%	2.4942%	4.3583%	1.8608%	-0.5158%	-1.4100%	-0.4717%	0.5217%	1.5733%	1.1633%
4	1.0475%	0.6583%	-1.6025%	1.5433%	1.2050%	0.8750%	0.5233%	-3.1717%	1.4133%	-0.5967%	2.0267%
5	-2.2433%	-0.7242%	0.0117%	0.5875%	1.1900%	-0.2942%	0.2900%	2.4375%	0.5300%	0.9658%	-2.6025%
6	-1.3175%	1.0167%	-1.4175%	0.4958%	0.9883%	1.0608%	-1.4658%	1.5325%	-2.7442%	-4.6508%	1.0717%
7	-1.1083%	-0.1750%	-2.5167%	-2.5467%	-0.7008%	2.0783%	-4.0683%	1.5433%	3.5475%	-0.9200%	0.7950%

Table 55 – Netflix model´s average AR evolution from day -10 to event day

Event	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
1	-2.4550%	-2.4667%	-0.0958%	1.4800%	-1.0125%	4.6358%	-1.4692%	1.7083%	-0.4375%	1.7108%
2	12.4592%	-0.6792%	-0.2625%	2.4958%	-0.3117%	-1.0508%	1.0675%	-3.3708%	0.8617%	-1.3683%
3	-1.8117%	-2.2358%	-0.4042%	-1.3367%	-0.5017%	1.4708%	-0.6358%	0.3758%	0.9242%	-0.2067%
4	9.1317%	4.3158%	3.0600%	0.1800%	4.4950%	-0.6325%	-3.2333%	-1.9250%	3.7892%	0.7450%
5	7.0442%	-0.6367%	0.0117%	-0.3392%	-2.9742%	-2.0617%	-0.7233%	0.9592%	-0.9617%	1.1392%
6	-6.1058%	-1.6583%	-2.5617%	-0.9308%	-0.1117%	-2.4192%	0.0517%	0.4133%	-1.3900%	-5.0525%
7	5.2525%	-3.0767%	-4.1408%	-0.2825%	1.9150%	-5.4558%	0.9367%	-1.7508%	-4.2350%	-1.8033%

Table 56 – Netflix model´s average AR evolution from day 1 after the announcement to day 10