The Incorporation of New Information on the British Equity Market surrounding Brexit - Empirical Evidence from the FTSE350

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Abstract

This thesis examines how investors in different industries on the British Equity Market incorporate new information surrounding the Brexit referendum, under the framework of the Efficient Market Hypothesis. By employing an event study on three different events surrounding the Brexit referendum the thesis finds significant abnormal returns and unexpected turnover ratio, using both parametric and non-parametric tests, for only one event: the publication of the referendum outcome. This supports the notion of market inefficiency at a semi-strong form around this event. The investors' response to this event was continued price movements in opposite directions depending on industry. For the other two events, the official announcement of the referendum and the official triggering of the referendum, evidence of market inefficiency was not found. A cross-sectional analysis provides additional supporting evidence of significant increased trading activity only around the announcement of the results of the referendum. Evidence of the Sequential Information Arrival Hypothesis and lack of consensus among investors offers reasons for the observed market inefficiency along with behavioural explanations such as overreacting to surprising information, Herding behaviour, Cognitive Dissonance Theory and Selective Exposure, and Anchoring.

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1. Introductory Chapter

1.1 Introduction

On the 23rd of June, 2016, a majority of 51.9% of the people of the United Kingdom voted in favour of the United Kingdom European Union membership referendum, expressing their desire for the UK to leave the European Union. The upcoming withdrawal is commonly referred to as "Brexit" – a portmanteau of Britain and exit – and has caused quite the stir in the UK and Europe, and on a global level. In response to the outcome of the referendum, the London Stock Exchange FTSE100 fell nearly 11%, the pound dropped to a 30-year low, and the global equity market lost more than 2 trillion dollars in value in the fallout (Burdekin, Hughson & Gu, 2018). Such a heavy response in the financial markets reflects the surprising outcome, as most predictions expected a close call, but in favour of the REMAIN-camp. Instead of continuing the previous established relationship, the now required procedure is expected to affect international trade and the geopolitical climate, as Britain prepares for a post-EU future. Since there has never before been a country withdrawal its membership of the EU (or any of its political predecessors), no precedent is established to predict how exactly the relationship between both parties will take shape after the two-year negotiation period. The event has caused much uncertainty about the future, and the market has adjusted to this new information, as the one thing investors can count on is that it will most certainly be different from the status quo.

Many studies have been published on the issue of how financial markets respond to news, and how this new information is incorporated in the valuation of securities. When examining the market response to new information, it is common to test for the Efficient Market Hypothesis (Fama, 1970). In theory, with the introduction of new information, prices quickly adjust to incorporate this information, and according to the No Trade Theorem no additional trading activity would be required, as all investors agree on the impact of the new information (Beaver, 1968; Foster, 1973). In practice however, increased trading activity is observed. Foster (1973) states investors adjust their portfolios for several reasons like consumption-timing and change in risk preference. This trading can be referred to as fundamental trading. Many event studies have found an increase in trading activity around events holding "information content" that cannot be explained by fundamental trading (Hendershott, Livdan & Schürhoff, 2015; Yuan 2015). Therefore, the excess volume can be defined as unexpected trading activity. Therefore, unexpected trading volume around information events can be an indication of lack of agreement among investors (Beaver, 1968; Foster 1973). Previous literature attributes this to two main drivers; the informedness effect, which results from asymmetric information among investors

(Karpoff, 1987), and the consensus effect, meaning heterogeneity in the interpretation of information (Harris & Raviv, 1993).

Current literature on Brexit is scarce, as most reports focus on the economical future for different divorce terms. The separation will have a different effect on different industries, as some are expected to fare better without the EU and others expect to see a decline as costs rise due to trade tariffs and reduced labour mobility (Ramiah, Pham & Moosa, 2017). A strong reaction on the financial markets was investigated by for example Krause, Noth, & Tonzer (2016), Oehler, Horn & Wendt (2017), and Smales (2017) who all find that increased uncertainty about the referendum outcome leads to lower returns for firms with high degrees of internationalization and a higher volatility in the market in general. Additionally, Wu, Wheatley & Sornette (2017) argue that the markets did not incorporate new information efficiently as the British Pound exchange rate did not adjust quick enough to keep up with election results in favour of Brexit.

1.2 Research Questions, Contribution, and Scope

The observations of other authors stated above lead us to question the capabilities of investors to accurately incorporate new information in an efficient manner, specifically considering Brexit. Therefore, this thesis aims to answer the primary problem statement:

> *"How do investors in different industries on the British Stock Market incorporate new information surrounding different events of the Brexit referendum process, under the framework of the Efficient Market Hypothesis?"*

The following sub-questions aim to answer different aspects of this research question that are grounded in existing literature.

- *Do individual investors display homogenous responses?*
- *To what extent is potential market inefficiency surrounding the events affected by the flow of information through the market?*
- *To what extent is potential market inefficiency surrounding the events affected by lack of consensus among investors?*
- *To what extent can behavioural interpretations explain whether differences between event characteristics result in different degrees of market efficiency?*

- *To what extent can the analysis of the response to Brexit be applied in other similar political developments?*

This thesis contributes to the current knowledge on market efficiency in two different aspects. First by investigating the Brexit case; a relatively recent event that has no direct precedent yet a large impact on the global economic environment. Limited research has already been published on the event, but this thesis distinguishes itself by comparing multiple events surrounding the referendum, as well as their impact on different sectors in the British economy rather than the market as a whole. Secondly, this thesis contributes to the existing literature examining both the average reaction of the market, as well as the aggregate response of individual investors. To do so, different theories on market efficiency and information incorporation are combined and examined in one analysis. This especially is an important factor for understanding the dynamics behind market movements in the fallout of surprising new information in periods with increased uncertainty.

Because this thesis is an exploratory study, we have chosen to limit our investigation to the British equity market of the London Stock Exchange. The stock market represents the most natural financial security, as stock prices are directly derived from expectations on future firm performance, which in turn is directly affected directly by any new information about Brexit proceedings. Other types of financial instruments and securities are interesting for further research, but will not be considered in this study. Additionally, our focus is solely on the London Stock Exchange, which represents the British economy. The effect of Brexit on the global markets is a topic for further research.

Unfortunately, the Brexit process will not be completed at the time of submission of this thesis, as the negotiations on the terms of separation are officially ongoing and the deadline is not until March 29th, 2019, almost a year after submission. Even though the EU has declared an “all or nothing” position on when the deal will be officially finalised, it is considerable that premature information on potential agreements will reach the market before this day. Therefore, we have chosen to limit the period under investigation and only gather market data up to and including 30-04-2017. This date includes the last event of our study, and allows us view the short-term impact of Brexit. The three events included in this study cover the first part of the Brexit process; the entire period up to the start of official negotiations, which we consider the final “point of no return”. Any new potential events regarding Brexit that result from the negotiation process in the time after this cut-off date will not be analysed in this thesis.

1.3 Structure

To answer the previously stated research questions, the thesis will adhere to the following structure:

First, we will provide a framework of background information, and present an overview of the concepts and theories that form the foundations of this thesis. This framework is accompanied with several insights from previous literature on the testing of market efficiency and unexpected volume, as well as already published studies on the impact of Brexit on the economy and the financial market.

The third chapter will introduce the empirical study this thesis is built upon. This includes a structured plan of the event study methodology applied, as well as a presentation and description of the data used. Additionally, this chapter covers the detailed methodology necessary to answer the sub-questions separately.

Next, we will present the results of the empirical study regarding our separate sub-questions, and provide observational subconclusions on these findings.

In the fifth chapter, we will analyse and further discuss our findings with respect to the main research question as we combine the answers to our sub-questions.

We will end with a discussion of limitations of our research and our findings, and provide suggestions for further research in the final chapter before the completing conclusion.

2. Concepts, Theory, and Previous Literature

A large body of scientific studies analyse stock performance, especially in attempting to predict future price movements. Niederhoffer (1971) is one of the first to address the response of financial markets to major news events with an empirical study. He states that “After studying the relation between world events and stock prices from a variety of viewpoints for more than three years, I am convinced that world events are a strong and compelling influence on stock prices.” (Niederhoffer, 1971, page 215). His study analysed price movements surrounding different major world events drawn from newspaper headlines during 1950-1960 and found a pattern suggesting that large changes were substantially more likely to follow these events opposed to randomly selected days, especially on the first and second day following the event. This chapter starts with a discussion of the concepts and theories surrounding financial markets and information incorporation that are applied in this thesis. An overview of existing literature on the impact of Brexit on the UK economy and financial markets follows, as well as a survey of literature on abnormal returns and valuation models, and a discussion of prior research into unexpected trading volume.

2.1 Concepts and Theory

The following section will introduce several established theories that focus on how information affects the financial market, from both a traditional and a behavioural perspective. With regards to security prices and returns, we will address how investors incorporate information in their valuations and the role uncertainty plays in determining the risk premium, specifically focussing on the source of the uncertainty. Furthermore, we will discuss how investor activity indicated by trading volume captures the aggregate opinion on prices of all traders in the market, and why these opinions may differ between individuals based on information availability and divergent probability beliefs.

2.1.1 Efficient Market Hypothesis

One of the central theories in finance and economics is the theory of efficient markets. The emergence of efficient market theories can be traced back to the 16th century (Sewell, 2011), and was pioneering by the theoretical contribution of Bachelier in 1900 and Cowle’s empirical research in 1933 (Campbell, Lo & MacKinlay, 1997).

However, modern literature of efficient market that caused the theory to gain popularity was by Fama (1970), who presented the Efficient Market Hypothesis. The fundamental idea of this theory is that a market behaves efficiently if the stock prices fully reflects all information available to traders, and that new information will be incorporated in the price rapidly after it becomes known (Fama, 1991).

The notion that the stock prices should fully reflect all available information suggests that the expected error $E(\varepsilon_{t+1}) = P_{t+1} - E_t(P_{t+1})$, meaning the difference between the actual price and the expected price, should on average be zero. Thus, the error should be uncorrelated with the available information at time t, which is known as orthogonality property. This property combined with the statement that new information should be rapidly incorporated in the price, imply that an efficient market is competitive such that arbitrage opportunities should not be possible (Cuthbertson & Nitzsche, 2004; Berk & DeMarzo, 2014).

The sufficient assumptions underlying the Efficient Market Hypothesis are that 1) the transaction costs of selling or buying a security are zero, 2) information is available to all traders free of cost, and 3) all market participants have a homogeneous opinion on the impact of the information on the price. These assumptions are not necessary to have an efficient market, they are merely sufficient, but a violation of these assumptions suggests a potential source of market inefficiency (Fama, 1970).

Fama (1970) defines three forms of efficient markets, dependent on the information set that affects the expectations of investors on future firm performance:

<u>Weak form:</u> In this form, the information set that the stock prices fully reflect consist only of all historical prices.

<u>Semi-strong form:</u> The semi-strong form is based on the assumption that stock prices fully reflect all publicly available information. This includes all historical prices, but also any other publicly available information that may affect expectations on future firm performance, such as for example the macroeconomic state of the economy or firm specific details from press releases.

<u>Strong form:</u> The last form is the strong form, where the stock prices account for all information that can possibly affect future performance. This form does not differentiate between whether the information is publicly available, or consists of insider information such as for example unconfirmed upcoming mergers.

Testing for the weak form efficiency, evidence supporting the hypothesis should display prices following a random walk. This means that the movement of the prices does not follow any measurable trend or pattern. Testing the semi-strong form looks at the speed of the adjustment of the prices after new publicly available information have been released. Here, an efficient market is one where the new information is quickly reflected in the prices. Finally, the strong form efficiency tests that no individual or group has access to information that can earn them profit, as all information possibly known is already incorporated in the price and thus every investor should agree on this price being the true value of the security. The empirical testing of the Efficient Market Hypothesis usually concentrates on the semi-strong form (Fama, 1970).

2.1.2 Normal Returns vs. Abnormal Returns

With the term *normal returns* we refer to what Fama (1970) described as the equilibrium expected return. The equilibrium expected return on a specific stock is dependent on expected future firm performance, and the risk involved with owning the right to these future payoffs. There are different theories on how to define and calculate this. In general however, it can be described with the following formula;

$$E(P_{t+1}|\psi_t) = (1 + E(R_{t+1}|\psi_t)) * P_t$$

Where P serve as the price of the stock and R the returns, ψ_t represented the information set available at time t.

So independent of which model used to determine the expected normal returns at time t+1, it should be determined based on all available information at time t. According to Fama (1970), this represents a fair game; the actual return at time t+1 minus the expected normal returns at time t+1 (referred to as *abnormal returns*) is expected on average to be zero. Therefore, it becomes impossible to earn a profit trading only on the information set available at time t.

Abnormal returns should therefore only exist when new information reaches the market between time t and t+1. The expected abnormal return should then again be zero for time t+2, as the price is expected to fully reflect the new information at time t+1, and it should not be possible to earn profit on trading on that new information anymore.

2.1.3 Stock Valuation, Risk Premium, and Uncertainty

The price of a stock in an efficient market should, as stated by Fama (1970), reflect all available information. Determining the value of the stock can be done by assessing the expected future cash flow of owning the stock. The fundamental value of a stock equals the present value of the expected future dividends (*D*), discounted by a constant rate (Berk & DeMarzo, 2014).

$$P_t = E_t[\sum_{i=1}^{\infty}(\frac{1}{1+R_r})^i D_{t+i}]$$

The discount rate is here represented by the investor's required rate of return, R_r. This return is determined by the investor to be sufficient to compensate for the inability to invest these specific funds in another security at the same time, and the risk related to holding the stock as its future cash flows are subject to uncertainty. Therefore, the discount rate is represented by the sum of the risk-free rate and a specific risk premium. The price calculated is equal to the fundamental value given the rational expectations for all investors (Cuthbertson & Nitzsche, 2004).

These models consist of many assumptions. What is the expected dividend?, should a growth rate be incorporated, if so what should it be?, is the firm engaging in risky investments?, etc. Therefore, it is not necessary that all investors' assessments of the stock price are the same; some investors may value the stock differently. Then the price is settled by supply and demand. Knowing some might be willing to sell the stock at a much lower price than another investor would buy it at, should lead buyers and sellers to revise their valuation. Ultimately, the price would reach an equilibrium. In this way, information and different valuations and views form the investors are averaged in the stock market and reflected in the price (Berk & DeMarzo, 2014).

In the above presented model of determine the stock price, it assumes that the required rate of return for the investors is constant over time. The required return used to discount the expected future dividends depends on different aspects; the risk-free rate and the risk premium. Within the risk premium the investors assess how risky they perceive the market and how risk-averse/neutral/loving they are (Cuthbertson & Nitzsche, 2004). If for example, they do not perceive the market as risky and they are risk-neutral, the expected future dividends should simply be discounted with the risk-free rate.

When news enters the financial market, it can affect either the systematic risk or the unsystematic risk. The unsystematic risk, also called idiosyncratic risk, is a firm or sector specific risk. This type of risk can be minimised by a perfectly diversified portfolio. The investors' risk premiums are consequently not affected by the unsystematic component of the financial risk. The systematic risk on the other hand, often referred to as the market risk, is perfectly correlated among all the assets, and cannot be reduced by diversification of investors' portfolio. Market risk often originates from economy-wide uncertainty, such as the threat of natural disasters, or political unrest related to election cycles and political transitions (Pastor & Veronesi, 2011). In democratic political systems, national elections may cause a redistribution of political power, leading to a potential change in government policy direction. This results in ambiguity on the future state of the environment in which firms operate. Examples of policy changes that highly affect firm performance are tax regulation, government spending, monetary policy, international trade and exchange rate policy, and military actions (Pastor & Veronesi, 2012; Segal et al., 2015; Baker, Bloom & Davis 2016; Abaidoo, 2017). Uncertainty about these issues can affect firm performance and growth through indecision, as corporations delay hiring and investments in large projects and households delay consumption, preferring wait for more stable information on the future (Bernanke, 1983; Davis, 2016). If investors are not diversified internationally, national macro-economic change will affect their portfolio equally. Therefore, investors incorporate this uncertainty as systematic risk in their risk premium and increased uncertainty leads to an increased required rate of return (Beja, 1972; Cuthbertson & Nitzsche, 2004). The assumption of constant required rate of return therefore seems unsuitable for the real world, where investors risk profile can differ over time and that uncertainty can change the general risk in the market.

2.1.4 Trading Volume in Efficient Markets

If the Efficient Market Hypothesis presented by Fama (1970) is correct and all investors in the market are strictly rational and homogeneous in their utility function, there would be no trading activity. That is because under these assumptions, all investors agree on the price presented in the market. Even with the introduction of new information, no trading activity would be required, as all investors agree on the impact of the new information on the value of a stock. This change in expected value is common knowledge (Aumann, 1976) and would be displayed in a change in price of identical fashion at time t+1. The No Trade Theorem states there would be no need for any investor to adjust his pre-information portfolio, because the change in desirability of the stock perfectly offsets the change in price. In this case, there would be a price reaction, but no reaction in trading volume (Beaver, 1968; Foster, 1973).

In a more realistic setting, trading activity can be observed and the assumption of homogeneous utility functions for every investor is too strict. Karpoff (1986) emphasizes the importance of the study on the relation between trading volume and stock returns. He argues the relation provides insight in the structure of the financial market, underlines inferences drawn in event studies and facilitates debate on the empirical distribution of speculative trading behaviour. A range of different researches have focused on this relationship, finding two distinct stylized facts: the correlation between trading volume and the absolute value of the stock price change is positive and the correlation between trading volume and the stock price change is also positive (Karpoff, 1987). These studies however, often lack the causal interpretations of a dynamic relation (Gallant, Rossi & Tauchen, 1992).

2.1.4.1 Origin of Trading Volume

Foster (1978) states that investors adjust their portfolios for several reasons, which can be divided into two general sets. The first set includes reasons like consumption-timing, taxation, change in risk preference and diversification. These reasons are non-informational. Instead they are motivated by the trader's need for liquidity (Benston & Hagerman, 1974; Branch & Freed, 1977; Petersen & Fialkowski, 1994). It is often referred to as liquidity trading or noise trading, because it does not behave according to efficient market models (Bodie et al, 2014). As this volume would occur regardless, it can be defined as expected, or *fundamental trading activity*.

Other transactions are initiated by traders who believe that the stated price is wrong. Many event studies have found an increase in trading activity around events holding "information content". Beaver (1968) defines an event to have information content under two requirements. The event must result in a change of expectations by an investor and this change must be sufficiently large that it induces a change in behaviour. Ajinkya & Jain (1989), Bamber (1986) and Chae (2005), amongst others, look at patterns around planned earnings announcements and find that in the days prior to the event, trading volume increases. When looking at unplanned events, such as acquisitions or news stories, Hendershott, Livdan & Schürhoff (2015) and Yuan (2015) for example find similar results. This pattern of increased activity around events containing information cannot be explained by the non-informational reasons behind the fundamental trading activity as posed by Foster (1978). Therefore, this change in volume can be defined as *unexpected trading activity*. This type of trading volume is sometimes referred to as abnormal volume, drawing comparisons to the existing methodology for studies related to abnormal returns. However, as explained before, returns are determined endogenous, as they directly derived of the value of the underlying security, and this value defines what is normal and what is abnormal. The level of trading volume observed is exogenous, and can therefore not be classified as normal or abnormal through a direct relationship with the value of the underlying security. Hence, this thesis will continue using the term *(un-)expected* trading volume.

To explain this excess volume, the assumptions underlying the Efficient Market Hypothesis has to be relaxed even further. If the No Trade Theorem requires agreement, then excess trading activity is the result of lack of agreement. If an individual investor disagrees with the general market and believes that the price in the market does not reflect the value of a stock properly, then that investor would have incentives to trade. The greater the divergence between this individual investor's beliefs on the correct price and the current price, the greater his incentive to trade (Morse, 1980). Unexpected trading volume around information events can be an indication of lack of instant agreement between investors regarding the impact of new information that affects the equilibrium price of a security (Beaver, 1968; Foster 1973). Verrecchia (1981) argues that this inference can be justified, but is still ambiguous. Previous literature indicates two separate drivers for lack of agreement amongst investors, with regards to information; the informedness effect and the consensus effect (Holthausen & Verrecchia, 1990). The informedness effect focuses on the degree at which investors become more knowledge and argues in line with asymmetric information, stating that some investors have information that others have not (i.e. different values in a likelihood function) (Karpoff, 1987; Chordia & Swaminathan, 2000). The consensus effect poses that disagreement is caused by heterogeneity in how investors interpret information (i.e. different coefficients in a likelihood function) (Harris & Raviv, 1993; Chordia, Subrahmanyam & Anshuman, 2001).

2.1.4.2 Informedness Effect

Many earlier studies credit divergence in asset valuation to asymmetric information (Akerlof, 1970; Beaver, 1968; Foster, 1973; Copeland, 1976; Morse, 1980, among others). In this case, the price at time t reflects all publicly known information and there exists a semi-strong efficient market. Grossman (1976) articulates this situation as private information prior to the event and individual investors can be divided between two groups; informed investors and uninformed investors. In this division, information asymmetry refers to the situation where informed investors have material, firm-specific information related to future public announcements and uninformed investors do not (Chae, 2005). For example, a specific investor may have private information regarding the level of a firm's annual earnings before the official earnings announcement. This private information often comes from an insider position of the investor; the investor has access to the information before it is made public. When insiders sell a stock heavily, the price falls by an abnormal amount and vice versa for when they buy heavily (Pratt & DeVere, 1970; Jaffe, 1974; Finnerty, 1976). This implies that insiders try to exploit their superior information if they are aware price changing information is about to go public, increasing unexpected trading activity (Kyle, 1985). This line of reason, however, would also require trading volume to return to the fundamental level once the new information has reached the public and does therefore not explain continued unexpected trading activity post-event.

Copeland (1976) first proposed the Sequential Information Arrival Hypothesis (SIAH), arguing that not all investors instantly receive information after it has been made public. Instead, information reach investors sequentially. It assumes a market in equilibrium as base state and initially one single investor who observes the new information. Therefore, the new information is not common knowledge instantaneously (Milgrom & Stockey, 1982). After interpretation and revision of his beliefs, he adjusts his demand function and trades accordingly to adjust his position into the new optimal portfolio. With the transaction, a new temporary equilibrium price is set where price and quantity match supply and new demand. Then the next investor becomes informed and follows the same process of adjustment, resulting in a second new temporary equilibrium. This process repeats itself until all investors in the market have become informed, and have adjusted their positions, resulting in a series of transactions that aggregated into increased unexpected trading volume. The SIAH assumes that the distribution of information arrival is random, and it is therefore not possible to know who is informed and who is not. After the last trader becomes informed and adjusts his position, the market reaches its final stable equilibrium and returns to a stable level of fundamental liquidity trading (Copeland, 1976; Jennings, Starks & Fellingham, 1981). Hong & Stein (1999) propose a similar theory, where different investors observe different pieces of private information at different points in time. Their gradual-information-diffusion model is mainly focused on returns, but offers an interesting inclusion of different types of investors; those who are externally informed and those who trade on internal price movements only (momentum). The latter are still speculative traders rather than noise traders, but do offer an explanation of why not every investor is equally informed at all times. Additionally, the intuition behind the model allows for uninformed investors to gradually become informed (Hong, Lim & Stein, 2000).

2.1.4.3 Consensus Effect

Evidence suggests that there is a relationship between volume and price, stating that changes in price are accompanied with changes in volume (Karpoff, 1986; 1987). Varian (1985) argues that under the assumption of market efficiency, stock prices reflect all information available to the market, including private information. Therefore, all investors should have the same knowledge available to them, whether it is directly from information itself, or indirectly through the stock price. As Tirole (1982) puts it, if one investor has private information that leads him to belief the market price is incorrect, then other rational investors should not want to trade with him, because they realise he must have superior information. This knowledge will quickly be incorporated in the stock price to the point the investor with private information is no longer willing to trade. In this case, the market returns to a situation of strong market efficiency, as described by Fama (1970). As such, asymmetrical information cannot be a cause of divergence in valuation, because investors could subtract the information from the price. This would again lead to a situation of no trade. Considering that reasons to trade other than information are caught by the fundamental trading volume as described before, Tirole (1982) states that excess trading on the arrival of new information can only arise if individual investors have different interpretations of the same information. Varian (1985) uses Bayesian inference to explain how informational events can adjust the opinion of an individual investor.

Bayes' Theorem with regards to inference states that

$$P(H|E) = \frac{P(E|H)\,P(H)}{P(E)}$$

With relation to an informational event occurring, the Theorem can be used to adjust one's opinion on the likelihood of a specific change in value caused by the contents of this new information. Here, *H* stands for any change in value whose probability may be affected by *E*, the evidence that is presented in the new information entering the market. *P(H)* is the prior probability; the estimated probability of *H* happening before the new information is acquired. *P(H|E)* is the posterior probability; the adjusted estimate of the probability of H happening after incorporating the new evidence. *P(E|H)* is the likelihood; the probability of observing the new evidence given the observation of the specific change in value captured by *H*. *P(E)* is the probability of the evidence being observed, regardless of whether a change in value occurs too (Harsanyi, 1983).

As discussed before, the price of a stock is dependent on the present value of expected future cashflows, which are dependent on the probability distribution of a range of different possible cashflows. If this probability distribution changes, the price changes. Heterogeneity in investors' beliefs about the probability of specific possible cashflows can result in a divergence in valuation in different ways. If investors are heterogeneous in their estimation of the prior probability, there will be divergence in the individual expectations of the new value of the stock after the event, even if there is a homogeneous understanding of the contents of the new information. If investors are heterogeneous in their estimation of the likelihood, there will be divergence in the individual expectations of the new value of the stock after the event, even if there is homogeneous understanding of the circumstances prior to the event.

Harsanyi (1983) argues that fully rational investors should have the same estimations of the prior and the likelihood, because fully rational investors should all interpret the same information in the same manner; the true manner. This suggests that the only plausible explanation for heterogeneous investors' opinions is the existence of irrational investors.

2.1.5 Irrational Investors with Behavioural Biases

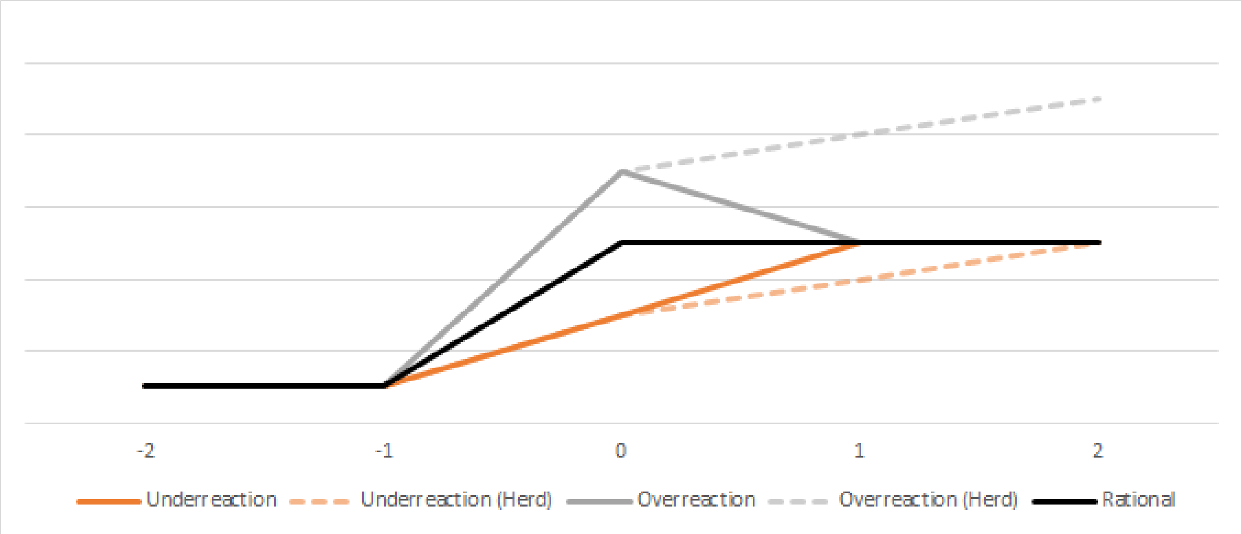
Traditional financial models mostly rely on investors being fully rational, thus holding homogeneous opinions about new information. Rationality in this aspect refers to two things. 1) if presented with new information, investors will update their beliefs correctly, in accordance to Bayes' law, resulting in a homogeneous new posterior probability for all investors, and 2) given these correct beliefs, rational agents will make normatively acceptable decisions; they will choose a strategy that optimises their subjective expected utility (Barberis & Thaler, 2003). The assumption of humans being fully rational was challenged by Herbert Simon in 1957, in response to consistent empirical evidence that did not support the notion. He proposed the concept of bounded rationality, stating that the second half of the rationality assumption was indeed true, but that humans do not update their beliefs correctly, because they are limited in their ability to make fully rational decisions (Gigerenzer & Selten, 2002). This limitation is caused by constraints in resources such as thinking capacity, availability of information, and time to make a decision. Bound by these limitations, an agent with bounded rationality updates his beliefs as well as he can, and then makes a decision that maximises his subjective expected utility. In order to compensate for the limits in resources, individuals draw on cognitive beliefs as shortcuts to make the most optimal decision as possible (Gigerenzer & Selten, 2002). Investors draw from different psychological biases and heuristics when they have to process new information to update their stock valuations and adjust their demand. Heterogeneous application of these biases and heuristics causes heterogeneous beliefs about new information among investors. The study of behavioural finance covers a range of biases and heuristics that cause bounded rationality, which are discussed in great detail by Barberis & Thaler (2003) in a inclusive Survey. We will only discuss a small set as to remain relevant to the topic of this thesis.

One of these psychological biases is Conservatism, which is based on the idea that investors update their beliefs only slowly when presented with new information, rather than instantly. Conservatism states that when presented with new information, people have a tendency to underweight that information and instead rely too much on prior, outdated beliefs (Barberis et al., 1998). In regards to the Bayes law as presented in the previous section, this means that investors do adjust their posterior probability in the right direction, however not instantly by the right magnitude. This suggest that when information arrives, the Conservatism bias will cause investors to underreact to that new information, and the price of a security will only gradually convert to the correct value (Barberis et al. 1998). The underreaction is visualised in Figure 1.

Not all new information is the equal. A subset of news announcements are those where the contents come as a surprise. For example negative earnings announcements where positive earnings were expected, or the sudden departure of a key figure in an organization, or a switch in political regime due to an unforeseen electoral victory of the opposition party. Any event that disconfirms, contradicts, or violates a prior expectation or belief can be considered a surprise, and these events elicit a different response than events that are confirmative or only moderately surprising. The magnitude of the surprise is related to the subjective difficulty of integrating it with the old beliefs to update them according to the new information. A higher level of surprise relates to a larger contrast between observed and expected outcome, and this inconsistency results in an increased need to “make sense” of the new information (Meyer et al, 1997; Teigen & Keren, 2003; Maguire et al., 2011). As cognitive resources are allocated to the new information during the updating process, they are drawn away from other sources of information, such as prior beliefs (Reisenzein et al., 2012). As a result, an investor weights the surprising information more heavily when updating his beliefs. Like the Conservatism heuristic, the investors do adjust their posterior probability estimate into the right direction, just not by the right magnitude. In this case, too heavily. Therefore, any underreaction can be moderated by surprise. However, for extremely surprising events, investors overweight the new information, which can lead to an overreaction (Choi & Hui, 2014). This response is visualised in Figure 1.

The incorrect magnitude of the price increase or decrease caused by underreaction and overreaction should gradually disappear as investors are able to better allocate their cognitive resources over time and the weights to old and new information are restored to proper division. As time passes, more attention to non-surprising news pushes the prices further towards the actual rational valuation and the initial underreaction is eliminated. An overreaction to surprising news is also reversed, as the urgency level of the initial surprise decreases and investors spread their attention more equally over old and new information. This correction can be observed in Figure 1. In some cases though, the limited information and high complexity of news can result in Herd (or Group) Behaviour among investors (Sornette, 2003). Herd behaviour refers to the tendency of individuals to copy the behaviour and actions of others, thus acting more as a group. Shiller (2000) states that herding behaviour on the financial markets often occurs as a result of an information cascade. In these situations investors disregard their own private opinions and signals in favour of imitating the actions of others, often because they are uncertain about the impact of the new information themselves and believe that others know better (Sornette, 2003; Tvede, 2007). This herding behaviour can drastically extend any over- or underreaction, as can be observed in Figure 1 as well.

Figure 1. Overreaction and Underreaction (and Herd Behaviour) to Positive Change



(*Figure is for illustrative purpose only)*

Aside from herd behaviour, extended under- or overreaction can also be caused by what Festinger (1957) defined as the Cognitive Dissonance Theory and the notion of Selective Exposure. This theory states that information that violates an already performed action or decision is often neglected by agents, as they try to mainly expose themselves to information that confirms their existing beliefs (Tvede, 2007). Consequently, stock prices continue the trend, rather than reverting to the actual rational valuation. The Anchoring and Adjustment heuristic results in a similar postponement of correction. It describes how the decision making process of an investor is influenced by a first impression and how they adjust their beliefs from this base point, the anchor. When using a starting point like that, any further adjustments will be biased towards the initial expectation (Barberis & Thaler, 2003). This can slow down the adjustment process towards the actual rational value.

2.2 Previous Literature

Brexit is still a very recent event, and as the negotiation process has not ended by the publication of this thesis, there is still only a limited body of research publicly available that investigates its effect on the financial market. Therefore the first section will introduce Brexit in more detail, identify the source of uncertainty that makes Brexit such a unique event, and discuss the few existing studies that look at investor behaviour on the financial markets surrounding the referendum. Additionally, a general perspective on market responses to macroeconomic news and uncertainty will be presented. The following sections discuss several studies with approaches for testing market efficiency and unexpected trading volume from a more general perspective.

2.2.1 On Brexit and the Effect of Macroeconomic News

2.2.1.1 How Brexit Affects the UK Economy

Since the EU has not previously experienced the withdrawal of one of its members, there is no precedent on the terms of the separation. Additionally, the EU has stated it will only confirm a deal once all aspects of the deal are agreed upon. As such, the exact outcome of the negotiations that will set the new economic environment for the UK is still uncertain. However, two different extreme scenarios have emerged; a soft or a hard Brexit (Emerson, 2016). In case of a soft Brexit, the UK will (to a certain degree) remain part of the European Economic Area, like Norway, Iceland, and Liechtenstein. As part of the single market, the UK will still enjoy the free movement of goods, services, capital, and labour, and pay for this in the form of annual contributions, but less per capita than under EU membership. It will lose all of the governing and voting power it previously enjoyed and will have to take any decisions made in the group as-is.

A hard Brexit will see the UK completely leaving the European Economic Area. As a result, its international trade is to be governed either by bilateral agreements with the EU (like Canada and Turkey), or without any special agreements and thus completely under the rules of the World Trade Organisation (like Russia and Brazil). In either of these cases, new trade agreements have to be made, not only between the EU and the UK, but also between the UK and the rest of the 163 members of the WTO, opening up the possibility for increased trade restrictions and costs. These two sides are the extremes of a range of possibilities, which are inspired by existing trade relationships between countries. Just prior to the referendum, Parliament (HM Treasury, 2016) has modeled the UK economy under the tree aforementioned models, with a long-term perspective in mind. The analysis shows that in each single case openness and interconnectedness would be reduced, lowering trade and investment flows, and ultimately leaving the UK poorer and with a lower GDP compared to the status quo, even if that status quo means large payments to the EU. This analysis is supported by several studies on the long-term and short-term effects, published by the National Institute of Economic and Social Research (for example Ebell, Hurst & Warren, 2016; Baker et al., 2016). These reports indicate an overall decline in the economy was to be expected as a result of the Brexit referendum, when they were published in the runup to polling day. The characteristics responsible for this general decrease, however, affect individual industries differently. KPMG Economic Insights (2017) published a report comparing UK sectors in their vulnerability towards Brexit, indicating access to the EU product market (exposure to export and import, in terms of regulations, tariffs, and the pound exchange rate) and access to the EU labour market as possible restrictions.

Two of the main concerns in the Banking, Financial Services and Insurance industries, if the results of the referendum became in favour of a LEAVE, is the risk of leaving the European single market and its passporting rights. The EU single market allows for free movement of goods, capital, services and labour and the passporting rights that allows UK banks/financial institutions or UK subsidiaries from non-EEA (European Economic Area) countries to perform cross-border activity with the rest of the EEA (Woodford, 2016). A loss of access to the single market could lead to lack of liquidity and increased cost and a loss of passporting rights could potentially lead to non-EEA countries companies moving there UK subsidiaries to a new country within the EEA. So the LEAVE-result of the referendum was expected to have a negative impact on the Banking, Financial Services and Insurance industries (KPMG Economic Insights, 2017; Lawrence, 2016(1)).

Consequences of Brexit for the Pharmaceutical and Biotechnology industry involve this sector most likely losing all R&D funding it currently receives from the EU. An exit from EU would make clinical trials harder and more costly, as they would no longer be part of the EU Clinical Trials regulations. This would also cause fewer trials performed in the UK by other EU countries, as is the case prior to the referendum; the UK is among the preferred countries to perform trials in. To continue the sale of pharmaceuticals to the EU, the approval process of new medicine or devices would become more challenging, as UK would have to set up new regulatory medicine authorities, and firms might have to apply for approval in both UK and EU to retain market share (Velthuijsen, 2016). So the effect of potentially leaving the EU would be expected to have a negative effect on the Pharma and Biotech industry.

If the UK leaves the EU there is a risk that they cannot negotiate a trading agreement that both parties agree on, which would leave the UK to trade under the tariffs of World Trade Organization (WTO). The implied tariffs imposed by the WTO vary significantly across countries and products. The average implied tariff for UK export to EU countries is for pharmaceutical product 0% so this industry is not expected to be affected by trade under the WTO, where products like tobacco, flours, meat and dairy have implied tariffs between 27% and 49% (Lawless & Morgenroth, 2016). This indicates that industries like the Tobacco, Agricultural and Food Manufacturing would be expected to be negatively affected by the risk of trading under the WTO, if the results of the referendum became a LEAVE (KPMG Economic Insights, 2017).

Leaving the EU could also put an end to the free movement of people between the EU and the UK. This could affect sectors with high exposure to EU labour. Sectors that have a high exposure to EU labour are for example Food and Drink Manufacturing, Pharmaceutical and Biotech, Hotels and Restaurant, and Oil and Gas, and they are expected to be affected negatively. Sectors such as Insurance, Real Estate, Shipping, Telecom and Leisure have low exposure to EU labour (KPMG Economic Insights, 2017).

The Mining sector is rather neutral in its expectations towards Brexit, even in consideration of LEAVE. Most of the firms listed on the LSE do not actually have any operations on UK soil, Euromines president Mark Rachovides states in an interview with Mining Weekly (Solomons, 2017). These firms may feel the effects of Brexit as they have a large export exposure to the EU, but Rachovides also points out it is unlikely EU-based consumers will be able to find alternative suppliers quickly. The biggest threat according to him is on the R&D cooperation between the EU and the UK. However, these long term issues are still very uncertain. In a shorter perspective, the situation is unlikely to change. Due to the high export exposure, deregulation of the market will not benefit the sector much, as firms will have to stick with EU standards. Additionally, most environmental restrictions resulting from EU law have seen the UK at the forefront (Hitchcock, 2016). As most mining companies make their money in dollar terms, a weak pound due to the outcome can be considered favourable, and with a strong gold price (due to its safe-haven characteristics in times of uncertainty), the industry has little adjustments to make in the short term, and too much unknowns to adjust for the long term (Reuters Staff, 2016). A similar response is found in the Oil & Gas sector. The global aspect of the sector exposes it to import and export, but as a commodity sold on the international market, the WTO poses no tariffs on basic oil sold in the EU. However, with the UK out of the single market, and thus the Internal Energy Market, a new trade agreement has to be settled with the EU. Additionally, impacts felt upstream and downstream supply chain may cause ripples in the industry (KPMG Economic Insights, 2017). The UK Government has kept tight control of its energy policies pre-Brexit, regulating licensing and taxation of oil and gas exploration, appraisal, development and production activities, and therefore little is expected to change on the short run. Some commenters even point out that Brexit may lead to much-needed change, as the Government will be motivated to keep the sector attractive and competitive to secure its survival, and the industry itself is active with collaboration in new and innovative ways (Norton Rose Fulbright, 2016).

The prospects of a potential LEAVE from the EU when the referendum was officially announced, caused much uncertainty in the UK economy and the pound to fell accordingly. A LEAVE result in the referendum would be expected to bring still more uncertainty and a weaker pound (Allen, 2016). A weak pound especially affects industries with high import rates, since it increases the cost of importing. This could be industries like automotive manufacturing, non-food consumer goods and industrial products, likewise is it estimated that one quarter of the food consumed in the UK is imported (KPMG Economic Insights, 2017). This means that the price on food and non-food consumer goods would become more expensive when the pound is weak, so the general public would have less purchase power, which could be expected to have a ripple effect on industries such as Support Services, Household Goods and Travel & Leisure.

2.2.1.2 Brexit on the Financial Market

Krause, Noth, & Tonzer (2016) point out that prior to the referendum, a high degree of uncertainty about the possible consequences could be observed on the financial market. An increase of the share of supporters of leaving the EU correlated with declining returns for bank indices, depreciating currency, and increased volatility on the European stock markets.

Wu, Wheatley & Sornette (2017) pose a challenge to the Efficient Market Hypothesis as they show that the British Pound market in US Dollars was delayed in reflecting the outcome of the Brexit referendum result on Brexit-night. They argue that the final outcome could be predicted with confidence after the live publication of 20 out of the 382 local voting results. The authors connect this delay with both generic inefficiency and a specific inertia/durable bias in the market.

Oehler, Horn & Wendt (2017) study the short-term effect of Brexit right after the referendum on the stock prices of the FTSE 100 on the London Stock Exchange. They investigate abnormal returns from both daily prices and 5-minute interval prices, on the percentage of domestic sales of firms, the firms' market capitalization and dummies reflecting the firm's sector. The results of the study show that firms with low firm-level internationalization, i.e. high degree of domestic sales, realized more negative abnormal returns compared to firms with high firm-level internationalization. The study finds that this is only applicable the first trading day after the referendum, which suggest a degree of semi-strong efficiency in the market.

Smales (2017) investigates how political uncertainty outside a general election affects the uncertainty in the financial market. He uses the case of the Brexit referendum as event. He examines implied volatility in UK and Germany, surrounding the announcement of the polling results, and finds that implied volatility increases when the uncertainty in the polling results increases. Thereby the author finds a significant positive relationship between the political uncertainty and the uncertainty of the financial market. Cox and Griffith (2017) find similar results, as they analyse bid-ask spreads, quoted depth, and volatility around political shock events such as the Brexit referendum outcome and the surprise victory of Trump in the 2016 US elections. Their evidence suggests uncertainty around political outcomes can increase information asymmetry and reduce liquidity, specifically immediately after the event, albeit not persistent.

Schiereck, Kiesel & Kolaric (2016) compare the reaction of EU banks on the Brexit referendum to that on the Lehman Brothers bankruptcy of 2008. Their analysis of stock market and CDS spreads suggests that the short-term drop in share prices was more severe at the, but increases in CDS spreads were lower, and concentrates mainly around EU banks. This indicates that there is less contagion to non-EU banks, which means the financial markets are more resilient towards uncertainty from unexpected economic policy changes.

Ramiah, Pham & Moosa (2017) examined the sectoral impact of the Brexit referendum by investigating abnormal returns for a 10-day event window. They argue that a proper analysis of the impact of Brexit on the UK economy is premature at the time of their publishing shortly after the referendum, but that the instant response of investors may indicate expectations about the future performance of the sectors. Therefore, the authors focus on the different responses (negatively or positively and in what magnitude) between sectors, and the change in short-term systematic risk captured by increased industry betas before and after the 24th of July 2016. They find the banking sector and sectors that face similar consequences due to passporting regulations, such as financial services, insurances, and investment funds, to be amongst those hit the hardest, as well as travel and leisure and household goods and home construction. The authors also observe increased systematic risk for these sectors.

2.2.1.3 Macroeconomic News and Market Uncertainty in a Broader Perspective

Although Brexit is the first event of its exact kind, no other country has ever left the European Union, new government policies or changes in the political climate that threaten the stability of the macroeconomic environment are not uncommon. Following are a few examples of studies in this direction.

The most rigorous threat of a change in economic environment is a change of regime after a national election. A multitude of studies have examined the US financial markets according to the Presidential Election cycle, dating back to Niederhofer et al. (1970) and Herbst & Slinkman (1984), who examine the US stock market between January 1926 through December 1977. They find evidence to support a 4-year cycle peaking in November just before the elections. This cycle has been further examined for example by Wong & McAleer (2009). These authors find a consistent pattern during the 4-year cycle where prices fall during the first two years after which they reach a minimum, then start rising again during the second half, and peak in the third or fourth year. The authors argue that often an incumbent government may manipulate economic policies in order to achieve re-election. This effect is more profound with Republicans than Democrats. The cyclical evidence may reflect market inefficiency as their existence violates the weak form EMH. Their findings are in line with other studies by, among others, Allivine & O'Neill (1980), Huang (1985), and Stoken (1993). In particular the last US election, the 2016 one, has caused a stir. Pham et al. (2017) find that the election created uncertainties for the US economy, do to the lack of clear policies and Trump's volatile character. They observe both negative and positive abnormal returns in the market for different industries. Additionally, they find that an increase in short-term systematic risk was experienced by 16 sectors right after Trump securing the nomination of the Republican party. Outside of the US, Pantzalis, Stangeland & Turtle (2000) investigate stock markets in 33 countries during political elections between 1974 and 1995. They find positive abnormal returns shortly prior to the election week, dependent on the degree of political, economic, and press freedom of a country. Additionally, whether or not the incumbent is re-elected has a significant effect, as well as an early (arguably manipulated) election. More positive abnormal returns occur when the opposition wins, especially in less free countries or with early called elections. The authors ascribe this effect to an initial increase in uncertainty prior to the election, and the decrease in uncertainty that follows the results. More recently, Białkowski, Gottschalk & Wisniewski (2007) investigate a sample of 27 OECD countries and find that national elections induce higher volatility, stating the shock is a result of surprise by the election outcome. They identify a narrow margin of victory, lack of compulsory voting laws, change in political orientation of new government, or a government without parliamentary majority to have a significant effect on the magnitude of the shock.

A lot of policy uncertainty stems from economic (especially monetary) policy, as these kind of legislation have a broad effect on the entire economy. Mezrich & Ishikawa (2013) and Gregory & Rangel (2012) also suggest that economic policy uncertainty is a significant indicator of the S&P500 fluctuation and earnings growth. They consider economic policy uncertainty to be a driver for the equity market uncertainty and sometimes it can be considered as better indicator for the implied market volatility than the VIX. News on economic policy uncertainty affects stock prices through discount rates as these indicate the state of the economic environment. More specifically, Kurov & Stan (2018) examined the influence of US macroeconomic announcements on equity, Treasury security, foreign exchange, and crude oil markets, as well as medium-term interest rates, under different degrees of monetary policy uncertainty. They found that the stock market and the market for crude oil respond less heavily to these announcements in times of higher monetary policy uncertainty, yet the markets for Treasury securities, foreign exchange rates, and interest rates responded more heavily. The authors argue that macroeconomic announcements impact these markets mainly through the expected reaction of monetary policy, especially in times of heightened monetary policy uncertainty when concrete information is scarce.

Political instability can also occur in the case of conflict. Abadie & Gardeazabal (2003) investigate abnormal returns for companies in the Basque Country during the terrorist activities of the ETA during the 1970s, 80s, and 90s. During periods of truce and good news, positive abnormal returns were observed, while at the end of the cease-fire, a period of bad news, negative abnormal returns were dominant. Brounen & Derwall (2010) take a larger perspective and include 31 different terrorist attacks since 1990, compared with a sample of 59 earthquakes. Terrorist attacks have significantly larger negative abnormal returns, but the market evaporates these abnormalities within a two day timespan. Negative cumulative abnormal returns dissolve on the third trading day. The authors thus suggest that the initial response was an overreaction. These findings are in line with Eldor & Melnick (2004) and Chen & Siems (2004).

To measure economic policy uncertainty, Baker, Bloom & Davis (2013; 2016) have developed the Economic Policy Uncertainty (EPU) index. For the US and 11 other major economies (including the G10), the index reflects the frequency of articles in leading newspapers that contain a trio of words relating to economy, uncertainty, and governmental terms like “legislature” and “congress”, which for the US spikes surrounding national elections, the Gulf Wars and 9/11 attacks, and fiscal policy disputes like the Financial Crisis of 2008. Additionally, indexes including terms related to healthcare and defense are created. They use this new measure to examine the relationship between policy uncertainty to volatility, investment rates, employment growth, and output. They find negative economic effects surrounding heightened EPU, suggesting increased EPU in the US and Europe has harmed macroeconomic performance. Brogaard & Detzel (2015) use the EPU index to find that EPU positively forecasts excess market returns, but not cashflows, thus suggesting increased EPU causes increased risk premiums.

2.2.2 On Market Efficiency Testing

As mentioned previously, the semi-strong efficient market form represent all public available data, and is tested by looking at the speed of the adjustment of the prices after new publicly available information have been released. Previously research in this area has tested the speed of adjustment of the prices, often by constructing an event study (Fama, 1991) as pioneered by Fama, Fisher, Jensen & Roll (1969). These authors investigate the stock market reaction to the announcement of stock split. They find evidence that the stock prices rapidly adjust to the new information and can therefore support the hypothesis of an efficient market (Fama, Fisher, Jensen & Roll, 1969).

Most early studies on the speed of adjustment of stock prices to new information, Fama, Fisher, Jensen & Roll (1969) included, were constructed on monthly data. In Brown & Warner (1985), they investigate the effect of using daily stock returns in event studies and found that using daily returns reinforces their results of previously studies done with monthly data. Most studies using daily data find evidence supporting the Efficient Market Hypothesis, and that the stock prices on average seems to adjust to the new information within a day (Fama, 1991).

Patell & Wolfson (1984) examine the effect of new earnings and dividend announcements on the stock price. The data they examine consist of intraday stock prices, almost down to the second. They find that the market appears to react to the new earnings and dividend announcement, within a few minutes, and that the large price changes occur between the first five to fifteen minutes. They can therefore conclude that their evidence support the notion that the stock market very quickly react to new information (Patell & Wolfson, 1984).

To obtain the expected returns to be able to test the speed of adjustment, Fama, Fisher, Jensen & Roll (1969), used the so-called Market Model. Which is a one-factor model where the expected returns are calculated based on a linear regression of the security's returns on the market returns. This model is widely used in event studies (Fama, 1991). However, Fama (1970) suggested that at that time the best theory to calculate expected returns was actually the one by Sharpe (1964) and Lintner (1965), more commonly known as the CAPM (Capital Asset Pricing Model).This model is also a one-factor model, but it also incorporate the risk-free rate, and therefore changes in the risk-premium.

It is not possible to truly reject the Efficient Market Hypothesis with these equilibrium models. Even with a result that supports a rejection of the hypothesis, which would imply the market is inefficient, there is a possibility that the equilibrium model used to calculate the normal (expected) returns is incorrect. This problem is known as the joint hypothesis problem (Campbell, Lo & Mackinlay, 1997; Cuthbertson & Nitzsche, 2004), meaning that the statistical test is testing both for the existence of abnormal returns, and the (in)correctness of the model at the same time. Therefore, any outcome of the test can be in support of either of these hypotheses and not unequivocally either of them.

Not only one-factor models have been used to calculate the expected return, also multifactor models have been broadly used. Examples of commonly used multifactor models is the APT

(Arbitrage-Pricing Theory) suggested by Ross (1976), where the expected returns are calculated by their sensitivity to various factors on the market, and the Fama-French 3 factor model by Fama & French (1993), which expands the CAPM model by adding factors with measurement of size and value.

2.2.3 On Unexpected Volume Testing

Existing literature continuously states the challenge of measuring investor divergence and information flow, mostly because this private information is valuable to the individual investor. Therefore, most studies either propose in depth mathematical models, filled with assumptions, to argue the effect of information on the divergence in investor opinion, or use a proxy to measure the degree of information and opinions.

Theoretical models can be found with Kim & Verrecchia (1991) as they set up a theoretical model where volume increases around public earnings announcements. Morris (1994) explores the possibilities of market efficiency under different types of asymmetric information, such as ex ante, interim, and ex post. Another example is Lang, Litzenberger & Madrigal (1990), who argue that a noisy rational expectations model is the most suitable under the assumption of private information in combination with price dynamics and information dispersion. Beaver (1968); Foster (1973) and Morse (1980) combine theoretical models with empirical evidence, and find that earnings announcements hold information as there is a dramatic increase in volume in the week of the announcements. Bamber (1989) expends this conclusion and argues that the larger the unexpected earnings, the larger the trading volume. Many of the studies following his lead refine their research techniques and benchmarks and apply different proxies to test the robustness of the conclusions, but find similar results.

Existing literature can be divided into three different proxy categories. Analyst-based proxies are used by studies that take the matter from an accounting perspective. The finance-focused literature suggests to take bid-ask spread or stock return volatility as proxy. Studies that approach the issue with a general market-mindset however, suggest that unexpected volume can be used as a proxy for divergent investor opinions. More recent studies that have access to order flow data suggest to use this variable as a proxy, as it separates supply and demand driven volume. However, Garfinkel (2009) demonstrates that without access to this information, unexpected volume is a more precise measure of divergence than the other proxies. With regards to measuring unexpected trading volume, existing literature heavily favours the use of turnover, defined as number of shares traded on a specific day divided by total number of shares outstanding. However, there is little agreement on the benchmark for expected and unexpected trading volume. Some studies use a firm-specific average volumes over an estimation period as benchmark. Other studies, however, follow the common methodology of abnormal return studies, and adjust for market related and firm-specific trading activity.

To assess the benchmark discussion, Tkac (1999) reasons that if a two-fund separation captures investors' diversification needs, then turnover for each firm should be equal to the turnover of all other firms and to the turnover of the market if all firms are equally risky. After identifying firm size, institutional ownership, option availability, and S&P500 inclusion as characteristics that could cause anomalous trading on a firm-specific level, Tkac (1999) finds that these characteristics have a significant correlation with the residuals of this model. Instead, a Market Model fashioned after those used in common event studies for abnormal returns, does filter for these characteristics, and its residuals are not significantly correlated with the four firm characteristics. The intercept, α, captures the average level of fundamental trading due to firm-specific characteristics, and the market coefficient, β, adjusts for market-related trading. After Tkac's (1999) discussion on the matter, Chae (2005) is the only study that uses an estimation period average as benchmark (the paper still uses a one-factor Market Model as robustness check), as Tkac (1999) concludes that a Market Model is a superior measure.

Measuring the degree of private information (or information flow in general) is equally tricky, as no informed investor will voluntarily reveal this. Among others, Ivine, Lipson & Pucket (2006) and Hendershott, Livdan & Schürhoff (2012) argue the use of trading activity as proxy, and measure institutional trading activity by customer order flow. They apply event study methodology to find a significant increase in institutional trading before news announcements. With calendar-time probit regressions, Hendershott, Livdan & Schürhoff (2012) also show that institutional trading can predict that an informational event is lurking.

The theory behind Copeland's (1976) SIAH is that information arrive to traders sequential, causing a lag/lead relationship between the trading volume and the volatility of the return. To test for sequential information arrival, difference approaches exists. Jena (2016) uses first a linear Granger Causality model and fails to support for the Sequential Information Arrival Hypothesis in the Indian derivative market, afterward she uses the non-linear GARCH framework that confirms the first findings. Mougoué & Aggarwal (2011) use the approach of a linear and non-linear Granger Causality and find significant lead-lag relations between the volatility of the returns and the trading volume, which is in support of the hypothesis. The models to test the hypothesis used in these literature are among the two most widely used, i.e. the Granger Causality model and the different ARCH models. Hong, Lim & Stein (2000) use a momentum trading approach to find evidence for the gradual-information-diffusion model proposed by Hong & Stein (1999), with several different portfolios over 6 month time frames, and divide these strategies over firms that theoretically should display a slower information dispersion, like stocks that receive little versus a lot of analyst attention.

Perhaps even more challenging is the estimation of the consensus effect. Garfinkel & Sokobin (2006) apply a standardized unexpected volume calculation that follows the reasoning of Holthausen & Verrecchia (1990). These authors argue that the informedness effect is reflected in price movements related to trading volume (which would support a fully strong EMH). The unexpected volume resulting from the Market Model as described before assumes price movements sensitive to the market equal during the event and estimation period, and therefore proxies both informedness effect and the consensus effect. Similar to Crabbe and Post (1994), Garfinkel & Sokobin (2006) include the absolute positive and negative returns from the earnings announcements into the Market Model to capture the effect of both liquidity needs and informedness on volume. They find statistically significant results that imply unexpected volume around earnings announcements can to a certain extent be a proxy for opinion divergence.

3. Empirical Study

In Fama's (1991) second paper on market efficiency, he concludes, that over the past 20 years since he first proposed the Efficient Market Hypothesis event studies have shown to give the most direct and clear evidence on market efficiency, especially when tested on daily returns (or even more frequent intraday data). Following his lead, as well as the majority of related literature that has been published in its footsteps, this thesis also adopts the event study methodology as presented by MacKinlay (1997). An event study is used to investigate whether or not a specific event has a significant impact on firm or industry variables, such as abnormal returns and unexpected volume like in this thesis. A widespread range of financial studies has applied this research tool, with firm specific events such as earnings announcements, mergers and acquisitions, or major world events that affect whole industries and markets, like Brexit. MacKinlay (1997) suggests the following procedure to conduct an event study:

1. Define the event of interest;
2. Identify the event window and estimation period;
3. Determine selection criteria for data to use;
4. Define and calculate normal levels of the variable of interest;
5. Calculate abnormal levels;
6. Test abnormal levels for significance;
7. Comment on insights gained from analysis.

This chapter focuses on the first 5 steps of this procedure, starting with a more detailed explanation of the case at hand and determining the relevant time periods. This is followed with an overview of the cleaned and processed data used for this study, and lastly an explanation of the specific methodology used to calculate normal and abnormal levels of return and unexpected volume, as well as the statistical testing process. The next chapter will address steps 6 and 7; the presentation of our empirical findings and comments thereon.

Additional to the event study, we will also perform a cross-sectional analysis on the effect of our individual events and test the informedness effect and the consensus effect to address the subquestions of this thesis. We will present the methodology of these tests in section 3.3 as well.

3.1 Determining Event and Time Period of Interest

When deciding on the event of interest, it is important to clearly define which exact day is to be considered the event day, since the actual day of the event on the calendar and the event day as used in the study, are not necessarily the same day. Company announcements are often published during business hours, but events with other origins could happen after the relevant stock market closes, or on weekends or holidays. In these instances, the effect of the event can only be incorporated in stock valuation at the first activity after opening on the next trading day, which should therefore be considered as *t0* (the event day of the study).

Many single case driven event studies focus on one event only, such as a national election or natural disaster. Studies intent on investigating a type of event on a larger scale, such as earnings announcements or stock splits, identify a specific event day for each firm in the portfolio and aggregate accordingly, ignoring that the events did not happen at the same calendar day. The Brexit process, however, consists of different individual events and announcement days that affect the market, and thus the whole market is effected on the same calendar day for each separate event. As such, we have selected three events that we believe present new information to the market, thus increasing or decreasing uncertainty.

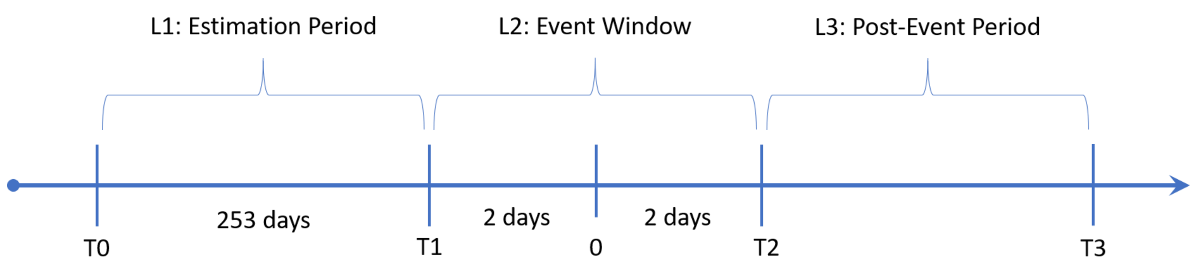
Event 1 - 22nd of February, 2016. Official announcement of referendum.
Regardless of prior rumours surrounding the decision for a referendum and a potential date for the Brexit polling day, the official announcement was made on the 20th of February. This day falls on a Saturday, which is not a trading day, thus the event day for the first event will be on the 22nd of February; the first trading day after the official news has been made public.

Event 2- 24th of June, 2016. Results of referendum.
The polling day of the referendum was on June 23rd, but the first local results as well as the final outcome came in late in the evening, after the closing of the trading day. As such, the London Stock Exchange market was able to react on June 24th earliest, which is thus the event day of the second event.

Event 3 - 29th March, 2017. Official triggering of Article 50.
The referendum was merely advisory, but the UK Parliament held its promise to honor the outcome. On the 29th of March (a Wednesday), new Prime-Minister Theresa May officially triggered Article 50 of the Treaty of Lisbon when the UK ambassador to the EU delivered a signed letter to the European Council president Donald Tusk shortly before May read an official statement to Parliament. The statement occurred shortly after noon and was published on both the official channels and other media outlets. Therefore, investors could have been well aware of the news before the end of the trading day. As such, the event day of event 3 is set on March 29th.

With these three dates as individual event days, *t0*, the rest of the event study time period can be established. The time period consists of an estimation period, an event window, and in some cases a post-event period. Figure 2 displays a graphic representation of the event study time period, from the first day of the data gathered at T_0, to cover the event window from T_1 to T_2, and the end of the post-event period at T_3. The figure displays this the time period as consecutive, but this is not required.

Figure 2. Event study time period



The event window is defined as a set of multiple days surrounding the event day, including at least one day prior and one day past, setting it at a minimum of (-1;+1) as proposed by MacKinlay (1997). Depending on the interest of the study, however, different windows have been applied as well. Ajinkya & Jain (1989) also consider (-3;+3) and (-5;+5), as do Kanas (2005) and Miyajima and Yafeh (2007), respectively. Longer periods can also be considered, as is demonstrated by Karafiath (2009) who extends the event window to (-15;+15). This thesis is mainly interested in short term responses, but acknowledges that the speed of adjustment of the market to new information can be multiple days from the announcement date (Dangol, 2008). Taking into account previous studies, we have selected (-2;+2) as a 5-day event window, as to capture possible delayed response but remain focused on short term effects.

The estimation period represents the data under normal circumstances, unaffected by the event (and must thus not include the event or event window). These periods are inconsistent across the literature, ranging from 30 days (Chae, 2005) to 300 days (Karafiath, 2009) or even 500 days (Litvak, 2007). MacKinlay (1997) suggests to take a full calendar year as estimation period to avoid seasonal bias in the results. A full calendar year is on average 250 trading days, excluding weekends and holidays at which the exchange is closed. Most studies set the estimation period right before the start of the event window, as also displayed in Figure 2. Our study however, requires a slightly different approach to the estimation period selection. Because we deal with a cluster of events that are related to one another, all affect the total market, and are less than a full year spaced apart, we argue that we cannot use any of the days after the first event day as estimation period. These observations may be contaminated by the first (and following) events and do not represent normal circumstances. With this in mind, we have set our estimation to be one full calendar year before the first event window, and apply the same estimation period for all separate events. This is inspired by Oehler, Horn & Wendt (2017), who also set a space of 25 days between the end of their estimation period and the start of their event window. To account for weekends and public holidays in the UK on which the London Stock Exchange is closed, our estimation period holds 253 trading days.

The post-event window can be used if studies are interested in the longer term effects of their events of interest (Benninga, 2008). However, the focus of this study stands with the incorporation of information as displayed in the response of the market directly after an information heavy event. Therefore, the post-event window is not of concern to this study.

3.2 Data

This section will present the data used in this thesis. First it will cover the selection criteria on which data was included in the study, and how it have been gathered, next will describe the process of cleaning the data. Fundamental variables for the empirical analysis are returns and volume in terms of turnover, which is therefore calculated and examined. Lastly an overall statistical descriptive of the data is presented.

3.2.1 Data Selection

To investigate the presented research questions, this thesis will examine quantitative data from the British stock market, as extracted from Bloomberg (2018). The London Stock Exchange has different market indices, the main ones being the FTSE 100, FTSE 250, FTSE 350 and the FTSE All-Share. We have chosen to examine is the FTSE 350 index, which consist of the 350 biggest companies listed on the London Stock Exchange, determined by market capitalization. The FTSE 350 index is made up from all companies included in the FTSE 100 index and all companies included in FTSE 250 index (FTSE Russell, 2018), and we have chosen it because it can provide a more general view of the market than the FTSE 100 or FTSE 250 could do individually. Even though we want to examine the general effect of Brexit on the British stock market, we have chosen not to use the FTSE All-Share because it also contain all the small companies that are not traded frequently and therefore do not have the same liquidity as bigger companies, which could lead to biases in the results.

To further examine any different reactions to the Brexit across the market, we have extracted the data from the 11 largest industry sectors in the FTSE 350 index. The classification of the companies into industry sectors are done by FTSE Russell that follows the guidelines of the ICB (Industry Classification Benchmark) (FTSE Russell, 2017). The classification consist of 41 different industry sectors, and we have, as mentioned, chosen to use the 11 largest industry sectors in this study. The reason for this is first of all to keep the number of sectors at a more manageable level, and that the last 30 industry sector each contribute with less than 1,2 % of the market capitalization of FTSE 350 index on average. Table 1 presents an overview of the 11 sectors.

Tabel 1. Overview of Industry

Industry	**Abbr.**	**% of FTSE 350 Market Cap.**	**Ex. Of firms in industry**
Oil & Gas Producers	OG	11.49	BP plc, Royal Dutch Shell plc
Banks	BA	10.56	HSBC Holdings, Aldermore Group plc
Pharmaceuticals & Biotechnology	PB	8.39	AstraZeneca plc, GlaxoSmithKline plc
Tobacco	TO	5.52	Imperial Brands plc, British American Tobacco plc
Mining	MI	5.04	Anglo American plc, BHP Billiton plc
Support Services	SS	4.91	G4S plc, Ferguson plc
Life Insurance	LI	4.72	Just Group plc, Phoenix Group holdings
Travel & Leisure	TL	4.54	EasyJet plc, Domino’s Pizza Group plc
Media	ME	3.84	Pearson plc, Sky plc
Household Goods & Home Construction	HH	3.45	Reckitt Benckiser Group plc, Berkeley Group Holdings
Financial Services	FS	2.71	3i Group plc, London Stock Exchange Group plc

The % of FTSE 350 market capitalization is calculated as an average over the extracted period; 01-02-2015 to 30-04-2017.

For each of the chosen sector and the FTSE 350 index, we extracted the price, trading volume and market capitalization from the period 01-02-2015 to 30-04-2017. To have sufficient pre-event data, we extracted data as early as February 2015, which we will employ as estimation period to determine the level of normal returns and expected trading volume.

The price as extracted from Bloomberg is a time-series of daily closing prices. The trading volume represents the amount of GBP traded each day, measured by the number of shares traded times their price in the traded moment. To obtain the turnover rate later in the analysis, we would also need the number of total shares outstanding per industry. We can apply the market capitalization per industry, measured in GBP, to obtain this number, measured in GBP, as a measure for the total shares outstanding as we also have trading volume measured in money value terms. This is because the daily market capitalization is calculated as the total number of shares outstanding multiplied the share price.

For the use of the CAPM later in this study, a measure for the risk-free rate needs to be considered. Theoretically, this would be the rate of return provided by a completely risk free investment. However, since even the safest investment does, in practice, always carry a small degree of risk, government bonds are often used as a proxy for the risk-free rate (Berk & DeMarzo, 2014). We have therefore chosen to use the United Kingdom 10 Years Government Bonds as our measure for the risk-free rate in the British market, which have also been extracted from Bloomberg.

3.2.2 Data Cleaning

A cleaning of the data set is necessary before we can start the analysis. The cleaning of the data consist of removing or modifying errors in the data set. Since we are only looking at British stock indices traded on the London Stock Exchange, i.e. the same stock exchange, the trading days for all the gathered industries should be the same. However, in the period of interest it appears that we have eleven days that display inconsistent data to a degree that they seem to be inaccurate, instead of extreme outliers. For those eleven days, the data only displays trading volume for some of the industry sectors, and the trading volume is so small that it on average consist of less than 1% of the total level of trading volume. Additionally, the data presents a share price of zero on these days. Both the unusually low trading volume and zero share price are indicators of potential errors in the data.

After further investigating the days in question, they all turn out to be public holidays on which the London Stock Exchange is closed for trading, so there should not be any data for these days to begin with. Therefore, we cannot explain why we get some small trading volume and a price of zero for some of the industries on these days, but we know that there should not be any trading activity on these days. The data from these eleven days should therefore be excluded from the analysis, as they could cause a bias in the results. We chose to delete the days from the data set. Afterwards the dataset looks fine, as there do not seem to be any more indicators of error and we have no missing data points in the time series.

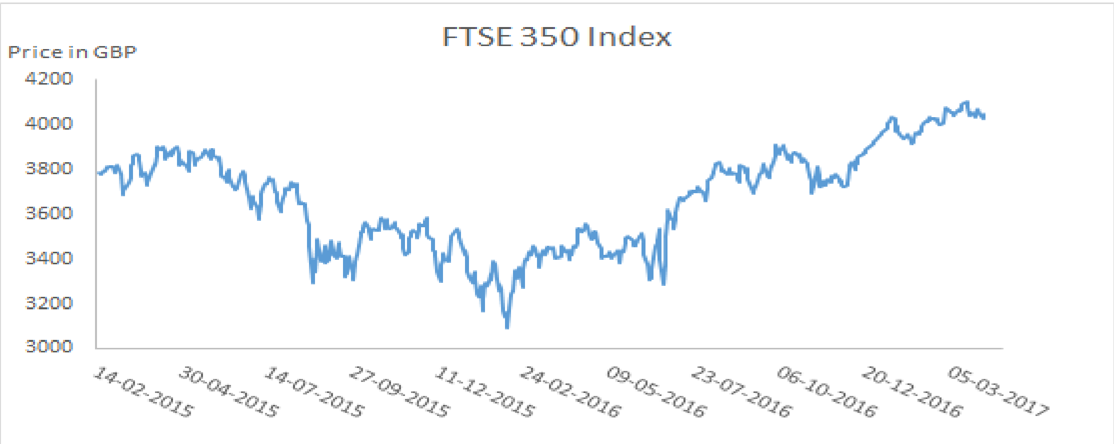
3.2.3 Returns

After cleaning the data, we calculate the percentage changes of the prices, i.e. the returns. This is done for all the time series of prices by calculating a simple return using the following formula:

$$R_t = \frac{P_t}{P_{t-1}} - 1 \qquad (1)$$

The reason that we are more interested in the return rather than the prices, is that they provide a more general and comparable measure of the performance of the investment than the actual price. Returns also tend to be more likely to be stationary rather that actual prices. To take one example of this we have the time serie of the price of the total FTSE 350 index presented below in Figure 3.

Figure 3. FTSE 350 Index price



The graph of the FTSE 350 index indicates that the mean level and variance do not appear stable over time, which is a condition for a stationary time series (Cuthbertson & Nitzsche, 2004). Upon calculating the returns, the graph instantly appears more stationary around the mean, as presented in Figure 4.

Figure 4. FTSE 350 Index return

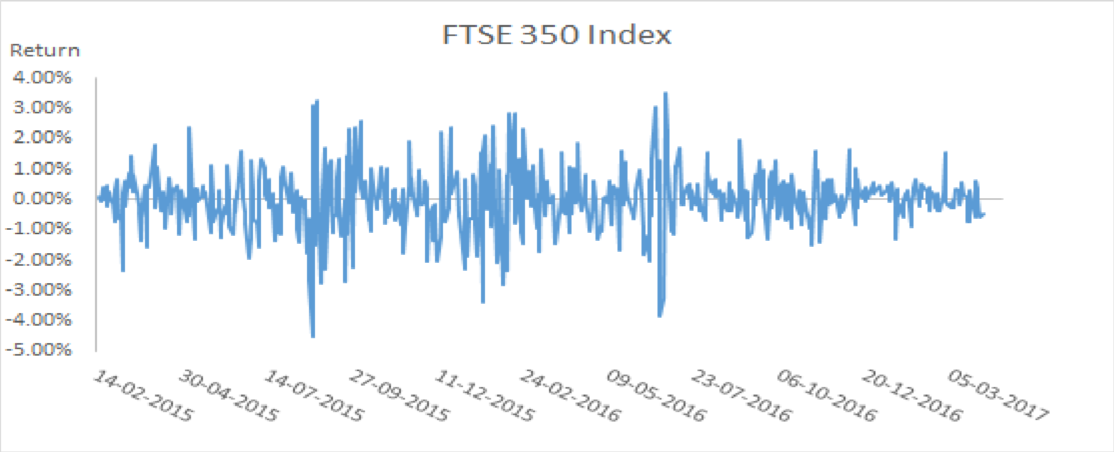
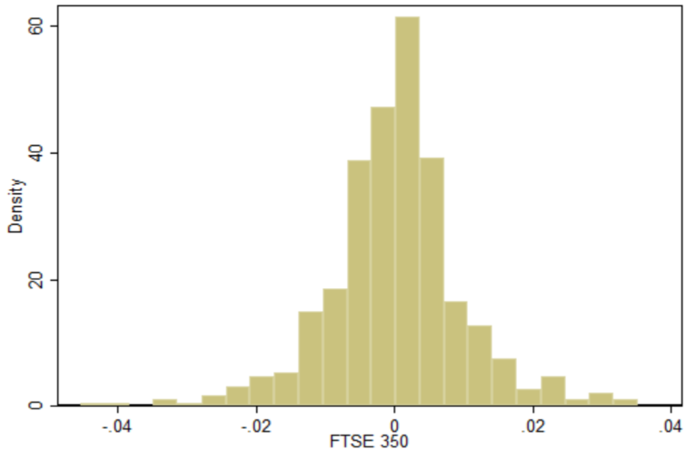


Figure 4 indicates that there are a relatively many outliers in the time period, this implies that the returns are most likely not normally distributed and probably have fat tails. The histogram of the returns in Figure 5 confirms this.

Figure 5. Histogram of FTSE 350 Index returns

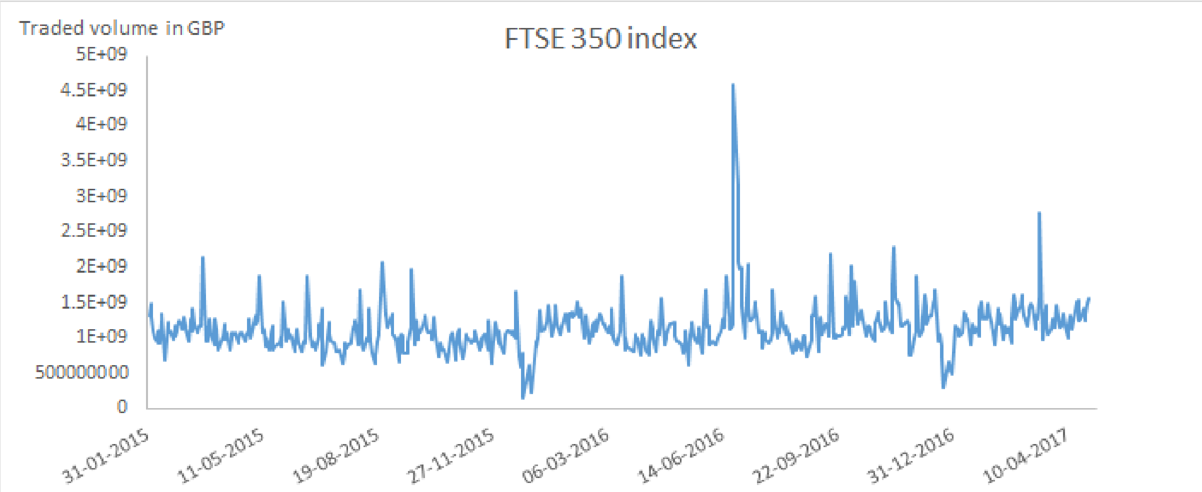


When doing this for all the industries, we get similar pictures as above. Many outliers, non-normal distributed due to positive excess kurtosis, and a histogram that indicates a leptokurtic distribution of the returns, meaning that is have higher peak higher and fatter tails than a normal distribution. The non-normal distribution of the the daily returns is in line with what Fama (1970) concludes on the distribution of daily returns. Likewise Jennergren & Korsvold (1974) and Fama (1965) find that returns of stock fits best with a leptokurtic distribution and fat tailed.

3.2.4 Turnover

The raw trading volume in our data set consist as previously mentioned of the GBP value of the daily traded shares. Again, the total FTSE 350 is displayed in Figure 6. The graph shows the traded volume for the FTSE 350 index which appears to be quite stable throughout the time period. Only a few outliers can be observed, especially peaks around the Brexit referendum and dips at both Christmas periods included in the sample. This however is not the general view when looking at the different indices, some appears quite volatile the whole time period and others seems to have increasing volatility over the period. The level of the trading volume differs depending on the indices. Therefore we chose to use turnover ratio as a measure for trading volume, in line with previous literature. We now obtain a more comparable measurement across the indices compared to the raw GBP value of the traded volume. The turnover ratio is calculated by dividing the daily GBP value of the traded volume by the daily market capitalization in GBP for each industry.

Figure 6. FTSE 350 Index traded volume



The turnover ratio does not appear to be normally distributed either, since the time series are positively skewed with a skewness between 1.6 and 7.1 and high positive kurtosis between 6.8 and 89.5. Previously studies on the trading volume, like Ajinkya and Jain (1989) recommend to log-transform the turnover ratio to obtain more normalized data if the data is not normally distributed. Accordingly, we use the formula in equation (2) to calculate the turnover ratio we will use in any further analysis.

$$TO_t^i = ln\left(\frac{\pounds\, value\ of\ shares\ traded\ on\ day\ t\ for\ industry\ i}{\pounds\, value\ of\ shares\ outstanding\ on\ day\ t\ for\ industry\ i}\right) \qquad (2)$$

After the log-transformation the data appears more symmetric and seems to follow a leptokurtic distribution, with a higher peak and fatter tail than a normal distribution, similar to the returns calculated before.

3.2.5 Sample of the Data

The returns and volume presented above shape the foundation for the data used in the analysis of this thesis, and a more detailed presentation of the data is therefore presented in Table 2 below in the form of descriptive statistics.

Table 2. Descriptive Statistics

Returns							
Index	Obs.	Mean %	Min %	Maks %	Std. dev. %	Skewness	Kurtosis
FTSE 350	567	0.0198	-4.5366	3.5197	0.9769	-0.1533	5.4014
OG	567	0.0256	-6.7735	5.9024	1.6421	0.1146	4.5936
BA	567	0.0074	-9.7748	6.1662	1.5288	-0.4135	7.6768
PB	567	0.0085	-4.1937	4.4428	1.1872	0.0599	3.9610
TO	567	0.0578	-5.2943	3.5358	1.1551	-0.1875	4.1840
MI	567	0.0479	-10.9047	11.1970	2.5577	0.1074	5.0783
SS	567	0.0318	-6.7081	3.7346	1.0438	-0.6194	8.3938
LI	567	0.0159	-12.7593	6.4281	1.6851	-0.8911	10.9673
TL	567	0.0256	-7.1367	3.5210	1.0621	-0.8199	7.8163
ME	567	0.0235	-5.0214	4.9626	1.1035	-0.1496	5.4830
HH	567	0.0591	-10.2755	4.3835	1.2342	-0.9198	12.0797
FS	567	0.0344	-10.5699	4.8567	1.3514	-1.3020	14.1051

Volume (Shares traded in GBP)							
Index	Obs.	Mean	Min	Maks	Std. dev.	Skewness	Kurtosis
FTSE 350	567	1.14E+09	1.51E+08	4.58E+09	3.23E+08	3.1757	29.2718
OG	567	7.41E+07	1.21E+07	4.55E+08	4.34E+07	3.7148	23.8074
BA	567	2.83E+08	3.25E+07	2.27E+09	1.45E+08	6.0623	70.9326
PB	567	1.85E+07	2.27E+06	5.50E+07	6.10E+06	1.5649	8.4420
TO	567	5.30E+06	6.53E+05	2.31E+07	2.15E+06	2.3778	14.2764
MI	567	1.07E+08	2.04E+07	3.62E+08	4.18E+07	1.6782	7.4296
SS	567	5.02E+07	4.16E+06	1.82E+08	2.11E+07	1.9891	9.9223
LI	567	5.02E+07	6.19E+06	3.52E+08	2.22E+07	5.6895	67.5416
TL	567	5.26E+07	5.05E+06	1.60E+08	1.72E+07	2.0348	11.8730
ME	567	3.94E+07	2.64E+06	1.66E+08	1.61E+07	2.4994	15.8188
HH	567	3.00E+07	2.35E+06	2.67E+08	1.76E+07	6.0016	67.9562
FS	567	3.13E+07	3.82E+06	2.22E+08	1.32E+07	6.2443	81.9351

Volume (Log trunover)							
Index	Obs.	Mean	Min	Maks	Std. dev.	Skewness	Kurtosis
FTSE 350	567	-7.5919	-9.5480	-6.1078	0.2682	-0.6716	12.5182
OG	567	-8.1733	-10.0806	-6.3610	0.4736	0.3864	4.0867
BA	567	-6.8468	-8.9670	-4.5025	0.4068	0.3463	7.6385
PB	567	-9.1964	-11.1839	-8.0428	0.3177	-0.5433	7.6593
TO	567	-10.0195	-11.9822	-8.5947	0.3716	-0.0363	5.1570
MI	567	-7.1198	-8.7636	-5.4723	0.5269	0.4538	2.6346
SS	567	-7.6976	-10.1329	-6.4396	0.3570	-0.2257	7.6660
LI	567	-7.6356	-9.7050	-5.6681	0.3845	0.0529	7.2143
TL	567	-7.6388	-9.9626	-6.4676	0.3207	-0.8291	11.1824
ME	567	-7.7740	-10.4204	-6.2708	0.3686	-0.3633	8.9001
HH	567	-7.9413	-10.3933	-5.6090	0.4262	0.2512	7.0396
FS	567	-7.7347	-9.8023	-5.7464	0.3376	0.0109	8.6201

3.3 Methodology

In this section we will presented the approach and models we will used to answer the presented research questions of the thesis. We will start with a further description of the event study, followed by a presentation of the cross-sectional analysis and ending with the approach and models for investigating the informedness and consensus effect as potential causes of market inefficiency.

3.3.1 Event Study

The purpose of this event study is to test the fundamental of the theory of the Efficient Market Hypothesis at a semi-strong degree, for each of the chosen industries. The general null and alternative hypothesis tested here are:

$H_0 = Efficient\ Market$
$H_1 = Inefficient\ Market$

The first part examine if there are abnormal returns around the events, to test the speed of adjustment to new information by the prices. The second part looks at unexpected trading volume, to test if there is agreement among investors, which is a fundamental condition for the Efficient Market Hypothesis to hold.

3.3.1.1 Returns

The next set of part of the event study procedure is to measure the impact of the event. For this we need to compute the abnormal returns, per industry *i* and time *t,* using this formula.

$$AR_{it} = R_{it} - E(R_{it}|X_t) \tag{3}$$

The abnormal returns (AR_{it}) consist of the actual returns (R_{it}) subtracting the expected normal returns, conditional on the choice of model ($E(R_{it}|X_t)$). The level of expected normal returns depends on the choice of equilibrium model, and one can compute the expected returns using different models, as previously mentioned. In this thesis we are will use the Market Model and the CAPM. We have chosen these two models because the Market Model is a widely used model in event studies (Fama, 1991), and it can be considered a statistical model, because it follows statistical assumptions about the asset return behaviour, not depending on the economic aspects (MacKinlay, 1997). The CAPM model on the other hand, can be considered an economic model as it is also based on assumptions on the investors' behaviour (MacKinlay, 1997), such as incorporating changes in the investors perception of risk in the market, in terms of changing risk premiums.

The Market Model is a linear one-factor model as presented below:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{4}$$

The parameters $\alpha_i$and β_i are estimated based on the returns of the industry $R_{it}$and the market returns R_{mt} over the estimation period prior to the event window since the two should not overlap. As mentioned we chose to follow MacKinlay (1997) and use an estimation period covering one year of trading, which for London Stock Exchange consists of 253 trading days, this should give a representative estimation of the general level of the returns.

The Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965):

$$R_{it} = R_{ft} + \beta_{im}(R_{mt} - R_{ft}) \tag{5}$$

where

$$\beta_{im} = \frac{Cov[R_i, R_m]}{Var[R_m]} \tag{6}$$

R_m is the return on the market portfolio, R_f represents the return of the risk-free asset. As stated under the data selection we use the United Kingdom 10 Years Government Bonds as our measure for the risk-free rate in the British market. The β_{im}provides us with an industry sensitivity to the market, as it is a measure of the systematic risk.

With the expected normal returns, it is now possible to calculate the abnormal returns. This leads to the final steps of the procedure by MacKinlay (1997): the aggregating and testing of the abnormal returns, will be presented just after next section on unexpected volume.

3.3.1.2 Turnover

In line with Garfinkel & Sokobin (2005), who determined that trading volume was the superior proxy for measuring divergence in investor opinions, we will use a similar indicator. As such, unexpected trading volume ($U(TO_{it})$) is defined as the difference between the actual turnover ratio (TO_{it}) measured at the event date and the expected turnover as predicted by the benchmark ($E(TO_{it}|X_t)$):

$$U(TO_{it}) = TO_{it} - E(TO_{it}|X_t) \tag{7}$$

With the discussion on a suitable benchmark for expected volume in mind, as presented in the previous section, we apply both an industry-Average Model and a Market Model. Tkac (1999) has determined the superiority of a Market Model because a firm-specific model overestimates the effect of the event on the firm, but these arguments hold mainly for studies that examine individual firms undergoing events that do not affect the market. We argue that a Market Model may underestimate the effects of the event, as we focus on industry groups which represent a large percentage of the market compared to single firms. Taking both the understated and the overstated results into account will provide better interpretation.

Our firm-specific benchmark is constructed in line with Chae (2005) as following:

$$E(TO_{it}) = \frac{\sum_{t=-253}^{t=0}(TO_{it})}{253} \tag{8}$$

The one-factor Market Model we apply is similar to those of for example Tkac (1999) and Lynch & Mendenhall (1997) and most of the studies applying this benchmark as mentioned in the previous section. This model is transformed directly from the Market Model for abnormal returns that is often applied in event studies, as suggested by Ajinkya & Jain (1989).

$$E(TO_{it}) = \alpha_i + \beta_i(TO_{mt}) \tag{9}$$

α_i and β_i are estimated with a prior regression during the same estimation period as applied for the industry-specific model described above, 253 trading days, and the market turnover is represented by TO_{mt}. Market turnover is captured in similar fashion as industry turnover; the log-transformation of money value of shares traded on day t divided by the money value of total shares outstanding on day t.

3.3.1.3 Significance Test

The significance test statistics can be classified as either a parametric or a nonparametric test. A parametric test assumes that the returns tested are normally distributed whereas the nonparametric test makes no assumption on the distribution of the returns. In our analysis, we will apply both a parametric and a non-parametric test statistic.

The first test is by Patell (1976), which is one of the most widely used parametric test statistic for event studies. The test builds on the concept of standardized abnormal return, where it standardized each abnormal return by a forecast-error corrected standard deviation that incorporates the increase in the variance consistent with predicting outside of the estimation period.

The forecast-error corrected standard deviation is calculated by multiplying the standard deviation with factor *C*, which is calculated in equation (10).

$$C_{i,t} = 1 + \frac{1}{T} + \frac{(R_{m,t} - \bar{R}_m)^2}{\sum_{r=1}^{\tau}(R_{m\tau} - \bar{R}_m)^2} \tag{10}$$

where *T* is the number of observations, which is 253 in our case since it is the length of our estimation period. The final test score is calculated using equation (11), where *V* is the standardized abnormal return for day t and *N* is the number of days included. For the cumulative test score, *N* is set to 5 days, which is the length of our event window, and *N* is 1 in the single-day test statistic.

$$z_{v,t} = \frac{\sum_{i=1}^{N} V_{it}}{\sqrt{\sum_{i=1}^{N} \frac{T_i - 2}{T_i - 4}}} \tag{11}$$

As a nonparametric test we will apply the Rank test by Corrado (1989), where the abnormal returns are transformed into ranks for all days in the estimation period and the event window. By doing so, the distribution of the returns becomes unimportant. To obtain the test statistics, each rank is divided by sum of the number of observations in the estimation period and event window, plus one. This transforms the data into a uniform distribution. To calculate the cumulative test statistics using the Rank test, we follow the adaption of Campbell & Wasley (1993) in equation (12).

$$t_{rank} = \sqrt{L_2}\left(\frac{\bar{K}_{T_1,T_2} - 0.5}{s_K}\right) \tag{12}$$

where L_2 is the length of the event window, and $\bar{K}_{T_1,T_2}$ is the average rank over the event window.

There is no standard specific test designed for testing the significance of unexpected volume. Instead, previously papers like Campbell & Wasley (1996) and Ajinkya & Jain (1989) have applied test statistics originally designed for testing of abnormal returns. Karafaith (2009) criticizes Ajinkya & Jain (1989) for using an EGLS and AR(1) model, and Cready & Ramanan (1991) and Campbell & Wasley (1996) for their use of parametric tests, and instead argues for a non-parametric test that is robust with respect to cross-sectional heteroskedasticity. Since we use industry indexes and not an aggregate of all firms for the calculation, we have no cross-sectional heteroskedasticity. Therefore, we will apply the same two test statistics for unexpected volume as for abnormal returns; the Patell test as a parametric test, and the Corrado Rank test as non-parametric.

For both abnormal returns and unexpected turnover, we use both the parametric and non-parametric test for each industry, and every day in the event window to test the hypothesis:

$H_0 = There\ are\ no\ single\ day\ abnormal\ returns/unexpected\ turnover$

$H_1 = There\ are\ single\ day\ abnormal\ returns/unexpected\ turnover$

Likewise for the cumulative test that covers our 5-day event window, we test the hypothesis:

$$H_0 = There\ are\ no\ cumulative\ abnormal\ returns/unexpected\ turnover\ in\ the\ event\ window$$
$$H_1 = There\ are\ cumulative\ abnormal\ returns/unexpected\ turnover\ in\ the\ event\ window$$

However considering the cumulative Rank test there is ground for some concern. The cumulative Rank statistics do not take into account the actual level of the abnormal returns/unexpected turnover. Therefore, if we have a high and a low rank that would both be significant outliers for single day tests, the sum of the ranks will become insignificant as the values of the ranks will average each other out. Instead, the Patell test-statistic looks at the actual value on the individual days, so if the highest value would be 2% but the lowest value would be -8% then the cumulative test would see that on average the returns are still different from zero and would most likely flag the cumulative value as significant. We still chose to use both cumulative test in our analysis, but the results of the cumulative Rank test must be interpreted with some caution.

3.3.2 Cross-Sectional Analysis

After establishing if there are abnormal returns and unexpected trading volume around our events, we can examine the magnitude at which our events have an effect on these measures. Yuan (2015) hypothesize that market-wide event cause increasing trading activity, because investors paying more attention to their portfolios when market-wide event happens. He looks at specific order flow to assess the effects of attention caused by news headlines and Dow records on trading volume. We hypothesize likewise that that our three market-wide events will have an increasing effect on the trading activity, and we will use his methodology to examine this for each industry and event, thus testing the null hypothesis:

$$H_0 = The\ marketwide\ events\ do\ not\ have\ an\ increasing\ effect\ on\ the\ trading\ activity$$

We will use turnover ratio as our measurement of trading activity and inspired by Yuan (2015) we will likewise use one day prior turnover ratio, one day prior returns and one year prior average returns as control variables. The purpose of these control variables is to control for economic information in the short-run and long-run. Beside the control variables we have our three events as individual dummy variables, where each on the variables is “*1*” in the five days included in the event window, and otherwise zero. The model we used to analyse the the null hypothesis that market-wide events do not affect trading activity, is presented in equation (13).

$$TO_{i,t+1} = \alpha + \beta_1(R_{i,t}) + \beta_2(R_{i,[t-253,t]}) + \beta_3(TO_{i,t}) + \beta_4(E1) + \beta_5(E2) + \beta_6(E3) + \varepsilon_t \quad (13)$$

In the regression i =1,..., 11 as it represent the industries, $R_{i,[t-253,t]}$is the one year prior average returns for industry i, *E1* is the event of the official announcement of the referendum, *E2 is* the results of the referendum and the *E3* is the last event; the official triggering of Article 50. All the variables, except the three dummy variables, are normalised to have unit variance, for ease of interpretation and avoiding biased results due to non-normality in the data. The regression will follow an ordinary least square regression, that will be run in the period from 02-02-2016 to 30-04-2017, therefore covering the 3 events and the time just before and after the events.

To measure the trading activity we chose to use the calculated turnover ratio as presented under section 3.2.4 and not unexpected turnover ratio, as otherwise used in the event study. The reason for this choice is that unexpected turnover is conditional on the choice of model to used to calculate the expected turnover ratio. This leads back to the joint hypothesis problem, that one cannot truly conclude inefficiency based on abnormal returns (here unexpected turnover), as the model used to calculated the expected normal returns (turnover) could be wrong. So to be able to conclude if these events have an increasing effect in trading activity in the selected time period, we chose to applied turnover ratio as it would not be biases by the choice of model.

3.3.3 Informedness and Consensus

Without data on private information of investors, or the institutional classification of customer order flow used as proxy by Irvine, Lipson & Puckett (2006) and Hendershott, Livdan & Schürhoff (2012), we will only explore the trading volume arising from the informedness effect in our dataset with regards to Copeland's (1976) SIAH, for which we will follow the methodology used in Mougoué & Aggarwal (2011) and Jena (2016). Where we will use the GARCH to determine the conditional volatility of the returns, and the linear Granger Causality test introduced by Granger (1969) to examine if a lag/lead relationship between volume and volatility is present in our data.

3.3.3.1 Estimating Volatility

To determine the relationship between trading volume and the volatility of returns, we test the Sequential Information Arrival Hypothesis as stated in the methodology. The trading volume is a directly observable variable and is here used in terms of turnover ratio, the volatility of the returns on the other hand cannot be directly observed and need to be estimated. For this purpose, we use the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by Bollerslev (1986). The GARCH(p,q) process is given by equation set (14).

$$\varepsilon_t|\psi_{t-1} \sim\ N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (14)$$

Where

$$p \geq 0, \qquad q > 0$$
$$\alpha_0 > 0, \quad \alpha_i\ \geq 0, \quad i = 1, \ldots, q$$
$$\beta_i\ \geq 0 \qquad i = 1, \ldots, p$$

ε_t denotes a discrete stochastic process given the information set ψ_{t-1}, which is here represented by the returns, the process approximates a normal distribution with mean zero and conditional variance h_t, *q* represent lags of returns and *p* lags of conditional variance. The GARCH framework allows the conditional variance to become time varying, which makes it useful as an estimator for the volatility of returns, since we cannot know for sure if the true variance is constant over time. The model we use to estimate the return volatility is the GARCH (1,1), which incorporates the first lag of the returns and the first lag of the conditional variance. The parameters of the model are then estimated with the use of a maximum likelihood estimator. The GARCH (1,1) is the simplest and most used GARCH for estimating volatility of returns.

3.3.3.2 Granger Causality

The Granger Cause was presented by Granger (1969) with the purpose of explaining the relationship between two stationary time series. Granger defines that if past observations of X have an effect on the movement of Y then X is said to strictly Granger Cause Y, and if past observation of Y also have an effect on the movement of X then there exist a so-called feedback relationship. If the Granger Causality test find a that X Granger Cause Y, then X is meant to hold a predictive power over Y (Granger, 1969).

The linear Granger Causality test, which we are going to use, assumes a linear relationship between two pairwise time series, here the turnover ratio (*TO*) and the volatility of the returns (*Vol*) . For each variable, a linear model is regress based on past observations of the two time series (Granger, 1969). For our model, it means that for each industry the model is given by:

$$TO_t = \sum_{j=1}^{p} c_j TO_{t-j} + \sum_{j=1}^{p} d_j Vol_{t-j} + \eta_t$$

$$Vol_t = \sum_{j=1}^{p} a_j TO_{t-j} + \sum_{j=1}^{p} b_j Vol_{t-j} + \varepsilon_t \qquad (15)$$

ε_t and η_t are uncorrelated white-noise series of the error terms and p is the number of lags used.

The linear models are estimated with and without past observations of the independent variable, and the residual sum of squares (RSS) statistic is calculated for both. To test the relationship, the difference of the RSS for the full model and the RSS for the model excluding the independent variable is tested using a χ^2 test statistic. If the predictive power becomes significantly worse when excluding the independent variable then it can be conclude that the independent variable Granger Causes the dependent variable (Granger, 1969).

The optimal number of lags used in the Granger Causality test is determined using the Vector Autoregressive model (VAR). The VAR was introduced by Sims (1980) and represent a vector of *n* linear functions, where each of the functions consists of one dependent variable that is explained by its own lagged observations and the lagged observations of the other variables, with p number of lags. We use the standard reduced-form VAR model that is given in equation (16).

$$\boldsymbol{Y}_t = c + \boldsymbol{\Pi}_1 \boldsymbol{Y}_{t-1} + \boldsymbol{\Pi}_2 \boldsymbol{Y}_{t-2} + \ldots + \boldsymbol{\Pi}_p \boldsymbol{Y}_{t-p} + \varepsilon_t\,, \qquad t = 1, \ldots, T \tag{16}$$

$\boldsymbol{Y}$ in the above formula represent a vector of *n* variables which shows the observations of the variables for time t and time t-p. $\boldsymbol{\Pi}_p$ is likewise a vector of *n* variables, for the estimated coefficients of the independent variable observations. With only two time series for each industry the model becomes similar to the linear function of the Granger Causality test. The purpose of the VAR model here is to find the optimal numbers of lags to use in the Granger Causality test, the VAR model will be run for each industry with 0 to 4 lags and we select the number of lags for each industry based on the Akaike Information Criterion (AIC).

3.3.3.3 Consensus

After investigating the informedness effect in the form of the SIAH, we want to examine the null hypothesis of consensus among investors surrounding the events. For this we will use the methodology of Garfinkel & Sokobin (2005) to create a new expected trading volume benchmark, [$E(TOI_{i,t})$], that includes both fundamental trading volume and the informedness effect, by including absolute positive and negative industry returns as presented in equation (17).

$$E(TOI_{i,t}) = \alpha_i + \beta_1^i(|R_{it}|)^+ + \beta_2^i(|R_{it}|)^- \tag{17}$$

Where α_i, β_1^i, and β_2^i, are estimated is a ordinary least square regression, based on the observation in the same estimation period as used earlier in the event study, that consisted of 253 trading days (a year) prior to the first event. $E(TOI_{i,t})$ now, according to Garfinkel & Sokobin (2005), holds the sum of the expected liquidity trading and informedness effect, but not the consensus effect. Therefore, when subtracting the new expected turnover from the actual turnover ratio a potential unexpected turnover would then suggest consensus effect, implying disagreement among investors. The set up of the new unexpected turnover follows the event study present previously in the methodology, likewise is the significance testing, done using the same parametric and nonparametric test, respectively the Patell and Corrado Rank test statistics, as presented in section 3.3.1.3.

4. Empirical Findings

In this chapter the data analysis as described in the previous chapter will be performed and presented, this includes statistical testing and a short discussion of the results. A further analysis of the results will be discussed in the next chapter.

4.1 Event Study

In this section we will test for evidence supporting the Efficient Market Hypothesis for each industry, surrounding the three events. To do so, we will, as mentioned previously, test the two null hypotheses:

$$H_0 = There\ are\ no\ single\ day\ abnorma\ returns/unexpected\ turnover\ in\ the\ event\ window$$

$$H_1 = There\ are\ no\ cumulative\ abnormal\ returns/unexpected\ turnover\ in\ the\ event\ window$$

If we find significant single-day abnormal returns or unexpected turnover, we have evidence supporting a rejection of that null hypothesis, and it can provide understanding as to when the market reacts to the event. Reaction only on the day of the event can still support the Efficient Market Hypothesis, however, multiple single-day significance and/or evidence against the hypothesis of no cumulative abnormal returns/unexpected turnover, can support a rejection of the Efficient Market Hypothesis and support the notion of market inefficiency.

4.1.1 Official Announcement of Referendum

4.1.1.1 Abnormal Returns

Table 3. Abnormal returns, 1st event Market Model

Market Model									
Official announcement of referendum									
Event Window	OG			BA			PB		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.015	-1.364	0.073	-0.011	-1.797	0.039	-0.014	-1.939	0.054
-1	-0.009	-0.820	0.185	0.001	0.104	0.541	-0.003	-0.356	0.320
0	0.019	1.678	0.942	-0.008	-1.219	0.093	-0.002	-0.231	0.390
1	-0.013	-1.198	0.093	-0.003	-0.431	0.297	0.003	0.382	0.680
2	-0.003	-0.308	0.405	-0.003	-0.443	0.290	0.004	0.578	0.745
Cumulative	-0.023	-0.900	-1.248	-0.024	-1.694	-1.934	-0.012	-0.700	-0.484
Event Window	TO			MI			SS		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.001	-0.121	0.440	-0.006	-0.315	0.378	0.005	1.153	0.915
-1	-0.001	-0.121	0.444	0.011	0.623	0.753	0.001	0.179	0.560
0	-0.008	-1.003	0.127	0.061	3.406*	0.992*	-0.004	-0.815	0.174
1	0.007	0.887	0.826	-0.012	-0.683	0.228	0.000	-0.038	0.452
2	0.009	1.116	0.888	-0.039	-2.153*	0.015*	0.005	1.136	0.911
Cumulative	0.006	0.339	0.352	0.016	0.393	-0.208	0.007	0.723	0.797
Event Window	LI			TL			ME		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.002	0.275	0.598	0.007	1.054	0.857	0.003	0.491	0.676
-1	-0.007	-0.970	0.162	0.008	1.231	0.907	0.006	0.991	0.880
0	-0.004	-0.558	0.282	-0.002	-0.354	0.340	-0.004	-0.665	0.228
1	-0.014	-2.073*	0.027*	0.007	0.997	0.834	0.003	0.582	0.737
2	-0.009	-1.311	0.089	0.002	0.348	0.629	0.002	0.415	0.629
Cumulative	-0.031	-2.074*	-2.091*	0.021	1.465	1.664	0.011	0.811	1.014
Event Window	HH			FS					
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	0.011	1.369	0.931	0.007	1.238	0.900			
-1	0.009	1.152	0.876	-0.002	-0.304	0.375			
0	-0.028	-3.604*	0.004*	-0.004	-0.734	0.212			
1	0.009	1.142	0.873	0.029	4.932*	0.996*			
2	0.012	1.580	0.958	-0.006	-1.033	0.147			
Cumulative	0.013	0.733	1.778	0.024	1.833	0.202			

*Significant at a 5% significance level

Table 4. Abnormal returns, 1st event CAPM

CAPM									
Official announcement of referendum									
Event Window	OG			BA			PB		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.012	-1.031	0.062	-0.010	-1.623	0.035	-0.014	-1.924	0.054
-1	-0.005	-0.493	0.151	0.002	0.269	0.521	-0.003	-0.341	0.320
0	0.022	2.011*	0.919	-0.007	-1.056	0.089	-0.002	-0.217	0.390
1	-0.010	-0.868	0.085	-0.002	-0.261	0.266	0.003	0.396	0.680
2	0.000	0.007	0.320	-0.002	-0.287	0.255	0.004	0.593	0.745
Cumulative	-0.004	-0.167	-1.501	-0.018	-1.323	-2.079*	-0.011	-0.668	-0.484
Event Window	TO			MI			SS		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.002	-0.191	0.448	0.001	0.049	0.317	0.004	0.806	0.919
-1	-0.002	-0.187	0.456	0.018	0.981	0.714	-0.001	-0.164	0.614
0	-0.009	-1.067	0.135	0.067	3.767*	0.988*	-0.005	-1.155	0.216
1	0.007	0.820	0.842	-0.006	-0.324	0.197	-0.002	-0.386	0.514
2	0.009	1.057	0.896	-0.033	-1.825	0.015*	0.004	0.811	0.927
Cumulative	0.004	0.193	0.430	0.047	1.184	-0.418	0.000	-0.039	1.074
Event Window	LI			TL			ME		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.005	0.688	0.568	0.004	0.589	0.888	0.002	0.382	0.718
-1	-0.004	-0.558	0.135	0.005	0.776	0.931	0.005	0.887	0.884
0	-0.001	-0.156	0.247	-0.005	-0.803	0.409	-0.005	-0.768	0.247
1	-0.011	-1.648	0.015*	0.004	0.535	0.880	0.003	0.475	0.757
2	-0.006	-0.913	0.066	-0.001	-0.088	0.683	0.002	0.318	0.672
Cumulative	-0.017	-1.157	-2.289*	0.007	0.451	2.012*	0.008	0.578	1.212
Event Window	HH			FS					
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	0.010	1.248	0.942	0.008	1.381	0.900			
-1	0.008	1.036	0.892	-0.001	-0.161	0.367			
0	-0.029	-3.723*	0.004*	-0.003	-0.593	0.201			
1	0.008	1.022	0.884	0.029	5.073*	0.996*			
2	0.012	1.474	0.958	-0.005	-0.894	0.131			
Cumulative	0.008	0.473	1.838	0.028	2.149*	0.147			

*Significant at a 5% significance level

The results of the first event generally give the impression that the official announcement of the referendum does not have an effect on the returns in the average market, but some individual industries do exhibit some significant abnormal returns. Looking at Tables 3 and 4, it can be seen that the Corrado Rank test and the Patell test statistics mostly agree on the conclusion on the significance of the abnormal returns, which provides some robustness to the results. The two test statistics mostly disagree about the cumulative test-statistics in the CAPM, which we did expect could happen, hence our concern mentioned earlier in the methodology regarding the cumulative Rank test.

Both the results from the CAPM and the Market Model show that the MI industry has significant positive abnormal returns on the day of the event and negative the second day after the event. The cumulative test of the MI industry is however not flagged as significant, suggesting that the effect of a event on the event day is eliminated the following days, the abnormal returns in our event window are therefore not significantly different from zero, so the evidence fail to reject the null hypothesis of an efficient markets. The same is the case for the industry HH, that only exhibit a highly significant abnormal return on the event day but the cumulative test are not significant different from zero. The FS and LI industries have significant abnormal returns on the first day after the event in both models. This suggest a delay in the response to the official announcement of the referendum and the cumulative test based in the CAPM abnormal returns for the FS and Market Model for LI do are both significantly different from zero which support a rejection of the null hypothesis of an efficient market. For the rest of the industries we do not have evidence to support a rejection of the null hypothesis for this event.

Since we only see a significant effect in a few industries there is a chance that it might be something industry specific that affected the price in this event window and not the official announcement of the referendum. For LI we saw a negative cumulative significance and single-day significance on day +1, which is the 23rd of february 2016 and on that day a Insurance Distribution Directive (IDD) from the European Commission came into force, stating all EU members should have incorporated the IDD into national law by 23rd of february 2018 (Staff, 2016). The news of the IDD, and its new stricter requirements to insurers, should be expected to have an impact on the price in the LI industry, and this industry specific news is most likely the cause of the significant negative abnormal returns in LI in our event study.

For FS there were also significant positive abnormal returns on day +1 in both models and cumulatively for the CAPM. This significance is also likely to be caused by an industry specific event, because on the 23rd of february 2016 the Bank of England and Financial Services Bill completes the Committee stage in the house of Commons (Slaughter & May, 2016). The Bank of England and Financial Services Bill proposes among other things to provide the financial system with greater resilience, with the purpose of ensuring financial stability (Lawrence, 2016).

The MI industry had significant abnormal returns in 2 days in the event window, these significant changes in the price was caused by increasing copper price, likely due to fear that China will cut back on the production of copper (Reuters, 2016; Sanderson, 2016). So the announcement of a Brexit referendum likely this did not cause the abnormal returns in this industry.

After accessing other possible explanations for the significance in the results of MI, FS and LI, we can conclude that the evidence supporting a rejection of the null hypothesis most likely did not come from the official announcement of the referendum. For the rest of the industries where we find no industry specific things, it is only the HH industry that seems to react to the announcement of the referendum, given abnormal negative returns on the event day itself. However the results display no abnormal returns in the following days, suggesting that the industry reacted efficiently to the news.Therefore for HH and the rest of the industries we can overall not support a rejection of the null hypothesis of efficient market due to the official announcement of the referendum.

4.1.1.2 Unexpected Turnover

Table 5. Unexpected turnover, 1st event Market Model

Market Model									
Official announcement of referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.101	0.296	0.683	-0.013	-0.071	0.479	1.284	-0.354	0.884
-1	-0.215	-0.629	0.259	0.215	1.152	0.888	1.080	-0.333	0.857
0	-0.454	-1.328	0.039	0.209	1.120	0.884	-0.731	-0.120	0.232
1	-0.015	-0.043	0.548	0.147	0.785	0.803	-0.691	-0.146	0.243
2	0.202	0.591	0.776	0.025	0.133	0.583	-0.235	-0.242	0.429
Cumulative	-0.381	-0.498	-0.304	0.583	1.395	1.772	0.707	0.316	0.226
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.043	0.169	0.618	0.545	0.972	0.768	-0.007	-0.045	0.490
-1	-0.076	-0.294	0.409	0.369	0.659	0.660	0.097	0.605	0.726
0	0.005	0.019	0.564	0.568	1.013	0.799	0.103	0.647	0.745
1	-0.039	-0.152	0.494	0.376	0.672	0.668	0.191	1.195	0.892
2	-0.285	-1.107	0.108	0.462	0.825	0.714	0.285	1.786	0.969
Cumulative	-0.351	-0.611	-0.478	2.321	1.852	1.730	0.669	1.873	2.061*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.235	0.989	0.888	-0.277	-1.065	0.127	-0.223	-0.919	0.135
-1	0.256	1.076	0.903	-0.354	-1.361	0.058	-0.130	-0.537	0.286
0	0.104	0.436	0.680	-0.333	-1.281	0.073	-0.411	-1.693	0.023*
1	0.210	0.883	0.834	-0.120	-0.462	0.332	-0.090	-0.372	0.371
2	0.110	0.464	0.699	-0.146	-0.563	0.282	0.498	2.053*	0.961
Cumulative	0.916	1.721	2.343*	-1.229	-2.116*	-2.536*	-0.356	-0.656	-1.128
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	-0.257	-0.672	0.251	0.207	0.913	0.853			
-1	-0.547	-1.427	0.046	0.039	0.174	0.618			
0	-0.180	-0.469	0.328	-0.202	-0.892	0.135			
1	-0.098	-0.255	0.440	0.265	1.171	0.915			
2	-0.527	-1.375	0.058	0.449	1.985*	0.973*			
Cumulative	-1.609	-1.878	-2.145*	0.759	1.499	1.549			

*Significant at a 5% significance level

Table 6. Unexpected turnover, 1st event Average Model

Average Model									
Official announcement of referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.278	0.601	0.761	0.169	0.454	0.730	1.243	-0.368	0.915
-1	-0.235	-0.508	0.317	0.195	0.524	0.745	0.624	-0.133	0.784
0	-0.184	-0.398	0.378	0.487	1.310	0.919	0.221	-0.050	0.595
1	0.079	0.171	0.622	0.244	0.655	0.788	-0.195	0.081	0.371
2	0.508	1.097	0.861	0.340	0.914	0.861	0.620	-0.009	0.780
Cumulative	0.447	0.431	0.683	1.435	1.725	2,404*	2.513	1.124	1.471
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.192	0.523	0.718	0.695	1.121	0.846	0.125	0.442	0.734
-1	-0.092	-0.251	0.398	0.353	0.569	0.649	0.082	0.290	0.683
0	0.232	0.631	0.764	0.797	1.285	0.876	0.305	1.079	0.900
1	0.040	0.109	0.552	0.456	0.736	0.703	0.261	0.924	0.849
2	-0.027	-0.072	0.475	0.722	1.164	0.849	0.514	1.818	0.958
Cumulative	0.346	0.421	0.635	3.022	2,18*	2,217*	1.287	2,036*	2,53*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.400	1.065	0.892	-0.146	-0.418	0.278	-0.079	-0.226	0.417
-1	0.238	0.633	0.757	-0.368	-1.058	0.081	-0.147	-0.417	0.309
0	0.355	0.945	0.849	-0.133	-0.381	0.290	-0.192	-0.546	0.220
1	0.297	0.793	0.811	-0.050	-0.145	0.386	-0.014	-0.040	0.514
2	0.395	1.052	0.888	0.081	0.232	0.618	0.747	2,127*	0,985*
Cumulative	1.684	2,007*	2,644*	-0.616	-0.792	-1.321	0.316	0.402	-0.087
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	-0.139	-0.319	0.359	0.356	1.025	0.884			
-1	-0.560	-1.284	0.069	0.023	0.065	0.541			
0	0.001	0.001	0.517	0.025	0.073	0.548			
1	-0.035	-0.080	0.483	0.344	0.992	0.873			
2	-0.322	-0.739	0.201	0.707	2,038*	0,988*			
Cumulative	-1.056	-1.082	-1.357	1.455	1.875	2,079*			

*Significant at a 5% significance level

Tables 5 and 6 display the results for unexpected turnover surrounding the first event, the official announcement of the referendum, for both the Patell parametric test and the Corrado Rank test. Comparing both the Average Model and the Market Model, the two models agree 108 out of 110 single-day results to be insignificant, providing some proof of robustness of these results. Of the remaining two results, the Market Model flags ME day 0 in the Corrado Rank test and ME day +2 in the Patell test to be significant, while the Average Model only points at ME day +2 in the Corrado Rank test to be significant. Besides these significant results, day +2 for FS is also positively significant in both models and test statistics. As expected, the Average Model shows more significant cumulative unexpected turnover results than the Market Model, because it probably overstates the effect of the event. The positive significant cumulative results in this model are found for the industries MI, SS and LI for both Patell and Corrado test statistic, and BA and FS only for the Rank test. The Market Model however, states TL to be significant for both test statistics, and ME, HH, and LI only for the Rank test. Since the results of the cumulative test differ much for the two models for many industries it is only the Rank test that is significant, we cannot completely support a rejection of the null hypothesis of no unexpected turnover in the event window.

4.1.1.3 Subconclusion

To conclude on the first event in the event study, we found no evidence of the official announcement of the referendum to support a rejection of Efficient Market Hypothesis. The significant abnormal returns we did find in MI, FS and LI were more likely caused by industry specific events, coincidentally occurring in this specific event window.

Keeping in mind that the returns represent the average investors expectation to the price, we also look at unexpected turnover to examine if the individual investors are agreeing on the price. Here we generally find no unexpected turnover looking at the single day returns, the significance in FS is most likely cause by the Bank of England and Financial Services Bill completing the Committee stage in the house of Commons, which we also suspect caused the abnormal returns in the industry. To this point the two different models and test statistics agree on the results, giving robustness to the results, only in the cumulative testing in unexpected turnover do the models seem to be conflicting, causing no clear conclusion on these tests.

Thus, we see no evidence supporting unexpected turnover or abnormal returns caused by this event. A reason why we do not see abnormal return or unexpected turnover could then be that the markets are efficient and investors agree on the information. If that were the case, however, we would have expected a little significance in the abnormal returns on the day of the event when incorporating the information in the price. A second reason could be that the referendum was anticipated and an official announcement of it did not bring information that was not already incorporated in the price. The second reason here will be discussed later in Chapter 5.

4.1.2 Results of Referendum

4.1.2.1 Abnormal Returns

Table 7. Abnormal returns, 2nd event Market Model

Market Model									
Result of British referendum									
Event Window	OG			BA			PB		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.006	-0.494	0.286	0.004	0.662	0.768	0.000	-0.056	0.479
-1	0.005	0.429	0.726	0.009	1.419	0.946	-0.008	-1.009	0.127
0	0.057	4.962*	0.996*	-0.054	-8.549*	0.004*	0.066	8.715*	0.996*
1	0.056	4.885*	0.992*	-0.036	-5.676*	0.008*	0.043	5.651*	0.992*
2	-0.024	-2.1*	0.015*	-0.001	-0.204	0.429	-0.002	-0.260	0.371
Cumulative	0.088	3.435*	0.803	-0.079	-5.522*	-0.538	0.099	5.832*	0.725
Event Window	TO			MI			SS		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.007	-0.903	0.139	0.005	0.273	0.641	0.000	0.057	0.506
-1	-0.005	-0.640	0.224	0.001	0.080	0.541	0.004	0.918	0.849
0	0.054	6.419*	0.996*	0.050	2.73*	0.981*	-0.023	-5.035*	0.008*
1	0.043	5.174*	0.992*	0.054	2.944*	0.985*	-0.038	-8.46*	0.004*
2	-0.006	-0.724	0.193	-0.022	-1.219	0.097	0.010	2.274*	0.973*
Cumulative	0.078	4.17*	0.069	0.088	2.15*	1.158	-0.047	-4.582*	-0.250
Event Window	LI			TL			ME		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.011	1.604	0.950	-0.001	-0.184	0.413	0.001	0.244	0.544
-1	0.001	0.107	0.537	0.000	0.027	0.510	-0.001	-0.185	0.409
0	-0.081	-11.824*	0.004*	-0.023	-3.404*	0.015*	-0.015	-2.554*	0.008*
1	-0.052	-7.587*	0.008*	-0.047	-6.981*	0.004*	-0.010	-1.663	0.054
2	0.031	4.535*	0.996*	-0.006	-0.836	0.181	0.006	0.948	0.865
Cumulative	-0.091	-5.888*	-0.009	-0.076	-5.088*	-2.145*	-0.019	-1.436	-0.966
Event Window	HH			FS					
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	-0.002	-0.221	0.413	0.009	1.530	0.938			
-1	-0.002	-0.306	0.375	0.008	1.428	0.923			
0	-0.071	-8.866*	0.004*	-0.066	-11.069*	0.004*			
1	-0.019	-2.391*	0.027*	-0.061	-10.331*	0.008*			
2	-0.005	-0.626	0.263	0.019	3.268*	0.996*			
Cumulative	-0.099	-5.55*	-2.211*	-0.090	-6.786*	0.575			

*Significant at a 5% significance level

Table 8. Abnormal returns, 2nd event CAPM

CAPM									
Result of British referendum									
Event Window	OG			BA			PB		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.002	-0.191	0.236	0.005	0.809	0.734	0.000	-0.042	0.479
-1	0.008	0.751	0.683	0.010	1.576	0.934	-0.007	-0.995	0.127
0	0.060	5.227*	0.996*	-0.054	-8.434*	0.004*	0.066	8.729*	0.996*
1	0.058	5.114*	0.992*	-0.035	-5.591*	0.008*	0.043	5.665*	0.992*
2	-0.021	-1.894	0.012*	-0.001	-0.121	0.332	-0.002	-0.246	0.371
Cumulative	0.103	4.028*	0.653	-0.075	-5.26*	-0.761	0.100	5.863*	0.725
Event Window	TO			MI			SS		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.008	-0.959	0.151	0.011	0.595	0.552	-0.001	-0.258	0.560
-1	-0.006	-0.702	0.232	0.008	0.422	0.483	0.003	0.590	0.884
0	0.053	6.392*	0.996*	0.055	2.982*	0.977*	-0.024	-5.301*	0.008*
1	0.043	5.161*	0.992*	0.057	3.148*	0.985*	-0.039	-8.699*	0.004*
2	-0.006	-0.743	0.220	-0.018	-1.022	0.054	0.009	2.063*	0.988*
Cumulative	0.076	4.092*	0.141	0.111	2.739*	0.857	-0.053	-5.19*	-0.087
Event Window	LI			TL			ME		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.013	1.968*	0.927	-0.004	-0.604	0.498	0.001	0.153	0.575
-1	0.003	0.499	0.498	-0.003	-0.414	0.571	-0.002	-0.285	0.432
0	-0.079	-11.441*	0.004*	-0.025	-3.74*	0.015*	-0.016	-2.615*	0.008*
1	-0.050	-7.277*	0.008*	-0.048	-7.273*	0.004*	-0.010	-1.703	0.077
2	0.033	4.771*	0.996*	-0.007	-1.128	0.286	0.005	0.907	0.892
Cumulative	-0.080	-5.134*	-0.105	-0.088	-5.885*	-1.754	-0.021	-1.585	-0.803
Event Window	HH			FS					
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	-0.002	-0.320	0.452	0.010	1.664	0.938			
-1	-0.003	-0.417	0.413	0.009	1.566	0.915			
0	-0.071	-8.935*	0.004*	-0.065	-10.948*	0.004*			
1	-0.019	-2.423*	0.027*	-0.060	-10.221*	0.008*			
2	-0.005	-0.660	0.332	0.020	3.373*	0.996*			
Cumulative	-0.102	-5.704*	-1.982*	-0.087	-6.515*	0.563			

*Significant at a 5% significance level

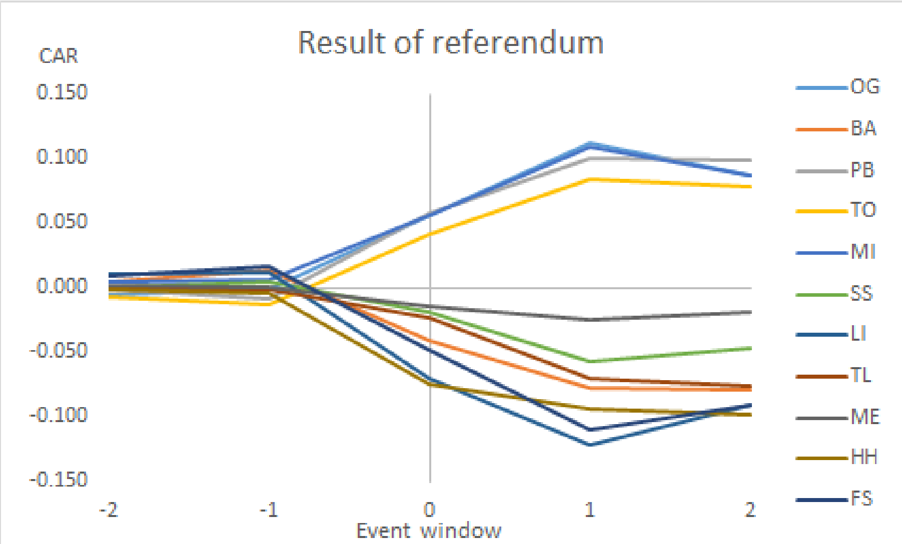
Table 7 and 8 display the results of the second event study, where the event day is the 24th June 2016: the results of the Brexit referendum reach the equity market. A first look at the tables shows that there are generally significant abnormal return around this event for all industries. Comparing the significant abnormal return of the CAPM and the Market Model, the two models agree 129/132 of the test statistics whether or not the abnormal return is significantly different from zero or not, which provides high robustness to the results. The two test-statistics completely agree on all single-day test results, where on the cumulative tests we see many industries that are significant in the Patell test and not the Rank test. This was to be expected, and is in this case likely due to the reversion in the opposite direction we see for the many industries on day +2 in the event window. As discussed earlier, the Rank test averages these out as both are on opposite sides of the significance spectrum. We do however not consider this a weakening of the results, as we are aware of the issue and take the Rank test results with caution in these instances.

The results of the second event can be divided into different groups. The industries in the first group are BA, PB, TO, MI, TL and HH, as these industries all have significant abnormal returns day 0 and +1 in the event window and they do also exhibit significant cumulative abnormal returns. The second group consists of the industries OG, SS, LI and FS, which all have significant abnormal returns on day 0, +1 and +2 of the event window. LI even shows significant abnormal returns on day -2 according to the Market Model. These four industries also have significant cumulative abnormal returns in the event window. The last industry, ME, only has significant abnormal returns on the event day and does not have significant cumulative abnormal returns. Therefore, the ME industry is the only industry where the evidence does not support a rejection of the null hypothesis of an efficient market.

The evidence for the other ten industries implies that the day the news of the result of the referendum reached the equity market, it had a significant effect on the abnormal returns. However, unlike Fama's (1970) theory that prices quickly adjust to new information, most often within a day (Fama, 1991), the news of the referendum result also had a significant effect the first trading day after the event day, and for some even on the second day after the event day. This and the fact that they all experience significant cumulative abnormal returns, supports a rejection of the null hypothesis of efficient market in the event window.

The event has a clearly significant effect on the abnormal returns for all the industries, but to obtain a better understanding on how the different industries have reacted to the news of the results, a graph of the cumulative abnormal returns is presented in Figure 7 below. Since the movement of the abnormal returns in the CAPM and Market Model are almost identical, we chose to only display the cumulative abnormal returns of the Market Model here. The graph of the cumulative abnormal returns for the CAPM can be seen in the Appendix 1.

Figure 7. Cumulative abnormal returns, Market Model



The movement of the cumulative abnormal returns shows that all industries are stable around zero until the day of the event. When reaching the event day, the industries split off into two groups. OG, PB, TO and MI all react positive to the results of the referendum, with positive abnormal returns on day 0 and +1 in the event window. For the last day in the event window, PB and TO flatten out. OG and MI display a negative movement on day +2, that reverses some of the effect of the previous days' positive responses, which could suggest an overreaction to the news. The other seven industries all react negative to the results of the referendum. They all have negative abnormal returns on day 0 and +1 of the event window, after which ME, TL, HH and BA remain stable around that new level, with either a slightly movement up or down. The last three industries, SS, LI and FS, all show upward movement with positive abnormal returns for the last day in the event window, reversing some of the previous days' negative response. This reversal again suggests an overreaction to the event.

4.1.2.2 Unexpected Turnover

Table 9. Unexpected turnover, 2nd event Market Model

Market Model									
Result of British referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.521	-1.523	0.039	0.311	1.664	0.927	0.240	1.178	0.876
-1	-0.611	-1.785	0.031	0.378	2,02*	0.954	0.098	0.480	0.699
0	-1.221	-3,473*	0,008*	0.676	3,52*	0,988*	-0.250	-1.196	0.093
1	-1.289	-3,704*	0,004*	0.619	3,254*	0,985*	-0.276	-1.335	0.073
2	-1.093	-3,174*	0,012*	0.523	2,78*	0,981*	-0.179	-0.877	0.197
Cumulative	-4.735	-6,109*	-3,751*	2.507	5,92*	3,637*	-0.368	-0.782	-0.875
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.141	-0.550	0.301	-0.060	-0.108	0.490	0.183	1.148	0.888
-1	-0.027	-0.107	0.514	-0.175	-0.312	0.471	0.046	0.289	0.591
0	-0.552	-2,092*	0,015*	-0.811	-1.408	0.035	0.135	0.824	0.826
1	-0.765	-2,925*	0,008*	-0.835	-1.466	0.031	0.251	1.544	0.942
2	-0.245	-0.946	0.143	-0.587	-1.041	0.181	0.368	2,29*	0,973*
Cumulative	-1.731	-2,961*	-2,367*	-2.469	-1,939*	-2,012*	0.984	2,726*	2,68*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.151	0.633	0.776	-0.285	-1.098	0.108	0.012	0.050	0.571
-1	0.441	1.854	0,981*	0.124	0.476	0.714	0.118	0.484	0.730
0	0.206	0.844	0.822	-0.191	-0.714	0.228	0.228	0.915	0.849
1	0.370	1.528	0.938	0.129	0.488	0.726	0.315	1.275	0.919
2	0.487	2,035*	0,985*	0.117	0.449	0.707	0.416	1.704	0.954
Cumulative	1.655	3,083*	3,119*	-0.106	-0.179	-0.027	1.089	1,98*	2,373*
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	-0.096	-0.251	0.425	-0.108	-0.475	0.313			
-1	-0.027	-0.070	0.506	-0.100	-0.440	0.340			
0	0.660	1.677	0.946	-0.494	-2,122*	0,015*			
1	0.958	2,458*	0,985*	-0.125	-0.544	0.290			
2	0.963	2,496*	0,988*	-0.190	-0.832	0.147			
Cumulative	2.458	2,822*	2,103*	-1.016	-1,974*	-2,175*			

*Significant at a 5% significance level

Table 10. Unexpected turnover, 2nd event Average Model

Average Model									
Result of British referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.361	-0.778	0.205	0.476	1.281	0.900	0.371	1.136	0.876
-1	-0.410	-0.885	0.170	0.585	1.572	0.927	0.262	0.802	0.822
0	0.567	1.192	0.900	2.517	6,589*	0,996*	1.211	3,614*	0,996*
1	0.102	0.217	0.637	2.050	5,424*	0,992*	0.860	2,595*	0,985*
2	-0.220	-0.471	0.344	1.422	3,801*	0,988*	0.534	1.627	0.954
Cumulative	-0.321	-0.324	-0.382	7.051	8,349*	3,589*	3.238	4,371*	3,324*
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.006	-0.017	0.490	0.076	0.122	0.564	0.303	1.073	0.892
-1	0.142	0.385	0.668	-0.005	-0.008	0.521	0.196	0.694	0.792
0	0.954	2,525*	0,988*	0.704	1.105	0.853	1.470	5,064*	0,996*
1	0.407	1.089	0.880	0.343	0.544	0.653	1.289	4,487*	0,992*
2	0.491	1.326	0.927	0.153	0.245	0.595	1.020	3,588*	0,988*
Cumulative	1.988	2,374*	2,265*	1.269	0.898	1.068	4.278	6,666*	3,366*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.300	0.799	0.807	-0.166	-0.478	0.255	0.142	0.406	0.683
-1	0.628	1.673	0.958	0.272	0.783	0.865	0.281	0.799	0.834
0	1.867	4,845*	0,992*	1.135	3,174*	0,981*	1.680	4,66*	0,996*
1	1.661	4,357*	0,988*	1.160	3,279*	0,985*	1.444	4,048*	0,988*
2	1.299	3,44*	0,985*	0.765	2,184*	0,977*	1.126	3,186*	0,985*
Cumulative	5.754	6,759*	3,474*	3.165	3,999*	2,434*	4.674	5,858*	3,095*
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	0.011	0.026	0.514	0.028	0.079	0.544			
-1	0.107	0.246	0.618	0.069	0.200	0.602			
0	1.854	4,137*	0,988*	1.011	2,837*	0,988*			
1	1.887	4,254*	0,992*	1.045	2,964*	0,992*			
2	1.546	3,521*	0,985*	0.545	1.562	0.950			
Cumulative	5.406	5,449*	2,488*	2.698	3,418*	2,458*			

*Significant at a 5% significance level

Table 9 and Table 10 display the unexpected turnover results of the second event, the outcome of the Brexit referendum, for the Market Model and the Average Model respectively. Both tables include results from the Patell (parametric) and Corrado (nonparametric) test statistics, which are mostly in agreeance with each other. The only divergences occur in the Market Model, where Patell considers BA day -1 to be significant and Corrado Rank test does not, and vice versa for LI day -1.

Unlike the two significance tests for each individual model, the two models present very different scenarios. For the Market Model, OG and BA show significant unexpected turnover for day 0 and the two days following the event, TO only on the event day and the day after, and FS only on the event day itself. SS and LI however are only significant on day +2.

Again, like expected, the Average Model shows more significant results; BA, SS, LI, TL, ME, and HH are all displaying significant unexpected turnover on days 0, +1, and +2, whereas PB and FS do so for days 0 and +1 and TO only for day 0. Remarkable is that OG shows no significant days for this model at all, whereas it shows 3 days for the Market Model. The reverse can be said for TL, ME and PB, which do not display any significant single-day results for the Market Model, but 3 days (2 for PB) for the Average Model. In the other industries, the Average Model shows longer stretches of significance in the event window. The two models do agree, however, on the 3 days significance spread for the banking industry, and complete lack of significance for any of the individual days of the MI industry, looking only at single-day test.

A closer look at cumulative unexpected turnover during the full event window also provides lot of disagreement. All of the industries that have significant single-days test in a specific model, are also significant cumulatively for that model. The MI in the Market Model also show cumulative significance despids no single-day significance. Interesting is that the models disagree completely on OG and MI (only significant in the Market Model) and PB and TL (only significant in the Average Model).

What is even more interesting is the disagreement in the direction of the unexpected turnover in some of the industries, yet both models flag as these days as significant. The TO and FS industries for the Average Model show positive unexpected turnover, whereas the Market Model claims it is negative. All this disagreement between the models provides little robustness to the results and therefore fails to provide evidence against or in favour of rejection of the null hypothesis. These results do however illustrate the importance of the joint hypothesis problem; we are testing for market efficiency as well as the validity of our models. In this instance, with little agreement between the models, we have found evidence to support rejection of the latter instead of the former. Therefore, these results must be interpreted with caution.

4.1.2.3 Subconclusion

The results of this event study suggest that the outcome of the referendum had an influence on prices and caused abnormal returns. The ME industry only showed abnormal returns on the day of the event itself, thus providing no evidence against the Efficient Market Hypothesis. The evidence from the other ten industries however all supports a rejection of the Efficient Market Hypothesis, due to abnormal returns on day 0 and +1, and for OG, LI, SS and FS even on the second day after the event as well. Exactly how intensely they responded to the event differs; OG, PB, TO and MI all obtained positive abnormal returns due to the event, whereas BA, SS, LI, TL, HH and FS all had negative abnormal returns following the news of the referendum outcome. Additionally, the findings show that several industries saw a little reversion of the movement in the cumulative abnormal returns on the second day after the event.

Opposite the robustness of the results just mentioned, the degree of disagreement in the models measuring unexpected turnover is more alarming. Therefore, we remain sceptical towards these results. Given the event being an economy-wide event, the market volume is also affected, which suggests a underestimation of the unexpected turnover and the Average Model's mathematical build up make it more likely to overestimate spikes in turnover ratio. This issue will be discussed further in the discussion. However looking at each model individually it is clear that something is happening with trade volume in the event window, and the two models do agree on positive unexpected turnover in BA, SS, LI, ME and HH, which could suggest some disagreement of the new price among the investors.

4.1.3 Official Triggering of Article 50

4.1.3.1 Abnormal Returns

Table 11. Abnormal returns, 3rd event Market Model

Market Model									
Official triggering of Article 50									
Event Window		OG			BA			PB	
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.003	0.238	0.637	0.000	-0.045	0.490	0.012	1.642	0.942
-1	0.008	0.677	0.788	0.007	1.175	0.900	-0.006	-0.857	0.154
0	0.007	0.643	0.784	-0.004	-0.568	0.247	-0.001	-0.186	0.425
1	-0.001	-0.052	0.517	0.002	0.378	0.645	-0.004	-0.495	0.286
2	-0.005	-0.461	0.305	0.000	-0.053	0.483	-0.004	-0.525	0.274
Cumulative	0.012	0.467	0.827	0.006	0.397	0.412	-0.003	-0.188	-0.653
Event Window		TO			MI			SS	
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.002	-0.237	0.375	-0.025	-1.404	0.077	0.000	-0.055	0.448
-1	-0.007	-0.867	0.143	0.012	0.662	0.753	0.002	0.376	0.656
0	0.010	1.183	0.896	0.005	0.293	0.641	-0.003	-0.752	0.197
1	0.000	-0.058	0.467	0.015	0.826	0.826	0.003	0.732	0.780
2	0.005	0.601	0.753	-0.010	-0.549	0.266	0.005	1.131	0.915
Cumulative	0.005	0.278	0.208	-0.003	-0.077	0.099	0.006	0.641	0.773
Event Window		LI			TL			ME	
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.002	-0.345	0.378	0.000	0.019	0.502	0.004	0.615	0.745
-1	0.003	0.415	0.676	-0.004	-0.563	0.270	-0.002	-0.381	0.332
0	-0.010	-1.464	0.058	-0.005	-0.737	0.201	-0.001	-0.163	0.417
1	-0.007	-1.079	0.143	0.002	0.330	0.625	0.004	0.758	0.822
2	0.000	0.057	0.529	0.003	0.507	0.687	0.013	2.257*	0.988*
Cumulative	-0.016	-1.080	-1.116	-0.003	-0.198	-0.334	0.018	1.380	1.254
Event Window		HH			FS				
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	0.005	0.642	0.749	0.000	-0.044	0.448			
-1	-0.008	-1.006	0.162	-0.004	-0.712	0.224			
0	-0.009	-1.121	0.135	0.010	1.662	0.950			
1	0.002	0.315	0.625	0.005	0.941	0.834			
2	0.000	0.026	0.502	0.004	0.625	0.749			
Cumulative	-0.009	-0.511	-0.508	0.014	1.105	1.098			

*Significant at a 5% significance level

Table 12. Abnormal returns, 3rd event CAPM

CAPM									
Official triggering of Article 50									
Event Window	OG			BA			PB		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.006	0.508	0.564	0.000	0.076	0.444	0.012	1.657	0.942
-1	0.011	0.955	0.764	0.008	1.299	0.876	-0.006	-0.843	0.154
0	0.010	0.911	0.745	-0.003	-0.449	0.205	-0.001	-0.172	0.425
1	0.002	0.206	0.444	0.003	0.490	0.595	-0.004	-0.480	0.286
2	-0.002	-0.200	0.224	0.000	0.064	0.432	-0.004	-0.511	0.274
Cumulative	0.027	1.064	0.376	0.009	0.661	0.081	-0.003	-0.156	-0.653
Event Window	TO			MI			SS		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	-0.002	-0.278	0.417	-0.020	-1.137	0.050	-0.001	-0.332	0.533
-1	-0.007	-0.910	0.162	0.017	0.946	0.714	0.000	0.094	0.722
0	0.009	1.145	0.903	0.010	0.562	0.525	-0.005	-1.027	0.263
1	-0.001	-0.093	0.502	0.019	1.088	0.749	0.002	0.470	0.857
2	0.005	0.564	0.772	-0.005	-0.287	0.205	0.004	0.866	0.934
Cumulative	0.003	0.192	0.400	0.021	0.524	-0.400	0.000	0.032	1.260
Event Window	LI			TL			ME		
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test
-2	0.000	-0.010	0.286	-0.002	-0.349	0.602	0.003	0.545	0.788
-1	0.005	0.752	0.583	-0.006	-0.941	0.367	-0.003	-0.456	0.371
0	-0.008	-1.127	0.054	-0.007	-1.101	0.290	-0.001	-0.232	0.444
1	-0.005	-0.752	0.100	0.000	-0.021	0.726	0.004	0.694	0.838
2	0.003	0.380	0.440	0.001	0.150	0.784	0.013	2.193*	0.988*
Cumulative	-0.005	-0.339	-1.615	-0.015	-1.011	0.418	0.016	1.227	1.447
Event Window	HH			FS					
	AR(t)	Patell	Rank test	AR(t)	Patell	Rank test			
-2	0.004	0.571	0.803	0.000	0.080	0.436			
-1	-0.008	-1.084	0.185	-0.003	-0.586	0.201			
0	-0.009	-1.191	0.162	0.010	1.783	0.946			
1	0.002	0.252	0.676	0.006	1.061	0.822			
2	0.000	-0.041	0.552	0.004	0.746	0.722			
Cumulative	-0.012	-0.668	-0.190	0.018	1.379	0.978			

*Significant at a 5% significance level

In Table 11 and Table 12, the results of the third event, the official triggering of Article 50, are displayed. These results show significant abnormal returns in the single-day test for day +2 for the ME industry. Aside from that, none of the other test-statistics are significant. The two models and the two test-statistics agree in all cases for the third event, which provides robustness to the results. That day +2 in the event window for the ME industry is the only test with significant results, could suggest that the returns on that day are randomly higher that the expected normal return or that some ME industry specific news reached the market on that day. In either case, the evidence do not support a rejection of the null hypothesis of efficient market around this event, based on the cumulative test results.

4.1.3.2 Unexpected Turnover

Table 13. Unexpected turnover, 3rd event Market Model

Market Model									
Official triggering of Article 50									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.744	-2,173*	0,019*	0.210	1.122	0.888	-0.161	-0.793	0.220
-1	-0.915	-2,675*	0,004*	0.103	0.551	0.761	-0.202	-0.994	0.158
0	-0.775	-2,265*	0,012*	-0.094	-0.502	0.301	-0.151	-0.742	0.239
1	-0.401	-1.171	0.097	-0.041	-0.220	0.432	0.046	0.228	0.637
2	-0.685	-2,001*	0,023*	0.015	0.080	0.556	-0.006	-0.028	0.533
Cumulative	-3.520	-4,599*	-3,655*	0.193	0.461	0.683	-0.474	-1.041	-1.110
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.230	-0.895	0.154	-0.286	-0.510	0.440	0.392	2,454*	0.969
-1	-0.276	-1.072	0.116	-0.781	-1.393	0.042	0.522	3,263*	0,992*
0	-0.187	-0.727	0.228	-0.758	-1.351	0.058	0.429	2,685*	0,977*
1	0.160	0.624	0.761	-0.741	-1.323	0.069	0.250	1.566	0.934
2	0.170	0.659	0.784	-0.806	-1.436	0.031	0.245	1.534	0.931
Cumulative	-0.363	-0.631	-0.713	-3.371	-2,689*	-2,897*	1.839	5,144*	3,589*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.099	-0.416	0.336	0.111	0.426	0.691	0.167	0.690	0.788
-1	-0.041	-0.171	0.448	0.205	0.788	0.819	0.234	0.963	0.865
0	0.303	1.271	0.923	0.168	0.646	0.768	0.027	0.112	0.610
1	0.227	0.954	0.865	0.127	0.487	0.718	-0.013	-0.053	0.529
2	0.450	1.889	0,985*	0.010	0.039	0.525	0.341	1.405	0.934
Cumulative	0.840	1.577	1.645	0.620	1.067	1.591	0.757	1.394	1.910
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	0.020	0.052	0.560	0.032	0.142	0.583			
-1	0.018	0.048	0.544	0.339	1.497	0.950			
0	-0.112	-0.293	0.409	0.125	0.551	0.737			
1	-0.247	-0.644	0.266	0.183	0.810	0.838			
2	-0.221	-0.576	0.282	0.227	1.000	0.873			
Cumulative	-0.542	-0.632	-0.683	0.906	1.789	2,307*			

*Significant at a 5% significance level

Table 14. Unexpected turnover, 3rd event Average Model

Average Model									
Official triggering of Article 50									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.728	-1.572	0.019*	0.226	0.607	0.768	-0.148	-0.455	0.270
-1	-0.764	-1.649	0.015*	0.259	0.696	0.803	-0.078	-0.240	0.359
0	-0.631	-1.362	0.042	0.054	0.146	0.622	-0.033	-0.102	0.429
1	-0.388	-0.837	0.193	-0.028	-0.075	0.479	0.057	0.174	0.583
2	-0.379	-0.817	0.201	0.330	0.889	0.865	0.245	0.750	0.834
Cumulative	-2.889	-2.79*	-3.162*	0.842	1.012	1.615	0.042	0.057	-0.039
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.217	-0.590	0.239	-0.273	-0.440	0.440	0.404	1.429	0.927
-1	-0.148	-0.403	0.293	-0.653	-1.053	0.166	0.635	2.246*	0.988*
0	-0.066	-0.178	0.448	-0.636	-1.026	0.189	0.537	1.900	0.969
1	0.171	0.465	0.710	-0.731	-1.179	0.085	0.260	0.920	0.838
2	0.428	1.163	0.907	-0.546	-0.881	0.251	0.474	1.678	0.946
Cumulative	0.168	0.205	0.153	-2.837	-2.048*	-2.133*	2.309	3.656*	3.378*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.084	-0.225	0.409	0.122	0.351	0.656	0.180	0.513	0.745
-1	0.100	0.267	0.602	0.317	0.911	0.915	0.357	1.017	0.884
0	0.436	1.163	0.915	0.275	0.789	0.876	0.144	0.411	0.687
1	0.239	0.637	0.764	0.136	0.391	0.668	-0.002	-0.007	0.514
2	0.734	1.958	0.981*	0.237	0.682	0.811	0.590	1.682	0.965
Cumulative	1.425	1.699	1.826	1.087	1.398	2.223*	1.269	1.617	2.018*
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	0.030	0.070	0.537	0.045	0.130	0.568			
-1	0.120	0.274	0.637	0.466	1.345	0.938			
0	-0.016	-0.037	0.498	0.246	0.709	0.795			
1	-0.238	-0.546	0.266	0.194	0.560	0.749			
2	-0.016	-0.037	0.490	0.484	1.397	0.942			
Cumulative	-0.120	-0.124	-0.111	1.436	1.853	2.325*			

*Significant at a 5% significance level

Table 13 and 14 display the results from the third event, the official triggering of Article 50 for the unexpected turnover. Comparing the two models, we see that they agree in the test statistics on a general level, although there are some different conclusions on a few of the cumulative Rank test statistics, as well as in the OG sector. Looking at the single-day test-statistics the Market Model displays significant negative unexpected turnover for day -2 (only Patell), -1, 0 and +2 for OG industry and a significant positive unexpected turnover for day -2, -1 and 0 for SS. The Average Model on the other hand shows generally less significant single-day results for OG it is only significant in day -2 and -1 (Corrado Rank test). SS has significant in the results of day -1. For both models we also see a significant unexpected turnover in day +2 of the event window for LI, both only for the Corrado Rank test.

The cumulative test-statistics seem to agree more between the two models, as both models contain significant cumulative results for OG, MI and SS, and for both the Patell and Rank test and in FS for the Rank test only. The Average Model also has two significant cumulative Rank test statistics for TL and ME. The significant results for the OG and MI industries display negative unexpected turnover, whereas the rest of the significant results are positive.

4.1.3.3 Subconclusion

In the third event we find no abnormal returns, except day +2 in ME, which is most likely caused by industry specific events. Regardless, since it is on the second day and it is the only significant result we observe, this suggests that we have no evidence to reject the Efficient Market Hypothesis. In the unexpected turnover Tables, however, we see significant test scores for the OG, MI and SS. We also see some in FS, TL and ME, but only for the Rank test, which we fear might not be accurate so we will not take these into account. The significant results for the OG and MI industries display negative unexpected turnover, meaning that this industries are traded less that the expected turnover, which does not support divergence in investor opinions, leaving only the SS industry that have positive unexpected turnover. This positive unexpected turnover suggests that there might be some disagreement among the investors, but it did not cause abnormal returns. Given that we only have significance in this industry and that the single-day significance lies primarily before the event, implies that it could be a result of a industry specific event, and not the official triggering of Article 50.

The conclusion on the third event is that we cannot reject the hypothesis of efficient markets and investor agreement due to the official triggering of Article 50, which presents the same scenario as in event 1. Again, maybe the event is anticipated and therefore did not provide new information to the investors.

4.2 Cross-Sectional Analysis

It is now established that there are abnormal returns around the second event with high robustness in the results, yet the event study of unexpected turnover did not seem to have robust results, due to large disagreement between the two models. It was however expected that the Average Model might overestimate the effect while the Market Model would underestimate it, given that it was a market-wide event.

This analysis therefore examines if the market-wide events have an effect in the trading activity, measured in terms of turnover ratio, and not unexpected turnover to avoid biased results due to different estimations of expected turnover. To do so we use the ordinary least square regression presented in equation (13) in the methodology. We do this to test the following hypothesis for each of the industries:

$$H_0 = The\ market\ wide\ events\ do\ not\ have\ an\ increasing\ effect\ on\ the\ trading\ activity$$

4.2.1 Assumptions of the Model

Before applying the model, we need to test the assumptions of a multivariate regression, which state that:

- Linearity in variables, meaning the relationship between the dependent and independent variables should be expected to be linear.
- The error terms are identical and independently distributed, and follows a normal distribution .
- The error terms have constant variance, also known as homoscedasticity.
- The error terms are uncorrelated, meaning they should not display any serial correlation.
- The independent variables display no multicollinearity (Newbold, Carlson & Thorne, 2013)

To control for the assumption of linearity in a multiple regression, we make a scatter plot of the regressions standardized residuals against each of the independent variables in the regression. This is done for all the eleven industries. None of the scatter plots show a clear nonlinear pattern. The scatter plot of one industry, OG, can be seen in Appendix 2. The scatter plots for the other industries look similar, and do not show any nonlinear patterns either. Therefore, we can conclude that the assumption of linearity holds for all the regressions.

When testing the above assumptions, we found that the error term was not normally distributed due to heteroscedasticity in the variance for the industries FS, BA and HH, with a 5 % significance level. The testing was done using the test originally by Breusch & Pagan (1979), a test that was later improved Cook & Weisberg (1983), that tests for the homoscedasticity in the error term. We likewise found evidence of serial correlation for all industries, except BA, by using the Breusch-Godfrey test of serial correlation by Breusch (1978) and Godfrey (1978).

To test for multicollinearity we compute the correlation between the independent variables for each industry. A correlation above an absolute value of 0.7 should give rise to a concern that the two variables cannot be considered as independent variables. A correlation above the absolute value of 0.8 would suggest some collinearity and should therefore be omitted from the analysis (Hair et al., 2010). The correlations vary within [-0.6719; 0.1706] across the different industries, thereby confirming there is no multicollinearity between the variables.

To get around the concern of heteroscedasticity in some of the industries and serial correlation in almost all industries, we use a Newey-West variance estimator. The Newey-West estimates the variance of the coefficients of the regression, taking heteroskedasticity and serial correlation into account (Stock & Watson, 2012). This provide us with a variance and therefore also a test statistic that is robust to heteroscedasticity and auto/serial correlation in the time series, solving our issue so that we can continue with the regression.

4.2.2 Findings

The result of the final regression and the test statistics (here p-values), calculated based on the Newey-West variance estimator can be seen in Table 15.

Control variables β1, β2, and β3 (one day prior returns, and one year prior average returns, and one day prior turnover ratio as control variables, respectively) show that all industries have an autoregressive aspect in determining the level of trade, and most take long term price developments into account, yet the one day prior returns have little impact on the turnover ratio.

Dummy variable coefficients β4 (official announcement of the referendum), β5 (results of the referendum), and β6 (triggering of Article 50) indicate whether each of the events has an effect on the turnover ratio. With no significant results for either β4 and β6, we cannot reject the null hypotheses, thus we cannot say that event 1 and event 3 had an impact on the turnover ratio for any of the industries. This confirms our earlier suspicions that any significant unexpected turnover for these events in the prior event studies may have been caused by industry-specific events, or due to faulty modeling.

Table 15. Regression results multivariate regression equation (13)

	α	β_1	β_2	β_3	β_4	β_5	β_6	R^2
OG	-0.021	-0.062	-0.341	0.437	0.264	0.360	0.072	0.529
	(0.595)	(0.115)	(0.000)*	(0.000)*	(0.401)	(0.248)	(0.815)	
BA	-0.029	-0.006	-0.128	0.480	-0.092	1.620	0.174	0.391
	(0.526)	(0.898)	(0.008)*	(0.000)*	(0.798)	(0.000)*	(0.633)	
PB	-0.013	-0.054	-0.168	0.416	-0.180	0.952	0.091	0.283
	(0.799)	(0.267)	(0.001)*	(0.000)*	(0.646)	(0.017)*	(0.817)	
TO	-0.019	-0.048	-0.157	0.485	0.035	0.883	0.241	0.344
	(0.693)	(0.312)	(0.002)*	(0.000)*	(0.926)	(0.019)*	(0.516)	
MI	-0.010	0.113	-0.301	0.528	0.246	0.180	-0.166	0.633
	(0.781)	(0.001)*	(0.000)*	(0.000)*	(0.386)	(0.517)	(0.551)	
SS	-0.017	-0.039	0.127	0.473	0.025	1.117	0.012	0.297
	(0.731)	(0.44)	(0.013)*	(0.000)*	(0.949)	(0.006)*	(0.976)	
LI	-0.031	0.025	-0.127	0.542	-0.194	1.416	0.443	0.429
	(0.481)	(0.571)	(0.007)*	(0.000)*	(0.575)	(0.000)*	(0.208)	
TL	-0.017	-0.047	0.011	0.468	-0.295	1.207	0.268	0.283
	(0.733)	(0.359)	(0.822)	(0.000)*	(0.449)	(0.003)*	(0.496)	
ME	-0.014	0.018	0.023	0.504	-0.192	1.292	-0.036	0.309
	(0.777)	(0.715)	(0.636)	(0.000)*	(0.619)	(0.001)*	(0.925)	
HH	-0.010	0.082	-0.131	0.573	-0.282	1.510	-0.276	0.482
	(0.807)	(0.058)	(0.005)*	(0.000)*	(0.402)	(0.000)*	(0.402)	
FS	-0.035	-0.025	0.065	0.477	0.547	0.919	0.396	0.276
	(0.487)	(0.621)	(0.198)	(0.000)*	(0.165)	(0.026)*	(0.311)	

*Significant at a 5% significance level

With significant positive results for β5 for most industries (except OG and MI), there is evidence to reject the null hypothesis for these industries. This supports the notion that the outcome of the Brexit referendum caused investors to engage more in trading activity than on non-event days. Because turnover is used as a proxy for divergence in investor opinions on the value of a security, this implies that the information contained in the event caused investors to disagree more. The LEAVE-outcome was not only unexpected, but also opened up a range of different scenarios for the future state of the economy, increasing uncertainty and creating room for disagreement. The insignificant results for the OG and MI industries fall in line with the neutral implications of a possible Brexit that were expected for these industries. Because Brexit is not likely to have major negative or positive impact on both OG and MI, investors did not need to incorporate this new information in their opinions in a way that may lead to disagreement, and as a result they did not have to trade significantly more or less following the outcome.

If we compare the results of event 2 to the results for event 1 and 3, which show no significance, we can infer that these events did not hold new information that could have caused disagreement, and they were perhaps already anticipated by investors. We will further discuss the notion of the informational aspect of events in the next chapter.

4.3 Informedness and Consensus

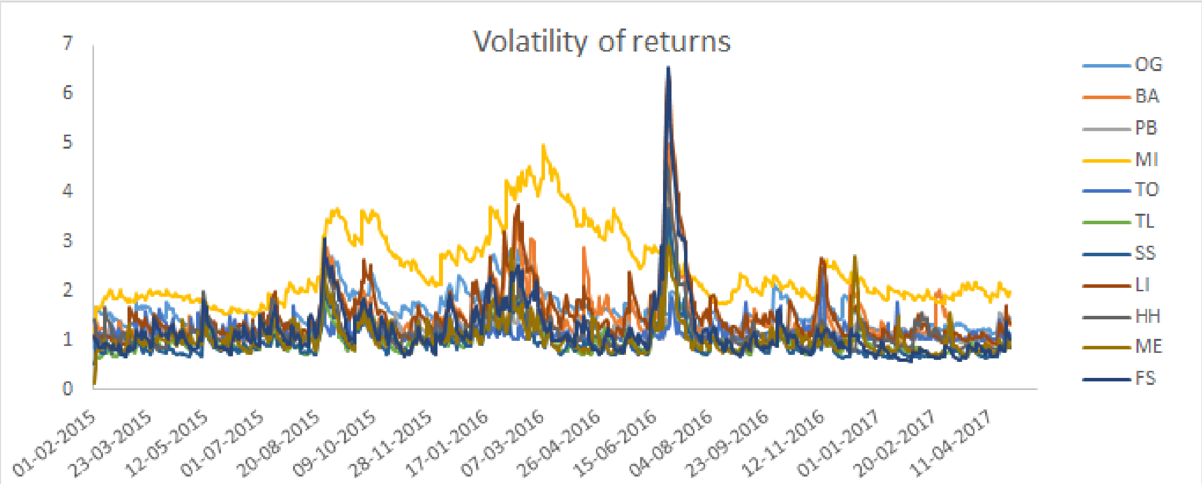
Now that we have established a positive significant relationship between the results of the referendum and the turnover ratio, indicating disagreement between investors, we can focus on the potential source of this disagreement. The following section will address two possible drivers for divergence of opinion: heterogeneous information and heterogeneous beliefs. The former by testing for support of the Sequential Information Arrival Hypothesis and the later by testing the null hypothesis of consensus among the investors.

4.3.1 Sequential Information Arrival Hypothesis

4.3.1.1 Estimating Volatility of Returns

As described in the methodology, the volatility of returns is not a directly observable variable and thus needs to be estimated. This estimation of the returns volatility is done using equation (14) for each of the different industries.

Figure 8. Volatility of returns



The above graph in Figure 8 displays the estimated volatility of the returns. The graph shows the volatility of all the industries except MI follow a similar pattern, that has a stable level over the time period and seem to experience spikes in the volatility at the same times, especially around the referendum in the end of June 2016.

4.3.1.2 Stationarity and Correlation

Stationarity is a requirement of the Granger Causality test and the Vector Autoregressive model (VAR), which is used to perform the Granger Causality test that will use to test the SIAH. If the time series are not stationary, it is impossible to conclude if trading volume holds a predictive power over volatility, since future values will differ from effect of the past and vice versa. There are two requirement that need to be fulfilled for time series to be stationary (Diebold, 2006).

- Stable mean over time
- Stable variance over time

To test for stationarity we use the Augmented Dickey-Fuller test (ADF). The ADF presented by Dickey & Fuller (1979) is a model to test the null hypothesis that a unit root is present in the time series. If one rejects the null hypothesis of a unit root in the time series, you can accept the time series as stationary.

For each of the eleven industries we have two time series, one for the estimated volatility of returns (Vol) and one for the trading volume measured by the turnover ratio (TO). This leaves twenty-two time series that we test for stationarity. When running the ADF we are able to reject the null hypothesis of a unit root in the time series in twenty-one out of the twenty-two cases, with a 5 % significance level. The only time series that we cannot accept as stationary is the volatility of the returns of the MI (MI_Vol). By taking the first difference of the time series, it is possible to transform it into a stationary process. To verify that the MI_Vol is now stationary, we run the ADF test again and can now confirm that we can reject the null hypothesis at a 5 % significance level. All variables is now stationary and can thus be used in the further analysis.

Another requirement of the VAR model, a model we will explain further in the next section, is that it assumes no perfect multicollinearity (Stock & Watson, 2012). If two time series exhibit perfect multicollinearity it means that one variable explains the other variable perfectly linearly. A way to check for multicollinearity is by computing the correlation between the variables. Again, correlation above an absolute value of 0.7 should give rise to a concern that the two variables cannot be considered as independent variables, and a correlation above the absolute value of 0.8 would suggest some collinearity and should therefore be omitted from the analysis (Hair et al., 2010). We therefore compute the correlation between each set of variables, hence the correlation between OG_Vol and OG_TO, BA_Vol and BA_TO, and so on for each industry. The computed correlations lie between [0.1380; 0.5889] which implies that the requirement of no perfect multicollinearity is satisfied.

4.3.1.3 Granger Causality

To test the Sequential Information Arrival Hypothesis, we use the linear Granger Causality test that is given by equation set (15) as stated in the methodology. The VAR model in equation (16) was used to find the number of lags to use in the Granger Causality test, the optimal number of lag is settled by the AIC, and depending on the industry it is determined at 2 to 4 lags, a overview of the specific lag per industry can be seen in the Appendix 3.

The result of the Granger Causality test can be seen in Table 16, presented below.

Table 16. Granger Causality test results

Granger Causality	χ^2	P-value	Granger Causality	χ^2	P-value
OG_TO —> OG_Vol	49.168	0.000*	OG_Vol —> OG_TO	17.748	0.000*
BA_TO —> BA_Vol	81.463	0.000*	BA_Vol —> BA_TO	3.399	0.334
PB_TO —> PB_Vol	42.711	0.000*	PB_Vol —> PB_TO	0.961	0.811
TO_TO —> TO_Vol	34.144	0.000*	TO_Vol —> TO_TO	3.780	0.286
MI_TO —> MI_Vol	45.644	0.000*	MI_Vol —> MI_TO	11.374	0.023*
SS_TO —> SS_Vol	15.864	0.000*	SS_Vol —> SS_TO	0.761	0.684
LI_TO —> LI_Vol	105.840	0.000*	LI_Vol —> LI_TO	6.106	0.191
TL_TO —> TL_Vol	38.289	0.000*	TL_Vol —> TL_TO	2.660	0.447
ME_TO —> ME_Vol	48.395	0.000*	ME_Vol —> ME_TO	6.981	0.137
HH_TO —> HH_Vol	39.174	0.000*	HH_Vol —> HH_TO	1.114	0.774
FS_TO —> FS_Vol	22.325	0.000*	FS_Vol —> FS_TO	3.623	0.459

*Significant at a 5% significance level

The left panel of Table 16 shows that for all the industries we detect Granger Causality running from turnover ratio (measuring trading volume as a proxy of information) to volatility of returns (measuring price) at a 5% significance level. The right panel only shows significant Granger Causality running from volatility of returns to turnover ratio for OG and MI industries. This means that these two industries display a bidirectional relationship, the so-called feedback relationship, while the other industries only display a unidirectional relationship.

The industries displaying a unidirectional lag-lead relationship support Copeland's (1976) Hypothesis of Sequential Information Arrival, as new information disseminates to one investor at the time. As this investor adjusts his beliefs and position according to his new demand function, prices change to reach a temporary market equilibrium until each investor has become informed. The evidence supporting the SIAH suggests that these markets consist of both informed and uninformed investors at a given time t in the period leading up to and following the referendum. As the Hypothesis assumes that the information arrival is random, such as no investor knows who is informed and uninformed, we can only conclude there is evidence that they simply trade on different information sets.

Copeland's (1976) SIAH did not allow for uninformed traders to learn the existence of the new information from volume and price changes, thus preventing speculative chart trading. Adding this option to the hypothesis (as Hong & Stein (1999) do with their gradual-diffusion-model) explains for a bidirectional relationship, where Granger Causality also runs from volatility in returns to turnover ratio, as investors adjust their demand functions in response to price changes rather than to actual information. We observe this relationship only for OG and MI, suggesting these sectors are more sensitive to speculative investment.

4.3.2 Consensus Effect

Table 17 shows the unexpected turnover for the result of the referendum, when calculated as a function of positive and negative returns, as proposed in equation (17). The Patell and Corrado Rank test statistics used to indicate significance are composed in similar fashion to those of the previous event studies regarding abnormal returns and unexpected turnover of section 4.1. The tables for event 1 and event 3 showed very little significance and since these events have shown not to have an effect on turnover ratio in section 4.2, we will focus solely on event 2 in this analysis. The result tables of events 1 and 3 can be found in Appendix 4.

Table 17. Consensus effect, 2nd event

Consensus model									
Result of British referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.187	-0.435	0.344	0.500	1.447	0.923	0.445	1.445	0.927
-1	-0.576	-1.340	0.039	0.416	1.204	0.907	0.328	1.065	0.873
0	0.632	1.432	0.919	1.059	2,986*	0,985*	1.042	3,293*	0,992*
1	0.069	0.159	0.645	1.001	2,851*	0,981*	0.882	2,817*	0,988*
2	-0.225	-0.520	0.286	1.162	3,345*	0,992*	0.385	1.241	0.903
Cumulative	-0.286	-0.315	-0.418	4.137	5,292*	3,565*	3.083	4,41*	3,402*
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.141	0.425	0.695	0.207	0.393	0.641	0.335	1.240	0.927
-1	0.204	0.614	0.757	-0.063	-0.119	0.502	0.089	0.329	0.649
0	0.820	2,402*	0,985*	0.818	1.513	0.923	0.904	3,263*	0,996*
1	0.367	1.087	0.896	0.694	1.297	0.880	0.602	2,194*	0,977*
2	0.336	1.005	0.869	0.094	0.178	0.587	0.666	2,452*	0,988*
Cumulative	1.868	2,474*	2,65*	1.750	1.459	1.609	2.595	4,239*	3,174*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.235	0.684	0.764	-0.111	-0.325	0.290	0.182	0.542	0.757
-1	0.571	1.665	0,977*	0.266	0.780	0.853	0.264	0.784	0.826
0	-0.174	-0.495	0.266	0.589	1.684	0.969	1.026	2,967*	0,988*
1	0.247	0.708	0.788	0.379	1.096	0.931	0.953	2,786*	0,981*
2	0.575	1.666	0,981*	0.710	2,073*	0,977*	0.863	2,547*	0,977*
Cumulative	1.453	1.891	1,988*	1.834	2,374*	2,367*	3.288	4,305*	3,162*
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	0.087	0.205	0.591	-0.024	-0.073	0.471			
-1	0.112	0.265	0.610	-0.081	-0.252	0.390			
0	0.403	0.926	0.865	-0.584	-1.760	0.023			
1	1.303	3,028*	0,988*	-0.376	-1.145	0.077			
2	1.432	3,361*	0,992*	0.051	0.156	0.579			
Cumulative	3.337	3,482*	2,41*	-1.015	-1.375	-1.495			

*Significant at a 5% significance level

The Patell and Corrado Rank test-statistics in Table 17 are mostly in agreement on the conclusion of significance of the unexpected turnover. The two statistics agree on 15 out of 17 single-day significant unexpected turnover levels, and on 7 out of 8 cumulative results. The limited amount of conflicting observations also all occur in the same industry, LI. This consistency provides some robustness to the results of the test.

Industries that are displaying significance range in intensity. First, the BA, SS, and ME industries all show consecutive significant positive values on day 0, day +1, and day +2 of the event window. The second set of industries consists of PB and HH, and shows significant positive results for two days, day 0 and day +1, and day +1 and day +2 respectively. In the last set, TO shows significance only on day 0, and TL only on day +2. All these industries also show significant positive results for the cumulative unexpected turnover during the event window. Therefore, all these industries support a rejection the null hypothesis of agreement among investors. This suggests that there is evidence of the consensus effect in these industries; i.e. there is evidence of heterogeneous beliefs among investors.

The sectors OG, MI, and FS show no significance at all, and can therefore not reject the null hypothesis. Investors in these sectors have similar interpretations of the new information.

Consistent significant results all occur on or after the 24th of June, the first trading day after the referendum results. This indicates that in the days leading up to the referendum, investors showed little divergence in their interpretation of any information related to expectations about the future. After the 23rd of June, however, the news that Brexit was really going to happen and the uncertainty on which shape would take, increased heterogeneity in beliefs amongst investors.

Several sectors show significant results beyond day 0, which indicates a continued lack of consensus and thus support a rejection of the notion that all investors should be able to learn the exact nature of information from movements in the price quickly.

Both TL and HH show significant positive results, but unlike the other industries, they do not start doing so on day 0. This suggests that investors in these industries initially showed similar interpretations of the new information, but diverged afterwards. A possible explanation for this phenomenon is that HH and TL are industries that are heavily affected by the state of other sectors, and as developments in other sectors deviated from initial expectations, investors who first shared homogeneous interpretations may have changed their beliefs according to this additional information.

4.3.3 Subconclusion

The results in Table 16 shows support for the SIAH, as there is significant Granger Causality running from turnover to volatility of returns in all industries. This indicates that informed investors and uninformed investors operate in the market at the same time, and there is a flow of information that gradually reaches each uninformed investor. Lack of a feedback relationship in most sectors suggests that uninformed investors do not learn from the change in price resulting from increased trading activity by informed investors. This suggests that there are no speculative chart traders active in these industries.

As informed investors adjust their trading activity and the price changes accordingly, the new information is captured in the return. After adjusting the expected turnover for this trading activity captured by positive and negative absolute returns, Table 17 shows the remaining unexpected turnover, which contains the trading activity caused by heterogeneous beliefs among investors. Here, we find evidence that not all investors interpret information in a similar fashion, as we see significant positive unexpected turnover caused by lack of consensus for several sectors, with varying degrees of intensity starting after the news of the outcome of the referendum.

5. Discussion of Findings

In this chapter we will discuss our empirical findings in a broader perspective. First, we will compare the expected results of the Brexit on the individual industries and our findings, and analyse the differences. Second, we will look a behavioural biases that can explain our findings while reviewing the informational contents of the events, and finally we will discuss how our findings can be relevant for future events with similar characteristics and uncertainty.

5.1 Expected Results vs. Real Results

The 24th June 2016 was the first trading day after the final results on the Brexit referendum came out the night before. As seen in the analysis so far, the second event in our study is the event that caused most reaction in the equity market.

For the industries BA, SS, LI, TL, HH and FS, we see that they all experienced abnormal negative returns due to the outcome of the referendum. A negative response for BA, LI and FS was expected if the outcome of the referendum became LEAVE. Like described in section 2.2.1.1, a yes to leaving the EU would put them at risk of leaving the European single market and its passporting rights, which could lead to lack of liquidity, increasing cost, and potentially a need to move UK subsidiaries to a new country within the European Economic Area. For SS, TL and HH, a negative response was also expected as a potential ripple effect caused by a weakened pound makes imported goods more expensive. High import cost affects especially industries like non-food consumer goods and industrial products, but also food since a quarter of consumed food in the UK is imported, causing the public purchase power to decrease.

The negative response observed for these industries however, was not only on the day of the event but also the following day(s), as well as cumulatively over the event window. This supports the alternative hypothesis of inefficiency in the market. Looking at the unexpected turnover for these industries, we see that despite high disagreement between the two models, in general, they do agree regarding the industries BA, SS, LI and HH, where the results display cumulatively significant positive unexpected turnover in the event window. This suggests significant disagreement on the price among the investors, even though the abnormal returns was negative as expected. Again, this supports the alternative hypothesis of inefficiency in the market. Positive unexpected turnover does suggest the potential of an informedness effect, where stocks are not traded on the same information set, and/or a consensus effect. We find evidence for both. A significant lag-lead relationship running from turnover to volatility of returns for all industries during the Brexit process suggests a dispersed information flow. Additionally, industries BA, SS, and HH all show significant unexpected turnover in the consensus model, suggesting that investors do not agree on the impact of the news or maybe not on the magnitude of it.

For the last two industries, TL and FS, the unexpected turnover models in section 4.1.2.2 provided inconclusive results so we cannot with a 5% significance level conclude on the event's effect on the unexpected turnover. However, when subtracting the sum of the expected liquidity trading and informedness effect in the consensus model, we find significant positive results. This suggests investors did not have homogeneous beliefs as to the effect of the outcome of the referendum in the TL industry. On the other side, we found no evidence against homogeneous beliefs between investor for FS.

For the two industries OG and MI, the expectations in section 2.2.1.1 were rather neutral towards the prospect of potentially leaving the EU. Due to the high export exposure to EU for the MI industry, deregulation of the market will not affect much, as firms will have to stick with EU standards, if they want to maintain the export. The biggest threat long term to MI is on the R&D cooperation between the EU and the UK, the magnitude of this potential threat is uncertain. Likewise, OG deregulation would not affect the industry as the government pre-Brexit had kept tight control of its energy policies and regulations. Leaving the EU means potentially trading under WTO if no deal is made, this is likewise not expected to have an effect on the industry as WTO poses no tariffs on basic oil sold to EU.

The results of the event study showed significant positive abnormal returns for both OG and MI not just on the day of the event, but also on the day(s) following, as well as cumulatively, all supporting an rejection of the null hypothesis. Therefore, despite an expected neutral response to the referendum results of leaving the EU, they both responded positively to the news. Reasons for this could be as stated in sector 2.2.1.1, that most firm in MI make their money in dollar terms, meaning a weakened pound due to the LEAVE-outcome would be considered favourable and the general uncertainty caused by the results could strengthen the gold price. Another reason for both OG and MI could simply be that since these industries were expected to not be affected by the outcome of the referendum, then became attractive for risk-averse investors as they would not be affected by the uncertainty Brexit would cause. The unexpected turnover around the event did not provide clear results as the Market Model claimed negative unexpected turnover yet the Average Model concluded that there was no unexpected turnover in the event window. Which of the results are true we cannot say, however the evidence does not suggest that the investors disagreed on the price since the actual turnover was lower or as expected. This is confirmed in the consensus model, where we do not find evidence against homogeneous beliefs among investors for these industries, also the cross-sectional analysis shows no significant impact on the trading activity for these two industries during this event.

The results for TO and PB both showed significant positive abnormal return for day 0 and +1 as well as cumulatively in the event window, despite the expectation for both industries being negative. This was due to potentially very high tariff on tobacco if no agreement is made and trade falls under WTO. This is not the case for PB, since WTO has no tariff on any pharmaceutical product. The reason for their expected negative response was instead that they would no longer have access to the single market, making clinical trials harder and more costly. To continue sale to the EU the approval process of new medicine or devices would become more challenging, as firm might have to apply for approval in both UK and EU. So the fact that TO and PB show positive abnormal returns, is a surprising result. A result that support the alternative hypothesis of an inefficient market. Both TO and PB show significant evidence for the consensus effect, thus suggesting that investors in the market are also in disagreement about the interpretation of the Brexit referendum results in these industries.

For the TO industry, the positive abnormal returns can might be explained by the Tobacco Products Directive (2014/40/EU) that should be applicable in the EU Member States on May 20 2016. The directive bans flavored tobacco like menthol cigarettes, and requires standardized packages with a minimum of 65% health warnings labels. Additionally, it prohibits internet sales and misleading promotions etc. (European Commission, n.d.). UK specific legislation built on this directive, but due to legal challenges, not all rules had come into force already on the day of the referendum. So this specific outcome of the referendum could be seen as positive for the TO firms as it provides a chance that remaining restrictions will the not come into force.

The unexpected turnover in the event study for TO and PB displays inconclusive results as the Market Model find no significant result, and the Average Model find significant positive unexpected turnover. Therefore based on these findings we cannot unequivocally conclude on the presence of unexpected turnovers around the event. However, as mentioned, we did find evidence of informedness and consensus effect, meaning both abnormal returns and trading volume support rejection of the EMH for these industries.

The last industry, ME, we found no clear expectation for the impact on the industry in case the result of the Brexit would become LEAVE. The analysis of the abnormal return shows that it was only significantly negative affected on the event day itself, suggesting that the null hypothesis holds for this industry, as it quickly adjusted to the news of the referendum. Regarding the unexpected turnover both models agrees that ME are cumulatively positive significant, this suggest that investors have disagreement on the price in the event window, which could be expected since we found no clear expectation as to the impact of Brexit on the industry. This is however in violation of the assumption on rational investor in the Efficient Market Hypothesis, supporting a rejection of the hypothesis. Additionally, a closer look at the results of the consensus model also shows that ME has significant unexpected turnover when modified for informedness, indicating lack of consensus between investors.

The first event February 20, 2016, when it was officially announced that there would be a referendum, the analysis of the abnormal return around this event showed some significance on single-days for the industries like MI, LI, HH and FS. However, further analysis showed that industry specific information, not related to the official announcement of the referendum, reached the market for most of these industries in the event window. News like a new insurance directive for European Commission that came into force, the Bank of England and Financial Services Bill that passed through the Committee stage in the house of Commons, and high copper prices affecting the MI industry. So only HH showed significant abnormal return on the day of the event that could not be obvious attributed to any other noticeable news in the period. The returns for HH, however, quickly adjusted to the new suggesting along with the evidence for the rest of the industries that the event do not support a rejection of EMH. Regarding the unexpected turnover in the event window, the two models do not provide conclusive results for most of the industries. For FS, both models suggest some positive unexpected turnover, which given the industry specific news in the event window most likely also is connected to that. For OG, BA, PB and HH the models do seem to agree that they do not experience unexpected turnover, so the first event do not support disagreement on the price between the investors.

When the official triggering of Article 50 occurred, it appear to have no significant effect on the abnormal returns, as only ME is effected on day +2. Since it is the only industry affected and only on the second day after the event, it suggest that it also here might be some industry specific news affecting the returns and not our event. For the unexpected turnover in the event window, the models agree there are significant positive unexpected turnover for SS, suggesting here a violation of the assumption of EMH of rational investors. Yet, for the rest of the industries there appear no support for this violation and the abnormal returns do not support rejecting the EMH.

Therefore, the first and third event do not seem to produce abnormal returns or unexpected turnover, suggesting either efficient market or simply lack of new information content in the events.

5.2 Behavioural Biases and Information Content

Expected fundamental trading results from investors' needs for liquidity and portfolio diversification, and occurs continuously in the market. Unexpected trading volume occurs when new information enters the market that leads investors to from different opinions on the implications of this new information. We treated all our events as equal when we tested for abnormal returns and unexpected trading volume, but found consistent lack of significant results for event 1 and 3 to not support a rejection of the EMH, yet event 2 did show evidence to do so. To further understand this difference, we turn to the information content of our events and analyse our results with a behavioural perspective, specifically the element of surprise and the complexity of the new information.

The announcement of the referendum was an unplanned event, since there was no guarantee it would happen on that exact moment. The set date of the referendum might have been irreversible, but the fact that there would be a referendum had no direct instant impact on the status quo. At this stage, there was still a very realistic scenario in which a majority of the voters could have voted to remain in the EU, and thus nothing would change. Additionally, the exact moment at which the information became public may have been unplanned, but prior developments in the negotiations between the UK and the EU that preceded the announcement, were already indicating an agreement was not going to be reached. Therefore, the financial market could have already anticipated the event to happen in the near future, and this specific event held no new surprising information large enough to make an impact on the market at all. Instead, by not responding at all, investors showed conservatism behaviour. A fully rational investor would have had to update his probabilities at least a little, because the possibility that there would not even have been a referendum, however small it was before, was now completely eliminated.

The outcome of the referendum shows quite the opposite circumstances. The date for the polling was planned, but the outcome was unexpected and would lead to a big change in the status quo. This resulted in a situation where surprising new information entered the market, and the content of this information was that big changes in the economy were ahead, yet it remained undefined exactly how the future would be affected. This news was not only surprising, thus demanding a lot of attention and exposure to overweighting, but also highly complex. This may lead not only to incorrect, irrational, valuations, but also largely divergent beliefs as investors are heterogeneous in their degree of susceptibility towards attention biases and the information set they have acquired. Therefore, these characteristics could explain the high levels of abnormal returns, as well as unexpected trading volume. The complexity of the information also provides an explanation for the continued positive (negative) levels in abnormal returns from day 0 to day +1 (Figure 7). The EMH states that all new information should have been incorporated in the new price instantly, thus being captured in the closing prices of day 0 and prices should remain stable at this new level afterwards. Instead, we can observe an continued abnormal returns, suggesting the possibility of herd behaviour, where investors are uncertain about their own valuation and imitate others instead, thus continuing an upward (downward) trend with extended abnormal returns. On day +2, a reversal towards the initial value can be observed for most industries through a decrease in cumulative abnormal returns, suggesting again evidence of an initial "panicked" overreaction on day 0 and day +1.

In contrast again, a similar pattern to that of event 1 can be observed for event 3, the official triggering of Article 50. Again, by not responding, investors show signs of conservatism, as they did not accurately update their valuations according to the new situation where the chance of not having a Brexit was officially completely eliminated. However, it is debatable if this possibility still even existed. The UK government had already promised to honour the outcome of the referendum, regardless of what this outcome would be. Therefore, once it became clear the majority of UK voters had chosen to leave the EU, investors had quite a guarantee this would indeed happen, and that the UK government would make this outcome official. Hence, the event of the official triggering held little new information about the future, and this information cannot be considered a surprise. Additionally, it was announced on the 20th of March already that the UK would deliver the official letter of withdrawal on the 29th of March. That means that this event was both planned, held no surprising outcome, and did not change the status quo, and can therefore be considered as non-informational at all.

The importance of information content is also suggested in the results of the Granger Causality test of section 4.3.1. We find consistent evidence for a lag-lead relationship running from volume to returns across all industries, yet little evidence for a bidirectional causality. The arrival of new information (proxied by trading volume) results in investors to adjust their demand functions, causing a shift in the market equilibrium and a new price, but that price change does not result in additional trading volume. This may suggest that during the Brexit process, instead of technical chart trading on observable price movements, investors mainly traded on actual news. This analysis however is in disagreement with the notion of herding behaviour, which would have suggested that investors imitate trading behaviour of other investors and thus continue price trends. This would have called for Granger Causality to run from price volatility to volume.

Instead, with the focus on information being so strong yet the complexity of the situation so high, investors may have applied different biases throughout the Brexit process. One could argue that during event 1 and event 3, investors had already been exposed to a first impression, and anchored their opinions from there. If this first impression was already that the referendum was going to be held and the UK Government would trigger Article 50 as promised, then any official confirmation did not require any adjustment. Therefore, they displayed the Anchoring and Adjustment heuristic. In contrast, a combination of the Anchoring and Adjustment heuristic with the Cognitive Dissonance Theory and Selective Attention heuristic, can explain a continued overreaction to event 2. After the initial surprise, investors had set their first impression too extreme and used this anchor point to further adjust. Afterwards, by mostly paying attention to news that confirmed this standpoint, adjustments were initially made in continuation of the overreaction, instead of towards a reversal.

5.3 Implications for Similar Events

Negotiations of the terms of the split between the EU and UK are still ongoing and the UK will at the earliest leave the EU on March 29, 2019; exactly two years after the official triggering of Article 50. However before leaving the EU, a withdrawal agreement needs to be made. According to multiple unofficial sources the chief negotiator for the EU Michel Barnier set the deadline for submission of a Withdrawal Agreement to October 2018, more specifically the 18th-19th October (Colson, 2018; Reuters Staff, 2018).The hope is that by this time they have a set of legal terms for the divorce between the EU and the UK and a political declaration stating the future relationship, like potentially a new trade agreement. The submission of a withdrawal agreement would not mean a finalized deal, as both the House of Commons in UK and EU Council would have to agree to it afterwards (Colson, 2018). A submission and presentation of a withdrawal agreement and political declaration could potentially have a large impact on the stock market.

We can compare it to the outcome of the referendum. In that event, investors knew when the referendum would take place, as they now know when to expect an announcement of a withdrawal or a statement that an agreement is not reached, stating the UK will not split with EU in March 2019. Either way it would affect the stock market as it holds new information, the degree to which it will be affected depends on the terms of the agreement. If the terms of the agreement are surprising, we argue earlier that if the information content of the new information was unexpected it should be expected to see high levels of abnormal returns in the following days along with increased trading activity and an overreaction to the news by the investors. As of March 2018 a transition deal has been made between UK and EU, stating that after UK officially leaves the EU the 29th of March 2019, there will be a transition period running until December 31, 2020, where UK will still be under EU rules and regulations (Blitz, 2018). Deals like this set the expectations to the final withdrawal agreement, and is therefore likely to be incorporated into the price as they are announced. However as the motto of the negotiations has been “Nothing is agreed until everything is agreed”, there is still a small possibility that this transition agreement could be altered in the final withdrawal agreement (Blitz, 2018), which would suggest there are potential for the announcement of the withdrawal agreement to become a surprise full event, just like the outcome of the referendum. On the other hand, if the terms of the agreement are as expected, then the agreement will present no new information. In response, the market might only adjust to the new certainty it will bring, but it will most likely not display high levels of abnormal returns or trading activity, like with the third event in the analysis.

The continued Brexit process is not the only set of events that show similar characteristics as the events in this study. As discussed in section 2.2.1.3, economic policy uncertainty elevates in a multitude of scenarios, such as the US Presidential elections. The 2016 election saw the victory of President Trump, and the markets responded accordingly. The unexpected outcome, combined with the substantial difference in economic policies between the two candidates especially regarding potential tax cuts, resulted in a lot of uncertainty on the market. With the Presidency and Congress in Republican hands, suddenly significant tax reductions for corporates were to be expected. At the same time, internationally oriented firms faced increased uncertainty about Trump’s ambiguous foreign policy plans regarding accumulated foreign earnings as well as possible trade wars. Wagner, Zechhauser & Ziegler (2017) find that high tax-paying firms displayed abnormal returns while the opposite was observed for internationally oriented firms. As their research is limited to the first 10 days of Trump’s Presidency, and no substantial policy changes had been implemented in these days, it is clear that the market responded solely to increased (decreased) uncertainty and updated expectations about policy changes, and not to actual policy changes themselves. Since the publishing of their paper and before the submission of this thesis, Trump has implemented his massive corporate tax cut and almost started a trade war with China and the European Union over import tariffs (Bradsher & Perlez, 2018). The onset of the latter especially may cause nervousness on the equity market. Currently, it is still expected to be resolved in a diplomatic, mature fashion, as the deadline of the implementation of the import tariffs is consistently being postponed to provide opportunity for negotiations (Smith, 2018). Therefore, the current situation is to a certain extend similar to that of pre-referendum Brexit. Big changes to the economic environment due to policy changes are looming, yet the expectations are still in favour of the status quo. If the tariffs are indeed implemented and China and the EU retaliate with equal measure, a shock to the equity markets similar to that following the referendum outcome could be possible. The same informedness and consensus effects can be in place, and comparable behavioural mechanisms may cause an extended overreaction to challenge the Efficient Market Hypothesis. The US is facing more elections in the near future, as November 2018 brings mid-term elections for one-third of the seats in the House of Representatives. Due to Trump's falling approval rates (Guskin, 2018), a big Democratic win is expected.

In Europe, 2017 brought a wave of elections, starting with the Netherlands. Analysts used this election as an indicator of the current political mood on the continent. Conservative and far-right seemed to be the big winners, but left-wing socialists still hold almost 40% of seats in this multi-party government system, requiring 225 days and 3 different formateurs before a coalition was formed. Next was France twice, for president and for the National Assembly, both surprisingly won by the party of Macron (liberal economically, left socially) and thus lost by the right-winged Front National, unlike the Dutch elections. The surge of anti-immigrant Alternative for Germany (AfD) in the September elections in Germany overshadowed a fourth win for Angela Merkel, and the formation of a new government has proved difficult as parties disagree on fundamental issues. Right-winged and conservatives also won in Austria in October, indicating a shift in its previously centralist government (Kroet & Oliveira, 2017).

2018 brings national elections in Russia, Italy, Sweden, and Hungary (and some smaller countries). Especially the Russian election is of global importance, even though the winner is most likely incumbent Putin. Italy's election outcome may sway the general direction of politics in the whole of Europe, as well as that of the Hungarians, whose political opponents are on different sides of the spectrum (Anderson, 2018).

The European Parliament itself has set the date for elections in 2019. At these elections, all eligible voters in the European Union can vote directly on representatives that will hold power over EU legislature, supervisory, and budget. As it follows a turbulent time in European politics, the outcome of these elections is far from certain.

With the current trend of political discourse, division, and surprise election outcomes, none of the expected election outcomes are predetermined. With increased political uncertainty, an increase in economic policy uncertainty follows. Like the Brexit referendum, each of the coming election results can be treated as a similar event. Surprising outcomes with market-wide effects can, like the Brexit referendum outcome, lead to strong extended overreactions on the market on the short-term.

6. Limitations and Further Research

There are several factors that might question the validity of this thesis, which directly leave room for further research. This chapter discusses several.

6.1 Source Credibility

In section 2.2.1.1 we comment on the general expectation to the effect of Brexit on different industries and sectors. The expectations builds among other things, on a lot of different consultancy reports. These consultancy reports claim to provide a economic insight to the effect of Brexit on different sectors, however, they mostly end with asking “What to do now?”, “Our suggestion” or “How can we help?”. This could suggest that they might be a little negatively biased in presenting theses expectations as to create a view of necessity for readers to acquire their services. The source credibility in this section can therefore be view a little lower that the rest of the thesis as it is possibly a little negative biases in the expected effect of Brexit.

6.2 Data Credibility

The stock returns used in this thesis are based on daily closing prices, a time interval often used within market efficiency event studies. However, news generally spreads fast today, through internet, television etc. and due to the widespread use of smartphones and computers, investors continually have access to the newest information and can receive and trade on news almost instantly. Therefore by using daily closing prices, we risk that we might see less movement in the price as effect of the news, whereas if we had had multiple intraday prices, such as 5 minute interval data, this could have showed more movement of the price, and thereby have captured more of the events effect. Using daily closing prices, we might also risk eliminating some of the more speculative trading, i.e. day traders and high frequency trading. This speculative trading is often done with time horizons shorter than a single trading day and daily closing prices thus do not pick up on it. Especially regarding the informedness effect, more updates on the market could have displayed a stronger effect, or even a bilateral relationship for all industries because speculative traders often hold their positions only shortly and trade based on price movement.

The thesis is build on the data of the different industry indexes, which do provides us with a average of the specific industry, which was intended. However using the industry indexes gave some limitations as to which models we could use to calculate expected normal returns in the event study. Because asset pricing models like the Fama & French’s (1993; 2015) three- or five-factor model, require firm specific factors like, book-to-market ratio and size measurement, which we cannot obtain due to the fact that we chose to use industry index data.

6.3 Model Credibility

As we have seen in the analysis, the Brexit referendum was an event that did not just affect a single firm or industry, but rather a market-wide event that affected a range of different sectors across the FTSE 350 Index. In our event study, both examining abnormal returns and unexpected turnover, we have use the so-called Market Model, which is one of the most widely used models in event studies. However, by using the Market Model to calculate the expected normal returns we risk underestimating the actual effect of the event, because when a spike happens for both the specific industry and the market index, some of the effect of the event for the industry will potentially be eliminated by the spike in the expected return, due to the same spike in the market. This potential underestimation is thought to be larger looking at unexpected turnover, because for returns some industries reached positive and others negative abnormal levels, thus averaging the effect on the market index. This is not case for unexpected turnover, where only positive ratios are possible. In the event study for unexpected turnover we also applied an Average Model. The risk of this model is that it overestimates the effect of the event. The reason for this potential overestimation is the mathematical buildup of the model, meaning that the expected turnover becomes constant. The Average Model will therefore not be able to differentiate between natural peaks due to for example seasonality (the dips at Christmas time) and peaks caused by an event, therefore causing overestimation to any spikes in turnover, as they will all be considered a possible effect of an event.

The estimation period should represent data under normal circumstances, a period unaffected by the event. Our results showed that the data appeared to be unaffected by the official announcement of the referendum, and the later analysis argued that it might had been anticipate before the announcement and thus already incorporated in the price. If this is the case, there is a potential risk that the estimation period was affected by the event to a certain degree. This is however not possible to measure as no specific event or date can be defined as to when the investors might have started anticipating this. Even if an estimation period earlier than the one used was chosen, we risk that the estimation period would no longer be a valid representation of the expected normal conditions in the event period. The length the estimation period is also a well discussed topic and many different recommendation are found, as mentioned in section 3.1. We chose to use a full trading year (253 days) prior to the first event, as suggested by MacKinlay (1997) as it seem most representative and accounts for seasonal biases. By deciding to use this estimation period, we also limit our results as other estimation periods might have provide slightly different results.

6.4 Further Research

The previously outlined limitations provide technical factors that must be addressed in further research.

First, more frequent market observations, with shorter time intervals, may show intraday trading patterns that can reveal more than daily closing data, as news arrives in the market in real time and investors can make trading decisions at any time during the trading day. Similarly, the use of different event windows can show the impact of specific events on a longer time scale than the short-term that is applied in this thesis. Additionally, data from other types of financial securities (such as foreign exchange rates, commodities, or bonds) or other financial instruments (such as derivatives) can show different reactions, as these have different dependency on expectations than equity. This thesis also focuses solely on the effect of Brexit on the London Stock Exchange, and not on other stock markets. Losing the UK as a participant of the free EU market will hurt many mainland industries that export and import to the UK, as will other global markets that engage in trade with the UK and are governed by European Union trade agreements. Investigating these stock markets will certainly be an interesting topic for further research.

On a more technical note, the use of more sophisticated models to calculate normal returns and expected turnover can eliminate the overestimation and underestimation issues faced in this thesis. This issue is especially important for unexpected turnover, because trading volume is always positive and therefore accumulates to capture the whole market, instead of averaging out negative and positive values (which is the case with returns). Furthermore, the use of a different, more sophisticated nonparametric significance test can overcome the pitfall of the Corrado Rank test regarding the cumulative levels of abnormal returns and unexpected turnover, providing results that are more robust.

Aside from the technical factors specific to this thesis, the case itself also provides ample opportunity for further exploration. With the Brexit process being far from over, continued monitoring of the market response to new information can provide a better understanding of when and how investors react to specific types of information. Testing for market efficiency through abnormal returns is an established method, but teaches very little about the origins and drivers of potential inefficiency. Therefore, we suggest further research that focuses on these aspects. Especially investigating different scenarios, types of events, and new information that result in inefficient responses from the market as well as individual investors can identify potential patterns and formulate possible explanations for these phenomena.

In this thesis, we picked three single events related to political and economic policy uncertainty, starting with the official announcement of a referendum, then the actual referendum, and ending with the official announcement of honoring the outcome of the referendum. However, in the period before the official announcement of the referendum, there were already rumours and speculation of the possibility of such an event. These events may have foreshadowed the actual announcement, decreasing its surprising power. Additionally, in the months leading up to the referendum, the different campaigns rallied and politicians, celebrities, and intellectuals alike picked sides, as well as the publishing of both positive and negative post-Brexit scenario reports to influence the public. Closing in on voting day, daily polls showed an increasing possibility of a potential vote in favour of Brexit. After the referendum, a waterfall of rumours and possibilities and forecast reports on different scenarios flooded the media and the market. Especially once the UK government and the EU published their personal wishes for the terms of their divorce, and the negotiations started. As long as the negotiations are not finalized, new information on potential agreements, albeit in the form of rumours, keeps arriving to the market. Therefore, further research into more detailed separate events and the continuous arrival of new information will provide a better understanding of how the market and individual investors responded to the increasingly higher probability of a Brexit, as well as the uncertainty on the exact terms of the divorce.

7. Conclusion

After a surprising majority of UK citizens voted to leave the EU on June 23rd, 2016, the financial equity markets responded with a drastic continued price movements in opposite directions for different industries, as well as a peak in trading activity in adjustment of the new information and sudden uncertainty about the future economic environment. According to Fama's (1970) Efficient Market Hypothesis, all new information arriving to the market should be incorporated in the price instantly and correctly. Therefore, a single price adjustment captures all information. Combined with the No Trade Theorem, this implies that if prices are efficient, no trading activity other than liquidity trading should be observed in the market. As this was not the case after the outcome of the Brexit referendum, this thesis aims to investigate this response, especially regarding the incorporation of information by the market and the individual investor. To do so, the event study methodology by MacKinlay (1997) was adopted to examine the market with regards to abnormal returns and unexpected trading volume for the different industries around three events related to the Brexit referendum.

For official announcement of the referendum and the official triggering of Article 50, we found no evidence against the Efficient Market Hypothesis. The significant abnormal returns and unexpected turnover we did found for a few industries could be attributed to other industry specific news unrelated to the event of interest. The actual outcome of the referendum showed that the results of the referendum did have a significant effect on the price and volume. All industries experience significant abnormal during the event window, the ME industry only on day 0, where the remaining ten industries was found abnormal returns on day 0 and +1, and even on the second day as well for some industries. The responds to the outcome of the referendum was not the same in the different industries, OG, PB, TO and MI they all experienced positive abnormal return, where BA, SS, LI, TL, HH and FS all display negative abnormal returns. The results shows that several industries saw a little reversion of the movement in the cumulative abnormal returns on the second day after the event, suggesting an initial overreaction to the news. Despite some inconclusive results for the unexpected turnover, we did generally find positive unexpected turnover for most of the industries at the second event. Consequently, the results for the investors' incorporation of the news of the referendum outcome support the alternative hypothesis of inefficient market across the industries.

The events analyses in this thesis can be characterized as market-wide, hence we remain skeptical towards the results of the unexpected turnover, as we expect Market Model might underestimate the effect and the Average Model is likely to overestimate all spikes in turnover ratio. Therefore, we investigate the effect of the event on the trading activity, measured by turnover ratio, while controlling for both prior returns and prior turnover. Here we found that neither the first or the third event caused a significant effect in the trading activity in any of the industries. The second event however, showed significant positive trading activity in the event window, except for MI and OG. This provides evidence that for most industries, the outcome of the referendum caused increased trading activity. In combination with extended abnormal returns for this period, this suggests market inefficiency.

To further explore this evidence for market inefficiency, we examine effect the flow of information have on trading volume, measured by turnover ratio. This is done using the Granger Causality test to test the Sequential Information Arrival Hypothesis. We find evidence supporting this hypothesis, with Granger Causality running from volume to volatility of returns for all industries, for OG and MI we even find a bi-directional causality. This means that the increased trading activity and unexpected trading could be caused by a sequential arrival of information, causing trade between uninformed and informed investors. Additionally, we adopted the notion that all information should be displayed in the price to capture the informedness effect, which makes is possible to isolate the consensus effect. The results of this model shows that we see significant positive cumulative unexpected turnover caused by lack of consensus for all industries except OG, MI and FS, thereby suggesting that the increased trading activity could be caused by the consensus effect for in these industries. Most of the industries responded to the second event as expected, except for TO and PB, which experienced positive abnormal returns despite negative expectations. The positive unexpected turnover along with lack of consensus suggests that investors do not agree on the impact the outcome of the referendum has on the valuation of these industries, or at least not on the magnitude of it.

Inefficient markets can be explained by the notion of bounded rationality. Investors are bound by constraints on their information processing resources, such as cognitive abilities, time, and the availability of information. Therefore, investors rely on behavioural heuristics as shortcuts to make decisions that are not always fully rational. The conservatism heuristic states that investors underestimate the importance of new information by not paying enough attention to it and therefore underweighting its impact as they update their beliefs. This may be the case for event 1 and 3, as the informational content of these events was anticipated. However, a sudden surge in attention compensates for this underreaction in events where the new information is considered a surprise. Instead of underweighting new information, the shock will cause investors to overweight its importance, which results in an initial overreaction. The data shows a decline in cumulative abnormal returns on day +2 for most industries, indicating a reversal to a rational price level. However, this reversal does not occur on day +1, which displays a continued trend of the initial abnormal returns as well as continued high levels of unexpected trading volume. This extended period of inefficiency may be the result of several behavioural biases, most likely a combination of Anchoring and Adjustment, and the Cognitive Dissonance Theory and Selection heuristic. This combination of biases states that an initial overreaction is used as anchor, from which further adjustments are made rather than from a rational lower level. At the same time, investors expose themselves to information that confirms their own beliefs and prior actions, resulting in a continuation of the upwards (downwards) trend. Only on day +2 this trend is reversed.

This thesis is one of the first studies investigating the effects of the Brexit referendum and the extended process surrounding it on the financial equity markets. Especially the focus on the average market response opposed to the formulation of heterogeneous investor opinions has, to the knowledge of the authors, not been done before. Therefore, this thesis presents exploratory steps into the matter, and presents a strong indicator that the markets are behaving abnormally. As the Brexit negotiations continue and the European Union (and other global economies like the US) is plagued by political unrest and division in its member countries, this field will remain relevant to academics and professionals alike. Thus, a lot more research can be conducted towards the impact of Brexit, the incorporation of new information, and the formulation of investor opinions in periods of elevated political and economic policy uncertainty.

8. Perspective

In this thesis, we applied a cut-off date of April 30th, 2017, which marked the first part of the Brexit process: starting with the official announcement of a referendum, the referendum and outcome itself, and ending with the official implementation of the outcome of this referendum. The second part of the Brexit process, the actual negotiations between the UK and the EU, were thus not considered. In this short “epilogue” to the thesis, we would like to address the political and economic developments since our cut-off date. Additionally, we will present our personal expectations on how Brexit will end, and where this will lead the UK and the future of the European Union.

On March 2nd, 2018, Theresa May delivered a comprehensive speech addressing some hard facts that were undeniable for anyone involved, as well as her wishes on a new trade agreement. She urged to be realistic, stating that the UK had to accept they could not get all the benefits yet none of the obligations, and that the UK would still be affected by decisions of the EU and its agencies to ensure alignment of regulations for smooth access to the market. In short, she would want to align most regulations (especially those in the financial sector, to regain passporting rights), continue relationships within education, science, and cultural programs, and seek membership to European medicine, chemical, aviation, and energy agencies (making adequate financial contributions). Yet at the same time, May wants the UK to negotiate better rights for fishermen, an open Irish border, and end the jurisdiction of the European Court of Justice in the UK (“‘Hard Facts’”, 2018).

If this sounds like getting *all* the benefits but *none* of the obligations, then we agree. So does Guy Verhofstadt, Brexit co-ordinator for the European Parliament, as he stated that an agreement could only be reached by compromise and not by giving the UK all the perks, and hoped May would come with “serious proposals” (“‘Hard Facts’”, 2018).

The EU still states it will only confirm a complete deal in which an agreement has been reached on all separate aspects. As the deadline for this final deal is on March 29th, 2018, we expect a lot of back and forth from both parties where they state they will not give in to “ridiculous” demands, and only agree on deals that are in the best interest of their own citizens. May will have to show she is fighting for the best deal, in order to retain support of the more conservative members of Parliament and hard-line citizens. The EU has to play tough as well to retain its reputation of strength and unity. If the UK gets a good deal and leaves the EU better off than it was as a member, other countries may want to abandon ship as well, especially countries that have strong economies themselves and contribute a lot to the EU. Were that to happen, it could lead to a potentially complete unravelling of the Union.

On a more realistic note, reaching a trade deal, any deal, is better for both parties than no deal at all. The EU is an important market for UK exports, as well as imports, and vice versa. Losing access to each other's markets would cost everyone a lot more than a compromise. In fact, they seem so scared of losing access to the EU market, the government has inserted the European Union (Withdrawal) Bill (or Great Repeal Bill, as it was named before). This Bill states that after the 29th of March, 2018, all EU law becomes UK law, as to avoid a black hole in legislation and to ensure UK products are still eligible for the EU market. Afterwards, the government can remove, change, and add new regulation that better suits its wishes ("EU withdrawal bill", 2017). The EU is also keen on retaining as much trade as possible and pushed for a transition period, which has already been agreed on. Regardless of what deal is reached, for 21 months after the deadline free movement will continue. This leaves businesses and organisations to prepare for new post-Brexit rules and more time for details of a deal to be worked out. Any other deals the UK makes in this time will not come into force until 2021 ("The EU and UK agree", 2018).

These developments show that while both parties seemingly play a game of chicken, waiting for the other to give in so they can keep face towards their own citizens, neither party really wants harsh separations. Therefore, we expect that a deal will be reached in time. Our personal opinion is that this deal will resemble the deal the EU has with for example Norway. Norway is part of the European Economic Area which gives it access to the single market, but it also has to accept free movement of people. This is something the LEAVE-campaign argued against however. Another option is the Customs Union, like Turkey, which would lead to retaining the EU's common external tariff and import conditions by the EU's preferential agreements, yet the UK is free to make its own external agreements. Exports and imports pass freely, without costly customs controls, which would resolve the border issue with Ireland. It does, however, require the UK to stick to a lot of EU regulations that ensure safety of products, and it installs tariffs (Emerson, 2016).

All these developments and expectations on the political and economic future of post-Brexit UK leave one question: how will the financial markets respond?

Evidently, this depends on the actual deal that is reached. However, as we discussed earlier in this thesis, much of the response is dependent on expectations, as these form the basis of any security valuation. With the Repeal Bill and the transition period already officially agreed upon and in place, no instant huge short-term changes will occur after the deadline. Therefore, the biggest possible surprise will come at the publication of the expected deal (as both parties are by then assumed to officially sign off on it after a vote). If this deal somehow states the UK will leave without any trade deals or access to the EU market at all, this will need to be updated in investor's valuations. However, as we expect a softer deal, with a lot of "the details will be worked out during the transition period", we expect only a mild response from the financial markets. This would be similar to the response of event 1 and 3. There are already heavy expectations on the deal which have been incorporated in investor's opinions, and any details will not be known until later, so adjusting valuation on that is still impossible. With the publication of more details during the transition period, the markets will respond and adjust accordingly when they come out, in a smoother process than our market-wide shock event that was the outcome of the referendum.

One thing that will however change, is that the EU now has precedent on members leaving. Personally, we think that none of the remaining members want to do so right now, but we also thought the UK would never actually vote to leave, so what do we know? We can argue the wake of the Financial Crisis of 2008 and economic decline following (such as increased unemployment and decreased budgets for social services) of tightened European rules had a big effect on the political unrest that eventually led to this decision. With the current state of heightened political division in Europe, a second financial crisis or decline in economic welfare could very well lead to unrest in other countries, such as economically strong Germany and France who could leave voluntarily. Countries with weaker economies may falter again and become dependent on the other members for financial aid, such as Greece, Portugal, Spain, and Italy were during the 2008 Crisis. And this time, the EU has a template for termination of membership, which would make doing so easier.

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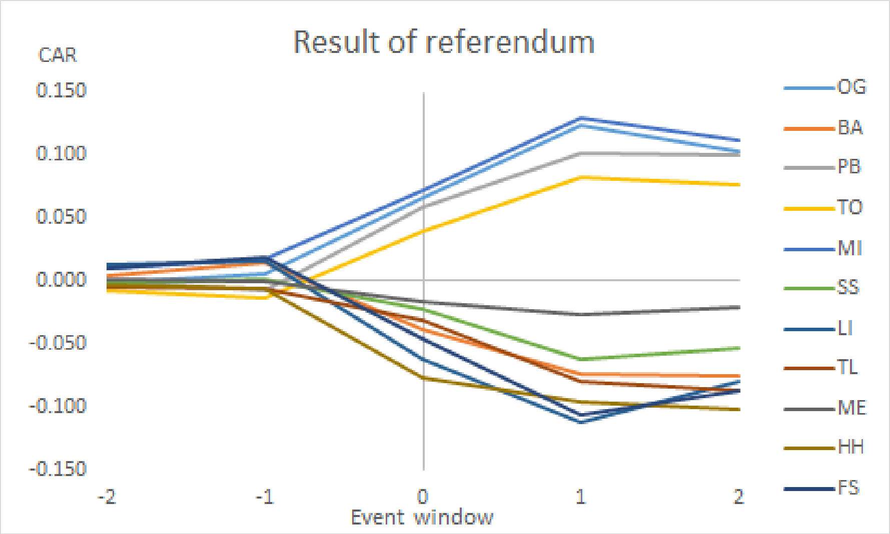
Appendices

Appendix 1

Figure 9. Cumulative abnormal return, CAPM



Appendix 2

Figure 10. Control of linearity, OG, R_t

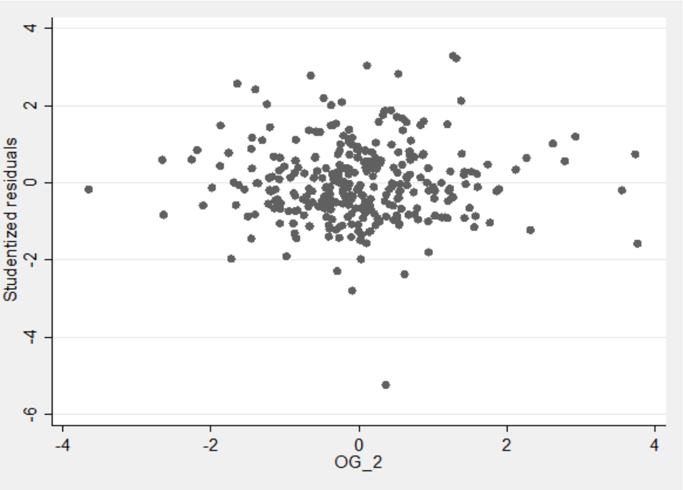


Figure 11. Control of linearity, OG, R_t-253,t

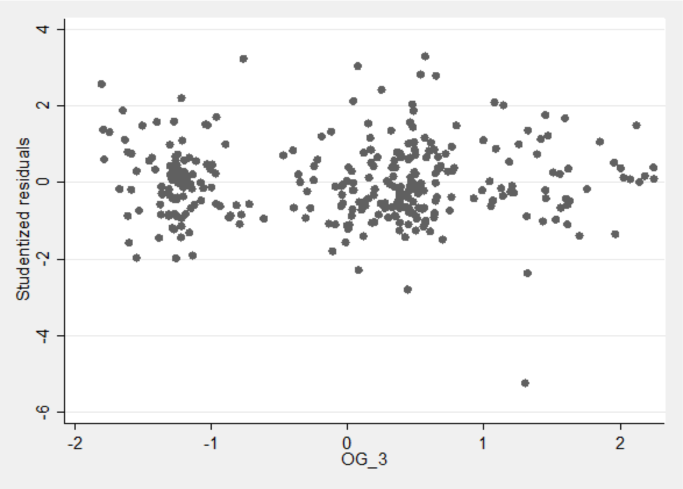
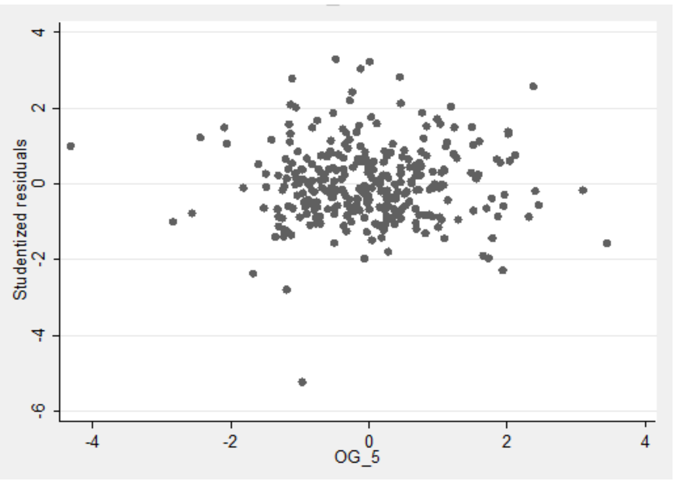


Figure 12. Control of linearity, OG, TO_t



Appendix 3

Table 18. Optimal lag selected using AIC

Industry	Lag
OG	2
BA	3
PB	3
TO	3
MI	4
SS	2
LI	4
TL	3
ME	4
HH	3
FS	4

Appendix 4

Table 19. Consensus effect, 1st event

Consensus model									
Official announcement of referendum									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.155	0.361	0.699	-0.011	-0.033	0.510	0.689	-0.336	0.807
-1	-0.212	-0.493	0.297	0.294	0.852	0.842	0.802	-0.121	0.838
0	-0.594	-1.380	0.031	0.545	1.579	0.946	0.235	0.014	0.625
1	-0.071	-0.164	0.506	0.145	0.421	0.737	-0.172	0.062	0.382
2	0.427	0.993	0.838	0.178	0.515	0.764	0.600	-0.157	0.780
Cumulative	-0.293	-0.305	-0.202	1.151	1.491	2,024*	2.155	0.964	1.453
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.220	0.662	0.776	0.678	1.288	0.884	0.203	0.751	0.803
-1	0.026	0.078	0.548	0.633	1.203	0.869	0.156	0.580	0.745
0	0.338	1.016	0.880	-0.520	-0.989	0.151	0.292	1.082	0.896
1	0.183	0.550	0.745	0.218	0.413	0.641	0.244	0.906	0.865
2	0.089	0.269	0.641	-0.123	-0.233	0.479	0.523	1.939	0,977*
Cumulative	0.856	1.151	1.700	0.885	0.753	0.815	1.419	2,351*	2,783*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	0.438	1.277	0.950	-0.074	-0.218	0.359	-0.015	-0.046	0.506
-1	0.227	0.662	0.764	-0.336	-0.988	0.097	-0.066	-0.196	0.386
0	0.352	1.028	0.907	-0.121	-0.356	0.293	-0.179	-0.533	0.216
1	-0.004	-0.010	0.463	0.014	0.040	0.514	0.013	0.039	0.560
2	0.111	0.325	0.649	0.062	0.182	0.591	0.711	2,111*	0,981*
Cumulative	1.125	1.467	1.922	-0.456	-0.599	-1.008	0.463	0.615	0.232
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	-0.078	-0.185	0.432	0.482	1.491	0.954			
-1	-0.525	-1.240	0.073	0.081	0.250	0.614			
0	-0.115	-0.272	0.398	0.032	0.100	0.533			
1	0.078	0.185	0.602	0.256	0.792	0.838			
2	-0.215	-0.508	0.290	0.504	1.561	0.965			
Cumulative	-0.855	-0.904	-1.098	1.355	1.875	2,187*			

*Significant at a 5% significance level

Table 20. Consensus effect, 3rd event

Consensus model									
Official triggering of Article 50									
Event Window	OG			BA			PB		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.597	-1.390	0.039	0.265	0.768	0.815	-0.092	-0.300	0.309
-1	-0.828	-1.927	0,012*	0.222	0.643	0.780	0.047	0.152	0.602
0	-0.636	-1.479	0.027	0.211	0.611	0.768	0.068	0.222	0.629
1	-0.212	-0.493	0.309	0.106	0.308	0.691	0.129	0.420	0.703
2	-0.344	-0.799	0.205	0.369	1.069	0.900	0.235	0.763	0.830
Cumulative	-2.617	-2,723*	-2,975*	1.174	1.520	2,265*	0.387	0.562	0.893
Event Window	TO			MI			SS		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.167	-0.503	0.274	-0.595	-1.131	0.116	0.441	1.636	0.954
-1	0.024	0.072	0.556	-0.697	-1.325	0.062	0.637	2,362*	0,992*
0	-0.109	-0.327	0.351	-0.459	-0.873	0.224	0.632	2,343*	0,988*
1	0.359	1.080	0.888	-0.626	-1.190	0.085	0.314	1.164	0.911
2	0.609	1.830	0.958	-0.577	-1.095	0.131	0.567	2,1*	0,977*
Cumulative	0.715	0.962	0.821	-2.955	-2,511*	-2,933*	2.592	4,296*	3,619*
Event Window	LI			TL			ME		
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test
-2	-0.073	-0.213	0.375	0.158	0.465	0.707	0.286	0.850	0.861
-1	0.130	0.380	0.672	0.388	1.139	0.942	0.431	1.280	0.938
0	0.511	1.491	0.965	0.336	0.988	0.919	0.231	0.685	0.792
1	0.279	0.813	0.834	0.198	0.583	0.757	0.061	0.182	0.614
2	0.793	2,311*	0,985*	0.312	0.916	0.907	0.608	1.805	0,973*
Cumulative	1.640	2,139*	2,073*	1.393	1.829	2,698*	1.617	2,148*	2,614*
Event Window	HH			FS					
	UTO(t)	Patell	Rank test	UTO(t)	Patell	Rank test			
-2	0.136	0.322	0.637	0.087	0.268	0.622			
-1	0.219	0.516	0.730	0.572	1.771	0.965			
0	0.036	0.086	0.541	0.206	0.638	0.799			
1	-0.157	-0.371	0.340	0.261	0.809	0.842			
2	0.052	0.122	0.556	0.590	1.824	0,973*			
Cumulative	0.286	0.302	0.472	1.716	2,375*	2,65*			

*Significant at a 5% significance level