MASTER THESIS

“Analysis of the reaction patterns observed in the Dutch stock market, in response to shocks caused by the financial crisis”

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List of abbreviations:

APT: Arbitrage Pricing Theory

AR: Abnormal Returns

CAPM: Capital Asset Pricing Model

CRSP: Center for Research in Security Prices

ECB: European Central Bank

EM (H): Efficient Market (Hypothesis)

RB: Rational Behavior

RQ: Research Question

Foreword - Personal motivation

This master thesis represents the conclusion of my studies in Economics & Business master program of Erasmus University in the specialization of Financial Economics. The choice of the above titled topic came after my participation in Behavioral Finance module through the academic year 2012-2013 and was further strengthened by my attendance of “Introduction to Accounting Research” module, of Accounting and Finance master program, which gave me further insights in financial accounting field. In particular the importance of investors’ reactions to major events, no matter the size or the direct relevance of the event to economics, attracted my attention around basic behavioral aspects of financial economics.

Further my admiration of E. Fama, awarded with the Nobel Prize in Economics last December, being the father of basic economic theories of our century and gaining value through real life practices, lead me on dedicating this paper to the analysis beyond the principle of Efficient Market Hypothesis leading to the explanation of variance in stock returns.

I would like to thank below the people supporting me during this whole period of selecting and writing this paper. My supervisor Tong Wang for her patience, advice and quick response on the short available time before submitting this thesis. My family for backing up my decision to study abroad and their mental support during this 2 year period. My boyfriend Giannis for bringing his cooling vibe and rational approach on this intense period of my life. Next I would like to thank my friends Polyvios for his help on structuring and implementing this analysis and Alexandra for her useful advice and her pressure additions.

And finally my inspirational quote of this whole process:

“You know what I say about worrying? Don’t.”

Abstract- Outline

This paper focuses on the search of specific behavioral reaction patterns of stock returns in Euronext Amsterdam, following extreme event periods. Conducting an event study using the 3 main indexes of the Dutch stock market gives us the ability to concentrate on recent years of financial development of a central European country in terms of its central stock market and in relation to the financial crisis affecting most of stock markets around Europe. Selecting market capitalization as the basis of index separation limits the size-effect that would probably lead to biased results.

The empirical tests conducted suggest that daily return data are consistent with underreaction following positive news and overreaction following negative news, though evidence is found to be weaker compared with other studies using the methodology of mean-adjusted returns. The analysis gives favorable testing ground for further examining the significance of the results under the influence of risk factors Fama and French (1996), calendar effects, or unique global financial crises, which have been detected as main drivers of anomalies in previous studies.

The scope and significance of this analysis is described in the first section, highlighting the importance of the research question under examination and driving the attention towards possible limitations of conducting a similar analysis to other stock markets. Furthermore EMH and several anomalies detected in similar studies are explained in the second section, along with the definitions of overreaction and underreaction which frame the main examination hypotheses of the study. Several tests, findings and limitations of event studies are described below, forming the literature review of the paper in the end of the second section. The next section, which forms the bulk of the paper, turns to the description of the main methodology and data under examination, and discusses how they could be used on conducting further tests for strengthening the evidence of market abnormal behavior significance. The paper ends with a brief discussion and conclusion.

Keywords: Efficient Market hypothesis, Overreaction, Underreaction, Abnormal returns, Shock events

1. Introduction

Trading in a capital market, being the most important element of every financial market, can advance savings into more productive channels and facilitate the circulation of securities into the economy, providing long-term chances of increasing wealth. The important role of the capital market has been extensively researched during the 70s, and onwards, and its efficient character has been supported until recently.

An efficient market can be resembled to an ideal market which, applied to stock markets, consists of financial cycles within which stock prices adjust in relation to fundamentals and where investors' responses to price changes should be immediate and error-less (RB). In particular the basic assumption following the norm of the efficient market is that "prices always fully reflect all available information". Under this definition agents fully and efficiently react only after the change, since the random walk property of prices implies that stocks' returns are unpredictable.

On the other hand observation of financial markets and stock prices of today, with investors losing hope of good return in capital markets of west, following the slow recovery of Eurozone after the major crisis years of 2007-2009 and reacting to news announcements around the world until recently -from a new threat of terrorism in Middle East to Ukrainian diplomatic and ground developments, to the deep fall of European inflation lately forcing the ECB to announce further actions as cutting interest rates to lower levels and stimulating a new ABS program- reveals how vulnerable international financial infrastructure is to shocks, even after years of reforms and emerging regulations.

The conclusion on unpredicted reactions lead by a substantial body of literature against the efficient character of markets, emphasizes major inefficiencies, or so called anomalies, of the market and will be analyzed further in this paper.

1.1. Problem statement

The effect of direct-economic or indirect-social events in the market value of firms has been an interesting topic of research drawing the attention of economists throughout the years. Those kind of studies classified in a separate type of researches named after event studies, resulted into significant evidence of securities' reaction in times of market stress. The most known types of reaction patterns detected resemble human behavior, thus voice investor's expectations for the future value of their decisions. Stock investing, being one of the most easily accessible markets in terms of publicly available current or historical prices, direct usable liquidity, can result into profitable returns if only strategies followed match the exact path of stock prices' behavior. For the above reasons forming a valuable portfolio should include characteristics of human's reactions to unexpected events which may occur any possible time and correspond to excess movements of prices. Analysts identified 2 specific characteristics under momentum and overreaction strategies, which appear to express the intuitive way of predicting but in practice indicate consistency with traditional models, to the extent that they reflect variations in risk, either over time or across assets.

Following the overreaction and underreaction tendency of investors towards any news events affecting their perspective level of wealth, we examine whether these types of human behavioral characteristics are reflected in the movements of stock prices. A more detailed description on the investigation of whether the behavioral hypotheses of overreaction and underreaction can explain abnormal stock prices movements or if prices fully incorporate all available information as stated in EMH, is the main purpose of this study. Moreover there is a crucial reason for evaluating whether the stock market is efficient or not, this is the investment's allocation decisions of agents.

1.2. Research question

The main aim of this paper is to check whether overreaction or underreaction had occurred on the years framing the recent financial crisis, or whether efficient reaction is supported. In the following sections, I will investigate whether the behavioral hypotheses of overreaction and underreaction can explain abnormal stock prices movements. The analysis will be achieved by investigating the short-period of 2003-2014 Dutch market reaction, which is a reflection of the market's expectations. For emphasizing the meaning of unexpected events stimulating the above types of reaction I concentrate on the years surrounding the recent crisis only.

The above remarks are summarized in the topic of research of this paper and are more in detail explained by further sub-questions; in particular:

RQ: What stock price reaction patterns are observed in the Dutch stock market, if any, in response to shocks caused by the financial crisis?

SQ 1: Which is the response of stock prices on agents' reaction after positive or negative events?

SQ 2: Are the results statistically significant in the years surrounding the financial crisis?

SQ 3: Do we observe any significant difference between indexes or throughout the years?

1.3. Research objective and significance of the study

Several other papers try to investigate crucial elements of stock markets: price movements, predictions of prices' behavior, modeling of investors' decisions, but in particular the connection between human behavior and prices' changes has been an interesting topic of research. The purpose of this paper is to contribute to the market reaction literature by providing a comprehensive investigation of abnormal stock prices' movements in a specific market. The results of this study therefore provides insights into better understanding the theory of market anomalies. The implications of excess volatility of market returns leading to short-term mispricing following news announcements causes investor's change of "attitude" and thus change of investment strategies; that transformation provides sufficient ground of testing effects on market returns. The literature provides strong and voluminous evidence of anomalous price behavior, when on the other hand important studies such as Fama (1998) impede generalizations by explaining that abnormal returns evidence is "due both to differences in expected returns and to chance sample-specific patterns in average returns" and thus deviations are expected under market efficiency.

For that, it is interesting to isolate the effect in a smaller scale and reply to this long-term rivalry by giving significant results of either the anomalous or efficient character of stock returns. In particular this paper contributes to the existing literature in the following ways:

- The financial turbulence of Eurozone in the past years had not revealed a clear pattern of reaction relative to the consecutive announcements of unexpected news. This study encompasses into the examination period the pre- and post- crisis years, making the results compatible with the effect of financial crisis on stock prices movements.
- The use of indices of stocks will help on investigating different firms on the same days and thus eliminate firm-specific factors that may be the cause of abnormal reaction.
- Dividing in scales and using size-based indices will give a better impression of different investors' strategies that using an all-share index would, giving false impression for the whole market. Grouping by market capitalization size, total value of market shares of a company, will also enable us on analyzing the size premium which has proved to be the reason of outperformance of specific-sized companies.
- Examining only one region of the huge world-wide equity market, by concentrating in one stock market giving a clearest picture of what is happening in larger scales, will highlight differences that are not apparent in large-scale studies.
- Many US stock markets were analyzed before for behavioral biases. The focus on a European market, will make this paper attribute to the European crisis, starting in 2008 following US and whose post-effects are observed till today. The majority of empirical work base their analysis on data drawn from US and/or UK stock markets due to stability and size matters; this analysis concentrates on a different but equally powerful market inside the borders of EU. The Amsterdam Stock Exchange being competitive and stable enough during the disputed years of Eurozone Crisis, provides a challenging testing ground in the search of any kind of stock prices reaction in major shocks' periods.

2. Theoretical background

After conclusions drawn by efficient markets' supporters, leading to the premium belief of a state where everything reacts efficiently based on fundamentals; stock markets were further researched and evidence showed that the above hypothesis could also be applied in the case of unanticipated events, where returns proven to be predictable contradicting with the previous stated. This opponent side of research, observing human reaction on new changes, have been supporting that mispricing and departures can occur, and in fact are rather common.

The traditional approach of a financial market with fully rational agents, meaning, resembling it to Bayes' inference, that agents change their beliefs in the "correct-optimal" way in response to any new market phenomenon, unfortunately didn't result in supporting empirical evidence of modeling those rational beliefs. On the other hand recent behavioral approaches more resemble human beliefs rather than Bayesian rationality. The analysis of the decision making process of individuals, namely bounded rationality, which in a way satisfies common behavior characteristics includes all "obstacles" that one may find towards the fully rational-optimal reaction. The most notable of these obstacles is the flow of information, informational limitations, respective with the 3 types of EM known by Fama (1970), and hence the level of rationality of an agent who is subjective to the available information. Beyond the efficient theory of an informational set that is anytime incorporated, De Bondt and Thaler (1985), immediately in asset prices, lies the relative informational hypothesis, which is the exception found in the Semi-strong form of EM, where all past and current information are already incorporated to stock's prices, but in addition some agents are able to use extra private information about the movements to follow.

As far as current information is concerned, prices can also exhibit trends over time, the random walk hypothesis implies that prices can vary at any point on time deviating from the equilibrium-current value, but any relevant information such as PE ratios, historical prices or past portfolio performance, should not have any predictive power over returns, and so the patterns observed have been taken as economically not significant from supporters of the EMH. Opposed empirical evidence though proved that stock prices do not adjust immediately after new information is released and that returns do have fluctuating distributions, depending heavily on profit announcements, the time-span measured and the correlation between returns, pointing out some puzzling results.

Studies intending to standardize this violation of efficiency, such as the "classic" paper of De Bondt and Thaler (1985) examining the predictability of market returns based on past data alone, conclude that stock prices are affected by extremes and their subsequent movement is driven by the kind of reaction (over- or under- reaction), the kind of shock (positive or negative) and its size (the greater the shock, the greater the disturbance and the later the adjustment). The first attempt to fit this anomalous behavior into the efficient market, comes from Fama and French (1996), who gave birth to the three-factor model constructed in a way of accounting for other characteristics of stocks that may be the reason of particular price movements' patterns.

In grounds of EMH, the basic theory is that compared to the risk-free rate any other security with higher return is also more risky. For that, there are no arbitrage opportunities, nor different assets with uneven risk and return trade-offs, and thus arbitrageurs cannot survive. However past analysis showed that financial markets could not be resembled with an efficient one, at least not on its wholeness and not on its regular forms. Even Malkiel (2003), keen supporter of EMH commented: “The market cannot be perfectly efficient, or there would be no incentive for professionals to uncover the information that gets so quickly reflected in market prices.” As a result fully rational expectations cannot survive. Evidence originated by the shock of Black Monday in 1987, caused not only by program trading as documented, but also by unreasonable market psychology, supports failure of market efficiency. The decline in S&P 500 by more than 20% on that October was caused by irrational behavior, documented as one of the exceptions of EMH (Malkiel, 2003). Is it thus possible to observe irrational investing patterns, projected in returns, in the latter financial crisis? The broadest meaning of this paper is to explore the arguments surrounding the above question, through the investigation of a particular stock market, without canceling out any similar activities in other markets.

2.1. Random walk hypothesis

Before a time series of daily closing stock prices is analyzed, it is crucial to discuss the Random Walk property of such series, which emphasizes the difficultness on forecasting subsequent price changes, being statistically supported by many studies, and statistically ignored by others.

Analysis of economic series is the basis of every financial study; commodities’ price series have drawn the interest of researchers a long ago, since the blow of the 20th century and have been thenceforth a largely researched topic. The guess of a price has always been an interesting game of the mind, the optimal estimate even more. Various academics examined price series, and in fact returns, giving out important evidence each in his own way along with the strengths and the weaknesses of his time. What I want to point out here is that finance theories have transformed during the years, connecting more and more theory with real life.

Early studies, as Working (1934), questioned time series’ characteristics, described as “*series commonly used as indexes of business activity*”, by supporting the notion of randomness strongly identified in stock prices. According to him past theory and techniques were insufficient to recognize the identical character of a series of random numbers and a series of stock prices changes. His theory corrects the misinterpretation of “*cumulative random series*” to “*random-difference series*” and totally disregards explanations that give series some trending or cyclical or any specific reaction tendency, supporting the unpredictability property. This random difference character series, built on several restrictions, have no relation with past or future changes.

One of the first papers to point the issue of randomness in economic series Kendal and Hill (1953) segregates long-term and short-term movements for the purpose of statistical analysis of series, as each are subject to different causal influences, as said. He concludes that price series appear to be so random as to overlap any systematic effect present and any cycles or trends identified are generated from short-term elements and should be disregarded. His empirical results of small serial correlation and unpredictability of stock changes, set the principle for the “*random walk model*”. At this point is important to intervene with Roberts

(1959) and his "*chance model*"[1], being the first attempt to explain patterns observed in stock series with empirical reasoning behind -technical analysis- although with no theoretical support -being usual for that period, as analysts impute it to statistics. His results approach some lately known as stylized-facts of stock returns, namely relative frequency and clustering, giving some first hope of predictability.

All the above evidence adding to economic theory of the 20th century around stock price behavior suggest, as Fama (1965) presents in a less complicated way, the "theory of random walks". The theory doesn't exclusively support the random walk principle, instead questions the degree of dependence of price changes through introducing the efficient market term, which will later evolve into the EMH. This paper provides a simple description of how one could be lead to the above implication by analyzing dominant random walks in stock markets. 2 known market practices, namely, Chartism and Fundamentalism, are employed in order to reach the conclusion that at any point in time, there should be an equilibrium price determined by actual stock prices and fundamentals called intrinsic value, which may lead to predictive prices if only several assumptions hold. The assumptions and their effects construct the main implications of efficiency, further analyzed below, whereas when those assumptions doesn't concern any change in the information or fundamentals' levels, a random selection of portfolio with no specific trading strategy followed will give the same profits as anything else.

The criticism on the interpretation of the existing theory and the real stock markets behavior came after the 70's. Although some "suspicious" spatial statistical evidence already existed in the above literature, for example Working (1934) and Alexander (1961) realized that autocorrelation could only be possible in time-averaged price series, not sufficient for ruining common beliefs and possible abolition assumption of the non-prediction property, and thus should be corrected by using end-of-period prices to construct returns which then fluctuate randomly. Considered as non-credible and non-realistic the predictability property of stock markets was also doubted, at the time, by another part of financial literature, which disseminated, though, that the size and sign of correlation coefficients in models of changes in stock prices, should have some deterministic value if translated in duration, direction and frequency of those changes. Such thoughts were not broadly recognized at the moment and faced as doubtful chartists' approaches, meant only for taking advantage of potential profitability, which would get corrected anyway by competition forwarding exceptional knowledge to be absorbed already by current prices (EMH).

2.2. EMH

The supporting fashion of independency feature of price changes and several similar statistical tests resulting in near-zero serial correlation evidence generated a complete body of literature which supported the approximation of stock prices movements by a random walk. Studies such as Samuelson (1965) prepared the ground for the theoretical reasoning behind this property, beginning with the observation that "*in competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen.*" and

[1] Chances are explained similar to Kendal's model as that stock indexes could be duplicated by a series of random numbers and the changes in those fabricated series is subject to predictions based only on relative frequencies accompanied by the assumptions of independence on a normal distribution with standard mean and stable probabilities.

concluding in the structure of EMH. Fama (1965), Samuelson (1965) and Cootner (1964), all provided evidence, around the same time, of supporting basically the informational hypothesis lying behind the efficiency theory, meaning that all available information in the market is already reflected in prices and lead to the unpredictability of returns. Fama interestingly quoted "*I know of no study in which standard statistical tools have produced evidence of important dependence in series of successive price changes*".

The "father" of the efficient function Fama gave the best explanation of the more resembling EMH to real-life transactions; testing whether the "fully reflect" element, and in general the capital market efficiency, can be as specific as stated in theoretical studies. He gave evidence of 3 special types of efficient markets that can exist in contrast of taking an unreasoned assumption of efficiency. The efficient market can be translated in a market where the real price of a security is the best estimation of its value, to this end Fama showed that the "*market equilibrium should be stated in terms of expected returns*", emphasizing by this way the importance of returns and risk projected in the following equation:

$$\mathrm{E}\left(\mathrm{p}_{\mathrm{i,t+1}}|\Phi_{\mathrm{t}}\right) = \left[1 + \mathrm{E}\left(\mathrm{r}_{\mathrm{j,t+1}}\middle|\Phi_{\mathrm{t}}\right)\right]\mathrm{p}_{\mathrm{jt}} \tag{1}$$

Fama posits the challenge that there should be a significant difference between the real price of a security and the expected value, as presented by $\mathrm{E}\left(\mathrm{p}_{\mathrm{i,t+1}}|\Phi_{\mathrm{t}}\right)$ in the above equation, based on an informational function Φ at every point t in time. He resembles correlations or divergences of stock returns to a "fair game" of the response based on Φ information. More specifically we can say that he concluded on supporting the notion that the characteristics of an efficient market (such as no transaction costs, informational facilitation etc.) cannot all exist in the same time, in practice "*these conditions are sufficient for efficiency, but not necessary*".

Following the above analyzed paper and all its descendants and as a consequence EM theory supporters; we can easily come up with its broadest implication: the market value of a security cannot strictly be its true value through time. The estimated outcome can be relaxed and described as the unbiased estimate of the true value of an investment, meaning that only errors in prices' estimation should be unbiased. The sure is that according to the EMH, when all available and all relevant information is used, non-systematic errors should be made in the reaction of agents. The above conclusion could imply that agent's preferences and reactions on changes in the market should be such efficient as prices are. Also as stated by Cuthbertson (1996) "...*any test of the EMH is a joint test of an equilibrium returns model and rational expectations*."

An overview of financial economics history leads to two main strands of literature aiming to explain markets' efficiency. Most EM supporters documented several extensions of the standard theory, trying to capture prices' movements inside EM framework; on the other hand the behavioral explanation has gained ground on identifying market's inefficiencies more recently. Actually it would be difficult and useless to explain financial activity with fundamentals, since the evolution of technology, in particular of internet, enabled access to more information and hence increased market's valuation. Heaton and Lucas (1999) define the most important reasons why stock prices have skyrocketed during the 90's: the popularity of stock markets during that decade, the increased participation of investors, the formation of more diversified portfolios, and as a consequence the proper allocation of risk. Furthermore financial market returns are partly predictable and; investing in stocks appears to be safe, but only profitable when accounting for investors' sentiment; this approach proves the significance of Behavioral Finance, in a way that is conflicting with the EMH.

2.3. Investors' preferences and beliefs

Though capable of easily explaining the decision-making of agents, the above hypothesis hasn't received significant statistical support. In the EM framework "*stock prices are right*", but behavioral finance's evidence detected particular and significant deviations from fundamentals, primarily explained by the impact of irrational traders in the market.

Is it possible that rational behavior could exist though? Coming from the 70's the traditional models were leaded by fundamentals and their properties. Past models not considering disorders on agents' expectations, but a perfect rational state, were afterwards criticized for this omission and considered failed. This body of empirical results that are difficult to reconcile with standard models helped the growth of a different more psychological-based approach. When deviations from the true value occur, an investment opportunity is created and it is available for agents who want to exploit it. The EM framework supports that rational agents are going to seize that opportunity in the correct way and lead the price again towards the equilibrium. On the contrary the behavioral approach is that agents are willing to benefit from that mispricing but such behavior will be exposed on risk and extra costs and as a consequence not followed by a rational agent. The result, also statistically supported, is that arbitrage is limited, hence the mispricing is persistent and prices are led by investors' decisions and preferences.

This agents-centered approach is a new one, but the interesting is how the main ideas originate from even older researches. Keynes already from 1936 stated that "*expectations matter*" based on the important role of market's sentiment. Economic models still tend to ignore the previous work on investors' psychology and still assume average rationality in order to give out significant evidence, nevertheless Simon's (1957) "*Model of Man*" had long given a better approach, that of "*bounded rationality*", meaning that people can show rationality but also irrationality on different types of actions through time. On a similar line Russel and Thaler (1985), researched the implications of this "*quasi-rationality"*, imported in the mapping of consumer behavior response process which violates the traditional microeconomic theory. They analyzed arbitrageurs' and entrepreneurs' role in the market and found that because of irrational behavior their rivalry cannot be profitable.

As proved a bounded rational agent is what may fit better in real-world's agent's characteristics, and hence Behavioral Finance modeling is influenced by people's preferences and beliefs. The conflict between the two main theories is coming from the fact that arbitrage opportunities may arise, and thus when rational and non- rational agents coexist in a market there is always the possibility of one taking advantage of other's irrationality. To this extent the answer of many theoretical papers is that irrationality has an impact on prices, which in fact do not reflect their fundamental value. This issue is a controversial one and it has been well explained by Barberis and Thaler (2003); namely the limits to arbitrage theory-hypothesis underlines that asset prices will be sometimes found deviating from the "right price", but this mispricing cannot lead to "free lunch", not corrected without cost and risk. In fact, Behavioral Finance analysis supports that irrational traders are the ones causing, not only prices' movements, but also preventing arbitrageurs from correcting them back to fundamental values, at least when this concludes to profitable strategies with no sufficient risk.

From the psychology's point of view the introduction of "Prospect theory" by Kahneman and Tversky (1974), pronounced the behavioral confusion on decision making under risk not based on probabilities, as it was accepted until then by Expected Utility theory, but on modeling agents' actions willing to enhance their wealth, affecting asset prices within outcomes. Psychological definitions of characteristics of human behavior, such as conservatism, wishful thinking, representativeness, overconfidence, is another way of resembling agents' decisions over financial problems. The behavioral decision theory mainly developed by Kahneman and Tversky (1974), includes heuristics that rule people's predictions not consistent with normative statistic rules. The analysis of, named otherwise as, rules of thumb (1974) influenced many subsequent papers on how or how much financial variables can be affected. Furthermore those findings led to "investors' sentiment", as proposed by Barberis, Shleifer and Vishny (1998), explaining that expectations and reactions are also influenced by the sequence of available news and the existence of unexpected events.

2.4. Anomalies in stock markets

Most financial studies of the 80's and onwards, have researched the properties of stock returns, and found different correlation evidence, depending on the stock market, its prior returns and the time-span analyzed. Public information and several macroeconomic variables can help forecasts of stock excess returns, in particular the predictability found to be improved in longer time-spans. Condemnation of the un-predictability property came first through behavioral tendencies; Slovic and Lichtenstein (1971) and Kahneman and Tversky (1973), ascribe moderation to forecast outcomes of anchoring and adjustment, but match the excess volatility property to representativeness and explain that "*people choose a prediction value whose extremity matches the extremity of the predictive information*."

Prior scattered evidence of market inefficiencies by survey studies like Ball and Brown (1968) and Ball (1978) identified in the form of strong anomalous behavior of post-earnings announcements changes, led to an extensive body of financial literature documenting the same patterns of reactions in stock price series due to asymmetric reaction of traders causing changes in prices not consistent with their true value, formed under the efficient market hypothesis. The evidence supporting the relative movements in stock prices comes from the fact that past returns can predict future returns giving a clear picture of those movements. Taking findings of De Bondt and Thaler (1985) and before from Shiller (1981a) and Kleidon (1981), the price-dividends sample couldn't explain stock prices' exaggerated movements, but earnings changes did. In particular Kleidon's findings of stock prices movements' strong correlations with following earnings changes, combines with his primal belief that investors attach more importance to short-term economic conditions than to dividends trends, into anomalous evidence.

2.4.1. Fundamentals

Common characteristics of stocks expressed with fundamental variables such as dividends yields, price-to-earnings ratio, price-to-book ratios, price-to-sales ratios, growth rates or earnings per share, are some of which researchers were based on to forecast future stock prices, helping investors to profit from the undervaluations or overvaluations of certain portfolios. Portfolios of stocks are evaluated after the level-performance of the above variables, exhibiting certain patterns on returns. The relating literature found evidence of stocks with low PE and PB ratios, generating high returns and finally outperforming the market, whereas stocks exhibiting a series of high dividends and good growth rates often give out “false alarm” of highly expected returns -overvaluation.

2.4.2. Size

Early research of stock returns performance isolating size characteristics, document the “small firm effect” which gave rise to a plethora of papers, Schwert (1983) and Dimson and Marsh (1989), showing that returns of small companies outperform that of large stocks, even after accounting for higher risk in small stocks. Later analysis of overreaction evidence observed in stock prices ascribe these findings to the small-firm phenomenon. The tendency of losers to outperform winners, leads to evidence of losers being small-size companies and thus not sustain overreaction significance. Zarowin (1990) and Ball (1995) among others provide sufficient evidence of the size phenomenon responsible for false predictions of abnormal profits.

2.4.3. Seasonalities

One of the main common property of stock returns’ series, volatility, have been generalized as the persistence of extreme returns identified by strong autocorrelation signs and lead to significant evidence of volatility events clustering in time. Anomalous returns related with a particular time period, where autocorrelations are reduced in the remaining period, indicates strong evidence of the seasonality effect or else various types of calendar anomalies.

The January effect documented by Rozeff and Kinney (1976) recognise the temporary extreme returns differences depending on the month of the year. In particular they find that prices and trading volume of stocks is increased in the first weeks of January. This pattern has been also explained by cross-sectional variation of stock returns, connecting it with the size effect; Keim (1983) reports that small stocks outperform large ones in January. The best possible explanation for this kind of reaction given by Branch (1977) is based on year-end tax loss shares that declined in value the previous calendar year and are on sale on the first month of the next year. There is an extensive body of literature studying seasonality in stock markets naming those phenomena by the time of the year the event usually happens, as the Monday or weekend effect, Smirlock and Starks (1986), generating higher returns on Friday and lower on Monday caused by non-trading period between the two days and the turn-of-the-month effect where stock returns show significant increase in the last trading day of the month.

2.4.4. FF factor model

Multiple studies gave out evidence of stock market anomalies disappearing after controlling for factors such as the bid-ask spread, firm size, and other firm-specific factors. On a more detailed analysis Fama and French (1993, 1996), henceforth FF, created the three factor model; a well-known CAPM including 3 macroeconomic variables meant to describe the abnormal returns of portfolios of certain stock-groups. The structure of this model requires stocks to be grouped in categories; small and large caps reflecting the total value of shares of a company, a measure of equity size of a company, and value and growth stocks, defined by fundamentals such as high dividends yield, low PE ratio and high growth rates and high earnings, respectively.

The above division of stocks meant on analyzing the documented phenomena of “size premium”, accounting for market capitalization of the company’s shares in the stock market, and “value premium”, identified and named by FF, using book-to-market ratio measures. FF as well as other researchers have shown that value stocks usually outperform the market, and as a consequence have higher returns than growth stocks. Past performance of prices and earnings may be overestimated in the case of growth stocks and agents misjudge the result of returns. As a conclusion there are specific reasons why investors may still prefer growth stocks, and lose in a longer horizon, instead of value stocks. The overestimation of a sequence of good performances and the increasing institutional demand for large stocks, the abnormal returns earned in the short-term and the riskiness contained in small-valued stocks, are a few to be mentioned.

2.4.5. Conclusion

The basic anomalies explained above, are the results of studies trying to analyze the puzzling properties of stock markets that cannot easily been explained by the standard CAPM. The behavior of stock returns is identified mainly by three factors, considered as the premium properties of stocks. Namely the “equity premium”, is found to give stock returns a high excess rate above other securities and include a risk premium in order to be preferred by investors, as well as “volatility” and “predictability”, mentioned above, due to the fact that stock returns are highly variable but predictable. In particular the excess volatility property was analyzed extensively during the 80’s, Shiller (1981a, b) and LeRoy and Porter (1981), where stock prices were pertained as heavily fluctuating compared to fundamentals. The predictability feature received many critiques, notably by Kleidon (1986) and Fama and French (1988), who examine the autocorrelations of stock returns and note that the mean-reverting price elements are the key reason of their variation.

Attempts of clarification of anomalous evidence have been numerous containing different models of factors that can explain abnormal performance of stocks by efficient means. However the persistence of certain anomalies was significantly supported by just as much papers, consistent with historical evidence and analyzed through different benchmarks than the EMH-based, thus using a behavioral and not a constant rational approach, forming the Behavioral literature further discussed below.

2.5. Literature review: Evidence of over- and under- reaction

Differences on behavior of agents are the main cause of stock prices movements leading to their overreaction and underreaction. The evidence underlining these two states can be expressed by the heuristics of representativeness and conservatism, respectively Barberis, Shleifer and Vishny (1998), leading in false prospects for the former and excessive backward looking, for the later.

2.5.1. Defining underreaction

Under the definitions Barberis, Shleifer and Vishny used for these "phenomena", underreaction is a rather short-horizon effect in which news becoming available to the market today are only reflected in prices and returns of tomorrow. When news are released in the market, investors underreact by persisting on the previous trend of prices, without noticing the sharp movement on the day of the shock; this behavior is changing later when the actual event is realized, thus a positive (negative) shock is followed by positive (negative) and increasing (decreasing) abnormal returns.

Conservatism in people's behavior leads investors on basing their decisions on their prior beliefs, this reliance moves the trending pattern observed in stock returns; thus stocks that underreact show greater returns in a period after good news, than in a period following bad news, a pattern that represents how slowly new information are incorporated into stock prices and justifies evidence of positive autocorrelation between abnormal returns.

2.5.2. Defining overreaction

On the contrary the overreaction phenomenon is observed as overconfidence that news will continue the way they did in the recent past and thus returns can be known by these news series' observation only; in reality this cannot be infinite and expectations are not fulfilled within real performance of returns. That is the tendency of investors to be optimistic on a series of good or bad news, when actual news sequence contradicts with their sentiment. News are translated into large and sharp reactions and thus move prices accordingly, immediately after news' release, a process that is corrected in the days following.

The overreaction hypothesis is observed when good (bad) news, incorporated in the market, decrease (increase) the price of a given stock on the following days. Statistical evidence supports that prices return towards their mean, as investors realize they attached more weight to recent news, thus overreacted Shefrin and Statman (1985) and Lehmann (1990). The initial price dip (peak) is corrected the next days followed by an upward (downward) move, this pattern characterizes the phenomenon also called return reversals.

2.5.3. Main findings

In 1985 one of the first and most influential papers on the field of Behavioral Finance was published, mainly analyzing people's systematic overreaction to unexpected events –shocks. De Bondt and Thaler (1985) support that: "*If stock prices systematically overshoot, then their reversal should be predictable from past return data alone*." Their research about this market anomaly, where extremes in stock prices are followed by opposite price movements, is reported as return reversals and is usually identified in the long term (5 year period). Specifically, past losers (winners) tend to have high (low) returns in the following years, something that clearly states that abnormal profits are possible using historic returns. On their following paper De Bondt and Thaler (1987) document additional evidence supporting the finding of overreaction.

Several papers attempted to explain the failure of EMH which captured the anomaly stated as overreaction, long-term return reversals, but unfortunately didn't support the notion of return continuation-momentum as found by Jegadeesh and Titman (1993), one of the first papers researching short and medium-term underreaction. Their evidence of returns' trending, where past winners continue to outperform past losers, is also known from Fama (1998) as the inability of stock prices to react on time with earnings' news and from Cutler, Poterba and Summers (1991) with evidence of autocorrelations in excess returns, trends. Indeed in their later paper Jegadeesh and Titman (2001) they show how this momentum in returns reverses in the longer-run.

The above interesting theories and profitable strategies about inefficiencies of equity markets were researched further to be given different explanations through various models. In a theoretical-survey scheme; behavioral models were used to explain empirical evidence of anomalies; Barberis, Shleifer and Vishny (1998) construct their model in a way that embodies expectations of agents on earnings by replicating their anomalous reaction of misinterpretation of fundamental news, resulting to psychological biases leading beliefs of mean-reversion and trending of returns. Similarly Daniel, Hirshleifer and Subrahmanyam (1998), highlight the importance of biases in interpretation when public and private information coincide, leading to overestimation of news. Another branch of behavioral models, indicationally Hong and Stein (1999, 2003) and Shiller and Campbell (2001), differentiates of the above by modelling the co-existence of heterogeneous beliefs in the market and how this conflict of different strategies and expectations declares abnormal behavior leading to persistent deviation of prices in response to news.

Other papers worked more on empirical models concerning different stock markets and types of reactions through time. These analyses put forward the examination of cross-sectional returns' predictability and establish autocorrelation findings over different horizons and factors of influence; De Bondt and Thaler (1985, 1987 and 1990) find substantial evidence in favor of overreaction and long-term contrarian strategy's profits, concerning the betas of stock groups under examination. In contrast Lehmann (1990) supports short-term reversals under the explanation that investors correct their overreaction on bad/good news. Jegadeesh and Titman (1993) on the other hand, speak about momentum strategies' profits that are variously linked to cross-sectional variability of expected returns in the short-run; Conrad and Kaul (1998) base this variation on significant time patterns observed on specific months of the year, whereas Fama and French (1988) stretch out the size effects on profitability and base variation in returns on dividends. On the same context Veronesi (1999), Lee and Swaminathan (2000) and Daniel and Titman (2000) all test reactions of stock prices on book-to-market effects, trading volume and related information incorporated in the market.

However some important questions arise after the variant evidence of the above reported findings. Fama (1998), have questioned whether indeed investors irrationally react to news, as he also did in Fama (1970) with a survey article. Also Malkiel (2003) supports the notion that information is directly incorporated in prices and the perception that neither technical nor fundamental analysis will enable investors on achieving greater returns. On a more specific direction, George and Hwang (2007) found evidence supporting that, the cause for returns reversals is not investors' overreaction but tax obligations. Other critics eliminate the above phenomena through rational explanations Zarowin (1990); adjust for size differences, Conrad, Cooper and Kaul (2003) attribute the findings of De Bondt and Thaler (1985) to data bias due to cumulative measurements, Lewellen and Shanken (2002), accuse the ignorance of investors on the processes of the matket, and Clement, Burgman and Norris (2009) support that the reason for these particular returns' patterns are probably omitted variables such as size and value and not the hypothesized behavioral biases of investor.

Furthermore -"*If there was a persistent tendency for the portfolios to differ on dimensions that may proxy for risk, then again, we cannot be sure whether the empirical results support market efficiency or market overreaction*."- De Bondt and Thaler (1985) state that researching behavioral biases using the standard CAPM model may be inaccurate. Factors' misperception was first captured by Fama's and French's (1996) 3-factor model, giving in a sense a more detailed CAPM model formatted to capture the patterns of average returns of a portfolio or stock in order to explain anomalies due to risk factors, and showed that when considering size and the ratio of market value to book value then any event's causation disappears. The problem of restrictions imposed by variant CAPM made early studies on abnormal effects of events, over the value of firms, sensitive and thus turned towards the use of market model to analyze abnormal returns for strengthening inefficient evidence.

Although academics posed several methodologies on the relative explanation of anomalous behavior through other factors, evidence of existing market inefficiencies remains large. Researches on the identification of anomalies, in various markets and time periods, showed robust overreaction and underreaction evidence even after returns were risk-, size- or value-adjusted. For example Spyrou, Kassimatis and Galariotis (2007) find short-term underreaction of medium and small sized firms in response to both positive and negative shocks, which remains highly significant over testing for risk factors (3-factor model), calendar effects or global financial crises' contagion.

The empirical literature on stock reactions is large and the papers discussed above are only indicative of the focus of the relevant research.

2.5.4. Event studies

In his opening paragraph, Bachelier (1900) recognizes that "*past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes"*, although this recognition lead to primal evidence of efficient market, Bachelier introduced the possible linkage of equity markets with events; the effects of such linkage are observed in analyses named after event studies. Event studies examine the impact of specific events in stock returns, the characteristics of which heavily affect the outcome in the sense of direction and robustness of stocks' reaction in periods of turbulence. The main procedure includes comparison of returns' around a known or unknown event period indicating the behavior of prices due to news' release; either firm-specific as earnings' announcements, finance-oriented as change of regulations, irrelevant politico-social factors such as wars or even important international conferences, such as the G20 summit.

2.5.4.1. Models presented

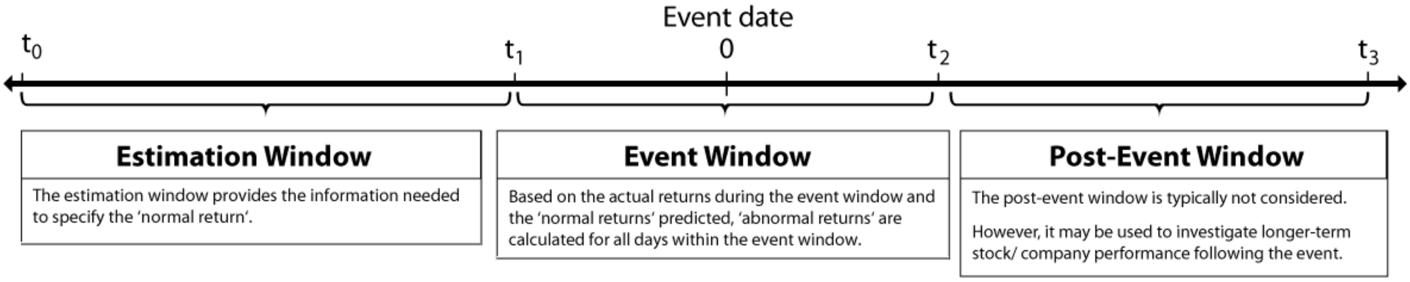
The main purpose of this study is to identify the kind of reaction of stock returns around a shock, in the case that these returns represent an abnormal deviation from normal returns of quiet times -no event period. The main difference of empirical models, used in event studies, is the method of estimation of normal/ actual returns and the deviation of returns in excess of an equilibrium, identification of abnormal return variance, the selection of such point of comparison defines each model. According to MacKinlay (1997, pp. 17-19) there are two categories of models, the statistical models: such as the mean adjusted model, the market model, which are concentrated on statistical assumptions around the behavior of returns, the multifactor models, which attribute abnormal behavior to various factors as industry specific or size, and the economic ones: such as the CAPM and the APT, which are mainly based on the investors' behavior impact. The methodology followed in this paper is the mean-adjusted model that even being one of the simplest models in implementation, is found Brown & Warner (1985) to yield results similar in power and robustness with more complicated models.

As the first authors to comment on such detail the interpretation of movements of stock prices, De Bondt & Thaler (1985) analyzed monthly returns of particular stocks (CRSP) by separating between winners and losers, using the cumulative market-adjusted excess return over consecutive 3-year (36-month) period. Many subsequent scientific research on the topic made use of the same or similar metrics in order to detect any interesting results. Their method and conclusion, though substantial, was criticized by Conrad & Kaul (1993), accused as misleading and biased. However the empirical part of event studies have been designated by even earlier studies, forming the main 2 methodologies followed in order to test the null of efficiency, thus to examine the impact of events on prices. As reviewed by Binder (1998), one method makes use of dummy variables in a regression model including returns before and after an event structured in portfolios, whereas the other, most used one, analyses the residuals of abnormal returns from a benchmark model, and is described in more detail below.

Early studies as Scholes (1972) estimate abnormal returns during a period t as prediction errors of the relation of the market return $\mathrm{R_{mt}}$ calculated over data prior to t, and the return on t $\mathrm{R_{it}}$, following one of the standard methods used in events studies. The most known papers, basically setting the start to such methodology in event studies, Fama, Fisher, Jensen and Roll (1969) and Ball and Brown (1968), examine the effect of stock split announcements during specific months around the event using the residuals of the market model as an estimator of the abnormal return during the event. Their method removes irrelevant factors of influence from the return leaving it attributable to firm specific information.

In response to the long literature of event studies, several following studies reviewed the methods used and measured the power of the most prominent ones Brown and Warner (1985) and MacKinlay (1997). The common element of most methods and their variations are the estimators used to measure the magnitude and direction of the shocked-reaction caused by a specific (or to identify a non-specified) event. The constructs used as such estimators include abnormal returns, several ways of computation are explained above, the average abnormal return ($\mathrm{AAR_s}$) during the period of the event t and the average cumulative abnormal return ($\mathrm{CAAR}_{\mathrm{t1,t2}}$) from time t_1 prior until t_2 after the event. The analysis of metrics though requires to set important guidelines before interpreting the statistical results, such as the settlement of prior-, during and post-event periods. For the ease of understanding we present the timeline below:

Figure 1: Timeline of event periods' estimates [2]



We set t=0 as the event date, from which each R_{it} is extracted for being compared with the normal return being computed over the estimation window from t_0 to t_1 . The estimation window is ended at t_1 before the actual event so to eliminate possible lead-up preceding the shock. Fama, Fisher, Jensen and Roll (1969), Brown and Warner (1985) highlight the importance of separating for removing any confounding events - disturbances, and avoid biased estimates of returns. Further (MacKinlay, 1997) stresses out the problems occurring in examination of known or unknown events, by limiting or increasing the event period to the interval of 0,+1 or -1,+1, respectively.

2.5.4.2. Timeframe and frequency of data

In the short-run of in-between 1 year we observe the "momentum effect", meaning that stock portfolios with satisfying history of high (low) returns continue on producing high (low) results over these horizons. The above pattern of reaction implies that current news are not immediately incorporated on prices, but with a time delay, predicting the correct signal only on the next period. On the same paste but with the contrary reaction, on long horizons of 1-5 years, stock prices exhibit consistent movements along with news records. Highly rated portfolios, proven to be mean-reverting, hence receiving high returns related to a "good" news series finally concluding on returns returning to the average. Evidence of short or long-term continuations and reversals of stock returns, using prior returns of particular stock indexes to compute average returns, indicates that results are sensitive to the number of total observations, the frequency of the data and the setting of estimation and event periods.

Long-term studies engage less frequent monthly stock returns, short-term analyses study daily or even intraday returns. Fama, Fisher, Jensen and Roll (1969) observe abnormal returns over a total window of 29 months previous to the shock to 30 months preceding the shock, but most studies separate using various estimation windows based on the judgment of the researcher, depending on the pervasive irregularities checked. For example Brown and Warner (1985) use 239 days prior to the event, Cox and Peterson (1994) 100 days and MacKinlay (1997) suggests 250 days.

The event window, used on assessing the significance of excess returns over the days following each event, should not overlap the estimation period for avoiding normal estimates influence, MacKinlay (1997) suggests a short event period of (-1,+1) but other studies range from t_1 (Figure 1Figure), between -10 to -5 days, to t_2, +1 to +20 days after the event, for example Brown and Warner (1985) use (-5,+5). In some cases the event period does not include the t=0 event date and thus measures average abnormal returns on spans beginning of +1 or later days, as Cox and Peterson (1994) who use (+4, +20).

[2] Source: (MacKinlay, 1997, pp. 19-20)

The purpose of this paper is to contribute to the market reaction literature to shocks using daily return data in order to identify whether overreaction or underreaction evidence is supported in the occurrence of an event, thus providing complementary evidence to previous studies examining short-term horizons. This research is motivated by non-overlapping windows used in Spyrou, Kassimatis and Galariotis (2007); in particular the estimation period used is set to 50 days allowing for a 10-day interval prior to the event (-60,-10 days) and the event window over which cumulative and average cumulative returns are observed is set to +1 to 20 days after the event.

2.5.4.3. Possible flaws

Number of problems have been mentioned in event studies and have been discussed in review papers of the corresponding methodology, Brown & Warner (1980, 1985), Binder (1998), MacKinlay (1997) and Boehmer, Musumeci, & Poulsen (1991). Most broadly recognised problems are mentioned below; some of these limitations directed to the methodology of this study are outlined in section 4.3.

1. Event study methods test the effect of events on returns. Increased variance of returns though have been identified as the main reason for such methods to fail Boehmer, Musumeci, & Poulsen (1991) the null of 0 effect is rejected too often, in cases when is actually true (type 1 error); they analyse the necessity for the hypothesis tested to be expanded in order to allow for varied variances.
2. The common statistical properties of stock series realised as obstacles; the non-normality property reported mostly in daily frequencies, because of extremes in distribution, and volatility because of the persistence of such extremes. Brown and Warner (1985) explain how the presence of outliers and high leverage data points in returns can influence the conclusion of an event study. Also Blume (1971) and Gonedes (1973) caution for statistical problems of excess returns, as the difference in variance, the intense correlation and the non-independency across firms, picturing the stationarity concern for the parameters used.
3. Binder (1998) stresses-out the concern that anticipated events, such as regulation change, can increase the probability of tests to accept the null when it is actually false (type 2 error). This low power of tests requires careful consideration of the dates of events examined but also microeconomic analysis of the impact of such event in a company.
4. The overlapping windows problem, regarding whether the event period is included in the estimation period, leads to biased estimate of normal returns because of the disturbance caused by exaggerated effects around the event. MacKinlay (1997) explains a simple design of periods examined (Figure 1) but also mentions the clustering of events as included into the overlapping problem.
5. Evidence of overreaction and underreaction has been argued to be the result of biased returns' computation. Cumulative returns, used broadly in event studies, is considered as a biased measurement which aggregates and exaggerates abnormal effects on returns, resulting in false anomalies' realisation Conrad and Kaul (1993).

3. Research Design

This chapter builds the infrastructure of examining the effect of any unanticipated event on a series of stock returns. First, the hypotheses, under which the main reason of research (RQ) is tested, are presented, as well as some sub-questions meant to give a further impulse on the interpretation of results. Secondly, the assumptions needed for setting estimations on are explained, extracted from previous research on returns and excess returns series, hence mainly event studies' methodology. Third the data used for this analysis are described; the indexes, the return metrics used and their distributional statistics are presented in Table 1.

3.1. Hypothesis development

In order to test the RQ reported in section 1 and before the method used is analyzed below, it is of crucial importance to split the main topic of this research into smaller targets. In particular the following hypotheses are set under examination:

Hypothesis I: Stock prices obtain overreaction in response to shocks.

Hypothesis II: Stock prices obtain underreaction in response to shocks.

The reaction of stocks on major events of the recent financial crisis is accounted for the purpose of this study. After anomalies in stocks returns have been introduced by other papers, as explained above, the objective of this event study has been clearly directed. Investors' behavior response to unexpected news appear in two patterns, inconsistent with EMH, that of overreaction and underreaction, which move in respect stock returns; this analysis examines the sequence of returns in the Dutch market and searches for evidence of inefficient movements caused by the release of shocks. For the confirmation of the results, stability over indexes and time is additionally appreciated by replying to the following questions:

Question I: Are the results derived statistically significant?

Question II: Do we observe any significant differences between indexes?

3.2. Assumptions

The essence of assumptions into economic models is crucial and their absence leads to imprecise economic interpretation. For that reason the statistical model followed here should be accompanied by the following assumptions[3]:

- In relation to the non-normality property of stocks, the assumption of returns and abnormal returns being independent is needed.
- There should not exist any overlap in the event windows, this could lead to biased estimates of abnormal returns.
- The mean adjusted return model followed in this study is consistent with CAPM under the assumption that the unsystematic, firm-specific risk is assumed zero.
- Aggregation of abnormal returns across the event window requires the assumption of non-clustering of events but also distributional independency among abnormal and cumulative returns.

[3] MacKinlay (1997) provides an extensive analysis of event studies methodologies and summarizes the main assumptions needed to be taken account for.

3.3. Data clarification

For examining the above hypotheses in the Dutch market, Euronext Amsterdam has been used as the source of data. The 3 different capitalization size indexes employed for empirical analysis are covering a wide range of different sector companies and are aggregated based on free-float adjusted market capitalization, accounting for the size-effect phenomenon. The price indexes used are the most used indicators of the Dutch stock market, when AEX reflects the performance of the 25 largest and most actively traded shares listed on Euronext Amsterdam, and AMX and ASCX are framed for middle and small-cap companies, respectively. Appendix B contains all detailed information for the 75 companies included in the sample. The objective posed by the research question requires an adequate period before the burst and after the recovery of the euro crisis to be engaged, for that and also for availability reasons the data used in this study consist of almost 11 years of daily closing prices, counting from start of 2003 to start of September 2014. A total of 2991, for AEX and AMX, and 2435, for ASCX, closing prices in Euro were employed for the application of the methodology described below; data were calculated through Excel and tables are built using SPSS analytics.

3.4. Methodology

Terms as unanticipated, unexpected, surprise, shock are more often used to describe a period of abnormal returns in event study's procedures. In order to check for abnormal differences in returns, it is essential that any change is properly interpreted. In the case where the market is disturbed by news' transmission; if the information penetration is higher than normally expected, it should be associated with an irregular increase in normal returns, if is lower, then it should be associated with a decrease. The difference of this analysis with other studies analyzing the effect of recurring events in a specific segment of the market, like for example quarterly earnings announcements, or CSR disclosures, or even once time events, like the announcement of war-practice outbreak in a country or the bankruptcy of a financial intermediary, is that the event is not determined and does not have the same influence throughout the market, for thus 3 stock indexes are tested separately.

In order to generate more informative and utilized observations the price indexes extracted need to be transformed into returns, according to the following:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{2}$$

Return $R_{i,t}$ is defined as the change of 2 sequent day's (t and t-1) closing stock prices of each index i separately.

To identify the exact period (day) in which the shock is said to occur, since the historical returns sequence is impaired, the daily returns of each index are compared with a moving average. According to MacKinlay (1997) this moving average is defined as the estimation period and should not overlap the event, "*this design provides estimators for the parameters of the normal return which are not influenced by the returns around the event".* In particular the estimator used for this comparison is equal to the expected return measurement, under the mean-adjusted method, calculated from the non-event period, estimation window. That is, the average of 50 observations starting 60 days and ending 10 days prior to the shock day, as proposed by Lasfer, Melnik and Thomas (2003), accounting for any possible additional provision by investors the days immediately preceding the event. For each day t of each index i, the expected return $E(R_{it})$ is given by:

$$\overline{R}_i = \frac{1}{n} \sum_{t=-60}^{-11} R_{i,t} \tag{3}$$

where $R_{i,t}$ is the return on each day of the estimation period (-60,-11 days) and n is the 50 observations consisting the window. Then shocks are defined by comparing normal return $\overline{R}_i$ with each day's actual return $R_{i,t}$; the appearance of a positive (negative) shock will be notified when the daily return (on day t) is 2 standard deviations above (below) the estimation window's average.

Following mainly the methodology of Spyrou, Kassimatis and Galariotis (2007) and in order to capture the event impact, the abnormal return of each trading day is calculated. The prior to shocks 50-day window is used as the short horizon estimation of expected returns, and the direction and magnitude of the deviation of daily returns from expected returns is analyzed for obtaining abnormal returns' performance on the event of either positive or negative shocks. Abnormal returns are computed by:

$$AR_{it} = R_{it} - E(R_{it}) \tag{4}$$

where the difference between the expected return $E(R_{it})$ on index i, the average return on index i over the estimation period of 50-days period ending 10 days prior to the shock, and the actual return R_{it} , are used to evaluate the impact of any possible shock on stock prices.

For evaluating the patterns observed in our sample aftershocks, hence giving evidence of over-, under- or efficient reaction, event observations are useful to be aggregated for the event window. Shocks days are isolated from the sample and Cumulative Abnormal Returns (CAR) are computed by summing the abnormal returns across the next 20 days following each shock.

$$CAR_{it} = \sum_{t=1}^{20} AR_{it} \tag{5}$$

Accumulation is applied across different types of shocks, indexes and days of the event window, and is assumed to be no clustering of shocks. (MacKinlay, 1997, pp. 21-24) highlights the importance of no overlaps across event windows per shock, due to the need of distributional independency of returns' metrics, ARs and CARs.

Each of the 1, 2, 3,..., 20 days' CARs following the shock (day 0) is averaged forming the Average Cumulative Abnormal Returns metric, for characterizing the behavior of each index in the case of positive or negative shocks separately.

$$ACAR_{it} = \frac{1}{N} \sum_{t=1}^{20} CAR_{it} \tag{6}$$

This results in ACAR $_{1, 2, 3\ldots}$ observations whose statistical significance is then examined with the t statistic , $t = \frac{\overline{ACAR}}{\sigma / \sqrt{N}}$, testing the null hypothesis of ACAR in each subsequent day of shock is zero, $\mathrm{H_0} : \mathrm{ACAR_t} = 0$. The reported statistics are calculated using σ and N of the CARs from which the average is obtained.

3.5. Descriptive statistics

Following the methodology sequence above, first the normal returns' series are constructed; Table 1 provides the summary statistics of daily returns for all 3 indexes separated in columns. The upper part of the table gives the statistics concerning the full sample of returns, starting from January 2003 for AEX and AMX and from January 2005 for ASCX (due to data availability) and ending August 2014 for all 3 indexes. The two following separate panels include statistics concerning the sample divided in two sub-periods, from the start of returns to the end of 2008 for sub-period A and from the start of 2009 to the end of the sample for sub-period B.

The selection of this sample serves on framing the financial crisis period in Europe, but also an adequate period of returns before and after it, resulting into more stable measurement of normal returns -averaged returns used in (formula 3) include non-extreme events' periods. In order to investigate the stability of results over time, division into two sub-periods is selected in a way that the two halves of the sample include the major crisis years for sub-period A and the recovery years for sub-period B; furthermore both sub-periods include major shocks for the purpose of reaction to shocks' analysis.

The full sample statistics show that the large-cap index, AEX, and the medium-cap index, AMX, including same number of companies (25) and same number of observations (2991), have similar dispersion measures (0.0135 and 0.0132, respectively) but with AMX having almost double the mean return of AEX (0.0309 and 0.017, respectively). AEX exhibits the largest return (0.105) of all indexes and AMX the most negative one (-0.095), extreme returns which are realized in sub-period A, containing the largest shock of the burst of financial crisis. ASCX forms a more compact distribution due to its moderate smallest and biggest returns (-0.079 and 0.0783, respectively). The minimum return of each index was realized at 6 October 2008, whereas the largest in 13 October 2008; events on and days after the 6th of October showed the severity of US financial crisis spread threat, with all leading share indexes of Europe experiencing severe losses on the 6th and major banks as well as governments and IMF announcing plans to combat the crisis the following days. This is the first indication of overreaction evidence on the appearance of severe negative shocks.

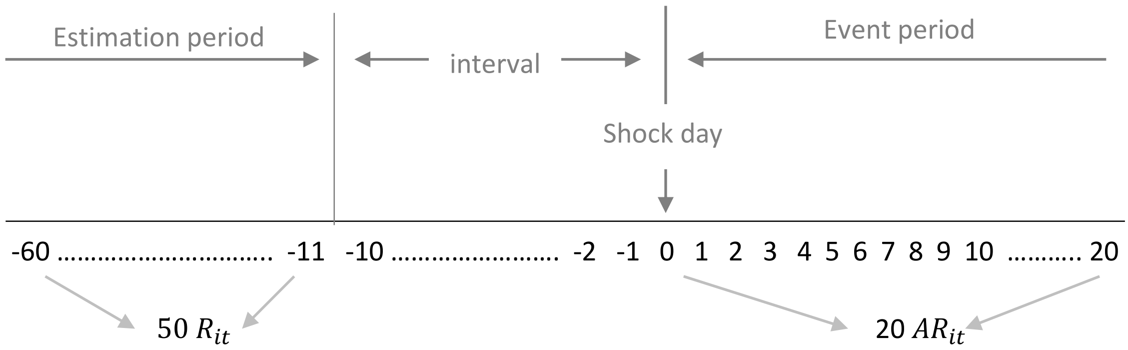
Panel A includes the same minimum and maximum returns for all 3 indexes, as explained above, showing the largest mean for AMX (0.0076). The other two indexes exhibit both negative means, with ASCX having the most negative one (-0.029), indicating a prominence of negative returns, result indicating the average type of shocks during that period. Note that in the period following the major crisis of 2008 all three indexes have almost half the minimum return of that in the previous period, but with AMX exhibiting again the most negative of all minimum returns and AEX the most positive (-0.0689 and 0.0733, respectively). ASCX in comparison with the other two indexes shows the least variation but with percentage mean similar to that of AEX (0.045 and 0.044, respectively).

4. Data analysis – Results

4.1. Main findings – Reaction to shocks

Reporting the main results of previous studies in the theory section; this chapter introduces this analysis' results for all 3 indexes' reaction to positive and negative shocks. In order to check the hypotheses of this study, the methodology sequence should be followed as presented in section 3.4. As a first step the criteria used for the shocks' definition, are summarized in Figure 2 below.

Figure 2: Timeline of shock periods



The formation of returns $\mathrm{R_{it}}$ is followed by the construction of a moving average series, which constitutes of estimation period's returns, as depicted above. Moreover this moving average provides the estimates of $\mathrm{E(R_{it})}$ needed for the calculation of abnormal returns, as described in formula 4. The first focus of this study is to identify the shocks occurred on the period and indexes under examination, and interpret their magnitude, direction and position through time. For that reason the period until the shock day is commented first; the window allowed between the estimation period and the day of the shock assists on isolating the shock from any interfering price turbulence before it. In that case a shock is said to occur, when $\mathrm{E(R_{it})}$ is above or below 2 standard deviations of the $\mathrm{R_i}$ series. Figure 3 shows the shocks realized for each of the 3 indexes. Consistent with the burst of the financial crisis timing, the largest shocks' clustering is seen between summer 2008 and summer 2009.

Table 2 provides a detailed view on the events responsible for major movements in returns of Euronext Amsterdam major indexes. The particular reaction of each index to shocks is measured by the abnormal return on the day of the shock and statistics of returns in response to those positive (negative) events are shown in the left (right) part of the table. Comparing between samples the largest mean abnormal returns is found to be exhibited by AEX in sub-period A, 0.05 for positive shocks and -0.045 for negative, as intended to be by the separation of sub-periods but also as depicted in Figure 3, since this is the period concentrating the major effects of the crisis. In fact AEX exhibits the biggest tension of reaction for all kind of shocks and all periods examined, 0.045 and -0.041 in the full sample, 0.05 and -0.045 in sub-period A and 0.039 and -0.037 in sub-period B, for positive and negative shocks respectively. AMX's and ASCX's lower means leads to the generalization, that the size of reaction to shocks reflects the size of the company, which translates to that investors trading shares of large companies showed a less consistent behavior throughout the crisis. This pattern of reaction is observed in all periods both for positive and negative shocks, hence smaller indexes have smaller mean reactions, a result that is better interpreted if the number of shocks per index is accounted for. AEX although showing the largest mean reaction of all, is distributed among the smallest number of shocks, 57 positive and 65 negative shocks in total. In contrast AMX, and even ASCX, showed more shocks both positive and negative, 71 and 62 for positive and 91 and 80 for negative, respectively. For all periods examined negative shocks are more than positive, meaning that investors react more exaggerated to negative than positive news, a finding consistent with evidence from other event studies.

For the clarification of the matter and although all means are found to be significant on 1% level for all periods, the differences between indexes still need to be examined for if they exhibit any significant similarities, due to the close estimates. The null of mean reaction being equal between indexes is tested by a comparison paired t-test, for all possible pairs of indexes tested by descending order. The results are shown in Table 3. The t statistics reported reveal the genuine independency of each reaction and thus the differences between indexes reaction are indeed significant. In particular all estimates for when positive (negative) shocks occur are positive (negative)and the before-mentioned pattern is confirmed as the numbers indicate that average reaction of AMX is lower of that of AEX and much larger of ASCX (t=1.905 compared to t=4.56). The same relations apply for negative shocks in similar volumes.

As for the exact timing of the events, those are observed in 24th November 2008 for the largest positive shock of 11.06% in AEX and on 6th October 2008 for the smallest negative shock of -9.6% seen in AMX. Negative shocks of the two other indexes are observed on the same date, whereas the rest of positive shocks are exhibited within the previous month, 20days earlier for AMX's 8.94% and almost 40days earlier for ASCX's 7.96%. If this outcome is to be resembled with the largest shocks of sub-period B, although smaller in magnitude, they are forming clusters only for negative shocks, when the greatest negative reaction is met on mid-February of 2009 and the rest within one month. On the other hand, the largest positive reactions are observed in May 2010 for AEX and AMX, 7.1 and 6.54, respectively, whereas ASCX exhibits its largest shock one year earlier very close to the date of its minimum negative shock. The observations above lead to the conclusion that when major shocks occur throughout the market, as the severance of 2009 events for EU financial crisis, no investor can remain unaffected.

4.2. Main findings – Patterns of reaction

In order to comment on the main goal of this paper, the reaction of each stock index should be analyzed over substantial period after the event. As shown in Figure 2, 20 abnormal returns following the shock day are collected and are accumulated onto the CAR measure, beginning day 1 subsequent to the shock and ending day 20. Table 4 presents the results of the average CARs in the 20 day-period following positive and negative shocks, upper lower panel, respectively. Evidence over Table 2 showed that negative shocks are more frequent, especially in smaller indexes than AEX; in AMX 20 negative shocks in excess of positive, in ASCX 18 more, full period. Further the mean abnormal returns of all indexes seem to exhibit a reaction similar in sign to the kind of news, first row in both panels of Table 4 shows the reaction of each index on day 0. What should be examined in more detail though is the following period's reaction, which will clarify if stocks have an anomalous or efficient movement. As mentioned above stocks' returns show evidence of overreaction when abnormal movement on the day of a shock is followed by a series of opposite direction returns; on the other hand underreaction evidence is supported when shocks are followed by the same sign of returns.

Table 4 reports 0.0455 of AEX mean abnormal return in day 0, as the biggest reaction of all 3 indexes, and next day's reaction at 0.00157, the smallest of all 3 1st days' reactions, compared with 0.004755 and 0.0049. The above observation not only reveals counter-movement after a positive shock for all 3 indexes on the day following the shock, leading to underreaction evidence, but also supports the notion that large companies react more severely in shocks, as commented in the previous section. The relation between indexes is kept the same for the whole event period and AEX exhibits the largest underreaction pattern, as its cumulative returns are smaller for the days following the shock but its first overshoot was the biggest. Figure 4 shows the graphical representation of reaction per index; consistent with the underreaction hypothesis, abnormal returns are positive and increasing following positive shocks, which shows that good news are followed by a drop on the prices' levels that return back during time. AEX shows a more turbulent pattern, which prolongs the adjustment period; estimates of day 4, turning 0.049 of the previous 0.00664, seems to show reversal which overshoots again on day 6; accordingly, day 15, 17 and 20, 0.023, 0.030 and 0.0400, respectively, exhibit peaks of reaction. This outcome could translate into severe reaction of investors in large-cap stocks, which is not projected gradually, but also could cover a period were more than 1 shocks were happening at the same time (see section 4.4). On the other hand the other two indexes show a smoother but more immediate balance. Overall AMX showed the biggest increase, a difference of 0.04271 of 1st to 20th day, a result that ensures its more immediate adjustment to changes. All results concerning positive shocks are significant, which gives us strong evidence of underreaction to all 3 indexes under examination.

On the panel concerning the reaction to negative shocks, negative initial abnormal returns are exhibited in all 3 indexes, as expected and subsequent reaction is both positive and increasing in the post-shock period for AEX and ASCX; on the other hand AMX exhibits negative returns for the 2 days following the shock, a pattern that is reversing afterwards and indicates a slower signal of overreaction. When extreme negative returns on the day of a negative shock are followed by the opposite sign of increasing returns, overreaction is supported. The statistical results significantly (t-statistics) support overreaction evidence for all samples examined In particular, AEX again shows some kind of more turbulent reaction which nevertheless cools down after one week, resembling the other two indexes. Figure 5 depicts the results presented above and further supports the significance of overreaction by a comparison with De Bondt's and Thaler's (1985) primal evidence of overreaction, although the sample's magnitude and horizon is different the pattern exhibited is the interesting similarity here. The black dotted line shows the increasing subsequent movement of cumulative abnormal returns of loser portfolios, resembling the lines created for ACARs of all 3 indexes under examination.

Figures 6, 7, 8 and 9 support the stability of results over time. The previous division into sub-periods is also followed here and the outcome reveals overall the same patterns of reaction, in different magnitude for sub-period B, underreaction in response to positive shocks and overreaction into negative ones. Sub-period A in particular show how intensively financial recession affected investors, projected by the turbulence and sharpness of Figure 6 and 7 and the apparent similarity with the full sample's patterns. In particular, the response of AEX in negative shocks is clearer than the other two indexes', this shows some small evidence of resistance to overreaction over the week following the shock for AMX and ASCX, a phenomenon that was also showed in Figure 5 but in a much smaller scale. On a similar context the years following the crisis, Figure 8 and 9, the patterns of reaction are overall the same, but now the difference of the intense reaction of AEX towards the other two indexes is more significant, as is the phenomenon of stability over the first week after a negative shock is occurred, explained above.

4.3. Limitations and directions for further research

Each method used in event studies for the recognition of news' effect on stock returns has its own advantages and disadvantages. Although Brown and Warner (1985) comment on the apparent power similarity of those methods, MacKinlay (1997) addresses the attention to the statistical or economic assumptions followed but recognizes their necessity. The main assumptions followed here have been reported in section 3.2, in relation to common flaws of event studies. Despite the fact that the model followed is quite general and widespread, the assumptions taken beforehand are not sufficient on covering the extensive framework of event studies' methodology. For that reason and in order to avoid any misinterpretations or generalizations of the analysis, the reader is cautioned over the main limitations.

Focusing in only one market for concluding on evidence over abnormal reaction of stocks may considered as one of the limitations of this study, as the primal theory over anomalies considers behavior of investors, which could better be defined over a broader analysis on opponent markets. It would be interesting thus to apply an analysis similar to the one presented here, in the direction that includes more countries' markets on the sample examined, this way could reveal how markets interact and possibly exhibit similar patterns over- or under- reaction.

The main limitation of this study could be considered as the overlapping of events been addressed in event studies' theory. The form of recognizing shocks in this analysis is not of taking into consideration known events concerning announcements of companies, as been extensively used in other studies, but to recognize a shock after statistical observation of the measurements framed. The financial turmoil years under examination is also another reason of many shocks occurring on the same period and on a very close range, then obviously there are events oversetting others and causing the entangle of effects and returns estimates. It is important that removing any confounding events around the event window leading to biased estimates of abnormal returns because of the disturbance caused by exaggerated effects around the event. The assumption of no overlapping periods and events is of crucial importance to the analysis of aggregating measures and is the limit settled here. However eliminating for such overlaps would derive more robust results. The clustering can be accounted for using a longer period of data compared with the event period- allowing for larger interval between estimation of events- or by using aggregation of stocks in portfolios.

To conclude, the methodology followed has been already broadly recognized among researchers as simple but with similar sensitivity and resultful as other more complicated ones, Brown and Warner (1985), although promising methods always include possible pitfalls.

Also the core idea of this study is to concentrate on to the finding of abnormal evidence and interpret it according to theory of the two basic anomalies identified in the behavior of investors affecting prices, and thus constraining the framework on that purpose. However this particular dataset could be used otherwise and conclude on a different result, thus there is always the possibility of alternative practicing and explanations when considering the wide ways of conducting an event study.

5. Conclusion

The short-term analysis of the reaction patterns observed in Euronext Amsterdam the years surrounding the recent financial crisis, gave out some particular and significant outcomes; Substantial evidence of overreaction in response to negative shocks and underreaction in response to positive. This result stays stable over-time and the supporting statistics show how sub-period's A data, hence including the beginning of the crisis, covered any efficiency that years before or after financial turbulence could bear. The above result could be compared with important studies as DeBondt and Thaler (1985), who except of introducing overreaction to financial literature, comment that the overreaction effect is more pronounced for loser than winner's portfolios. On the other hand Brown, Harlow and Tinic (1988) who examine NYSE companies' reaction during middle 20th century contradict with confirming underreaction after extreme negative news.

Overall the most important conclusion that can be drawn is that AEX, the large capitalization index, have been the most significant and clear representation of both anomalies. Of course the lines drawn in support of the statistical results cannot be spotless, as explained above, and the clustering of events in a specific period, 2008 included in A sample and 2009 in B, lead into rough evidence. Investors trading shares of large companies showed a less consistent behavior throughout the crisis, when as expected, large tradors need to be more cautious on the appearance of shocks and hence react more efficiently. Furthermore the behavior of the smaller indexes have been proved as more mediocre, but again with evident anomalous reaction. The above result of the tension of reaction to shocks resembling in volume the size of the company, is also accounted for in studies like Hong and Stein (1999) who conclude that momentum profits largely increase with size and Daniel, Hirshleifer and Subrahmanyam (1998) who support that abnormal profits decline with book-to-market ratio; This result is consistent with the majority of studies comparing trading volume to information uncertainty and highlighting the importance of investors' psychology on stock prices.

The results of overreaction to negative news and underreaction to positive, as well as the prevalence of negative shocks are consistent with evidence of previous event studies, such as the main reference of Spyrou, Kassimatis and Galariotis (2007) finding more negative news in FTSE analysis, but confirm only the underreaction phenomenon nearly to all cases under examination. Although most of the literature on the field comment on the analysis of similar results on US or UK markets, EU investors are also influenced onto that direction, as financial markets are exposed to greater instability risk and thus contagion effects could lead to the outspread of financial turbulence across markets.

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7. Appendix A –Tables

Table 1: Descriptive statistics for returns and abnormal returns distributions of all stock indexes.

Full Sample (2003/2005-2014)

Index	AEX	AMX	ASCX
Start date	Jan 2003	Jan 2003	Jan 2005
Observations	2991	2991	2435
Mean	,0170	,0309	,015
St. Deviation	,01359	,0132	,0108
Min	-,0914	-,0950	-,0790
Max	,1055	,0830	,0783

Panel A: Sub period A (Mar 2003 – Dec 2008)

Index	AEX	AMX	ASCX
Observations	1536	1536	980
Mean (%)	-,0089	,0076	-,029
St. Deviation	,0153	,0132	,0122
Min	-,0914	-,0950	-,0790
Max	,1055	,0830	,0783

Panel B: Sub period B (Jan 2009 – Aug 2014)

Index	AEX	AMX	ASCX
Observations	1455	1455	1455
Mean (%)	,044	,055	,045
St. Deviation	,0124	,0130	,0093
Min	-,0520	-,0689	-,0456
Max	,0733	,0684	,0472

The table reports the first two moments of the returns distributions of all stock indexes, as well as the min and max returns. Normal daily returns are denoted as R and calculated by $R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$. Panel A and Panel B report the descriptive statistics of returns of 2 sub-samples, until the end of 2008 and since the start of 2009, respectively.

Table 2: Description of reaction to shocks

Full Sample (2003/2005-2014)

Positive shocks				Negative shocks			
Index	Mean	Max (%)	N	Index	Mean	Min (%)	N
AEX	,045507 (16,54)*	11.06 (24.11.2008)	57	AEX	-,041486 (-23,35)*	-9.11 (6.10.2008)	65
AMX	,038506 (24,13)*	8.94 (4.11.2008)	71	AMX	-,037378 (-30,27)*	-9.6	91
ASCX	,031126 (25,66)*	7.96 (13.10.2008)	62	ASCX	-,029763 (-25,02)*	-7.89	80

Panel A: Sub period A (Mar 2003 – Dec 2008)

Index	Mean	Max (%)	N	Index	Mean	Min (%)	N
AEX	,050537 (10,70) *	11.06	30	AEX	-,045487 (-14,81)*	-9.11	34
AMX	,040947 (17,07)*	8.94	40	AMX	-,038598 (-18,92)*	-9.6	46
ASCX	,032512 (16,97)*	7.96	34	ASCX	-,032301 (-15,72)*	-7.89	42

Panel B: Sub period A (Jan 2009 – Aug 2014)

Index	Mean	Max (%)	N	Index	Mean	Min (%)	N
AEX	,039918 (18,83)*	7.1 (10.05.2010)	27	AEX	-,037108 (-31,01)*	-5.3 (5.03.2009)	32
AMX	,035134 (23,39)*	6.54	40	AMX	-,036132 (-26,29)*	-6.81 (17.02.2009)	45
ASCX	,029443 (22,42)*	4.75 (2.04.2009)	28	ASCX	-,026959 (-30,44)*	-4.69 (3.03.2009)	38

The table is divided in the reaction of all indexes in positive (left) and negative (right) shocks. Reaction on positive or negative shocks is measured by abnormal daily returns and calculated by $AR_{it} = R_{it} - E(R_{it})$, where its day's abnormal reaction is the difference of the return on that day from a mean-adjusted forecast. Expected return $E(R_{it})$ used, by mean-adjusted returns model is the average return of the estimation window, here specified from 60 days to 10 days before the possible shock day, which is identified when R on that day is above (below) two standard deviations of the population. The mean of the reaction is recorded and is calculated as the average abnormal return $\mathrm{AAR_i} = \frac{\sum \mathrm{AR_{it}}}{\mathrm{N}}$ for each kind of shock. Panel A and Panel B separates the data in 2 sub-periods. Max and Min (%) columns give the maximum positive shock and minimum negative shock in the period of examination, respectively. The dates in parentheses define the date of the biggest shock per period.
The t-statistics are shown in parentheses and * denotes significance at 1%.

Table 3: T-test of comparing means for identification of differences between indexes

Positive shocks	AMX	ASCX
AEX	1,905*	4,560*
AMX		4,267*

Negative shocks	AMX	ASCX
AEX	-1,457*	-5,136*
AMX		-4,825*

The t-test searches for significant differences between the reactions of each index, separately for positive (upper table) and negative (lower table) shocks. Each t-statistics in the table tests the null of similarity between each pair of indexes by $t = \frac{\bar{x}_i - \bar{x}_j}{\sqrt{\frac{S_i^2}{N_i}} + \sqrt{\frac{S_j^2}{N_j}}}$. Pairs are tested by the biggest to the smallest index's direction (ex: AEX to AMX) and the series examined are constructed of the ARs of each index and each type of shock, by $AR_{it} = R_{it} - E(R_{it})$. Significance on the 1% level is noted with *.

Table 4: Initial and subsequent reaction to shocks, Full sample

POSITIVE SHOCKS	AEX	AMX	ASCX
Initial reaction	0,045508	0,038506	0,031126
ACAR 1	0,001577	0,004755	0,004934
	(0.555)*	(1.703)*	(2.513)*
ACAR 2	0,000392	0,006783	0,010878
	(0.087)*	(1.812) *	(3.293) *
ACAR 3	0.00664	0,00837324	0.012538
	(1.271)*	(1.383)*	(2.249)*
ACAR 4	0.00491	0.009133	0.013119
	(0.752)*	(1.412)*	(2.487)*
ACAR 5	0,004708	0,011316	0,015435
	(0.828)*	(2.454) *	(3.263) *
ACAR 6	0.011881	0.015652	0.014643
	(1.899)*	(3.485)*	(2.840)*
ACAR 10	0,015627	0,018490	0,022615
	(1.588)*	(2.520) *	(3.200) *
ACAR 14	0.0178	0.028296	0.030421

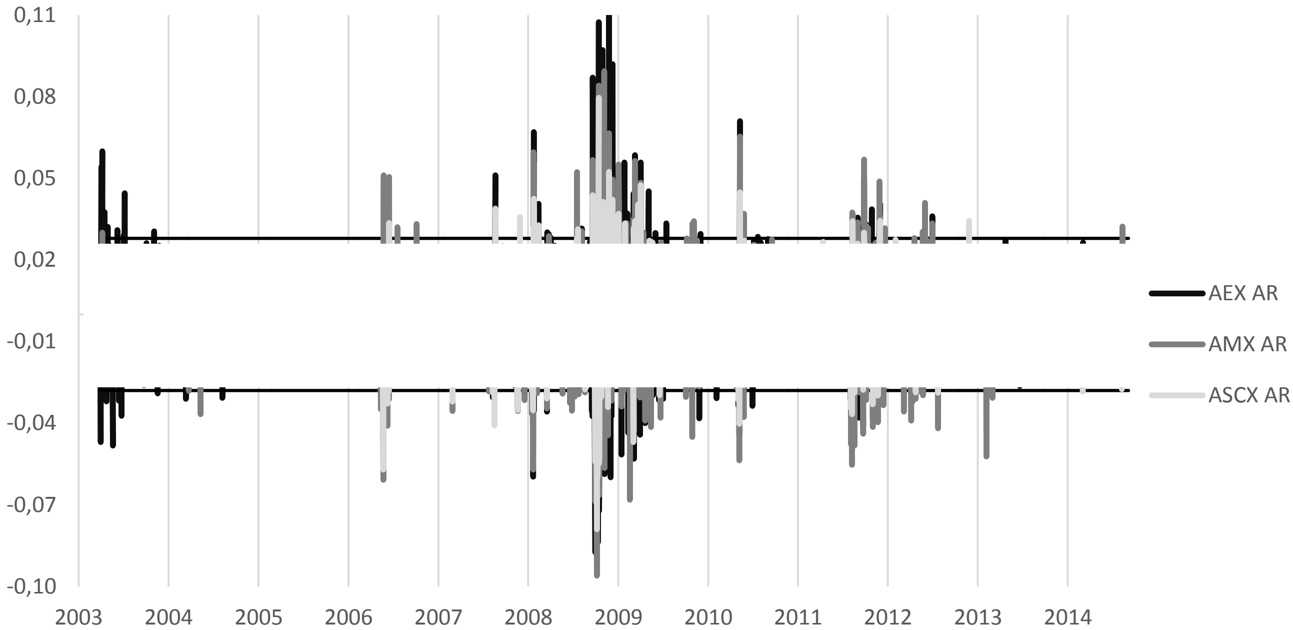
	(1.395)*	(3.519)*	(3.654)*
ACAR 15	0,023253	0,032685	0,03218
	(1.815)*	(3.444) *	(3.206) *
ACAR 17	0.030	0.036921	0.037718
	(2.403)*	(4.508)*	(4.055)*
ACAR 20	0,040082	0,047465	0,038942
	(2.885)*	(4.448) *	(3.522) *

NEGATIVE SHOCKS	AEX	AMX	ASCX
Initial reaction	-0,041486	-0,037378912	-0,029763779
ACAR 1	0,002198	-3,25284E-05	0,000881961
	(0.560)*	(-0.013) *	(0.388) *
ACAR 2	0,0053376	-0,001554433	0,001763921
	(0.967)*	(-0.391) *	(0.388) *
ACAR 5	0,013179	0,005116752	0,000627463
	(1.929)*	(0.841) *	(0.099) *
ACAR 10	0,012829	0,019025882	0,009729564
	(1.142)*	(2.431) *	(1.256) *
ACAR 15	0,027605	0,022284533	0,016698853
	(1.942)*	(2.361) *	(1.921) *
ACAR 20	0,037198	0,034533634	0,021540814
	(2.472)*	(3.373) *	(2.240) *

The table shows the average cumulative returns $\mathrm{CAR_{it}} = \sum_{t=1}^{20} \mathrm{AR_{it}}$ over 1,2,5,10,15 and 20 days subsequent the shock day, the day of the shock $\mathrm{AR_{it}}$ is indicated in the table as the initial reaction for the ease of comparison of the reaction of stocks after positive (upper half) and negative (lower half). Positive shocks' panel includes additionally ACARs of days 3, 4, 6, 14, 17 for the ease of results' interpretation. Cumulative reaction is represented by $\mathrm{ACAR_{it}} = \frac{1}{\mathrm{N}} \sum_{t=1}^{20} \mathrm{CAR_{it}}$, over the entire population of positive (negative) shocks in the upper (lower) part of the table. The t-statistic on the significance of each ACAR is shown in parentheses and is computed as $\mathrm{t} = \frac{\overline{\mathrm{ACAR}}}{\sigma / \sqrt{\mathrm{N}}}$.
* denotes the 1% of significance

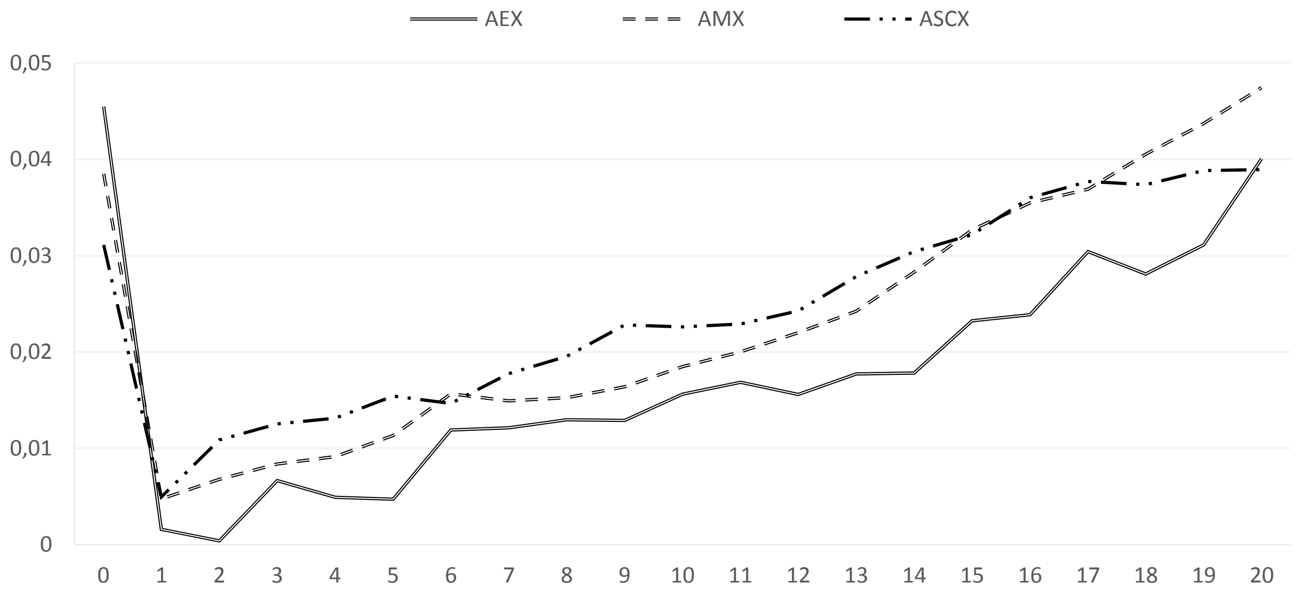
8. Appendix B – Figures

Figure 3: Shocks representation



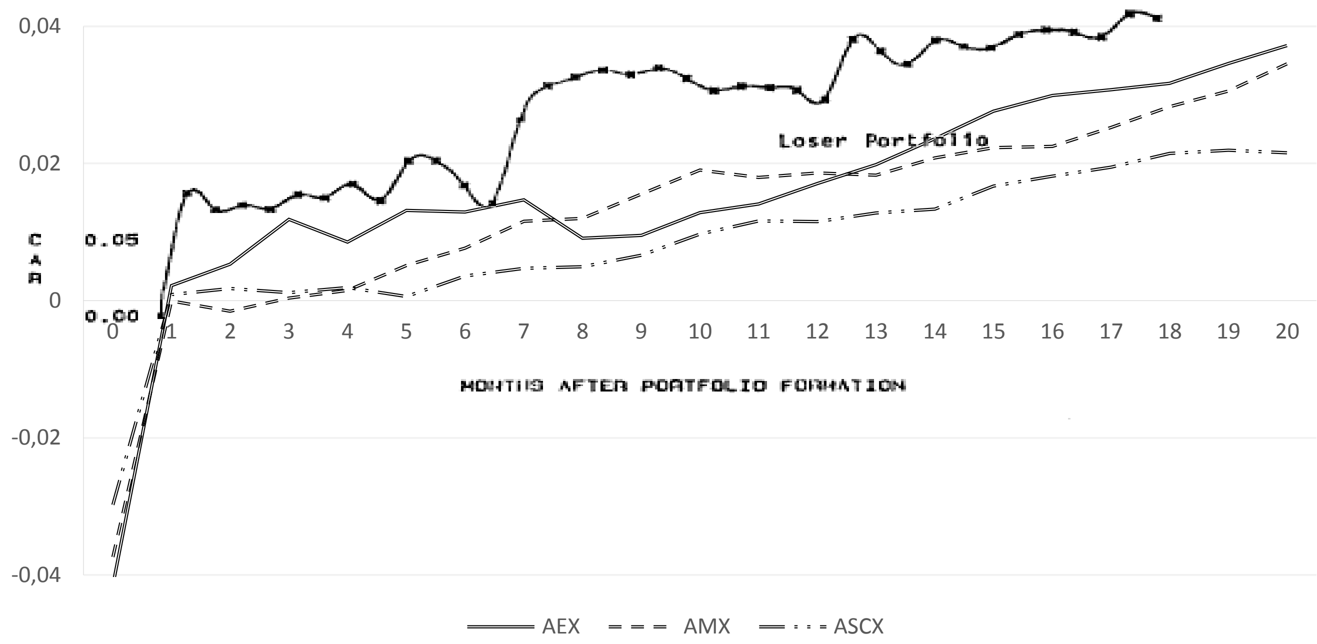
X axis represents the examination period, starting from March 2003 and ending August 2014. Y axis reports the difference $\mathbf{E(R_{it})}$ with $\mathbf{R_{it}}$, thus the abnormal returns measurement. $\mathbf{AR_{it}}$ series are compared with the 2 standard deviation thresholds, +/- 0.0279 for AEX, +/-0.0262 for AMX and +/- 0.0212 for ASCX, all represented by an average thick black line, due to the small variation in all three estimates. Positive (negative) shocks are depicted in the upper (lower) part of the graph.

Figure 4: Underreaction evidence for positive shocks, Full Period



X axis show the event period and Y axis show the ACARs following the day of the shock. Day 0 is the day of the shock and is not included in the accumulation. Subsequent days are cumulated over abnormal returns for positive shocks of each index and the averages are presented by a trendline per index.

Figure 5: Overreaction evidence for negative shocks, Full Period



X axis show the event period and Y axis show the ACARs following the day of the shock. Day 0 is the day of the shock and is not included in the accumulation. Subsequent days are cumulated over abnormal returns for negative shocks of each index and the averages are presented by a trendline per index. The black dotted line presents the loser portfolios CARs measurements of De Bondt and Thaler (1985) study, as a comparison measure with the first paper to comment on overreaction evidence; negative stocks returns' representation is only included here. De Bondt's and Thaler's CARs position in the figure does not match Y axis of this study, as observed in points.

Figure 6: Underreaction evidence for positive shocks, Sub- Period A

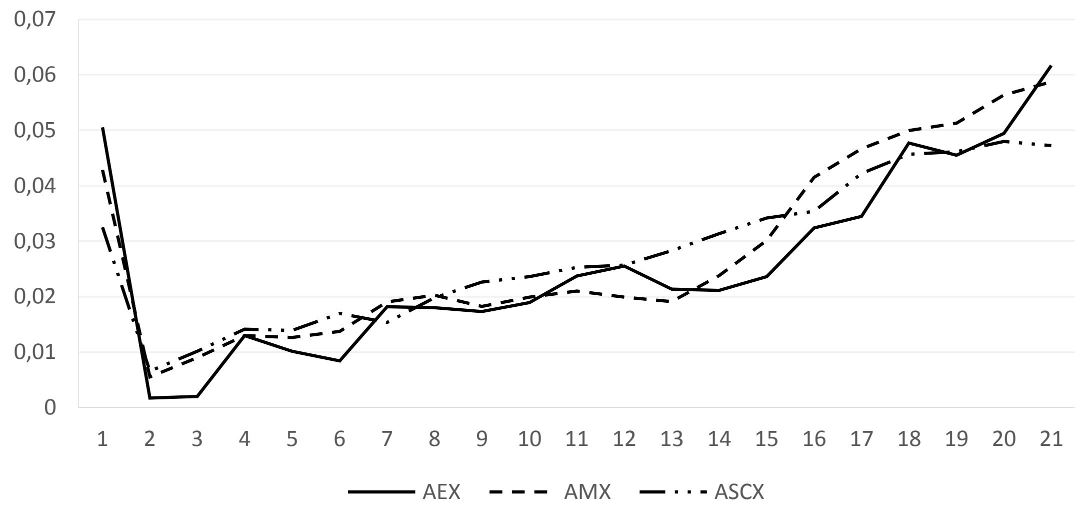
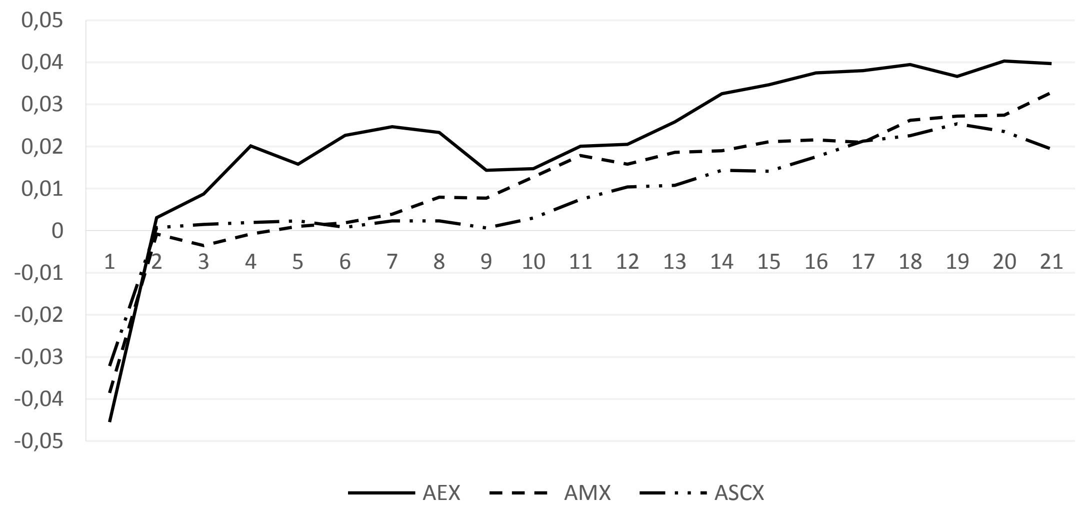


Figure 7: Overrreaction evidence for negative shocks, Sub- Period A



X axis show the event period and Y axis show the ACARs following the day of the shock. Day 0 is the day of the shock and is not included in the accumulation. Subsequent days are cumulated over abnormal returns for negative shocks of each index and the averages are presented by a trendline per index.

Figure 8: Underreaction evidence for positive shocks, Sub- Period B

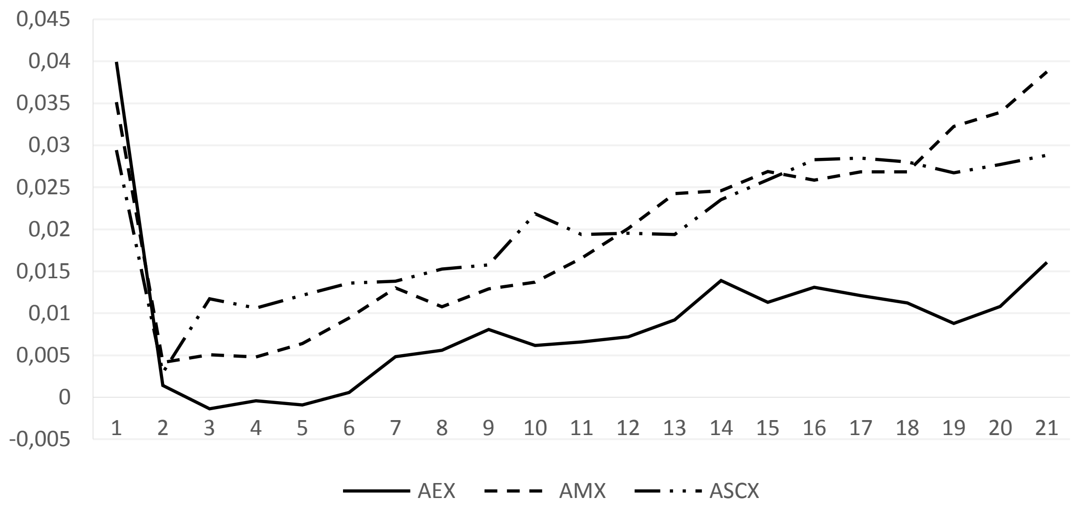
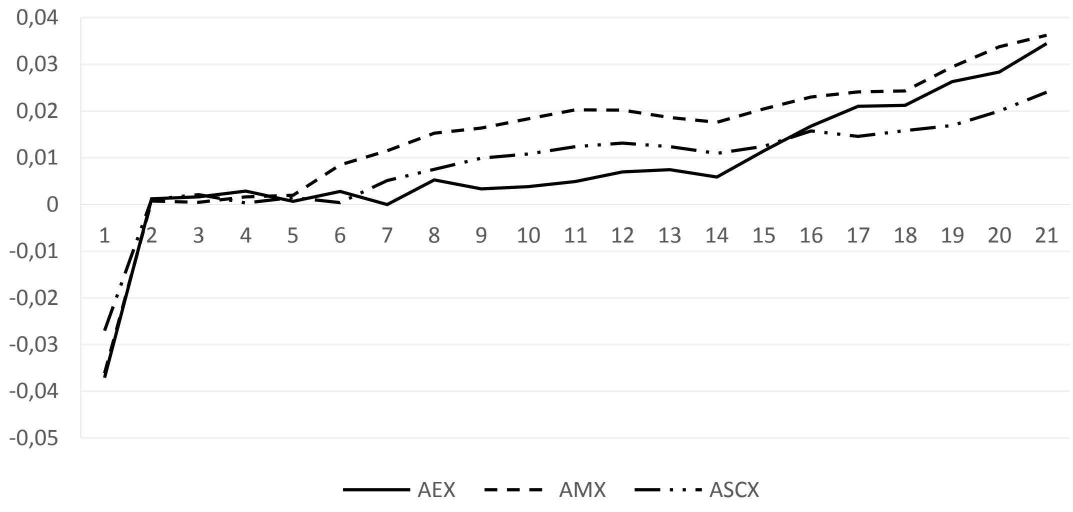


Figure 9: Overrreaction evidence for negative shocks, Sub- Period B



X axis show the event period and Y axis show the ACARs following the day of the shock. Day 0 is the day of the shock and is not included in the accumulation. Subsequent days are cumulated over abnormal returns for negative shocks of each index and the averages are presented by a trendline per index.

9. Appendix C – Indexes

AEX	AMX	ASCX
AEGON	AALBERTS INDUSTR	AMG
AHOLD KON	ACCELL GROUP	AMSTERDAM COMMOD.
AKZO NOBEL	AIR FRANCE –KLM	BALLAST NEDAM
ARCELORMITTAL	APERAM	BE SEMICONDUCTOR
ASML HOLDING	ARCADIS	BETER BED
BOSKALIS WESTMIN	ARSEUS	BRILL
CORIO	ASM INTERNATIONAL	DOC DATA
DELTA LLOYD	BAM GROEP	DPA GROUP
DSM	BINCKBANK	ESPERITE
FUGRO	BRUNEL INTERNAT	GALAPAGOS
GEMALTO	CORBION	GRONTMIJ
HEINEKEN	EUROCOMMERCIAL	GROOTHANDELSGEBOUW
ING GROEP	EXACT HOLDING	HEIJMANS
KPN	NIEUWE STEEN INV	ICT AUTOMATISERING
OCI	NUTRECO	KAS BANK
PHILIPS	POSTNL	KENDRION
RANDSTAD	ROYAL IMTECH	NEDAP
REED ELSEVIER	SLIGRO FOOD GROUP	NEWAYS ELECTRONICS
ROYAL DUTCH SHELLA	TEN CATE	ORANJEWOUD A
SBM OFFSHORE	TKH GROUP	ORDINA
TNT EXPRESS	TOMTOM	STERN GROEP
UNIBAIL-RODAMCO	USG PEOPLE	TELEGRAAF MEDIA
UNILEVER DR	VASTNED	VALUE8
WOLTERS KLUWER	VOPAK	WESSANEN
ZIGGO	WERELDHAVE	-

AEX, includes the 25 largest and most actively traded shares listed on Euronext Amsterdam.
AMX, includes the 25 second largest and actively traded shares listed on Euronext Amsterdam.
ASCX, currently includes the 24 highest ranking companies that are not included in AEX or AMX and qualify for selection and actively traded shares listed on Euronext Amsterdam.
All companies enlisted trade on Euronext under fulfillment of trading form, classification, minimum price and trading in euro criteria.