Master Thesis in Financial Economics

Master of Science in Economics and Business

THE EARNINGS SURPRISE AND THE EFFECT ON STOCK RETURN

EVIDENCE ON LEARNING THEORY

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Abstract

This thesis investigates the earnings surprises and the effect on stock returns proving further support to the learning theory as it was introduced by Pastor and Veronesi (2003). I prove that the growth/value phenomenon (market-to-book effect) can be highly attributed to the uncertainty that investors face when value these companies. Negative earnings surprises have higher impact on stock returns of young companies and this effect tends to decrease as the firm is aging. Furthermore, I show that uncertainty plays also a crucial role in the accuracy of analysts' forecasts. Using uncertainty factors like the size of the company, the coverage (analysts following) and the forecast horizon I present the negative relation between them and the forecast error. I also show that this relation varies among countries, industries and examined period. All these facts provide extra evidence to La Porta (1996) and Dechow and Sloan (1997) that connected the expectational errors made by investors to the reliance on analysts' forecasts, but also to Skinner and Sloan (2002) who related the effect to the asymmetric response to negative surprises. Conversely, my work comes in opposite with Lakonishok et al (1994) who related the expectational errors to irrational investors. Investors are well-informed and sophisticated, and they change their investing behaviour as they gain more information and resolve their uncertainty.

Keywords: growth stock, value stock, earnings surprise, forecast error, forecast accuracy, forecast bias, learning theory, uncertainty, market-to-book effect, old stock, young stock

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Table of Contents

List of Tables

List of Figures

1 Introduction

This thesis investigates the earnings surprises and the effect on stock returns using the learning theory. Specifically, it provides as an explanation to the large asymmetrical negative price response of growth stocks to negative surprises, the uncertainty about the profitability of these firms and how the effect decreases as the firm is aging. In a second level, the thesis explores the role of uncertainty in the forecast accuracy and how the analysts' estimations tend to be more precise when more information is available. Before continuing to a more detailed explanation of the research scope of this thesis, it is essential to determine the term of earnings surprise and the documented impact on stock returns. Subsequently, the incentive and the aim behind the selection of the research topic is introduced.

In the new global economy, financial health and long-term viability is a fundamental indicator for any business's success. Investors and researchers are constantly trying to find new ways of measuring the profits of a company because it is a key element of the economic conditions for earning profits and reveals the general performance of a company. A company's earnings performance can play a crucial role in determining the fluctuation of a stock price. There is a growing body of literature that recognizes the importance of the impact of an earnings announcement on the share price of a company and can be characterized as a significant area of interest for analysts and researches throughout the years. As earnings are important financial updates able to affect the future returns of the stocks, are instrumental in our understanding of the performance and profitability of a company.

Evidence has shown that the earnings announcements are highly related to the market expectation, which is depicted through the analysts' (consensus) forecast. When companies deliver their quarterly results, investors compare these results to the analysts' estimates and try to develop ways of improving the company's general performance. Traditionally, if the company "surprises" the market with better-than-expected earnings, the stock usually "jumps" (rises). On the other hand, if the results are disappointing can cause the stock to drop down. Bartov, E., Givoly, D., and Hayn, C. (2002) highlighted the importance of this "expectation game" showing that companies which managed to beat or meet analysts' estimate tend to have higher returns than firms which fail to do so. Specifically, firms whose quarterly earnings releases constitute a favourable surprise show higher growth in sales and earnings in subsequent years, and a higher Return on Assets (ROA) and Return on Equity (ROE), than firms with the same earnings performance but with unfavourable earnings surprises.

A well-established financial phenomenon that can be linked to the earnings surprises is the underperformance of ‘growth’ or ‘glamour’ stocks relative to value stocks in terms of realized stock returns over the five years of portfolio formation. Skinner and Sloan (2002) provided evidence that this stock anomaly is the result of expectational errors from the investors about future earnings performance. Particularly, the price difference between these stocks can be explained by the fact that glamour stocks present an asymmetric response to negative earnings surprises. Investors tend to be driven by over-optimism about the future performance of growth stocks, and the opposite happens with the value stocks. When their expectations are not met, the stock prices face a decline, but surprisingly the magnitude of this decline is higher in cases of negative surprises than in positive ones and this asymmetry in response to earnings surprises increases as growth rate increases. La Porta (1996) and Dechow and Sloan (1997) provided an alternative explanation to the growth/value phenomenon, attributing the reactions of investors to naïve reliance on analysts’ forecasts. Therefore, two questions are inevitably raised:

Which are the factors that drive investors’ expectations and make them react more intensively in negative surprises for growth stocks? And additionally, what are the determinants of forecast accuracy?

In this research, I try to approach the abovementioned research questions based on the learning theory. Pastor and Veronesi (2003) highlighted the importance of learning in their valuation. They proved that uncertainty contributes to the higher assessment of young firms, and this uncertainty tends to stabilize over time, as the firm is aging. Using as a proxy of uncertainty the age of the firm, they found that the younger the firm is, the higher the valuation of the company would be, as it was depicted by the market to book ratio. The fact that investors have less information (uncertainty) about the future performance of young stocks is capable of explaining their over-optimistic expectations, their high valuations and the asymmetric responsiveness to the earnings surprises thus providing clues in the first empirical part of this thesis.

Regarding the second section of this research and the role of learning in forecast accuracy, there is growing literature that studies essential determinants of analysts' estimations which are highly related to the uncertainty about future performance. These factors provide insightful information to analysts in order to generate better forecasts. Among these determinants, I distinguish the work of Chopra (1998) underlying the economic situation as a factor of affecting the estimations, the importance of forecast horizon (Richardson, Teoh & Wysocki, 1999), the industrial sector (Brown, 1997), the coverage of the firm (Alford and Berger 1999), the size of the company (Walther, 1997; Pastor, Veronesi, 2003) and the country where the firm has its operations (Capstaff et at, 2001). Undoubtedly, there are also other factors that could affect the forecast accuracy, but they are not closely related to the uncertainty like the earnings type-profit vs. losses, increases vs. decreases (Ciccone, 2005; Dowen, 1996) or the firm's business activities (Dunn & Nathan, 1998).

After conducting my analysis in European Countries for the period 2000-2018, I confirm that the return differentials between growth and value stocks are subjected to the uncertainty about firms' performance, using as a proxy the age of the company. Subsequently, I show that one of the main responsible factors of the market-to-book effect is the asymmetric impact of negative earnings surprises on young stock returns, and this asymmetry tends to decrease over the years. After highlighting the importance of uncertainty in explaining the growth/value phenomenon, I move to the second phase of this research. I prove that the numbers of analysts' following a firm, the size of the company, the forecast horizon, the industry, the country as also the examined period are crucial determinants of forecast accuracy and can provide extra support to the learning theory.

The second section of this research reviews the existed literature on growth/value phenomenon, the learning principle and the forecast determinants. In the third section I form my main hypothesis and the expected results, while in the fourth section I go into detail regarding the methodology I used in capturing the abnormal returns, the regressions for testing my hypothesis, the construction of the variables and the robustness checks for my data. Section five covers the data selection and section six depicts the empirical part through descriptive evidence, regression analysis and the discussion on the results. Lastly, section seven concludes the main findings, reveals the implications of this study and suggests ideas for further research.

2 Literature review

This chapter focuses on two main parts that cover the entire research scope of this thesis. Firstly, financial literature on the relation between earnings surprises and growth/value stocks is presented, while the effect on stock prices explains the MB effect. Secondly, I introduce work already established in the field of forecasting, which is of relevance for the determinants of forecast accuracy. The most significant part of this review is covered by variables that indicate uncertainty about a firm’s profitability and how learning and information can help analysts to form more accurate predictions.

2.1 Earnings Surprises in Growth and Value Stocks

A substantial part of the existing literature about the earnings surprises relates them tightly to value and growth stocks. Research typically defines a value stock as the stock which the market price is relatively low in relation to earnings per share (Basu, 1977), cash flow per share (Lakonishok, Shleifer and Vishny, 1994), book value per share (Fama and French, 1992) and dividends per share (Blume, 1980). In other words, a value stock is a security, traded at a lower than the expected price given its fundamentals (performance of the company and key performance indicators of the stock), thus an undervalued security. On the other hand, growth or glamour stocks are commonly described as the stocks which have relatively high prices regarding the same fundamentals (Bauman, Conover and Miller, 1998), i.e., they are expected to grow more than the market.

Numerous scientific studies have shown that growth or glamour stocks underperform realized returns in comparison to the value stocks, five years after the portfolio formation. The value investment strategy implies to buying stocks that are underestimated in the market place, so they are trading less than their intrinsic value (book value). These stocks are documented to provide superior returns to the future. (Basu, 1977; Jaffe, Keim and Westerfield, 1989; Rosenberg, Reid and Lanstein, 1985; Chan, Hamao and Lakonishok, 1991; Fama and French,1992; Debond and Thaler (1995)). The previous authors came to the same conclusion after studying several indicators of value measurements like the book-to-market ratio, cash flow-to-price ratio or the earnings per share.

Chan (1988) provided considerable criticism to the strategy of buying “market losers” and selling “winners” by showing that the realised abnormal return of this contrarian strategy is too small and statistically insignificant. In line with the previous author, Ball and Kothari (1989) proved that the negative serial correlation in stock returns can be highly attributed to the changing risk of economic environment. Besides these arguments, the value strategy is generally accepted and established among the scientific society.

Having described that value stocks outperform growth stocks, the reasonable question of why this is happening arises. Researchers have offered a variety of possible explanations, out of which there are three dominant reasons answering this question.

Fama and French (1992) attributed the outperformance of value stock relative to growth stocks, to the associated risk of these securities. Value stocks are fundamentally riskier due to the higher cost of capital and the business endanger. Thus, the superior return to the investors that hold these securities is just a compensation for the extra risk.

Secondly, Lakonishok, Shleifer, and Vishny (1994) did not find any evidence in their studies that the value stocks are riskier based on conventional systematic risk. Their explanation of the abovementioned phenomenon relied on several behavioral and institutional factors. They proved that indeed glamour strategies provide inferior returns compared to buying value stocks for the period 1968 to 1990, but they link this establishment to the fact that the future growth rates of companies with large MB ratio tend to be much lower than they were in the past. Specifically, market analysts are subjected to systematic errors in pricing due to optimistic expectations about the forecasts of growth stocks, which result in lower subsequent stock returns when these expectations are not met. Notably, investors tend to believe that current good (poor) performance of the securities will persist in the future so they continue buying (selling) growth (value) stocks. Friesen and Weller (2006) described these behavioral biases, as strategic incentives. The contrarian investors bet against this naivety and this is the source of the outperformance of value stocks in the following years.

Contrary to Lakonishok, Shleifer, and Vishny (1994), Dechow and Sloan (1997) and La Porta (1996) found no systematic evidence that the returns following contrarian strategy are attributed to the expectational errors about future performance of the company based on the past results. They suggest that the naïve reliance of investors to analysts' forecasts is responsible for the return differential between these kinds of stocks. Forecast errors tend to be higher in high projected growth rate stocks than in low. More specifically, they highlighted the fact that low expected growth rate stocks beat high expected growth rate stocks, and analysts tend to revise their expectations after the realised earnings announcement.

In line with the previous results, La Porta et al. (1997) proved that the differences in earnings announcements between value and growth stocks could describe 25-30% of the annual return difference in the first two or three years after portfolio formation and 15-20% the next year following till year five. More precisely, they investigated the price reactions on the earnings announcement for value and growth stocks, over a five year time period after portfolio formation. A sizable proportion of the return difference between these two kinds of stocks is caused by the fact that positive surprises are significantly more in number for value stocks, which is not the case for growth stocks. Abarbanell and Lehavy (2000) and Brown (2001) documented the fact that there are more negative than positive surprises for growth stocks, which reflects the analysts' over-optimism in forecasting.

Consistently with the expectational error explanation, Skinner and Sloan (2002) attributed the underperformance of growth stocks not in the difference of positive and negative surprises but in the asymmetric response to the negative ones. According to this approach, positive and negative surprises are equally distributed in growth stocks, but in contradiction with the rational expectations, the negative surprises effect has a larger impact than the average realized positive return to the positive earnings surprises.

Doukas et al. (2002) observed notable differences in the findings of the pre-existed studies which are inconsistent with the behavioural perspective. By analysing forecast errors and revisions between 1976 and 1997, the authors realised that investors are not excessively optimistic about the future of growth stocks. Forecasts errors are bigger for high book-to-market stocks and these value shares also display a more considerable downward forecast revision as the release date of EPS announcement is approaching.

2.2 Learning and uncertainty

Learning in Finance can be characterized as one of the main determinants that drive investors' expectations. Researches on growth and value stocks use the MB ratio to measure the perception of investors about the value of the firm and by extension, the growth characteristics of the company. A low ratio -below 1- indicates that the stock is undervalued and a higher than 1 ratio could mean that the stock is over-valued, so its market capitalization is greater than the accounting value of the company. So, value stocks are identified as having low MB ratio and growth stocks high MB ratio.

Pastor and Veronesi (2003), in an attempt to discover a model of valuing stocks based on learning, they found that the age of the firm can be used as a proxy for the uncertainty and this variable is negatively related to the MB ratio and the idiosyncratic return volatility. This fact indicates that the MB ratio tends to decline as time passes because analysts have more information about the actual performance of the companies. Thus, young stocks have higher MB ratio than older stocks, and this fact is more prevalent when stocks pay no dividends. Additionally, they showed that uncertainty resolves quicker for new companies. They based their findings on extremely high ratios of newly listed firms in US stock exchanges between the years 1980 and 2000. Their explanation relies on the high expectation and over-optimism of the analysts regarding the future performance of a new company.

Frank Zhang (2006) investigated the forecast accuracy from information perspective. He found that analysts revised their forecasts about the earnings of the company and their beliefs when more information is available. Additionally, he showed that greater information uncertainty produces bigger forecasts errors which are more negative in case bad news is following or more positive in case of positive news.

2.3 Forecast Accuracy Determinants

Coverage, as a determinant of forecast accuracy

The effect of uncertainty in analysts' forecasting is a well-documented phenomenon. Stevens, Barron, Kim, and Lim (1998) found that forecast accuracy decreases in a high uncertainty environment. Additionally, Ackert and Athanassakos (1997) showed that analysts tend to be overoptimistic when they face uncertainty in forecasting. Uncertainty in their research is measured by the standard deviation of earnings surprises. The number of analysts following a firm is found to influence the uncertainty about a company's profitability. Alford and Berger (1999) reported that the bigger the coverage of the firm is, the more accurate the prediction would be. Additionally, high coverage can be an indicator of certainty as according to O'Brien and Bhushan (1990) and Chung and Jo (1996) analysts have a tendency to follow large, well-established firms with more information disclosure and more transparent and public-revealed operations.

Firm size, as a determinant of forecast accuracy

The size of the company is an important factor that can affect forecast accuracy. Studies throughout the years have shown that bigger companies are under more scrutiny from analysts, have a more detailed and transparent reporting, stable earnings announcement dates, and are followed by more analysts. These factors contribute to resolve the uncertainty of forecast errors (Pastor and Veronesi, 2003) and thus have better accuracy in forecasting. In line with these findings, Walther (1997) found a statistical positive association between firm size and forecast accuracy.

Forecast horizon, as a determinant of forecast accuracy

Ackert and Athanassakos (1997) and Richardson, Teoh, and Wysocki (1999) recognised that uncertainty resolves as we are getting closer to the realized EPS. This phenomenon occurs due to the fact that more information is revealed during that period, and so the shorter the forecast horizon is, the better the prediction would be.

Beyond the aforementioned determinants, significant differences in forecast accuracy among industries and countries have been explored in several studies. Numerous accounting, legal, and institutional environments are responsible for the errors made in forecasting.

Industry, as a determinant of forecast accuracy

Brown (1997) documented optimistic bias in analysts' forecasts for 11 out of 14 industries in the US exchange the years 1985 till 1996. It seems that analysts in specific industries are capable of providing more accurate forecasts. Patel et al. (2002) found that transparency and disclosure (T&D) are positively correlated with the valuation of the firm and observed a significant upward trend (+15% of them) in Asian emerging markets over the three years ending in 2000. T&D scores' increases were below average for Telecommunication and Services and Technology Sectors while the smaller increases of 3% and 4% experienced the Utilities and Energy sectors. Capstaff et al. (2001) investigated the analysts' forecasts of earning per share (EPS) among nine European countries. Segmenting the sample by industry, analysing the forecast accuracy and the forecast bias, they realized that Healthcare and Public Utilities sectors have the most accurate forecasts while Consumer Durables and Transportation are the more volatile. Finally, De Fond and Hung (2003) predicted that cash flow forecasts are associated with accounting, operating, and financing characteristics which vary in each sector.

Country, as a determinant of forecast accuracy

Taking into consideration the significant differences among countries, it is reasonable for someone to expect that the forecast characteristics would also be different. According to Capstaff et. Al. (2001), who conducted their research on European countries, showed that the forecast environment of each country is essential in understanding the prospects of a company. Differences in earnings behaviour, in the accounting system, in the taxation (Basu, 1990) and the quality of information disclosure are highly important to describe the volatility of forecast errors across the countries. Published literature and research covering the entire world has documented an optimistic bias and over-reaction in analysts' forecasts for most of the countries. Results from studies in the two past decades have shown that the Netherlands, UK, and Ireland produce the most accurate forecasts because they have the smallest connection between taxation and financial reporting and the highest quality of information disclosure. The countries with the most optimistic bias are Italy, Spain, and Switzerland, although in all countries this overoptimism underlies, but at a lower level.

Time, as a determinant of forecast accuracy

The economic environment is highly correlated with the examined period, as important events in society and economy can change the regulation of a country or an industry, and by extension, the accuracy in forecasting. Studies conducted in the US revealed that throughout the years, the forecast errors have changed, shifting from pessimistic to optimistic. In Europe, from 2000 until now, there are many financial shocks that have undoubtedly affected the economic situation. Main events that took place were the entrance of many countries in the Eurozone like Greece, Cyprus and Estonia, the introduction of coins and notes in 2002, the global financial crisis in 2007-2008 and the European debt crisis which followed the next years starting from Greece and then expanded in other countries like Portugal, Ireland, Cyprus and Spain. All these events came with a loss of confidence in European businesses, downgrading of the rating agencies, and collapse of the financial institutions.

Firm-specific effects, as a determinant of forecast accuracy

Dowen (1996), Hwang, Jan and Basu (1996), Degeorge, Patel, and Zeckhauser (1999) highlighted the importance of profits and losses in their studies, indicating that positive surprises are superior in number when a firm has a good performance. Brown (1997) examined the S&P 500 firms from 1984 to 1996 and compared the returns with I/B/E/S, documenting a significant rightward temporal shift in mean earnings surprises. These results came in parallel with previous findings showing that managers seek to report earnings that can be covered by the forecasts. McNichols and O' Brien (1997) detected that analysts prefer to cover stocks from companies for which they have an optimistic view while mentioned that the incentives for gathering information are greater for stocks that are performing good. The aforementioned findings can provide an additional factor that potentially explains the asymmetric distribution between positive and negative surprise between value and growth stocks.

3 Hypothesis- Expected Results

In this chapter, I develop the hypotheses, which helped me answer the research question of this thesis. Hypotheses 1-3 provide answers on the first research part of this thesis while the rest of the hypotheses are based on the second empirical section.

Hypothesis 1

Stock returns after the EPS are strongly correlated with the earnings surprise and the age of the firm.

Based on previous studies, I am expecting that both the surprise variable and the age of a firm which is used as a proxy of the uncertainty of a company's profitability, have a positive impact on the abnormality of stocks' returns after the realized EPS. Specifically, a positive surprise will drive the prices up, and a negative surprise will drop them further. Regarding the age variable, the lower the age of the firm is, the higher the uncertainty of the investors would be about the firm's performance (Pastor and Veronesi, 2003) and the higher the impact on stock returns.

Hypothesis 2

The sensitivity of abnormal returns to earnings surprises varies as a function of the uncertainty quintile to which the stock belongs based on its age.

Past studies established that investors tend to set their expectations too high for growth/young stocks and lower for value/old stocks due to uncertainty about the actual profitability. Over the time and after subsequent earnings announcements they realize that their initial expectations were quite optimistic and not sustainable, so they revise them downwards. Therefore, I am expecting that stock returns of high uncertainty/young firms are more sensitive to earnings announcements than those of low uncertainty/old firms.

Hypothesis 3

Bad earnings surprises have a higher magnitude effect on abnormal returns than the good earnings surprises on high uncertainty/young firms. This asymmetrically large stock return decreases as the company's aging because investors learn about a firm's profitability and they revise their expectations.

Basu (1977), Dreman and Berry (1995) and Skinner and Sloan (2002) have established that growth stocks show a higher response in bad earnings surprises than in good compared with the value stocks. Based on this establishment, I assume that the magnitude of a bad earnings surprise on an abnormal return of high uncertainty/young firm is higher than in case of a good earnings surprise.

Hypothesis 4

The accuracy of analyst forecasting is significantly related to the country, industry, coverage as also the size of the company.

Relying on the paper of Coën, Desfleurs, L'Her (2009), I am expecting to observe sharp contrasts among the countries and industries in terms of their dynamic in leading the analysts' forecasting. Coverage and size expect to be negatively related to the forecast error.

Hypothesis 5

The forecast horizon has a significant impact on the projection of the analysts. Additionally, the accuracy of forecast errors has changed overtime shifting from pessimistic to optimistic mainly due to the financial crisis.

Approaching the EPS announcement, I am expecting that analysts will release more pessimistic predictions to beat the target. Longer forecast horizons (91-360 days before EPS) are more optimistic. Therefore, the intercept for the absolute forecast error should be the lowest and statistically significant at horizon 1. During the crisis, I am expecting to observe more significant differences in the explanatory variables, biggest forecast errors and more optimistic bias.

4 Methodology

4.1 Abnormal returns and Earnings Surprises

4.1.1 Event Study Methodology / Buy and Hold Abnormal Return

In order to address the research questions of this thesis, I use the event study methodology as it is introduced by Campbell, Lo and Mackinlay (1997) for capturing the abnormal returns in case of a quarterly earnings announcement and a regression analysis for further elaboration of the hypotheses. The event study methodology analyses the difference between the returns that would have been expected if a corporate event did not take place. Corporate events could be considered mergers and acquisition, takeovers, or spinoffs. Undoubtedly, EPS should be included in this category as well. The present study is focusing on analyzing the earnings surprises event.

To the extent of estimating the excess returns of securities in each event study, a specific order of steps should be followed. Firstly, it is crucial to define the exact event date for each stock; in other words, the day when the actual announcement of earnings happened. Secondly, determination of the event period for studying the impact of earnings surprises and the estimation period from which someone can observe the pattern of stocks returns without the presence of any corporate event.

In similar cases like this study, the event window starts 12 trading days before the end of the fiscal quarter and stops one trading day after the announcement of actual earnings. This timeline covers the entire effect of an event and can be used to test the persistence of any abnormal observation. If price fluctuations persist for an extended period, this is evidence against the Efficient Market Hypothesis (EMH), which suggests that prices quickly reflect any available information. The selection of this time interval is not random. Skinner and Sloan (2002) suggested that this period has the most significant explanatory power among the four events windows that they examined. Consistent with that, Skinner (1997) and Soffer et al. (2000) indicated that 75% of the earnings preannouncements occurred in the abovementioned time interval.

The normal or expected return of the stocks is calculated using an estimation period of two years (seven hundred and twenty calendar days), starting from the second day after the announcement of the realized EPS. My goal is to include at least a hundred trading days into this period. Taking this time interval, I eliminate the chances of a future event period so that I can assure the stock returns are normal and not affected by any surprises. Then a size-matched portfolio is constructed by allocating all quarterly firm's observations in the sample into decile portfolios under the principle of market capitalization at the beginning of the quarter. A portfolio return that is equally weighted is computed for each size portfolio in each quarter (Skinner and Sloan, 2002). Market capitalization is equal to the share price multiplied by the number of shares outstanding. Having available the future daily close prices of the stocks and the return of a size-matched portfolio, the market model will be employed for the calculation of the constant term or alphas (a) and the beta (b) which depicts the sensitivity of the firm to the market.

The model is: $R_{j,t} = a+bR_{m,t}+e_{j,}$ (1)

The abnormal return is the difference of the actual return after the earnings announcement and the normal return coming from the prediction of the return using the previous model where now alphas, beta, and market return are known. Specifically: $AR_{j,t} = R_{j,t}-(a+bRm)$. (2)

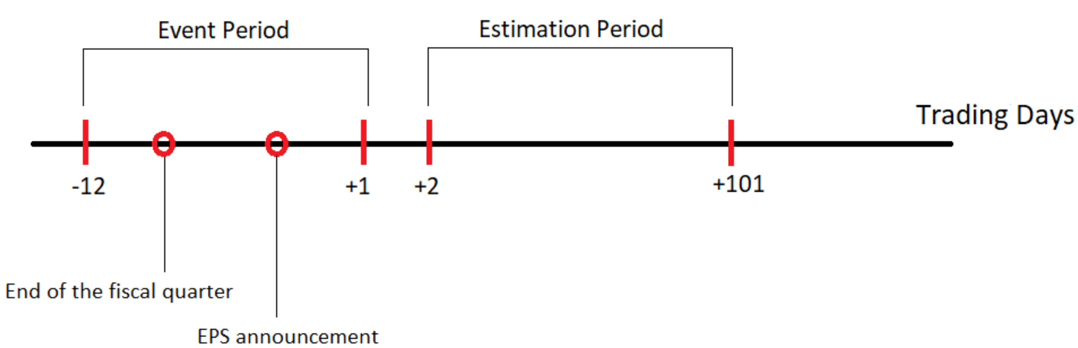

Figure 1 Event Study Timeline

The return-based methodology as introduced by Fama, Fisher, Jensen and Roll in 1969 focuses on short term effects in which the total influence during the whole event period can be captured either with the Average Abnormal Return (AAR) or with the Cumulative Average Abnormal Return (CAAR). In my case, the event periods expand many days before the event and end one day after the realized EPS announcement; thus the Buy and Hold Abnormal Return (BHAR) approach can fit better the purposes of this research. The buy and hold is an investment strategy where an investor buys stocks and holds them for a long time. The BHAR in the current research is the geometric sum of the Abnormal Returns starting twelve days before-the-end of the fiscal quarter and ending one day after the realized EPS.

In the following graph, the development of ABHAR (Average of Buy and Hold Abnormal Returns) over the years, can be observed.

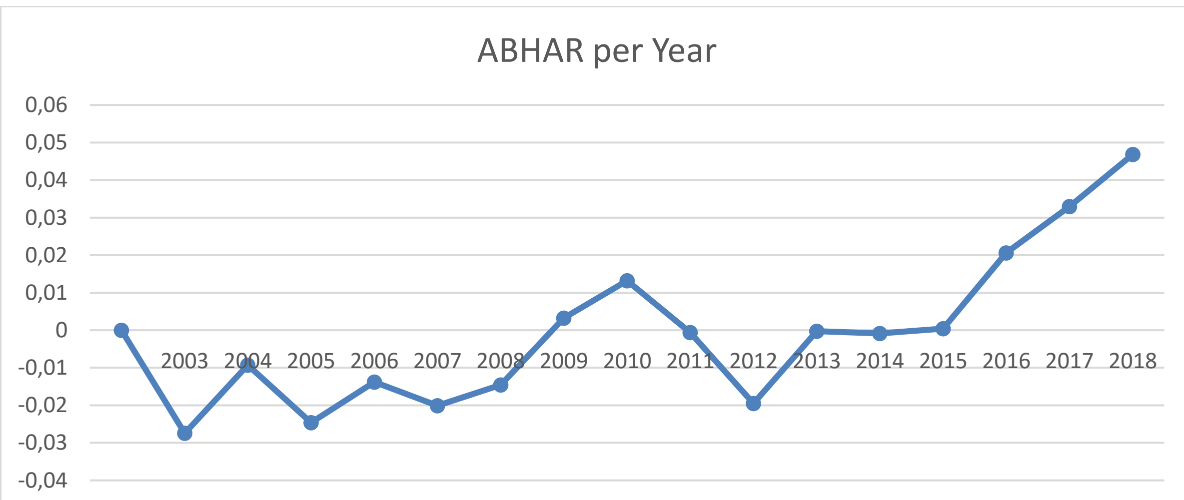

Figure 2 Development of yearly Average Buy and Hold Abnormal Return

4.1.2 Age and Surprise Variables

Beginning with the surprise variable, my sample is classified into two categories, positive (good) or negative (bad) earnings surprises. The term positive earnings surprises refers to those surprises in which the actual EPS announcement is bigger than the consensus forecasted EPS by analysts for the same quarter and vice versa for the negative earnings surprises. The quarterly earnings surprise is measured by subtracting the median forecast of quarterly EPS from realized quarterly EPS. Following the methodology used by Skinner and Sloan (2002) regarding a firm's quarterly observation, I created four variables – Surprise, Good, Bad and Zero- in order to test my hypotheses. The variable Surprise takes the value -1 in case of negative surprises, 1 for positive surprises, and 0 otherwise. Good, Bad and Zero variables are the three indicators of the Surprise variable.

Using the methodology of Pastor and Veronesi (2003), I define the age variable as the reciprocal of one plus the firm age. The firm's age is calculated as the difference between the initial public offering date of the company as it was extracted from WRDS and the year of the forecasted quarter. The equation (3) is:

$$Age = \frac{1}{1+firm\ age} \quad (3)$$

The above form describes the relationship between uncertainty and firm age. As the firm is getting older, the uncertainty resolves.

4.1.2 Hypothesis testing - H1

After creating the dependent variable and the predictors, I insert them in an OLS linear regression to test their relationship. I begin with the first hypothesis by regressing the buy and hold abnormal stock return in the event window on the age variable and the earnings surprise.

$$BHAR_{it} = a + \beta_1 \cdot Age_{it} + \beta_2 \cdot Surprise_{it} + \varepsilon_{it} \quad (4)$$

where

$BHAR_{i.t}$: the abnormal stock return of company i in quarter t

$Age_{i,t}$: the reciprocal of one plus the firm (i) age in quarter t

$Surprise_{i,t}$: earnings surprise of company i in quarter t. This variable takes the value 0 in case of no surprise, -1 in case of negative surprise and 1 in case of positive surprise

The regression of stock return on Age and Surprise variable is used to validate the H1. The intercept gives an estimate of the expected quarterly abnormal return for low uncertainty/old firms in case of no earnings surprise. The coefficient on age variable depicts the correlation between the firm's age and abnormal return in case of no surprise; thus, I am expecting a negative "β_1". In a similar manner, the coefficient "β_2" captures the sensitivity of AR to earnings surprise, so it is expected to be positive and significant.

4.1.3 Hypothesis testing - H2

In my second hypothesis, I include an interaction term between the two main variables to capture how sensitive the abnormal returns are to earnings surprises as a function of the age. The general form of the regression is the following:

$$BHAR_{it} = a + \beta_1 \cdot Age_{it} + \beta_2 \cdot Surprise_{it} + \beta_3 \cdot (Age_{it} * Surprise_{it}) + \varepsilon_{it} \qquad (5)$$

where

$BHAR_{i.t}$: the buy and hold abnormal stock return of company i in quarter t

$Age_{i,t}$: the reciprocal of one plus the firm (i) age in quarter t

$Surprise_{i,t}$: earnings surprise of company i in quarter t. This variable takes the value 0 in case of no surprise, -1 in case of negative surprise and 1 in case of positive surprise

$Age_{it} * Surprise_{it}$: the interaction term between the age of the company (i) and the surprise variable in quarter t

In extension to hypothesis H1, H2 includes the interaction term between the two main effects, the Age and the Surprise variables. If investors indeed learn about the profitability of the firms throughout the years, then I am expecting a positive and significant "β_3" indicating that the stock returns of high uncertainty/young firms are more receptive to earnings surprises than those of old firms.

4.1.4 Hypothesis testing - H3

$$BHAR_{it} = a + \beta_1 \cdot Age_{it} + \beta_2 \cdot Good_{it} + \beta_3 \cdot Bad_{it}{}^{1} + \beta_4 \cdot (Age_{it} * Good_{it}) + \beta_5 \cdot (Age_{it} * Bad_{it}) + \varepsilon_{it} \qquad (6)$$

[1] As indicated in the methodology part, the Good, Bad or Zero are the three indicator of the Surprise variable so the coefficients estimate the differences between the examined indicator and the reference point which can be the Bad or the Zero surprise.

where

$BHAR_{i.t}$: the buy and hold abnormal stock return of company i in quarter t

$Age_{i,t}$: the reciprocal of one plus the firm (i) age in quarter t

$Good_{i,t}$: positive earnings surprise of company i in quarter t. This variable takes the value 1 in case of positive surprises, and 0 otherwise.

$Good_{it} * Surprise_{it}$: the interaction term between the age of the company (i) and the good surprise variable in quarter t

$Bad_{i,t}$: negative earnings surprise of company i in quarter t. This variable takes the value 1 in case of negative surprises, and 0 in case of positive or zero surprises.

$Bad_{it} * Surprise_{it}$: the interaction term between the age of the company (i) and the bad surprise variable in quarter t

The above regression allows for a differential response to good and bad earnings news. In this specification, the intercept measures the sensitivity of abnormal returns to low uncertainty firms in case of no earnings surprise. The coefficient on Age measures the return differential in no earnings surprise for several uncertainty portfolios. The coefficient "β_2 ("β_3") measures the differences in correlation between the Good (Bad) variable and the abnormal return for low uncertainty/young firms comparing with the reference point which can be the Bad or Zero Surprise. Based on previous studies, I am expecting a significant and positive (negative) "β_2" ("β_3"). Finally, I am expecting that both coefficients of the interaction terms "β_4" and "β_5" follow the same pattern as the main effect.

4.1.5 Robustness checks

In this paragraph, I describe the robustness checks on the data and results of the Ordinary Least Square regression. In principle, the data should meet some criteria and assumptions to drive in safe and not misleading conclusions. Individually, I checked and removed any outliers from my data, tested if the residuals follow a normal distribution and are free of heteroskedasticity and finally estimated the relationship of my explanatory variables for capturing any multicollinearity problem.

Through the use of scatterplots in Stata, I located some points that are unusual compared to the rest and can make substantial differences in my results. These points indicate an extreme observation or can be a data entry error. I tried to exclude any possible outliers from my data by winsorizing the 1% tails of BHAR distribution for each value of age or sign of the earnings surprise.

The normality tests require that the errors are independently and identically distributed. The Kernel density plot with the normal options (graph 13, Appendix) and the standardized normal probability plot (graph 14, Appendix) confirm that the residuals are close to normal distribution.

Regarding the heteroskedasticity, to check if the residuals are homogenously distributed across each value of the dependent variable and have a constant variance, I plotted the regression residuals. Graph (15) in the Appendix illustrate the distribution of these errors against the stock returns, confirming the absence of any heteroscedasticity problem but also robust my standard errors to make my inferences more valid in case of existed heroskedasticity

A perfect linear relationship across the independent variable is a significant problem in an OLS regression as the individual coefficients as also the standards errors cannot depict the real situation. To test the relation between my regressors, I used the tolerance value, which is lower than 0.1 providing evidence of no multicollinearity.

The magnitude of individual coefficients tested with their attached t-statistics and p-value coming from the regressions. Mainly, p-value provides us information if the variables are significant in 1%, 5% or 10% confidence level.

4.2 Determinants of Forecast Accuracy

4.2.1 Forecast errors and forecast bias

The term "Forecast Accuracy" attributes the capability of analysts to predict the earnings of a company several days before the actual EPS announcement. This study tries to capture this term using two kinds of measures. The first is the Absolute Forecast Error (FE) which is defined as the absolute value of the difference between the actual reported earnings (RE) and the forecasted (F) divided by the RE as it was revealed by the EPS announcement. This kind of measurement does not consider the direction of the error but only the magnitude of this. The formula is:

$$FE = \left|\frac{RE-F}{RE}\right| \qquad (7)$$

In line with previous studies, I excluded from my sample the firm-quarter observations when the absolute forecast error was greater than one.

The direction of the Forecast Error can be captured with the second type of forecast accuracy, which is the nominal value of the numerator of the above measurement divided by the absolute value of RE. This formula provides information about any bias that analysts may have in terms of predicting the EPS. A positive Forecast Error means that the numerator is positive, so companies beat the analysts' forecasts, which can be characterized as pessimistic. On the other hand, if analysts are optimistic about the profitability of the firms, then the FB would take negative values.

$$FB = \frac{RE-F}{|RE|} \qquad (8)$$

4.2.2 Industry, Country, Coverage and Size Variable

Industry: Using the Standard Industry Classification (SIC) code, a four-digit number for classifying firms to industries, I created the industry variable. I have in total ten industrial sectors: Agriculture / Forestry / Fishing, Mining, Construction, Manufacturing, Transportation / Public Utilities, Wholesale Trade, Retail Trade, Finance / Insurance / Real Estate, Services, and Public Administration. In order to code ten qualitative industries categories, we need nine binary variables that take the values 1 or 0 and one control member which is assigned as zero on all the dummy variables (dummy coding). The control member of my research groups is the fourth industry in the above mapping, the Manufacturing. This leads to a contrast matrix table generated by Stata.

Country: In a similar way of construction of the industry variable, I created twenty-two binary variables to compare them with the reference point, which is Germany.

Coverage: The number of analysts following the company. Based on previous studies, I excluded those firm-quarter observations in which the company was followed by less than three analysts. Through Stata, I categorized this variable in four quantiles.

Quantiles	Number of Forecasts
1	[3,5]
2	[6,9]
3	[10,15]
4	>15

Size: I estimated the size of my sample's firms in each quarter using as a proxy the natural logarithm of total assets in a similar manner to Pastor and Veronesi (2003). I used the total assets at the end of the quarter before the forecasting. Then I categorized the firms into five portfolios according to their size for the two subperiods.

4.2.3 Hypothesis testing - H4

To test if the aforementioned factors have any influence on the forecast accuracy, I run the following OLS regression in Stata. The above general form refers to the forecast accuracy of analysts in predicting the earnings of the company i in quarter t.

$$FA = a + \sum_{s=1}^{10}(\beta_{1,s} * S) + \sum_{c=1}^{23}(\beta_{2,c} * C) + \beta_3 * Coverage + \beta_4 * Size + \varepsilon \qquad (9)$$

where

FA: the forecasted accuracy being tested with the absolute Forecast Error (FE) and the Forecast Bias

S: categorical variables representing the industry based on the Standard Industry Classification code

C: categorical variables representing the country in which the company operates

Coverage: variable indicating the group that the firm belongs to in each quarter based on the number of analysts that generate forecast

Size: the size quintile into which firm i falls in quarter t (where 0 denotes the smaller firms, and 5 denotes the larger firms) and size is measured as the firm's total assets at the end of quarter t-1

The coefficients $\beta_{1,s}$ where s=1,2,…..,10 display the impact differential on forecast accuracy between the industry s and the manufacturing sector. Based on the current literature, I am expecting many significant negative differences as the manufacturing industry is the sector where most of the growth stocks are gathered, so the analysts are overoptimistic about the future of these companies. On the contrary, the financial sector is expected to be the most stable regarding the analysts' forecasting as it includes well-established and covered firms.

On the same page, coefficients $\beta_{2,c}$ where c=1,2,……….23 depict how the country of a firm can affect the projection of the analysts. Using as a reference point Germany the coefficients provide information about the differential impact among the states. Similarly, the effect of a country depends on the sector, which is more prevalent there.

Coefficient β_3 measures the relationship between the coverage of the firm and the forecast accuracy. If analysts' accuracy improves with the number of analysts following a firm, then the coefficient should be negative and significant.

Finally, the coefficient β_4 captures the sensitivity of analysts generating forecast to the size characteristics of the company. The higher the size of the company, the more the information disclosure and the more accurate the prediction, which lead to lower forecast errors, thus a highly significant and negative coefficient should be expected.

4.2.4 Hypothesis testing - H5

The above OLS regression is repeated for the four forecasts horizon (days before the realized EPS) counting 90 days each and for the two periods, 2000-2007 and 2008-2018.

5 Data Collection

In order to conduct the statistical analysis for testing my hypotheses, I have employed several datasets which derive from different financial databases. In this chapter, there is a detailed description of the data sources and the collection procedure which I have followed. I divide the content into smaller sections related to each variable with the right time order that was obtained.

5.1 Earnings Surprise Data

Data gathering starts with the analysts' quarterly forecasts regarding earnings announcements and the corresponding realized EPS for the period 2000-2018. The dataset is coming from the Institutional-Brokers-Estimates-System (IBES), a historical earnings estimate database from

Thomson Reuters containing analysts' estimates, actual values of EPS and other forecast measures covering both the U.S and international companies. This source provides me with 1,565,251 firm-quarter observations for the whole period containing the median forecast value, the announcement date of the forecast, as well as the realized EPS value, including the actual date of the quarterly announcement. It also includes the forecast period end date and the number of estimates per firm's quarter observation, which is a sign about the coverage of a firm. After controlling for missing values, I deleted 175,837 observations.

Additionally, I excluded the analysts' forecasts, which took place after the end of the forecasted period reducing my sample by 244,873 observations. Also, I did not take into account the events in which the announcement day of earnings happened a quarter after the finish of the corresponding forecasted period. (2000-2018: 24,421 obervations deleted).

At this point, it is crucial to be mentioned that for the first empirical part of this research I only selected the last median forecast under the condition that is generated before the end of the forecasted period. This is described by IBES so as to offer a reliable and transparent measure and to be assured that the estimation is not affected by any pre-announcement. This chronological snapshot is of the Thursday before the third Friday of the last month of the forecasted quarter. Finally, I excluded observations for which the announcement date of the actuals takes place after a quarter of the end of the forecasted period. This eliminates from my sample 960,470 observations for the whole period. The final dataset consists of 159,650 observations. It is highly important to be noted that this is the international file of I/B/E/S database which includes EPS estimation for countries outside the United States. The size of the sample will be reduced further after excluding the not European regions and possible mergers-acquisitions.

5.2 Mergers and Acquisitions

Using the Sedol codes of the above companies I searched in the Thomson One database which of them participate in a merger or acquisition activity in this period either as target company or acquirer and excluded these firms from my sample. I deleted a total of 693 firms for the entire period.

5.3 Index Constituents

Compustat Global provides me with all stocks traded outside of U.S in 2000-2018, including their origin, their ISIN code, and their Standard Industry Classification (SIC) code[2]. I manually selected the countries which belongs to the Euro Area. After merging the two datasets (IBES-Index Constituents) I have 22,022 observations for the years 2000-2018.

5.4 Securities daily Prices[3]

Based on the ISIN code of the covered firms, I obtained the daily prices from the Compustat Securities Daily Database. The clean sample for the whole period consists of 3,903,051 daily observations. A highly important adjustment that I made is regarding the currencies of some firms. Not all of these firms use the Euro as their currency the whole period, so in many cases, the close price and some firm characteristics data like the assets and liabilities are expressed in the local currency. In that case, I converted all the foreign currencies into Euro using the exchange rate time series from the European Central Bank. In total, I converted 16 currencies: Bulgarian lev, Czech Koruna, Cyprus Pound, Danish Krone, Esthonian Kroon, Greek Drachma, Hungarian Forint, Iceland Krona, Lithuanian Litas, Norwegian Krone, Polish Zloty, Slovenian Tolar, Swedish Krona, Swiss Franc, UK pound and USD.

After merging the companies which are covered with the analysts with the daily prices of these stocks we have:

Period 2000-2018: 11,410,202 daily observations, 17.529 firm-quarter observations, 943 companies.

For the second part of my analysis, I used the entire sample of analysts' forecast for Europe. Unfortunately, the number of estimations is too low before 2004, so in my analysis, I display the

[2] I used the Compustat Global-Index Constituents database in order to take the isin code for the companies that are covered by IBES analysts and their origin country. The IBES database could not provide me with this information so I downloaded all the traded companies outside the U.S for the sample periods and through merging (using company name) with IBES file and filtering the Euro Area countries, I had my complete sample of analysts' estimations.

[3] For the Securities Daily file (Compustat Global) the downloaded sample ends two year after the sample period (i.e for sample 2000-2007, I take data till 2009) to cover the estimation period of the events that take place in the last year of my analysis.

years from 2004 to 2018. The total number of forecasts made in this period are 50,040 distributed across industries and countries (see tables 10 and 11, Appendix)

6 Empirical Results

In this chapter, I present the results which can provide sufficient answers to the hypotheses developed. I begin by reporting the descriptive evidence on my predictions, and I continue with the formal statistical test of my predictions using the regression analysis for each of the five hypotheses.

6.1 Descriptive Evidence

6.1.1 Uncertainty, EPS Surprise and Stock Returns

Table 1 provides descriptive evidence of the effect of age and earnings surprises on stock returns. According to my methodology, the firm-quarter observations were stratified into quintiles, and then each quintile was divided into three categories related to the sign of earnings surprises. Each cell of the table reports the mean Buy and Hold Abnormal Return (BHAR), the number of observations, and the proportion compared to the entire uncertainty portfolios. The last row of the table displays the overall result for each surprise, whereas the rightmost column reports the grand averages across each of the quintiles. Finally, the table shows a mean comparison test at a confidence level of 1%, 5%, and 10%.

Focusing on the rightmost column and the gross average across each uncertainty portfolio, we can observe clear evidence on the documented MB effect. The mean BHAR declines from 0.81% for low uncertainty firms to -0.41% for high uncertainty firms. This can be translated into 1.22% return differential between the older and younger companies for the quarter and 4.88% for the year. This percentage is very close to 1.24% documented by Skinner and Sloan (2002) but significantly lower than the compound annual difference documented by previous researchers.

Table 1 Mean quarterly buy and hold abnormal stock return stratified into quantiles portfolios and earnings surprise

	Earnings Surprise Portfolio			
	Negative	Zero	Positive	All
Uncertainty Portfolios				
1. Low Uncertainty/Old firms	-0.87%***	0.78%	2.53%***	0.81%***
	1837	119	1783	3739
	(49.1%)	(3.2%)	(47.7%)	(100.0%)
2.	-1.19%***	1.65%*	2.87%***	0.87%***
	1654	151	1642	3447
	(48.0%)	(4.4%)	(47.6%)	(100.0%)
3.	-2.53%***	0.51%	2.29%***	-0.21%
	2091	199	1881	4171
	(50.1%)	(4.8%)	(45.1%)	(100.0%)
4.	-3.60%***	-1.22%	1.68%***	-1.17%***
	1732	135	1475	3342
	(51.8%)	(4.0%)	(44.1%)	(100.0%)
5. High Uncertainty/Young firms	-2.56%***	0.55%	2.13%***	-0.41%*
	1510	73	1247	2830
	(53.4%)	(2.6%)	(44.1%)	(100.0%)
All Uncertainty Portfolios	-2.15%***	0.47%	2.33%***	0.00%
	8824	677	8028	17529
	(50.3%)	(3.9%)	(45.8%)	(100.0%)

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1%

The bottom row of the table can provide us with two conclusions. The first one is related to the positive relation of earnings surprises and abnormal returns. When a firm experiences a positive earnings surprise, then the average BHAR increases by 2.33% whereas the BHAR declines by 2.15% when the analysts overestimate the performance of the company. Furthermore, analysts are more likely to present a negative surprise of 50.3% against 45.8% of positive surprises, which is consistent with the conclusions of Abarbanell and Lehavy (2000) and Brown (2001).

Studying the rest of the table, I try to accommodate the hypothesis referring to the asymmetric response on negative surprises. Zero and positive surprises portfolios show no systematic trend as a function of Age variable. The results are not statistically significant for zero surprises and for positive surprises the quarterly return differential is too low (-0.5%) to explain to MB effect. This finding is contrary to Skinner and Sloan's (2002) claims, who found that the MB effect did not make its appearance in these surprises. However, negative earnings surprise portfolios decline monotonically from -0.87% for low uncertainty firms to -2.56% for high uncertainty companies. This return differential of -3.43% is close to -3.75% documented by Skinner and Sloan and capable to justify the MB effect. Therefore, the MB effect derives mostly from the asymmetric response to negative earnings surprise.

6.1.2 Forecast Accuracy Determinants

Forecast Horizon:

Figure 3 illustrates the average forecast error or otherwise the Forecast Bias over time. The forecast measures are broken up by forecasted horizon. As the main outcome of the table, I conclude that the FB in all horizons follows the same pattern. This pattern could be characterized by many fluctuations and mainly negative prices in the peak of the European debt crisis (2010-2013), before this by the global financial crisis of 2007 and the contagion effect the next year with the collapse of Iceland's banking system. In other words, it demonstrates the inability of companies to beat analysts' expectation and the overoptimism in the forecasting. Around 2016 FE tends to stabilize around 0% and shows an upward trend the recent years. Regarding the forecast error taking into considerations the time horizon, the last forecast of analysts, which is closer to the realized EPS (horizon 1: 1-90 days) remains relatively stable and less volatile compared to horizon 2. Forecast bias for the 181-270- and 271-360-days horizon is more pronounced, presenting larger and negative forecast errors which indicate that analysts are more optimistic in their analysis. The results are in line with previous papers documented that forecasts are more accurate as we are getting closer to the announcement date.

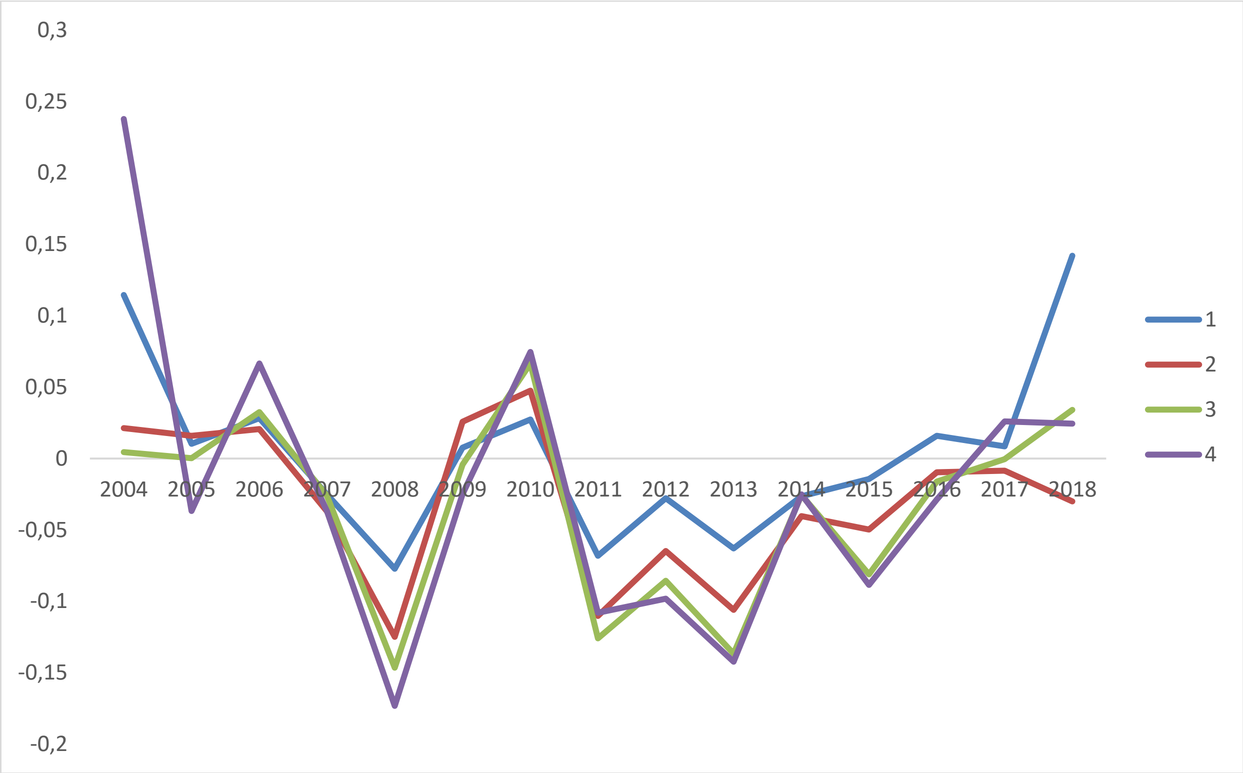

Figure 3 Development of Forecast Errors (forecast bias) per forecast horizon through the years

Figure 4 displays the average forecast error. This graph provides supporting evidence to the above statement; as we are getting closer to the EPS announcement, the forecast error tends to be smaller. From the start of the recession 2007 - 2009, the absolute forecast error for horizon 1 increases from 0.2 to 0.28 and from 0.25 to 0.34 for horizon 4. After 2009, the absolute FE appears a downward trend.

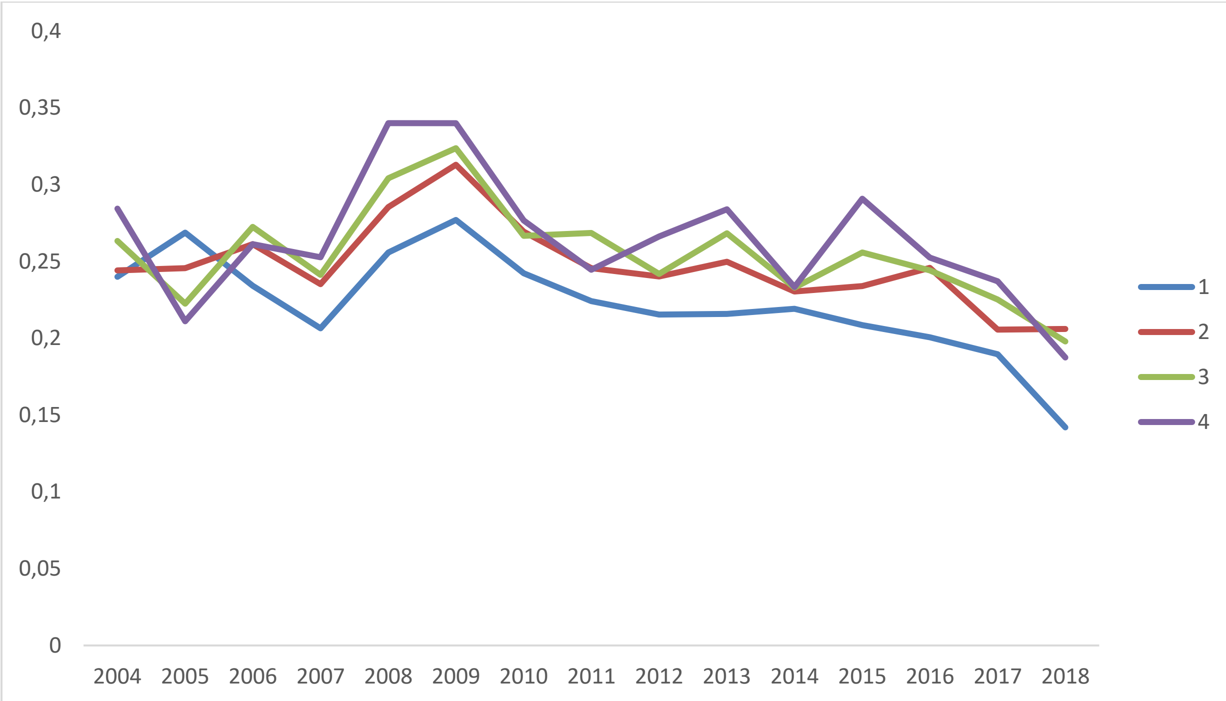

Figure 4 Development of Absolute Forecast Errors per forecast horizon through the years

Industry:

Figures 5 and 6 illustrate the absolute forecast error for each industry and forecast horizon for the periods 2004-2007 and 2008-2018, respectively. In line with my previous statement, I also support that the forecast errors are significantly higher in horizon 4 and lower for the first horizon almost for all industrial sectors and especially during the crisis. Focusing on the overall result, industries like Mining, Wholesale Trade, Public Administration, Manufacturing appear larger in magnitude forecast errors in both time frames while Finance and Services are more pronounced in the first period and Construction in the second. Comparing the two-time intervals, I conclude that the absolute FE is slightly higher in the second period probably due to the crisis for almost all the industries.

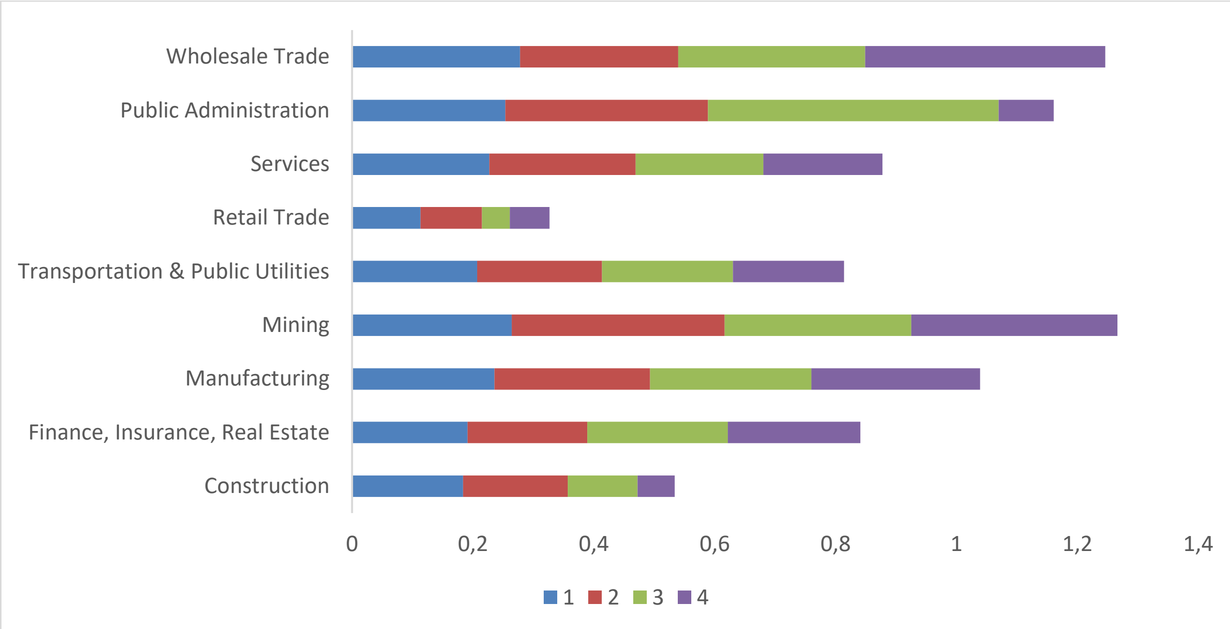

Figure 5 Absolute Forecast Errors by industry and forecast horizon in the period 2004-2007

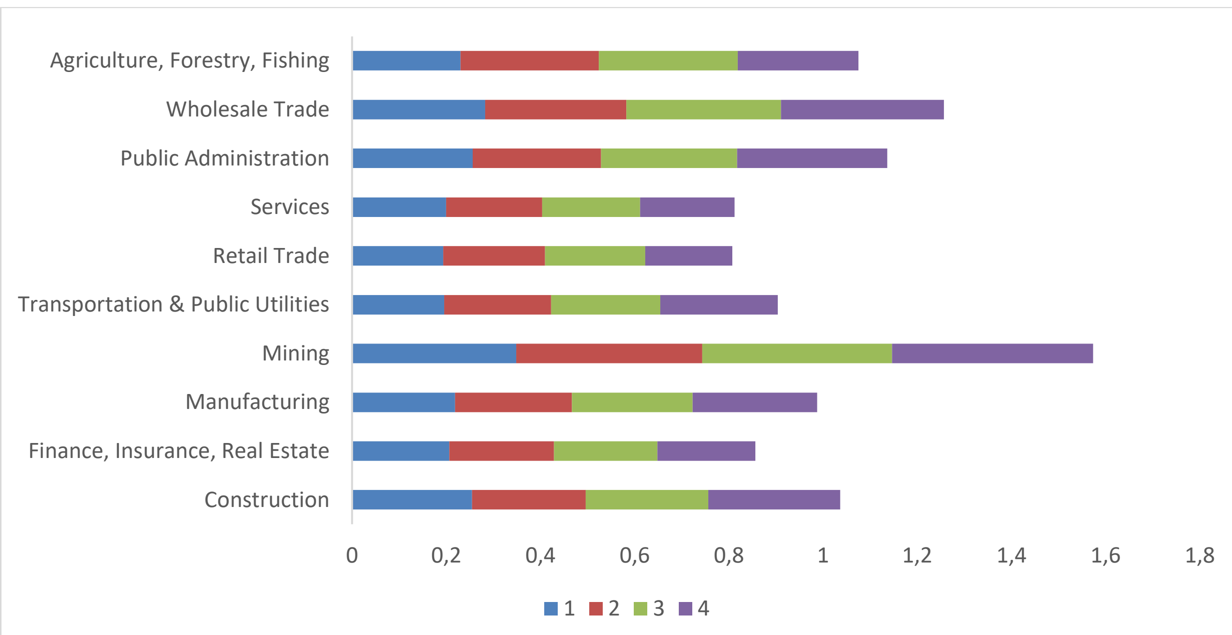

Figure 6 Absolute Forecast Errors by industry and forecast horizon in the period 2008-2018

Moving now to the forecast bias in the two periods and Figures 7 and 8, someone could identify obvious differences in the direction of forecast errors across the industries. Referring to some years before the crisis, analysts tended to produce both optimistic and pessimistic forecasts depending on the industrial sectors. Someone could see that the forecast errors are negative for Wholesale

Trade, Public Administration and Mining and Services indicating that analysts have a more optimistic view about the performance of these companies and firms cannot beat these expectations. On the contrary, in the other industries and especially the financial sector the earnings surprises are mostly positive. Referring to years after 2007, analysts have a more optimistic view for all the industries excluding the financial sector where the forecast errors continue to be positive but less pronounced compared to the first-time frame. Surprisingly, the forecast in Retail Trade and Services are more optimistic, presenting the most negative forecasts across the other sectors. This evidence is not against to what we expected. There is a growing body of literature indicating that industries like Mining, Retail Trade, Services, etc are vulnerable to exogenous shocks that can affect their performance whereas some other industries like Finance are more stable; the information disclosure is significantly higher and the coverage of the analysts much bigger.

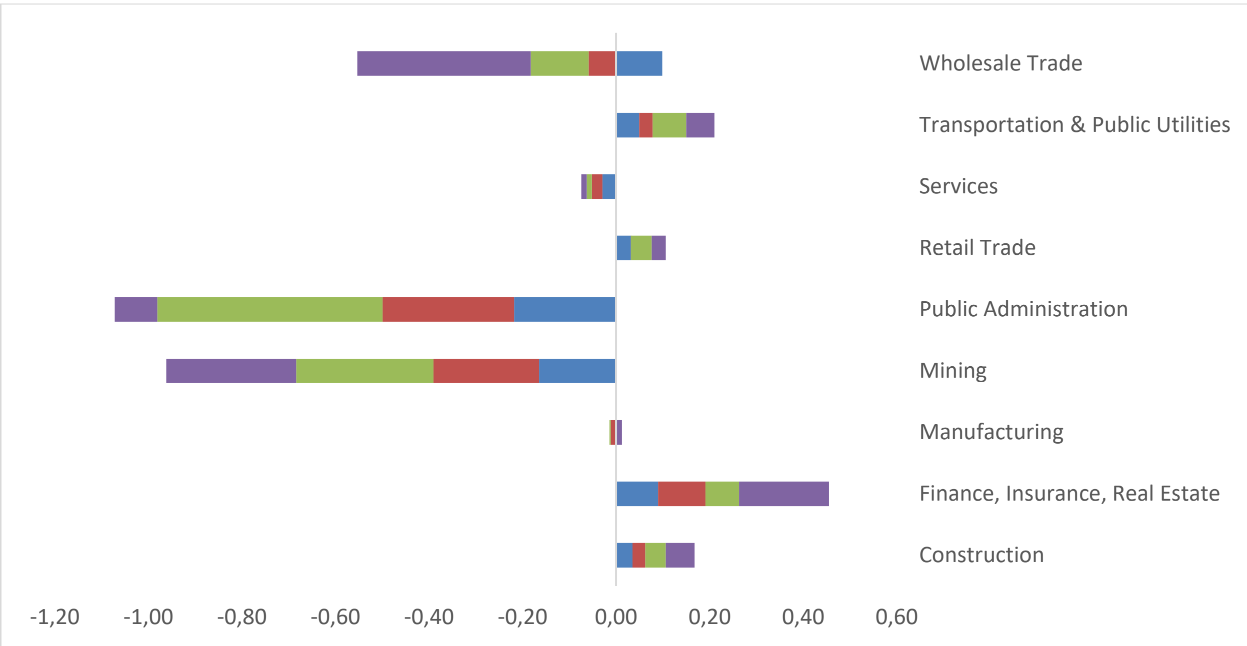

Figure 7 Forecast Errors by industry and forecast horizon in the period 2004-2007

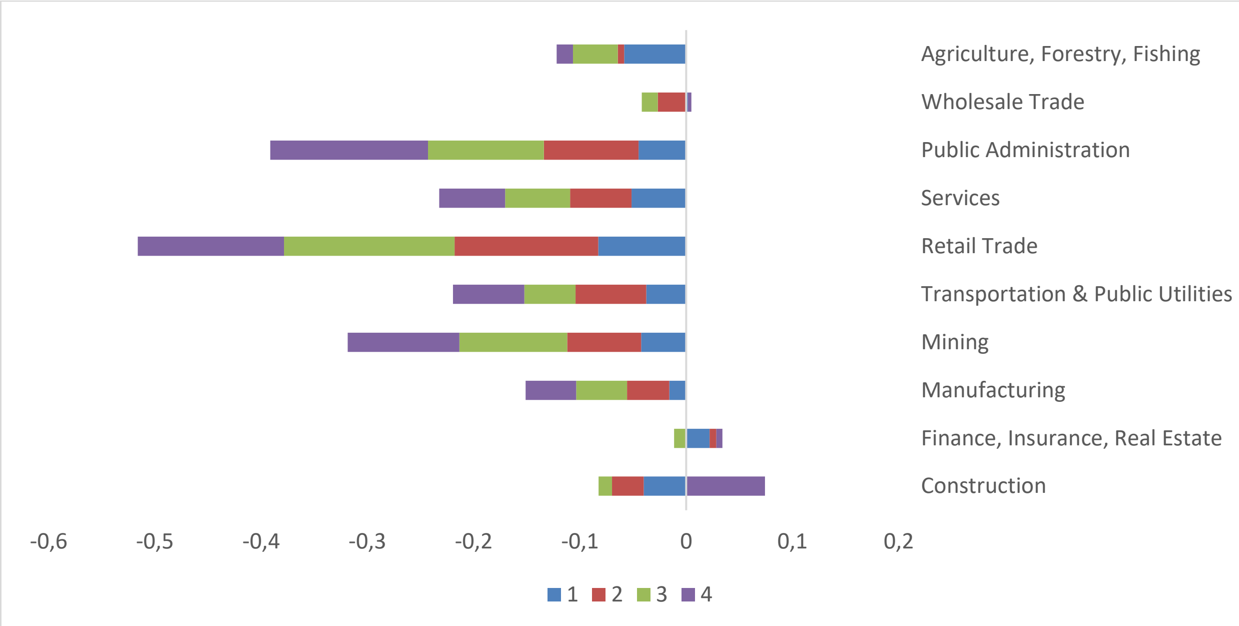

Figure 8 Forecast Errors by industry and forecast horizon in the period 2008-2018

Coverage and Firm Size characteristics:

Moving to the next pair of figures (Figure 9 -12) someone could observe the movement of the absolute forecast error and forecast bias related to the size and coverage characteristics of the firms for the two periods. Starting with the size variable measured with the natural logarithm of total assets of the company at the end of the previous quarter, I locate a negative relation with the absolute Forecast Errors in both periods presenting a decline of 1% between the 1^{st} and 5^{th} quintile firm size portfolio. These results are in line with previous papers. The firm size is an indicator of analysts' expectations of how much profitable a company is. Regarding the forecast bias (Figure 9) someone could observe that there is a positive relationship between size and pessimism till quintile 3, then we observe a negative relation until quintile 4 and then again positive.

As expected, the more significant the analysts' firm coverage, the smaller the absolute FE mostly in the period of crisis confirming the theory that more information should improve the quarterly forecasting. The relation of coverage and forecast bias seems to follow the same pattern (pessimistic forecasts) but again only for years 2008-2018, whereas the previous period displays an opposite direction which is changed when companies were followed from more than 10 analysts, Figures 11 and 12.

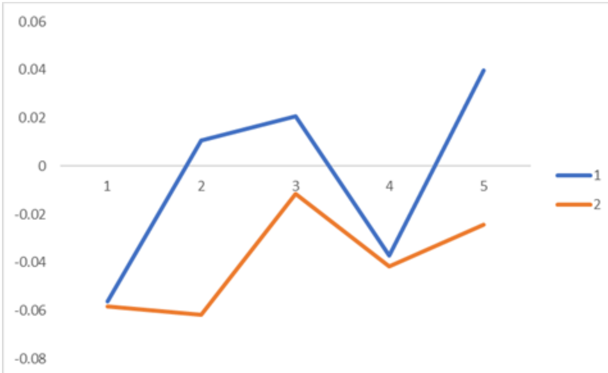

Figure 9 Relation of Forecast Errors and size variable in two periods

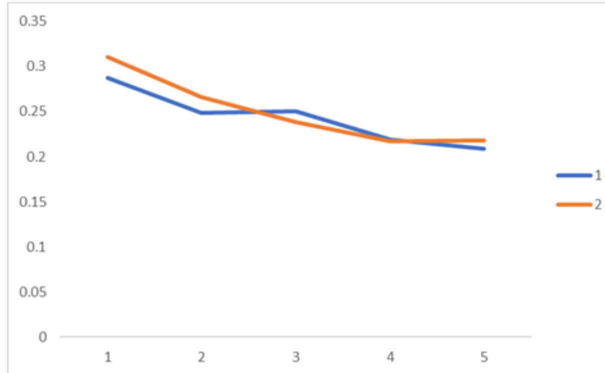

Figure 10 Relation of Absolute Forecast Errors and size variable in two periods

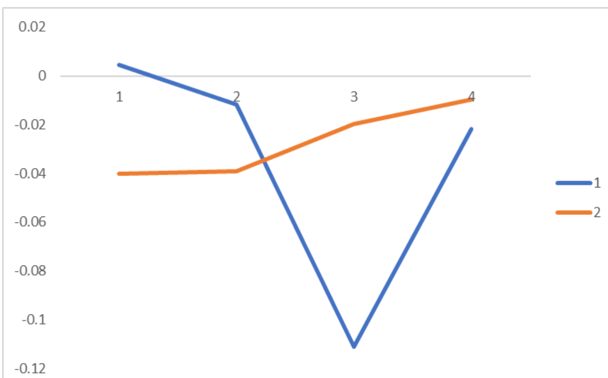

Figure 11 Relation of Forecast Errors and Coverage variable in two periods

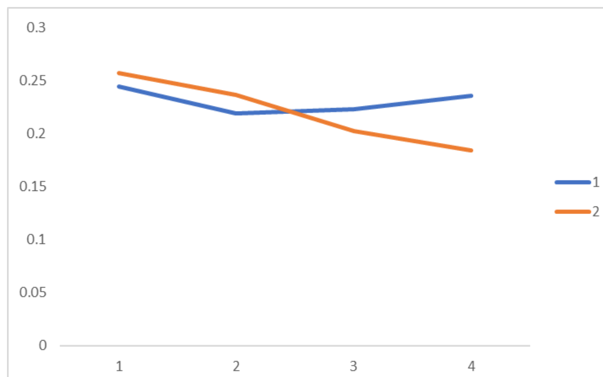

Figure 12 Relation of Absolute Forecast Errors and Coverage variable in two periods

Countries:

Moving forward to the absolute forecast error and forecast bias across the countries (Table 2), I conclude that the average absolute forecast error for the whole period (2000-2018) is almost the same for all the countries and it's fluctuating between 0.2 and 0.25. The same is also true for the two subperiods. Countries like Greece, Cyprus, Norway, Hungary, and Portugal seem to have an average |FE| above medium whereas the analysts' forecasts seem to be more accurate in Czech Republic, Denmark, France, Spain, Sweden, and Poland. Regarding the direction of the forecast errors, analysts have a slightly optimistic view about the future performance of the companies which is evident as the average FE in the first period is -0.3 % and in the second-0.1%. Moving to an individual level, someone could observe that the average FE takes high positive value for Greece (second period, +10%) while takes negative values (-32%) for Cyprus in the 1st time frame. The above results are completely in line with previous papers. I can undoubtedly locate an optimistic view across all countries in the whole period whereas countries like Greece, Portugal and Cyprus which were among the governments that announced huge debts and received bailouts from the IMF have the biggest forecast errors.

Table 2 Average Forecast Errors and Absolute Forecast Errors by country and time period

Countries	2000-2007		2008-2018		2000-2018	
	Average FE	Average |FE|	Average FE	Average |FE|	**Average FE**	**Average |FE|**
Austria	-0.08	0.17	-0.05	0.28	-0.07	0.22
Belgium	0.08	0.25	0.05	0.21	0.06	0.23
Cyprus	-0.32	0.32	-0.15	0.35	-0.23	0.33
Czech Republic			0.04	0.09	0.04	0.09
Denmark	0.12	0.17	-0.01	0.20	0.05	0.19
Finland	0.00	0.26	-0.05	0.27	-0.02	0.26
France	-0.01	0.12	-0.01	0.16	-0.01	0.14
Germany	0.02	0.23	-0.02	0.22	0.00	0.23
Greece			0.10	0.42	0.10	0.42
Hungary			-0.01	0.33	-0.01	0.33
Ireland			0.01	0.21	0.01	0.21
Italy	-0.08	0.19	-0.09	0.28	-0.09	0.24
Luxembourg	0.06	0.18	0.19	0.34	0.13	0.26
Netherlands	-0.01	0.21	-0.01	0.19	-0.01	0.20
Norway	-0.01	0.34	-0.08	0.33	-0.04	0.34
Poland			0.03	0.17	0.03	0.17
Portugal			-0.03	0.29	-0.03	0.29
Spain	-0.11	0.14	-0.02	0.19	-0.07	0.17
Sweden	0.00	0.19	-0.03	0.20	-0.01	0.19
Switzerland	0.04	0.21	-0.02	0.21	0.01	0.21
United Kingdom	-0.09	0.16	-0.09	0.25	-0.09	0.21
Total	-0.03	0.21	-0.01	0.25	-0.01	0.23

6.2 Regression Analysis

6.2.1 Earnings Surprises and asymmetric effect on stock returns

In this section, I provide statistical tests of my predictions using regression analysis. In the following table, I regress Buy and Hold Abnormal Returns on the age-uncertainty portfolios and the earnings surprise. I further allow for an interaction term between the two main effects. In this way, I can test the first two hypotheses of my research capturing the MB effect and the positive correlation of earnings surprises and stock returns. Additionally, the interaction term allows me to test the sensitivity of young firms (high uncertainty) to earnings surprises than those of old firms.

Table 3 Estimated coefficients (t-statistics) from regressions of quarterly buy and hold abnormal returns on the age portfolios and the sign of earnings surprises

	H1	H2	H3		
			3.1		3.2
			3.1.1	3.1.2	
Intercept	0.013	0.013	0.017	-0.009	-0.004
	(6.27)	(6.65)	(3.38)	(-4.08)	(-1.30)
Age	-0.004	-0.004	-0.004	-0.004	-0.006
	(-6.39)	(-6.29)	(-6.38)	(-6.38)	(-6.61)
Surprise	0.022	0.017			
	(24.43)	(8.40)			
*Age * Surprise*		0.002			
		(3.02)			
Good			0.019	0.044	0.033
			(3.94)	(24.42)	(7.79)
Bad			-0.026		
			(-5.50)		
Zero				0.026	0.021
				(5.50)	(1.83)
*Good * Age*					0.004
					(3.00)
*Bad * Age*					
*Zero * Age*					0.002
					(0.39)
Adjusted R^2	3.56%	3.62%	3.55%	3.55%	3.59%
Observations	17.529	17.529	17.529	17.529	17.529

Considering the first hypothesis and then seeing the first column of the results, Age variable as a proxy for uncertainty loads with a significantly negative coefficient -0.42% (t-test= -6.39), providing clear evidence on MB effect. Furthermore, in line with results of previous researches, I find a positive and highly significant coefficient on Surprise variable (2.22%, t-test=24.43) which confirms the positive correlation of earnings surprises and stock returns. These variables could explain the 3.56% of the movement of stock prices after EPS as can be seen by the adjusted R squared. Dividing the Surprise Variable into three dummies, we can see how the individual surprise can affect the stock returns. Regression 3.1.1 and 3.1.2 reveal the return differential of each surprise compared to zero surprises (specification 3.1.1) and to bad surprises (specification 3.1.2). In both cases, I acknowledge that positive surprises have a more positive impact on abnormal returns compared to zero surprises (1.9%) and to bad surprises (4.4%). Additionally, stock returns' response to negative news is by 2.6% lower than no news (t-value=-5.50).

The second regression includes the main effects and the interaction between them. This regression grants the sensitivity of abnormal returns to earnings surprises to vary as a function of the age quintile to which the stock belongs. The coefficient on age remains negative -0.41% and statistically significant (t-test=-6.29). The coefficient on surprise is persistently positive and significant (1.65%, t-test=8.40) indicating a high correlation between earnings surprises and stock returns. Finally, the coefficient of the interaction term "surprise*age" is positive and significant (0.2%, t-test=3.02) which is in line with our methodology indicating that stock returns of high uncertainty young firms are more responsive to earnings surprises than those of low uncertainty old firms. The addition of the interaction terms increases the explanatory power of our regression by 0.6% to 3.62%.

Thus far, I assumed that the effect of age (uncertainty about the profitability of the firm) on the stock returns is the same for any kind of surprise. However, existed literature provides clear evidence that this is not the case. For instance, the effect of age may be different for negative surprise than for positive or no news. The last column of table 3 allows for the asymmetrical response to positive or no news compared to negative news using the interaction terms. The following table estimates the separate slope coefficients of age for positive, negative, and zero earnings surprises.

Table 4 Separate slope coefficients of age variable in each kind of surprise

	Coefficient	Standard Error	t-value	p-value
Positive Surprise				
Constant (a)	0.029	0.003	9.98	0.00
Age	-0.002	0.001	-2.22	0.03
Zero Surprise				
Constant (a)	0.018	0.011	1.58	0.11
Age	-0.005	0.004	-1.26	0.21
Negative Surprise				
Constant (a)	-0.004	0.003	-1.26	0.21
Age	-0.006	0.001	-6.39	0.00

Considering previous studies and specifically the paper of Sloan and Skinner (2002), the MB effect should manifest itself only in negative surprises. According to them, I should observe a negative and statistically significant coefficient of Age only in these kinds of news and a positive coefficient if companies beat the analysts' expectations. Interestingly, the age effect is concentrated in firms reporting all kind of news (negative coefficients), but the magnitude of this effect is much larger for negative surprises (-0.6%) and highly significant (t-value=-6.39). The coefficient of age for positive surprises is smaller by 0,4% compared to negative news, and this difference in magnitude is statistically significant (t-value=3.00), see Table 3. Thus, the results in both tables indicate a more substantial response in negative surprises for high uncertainty/young firms.

Elaborating more on the results of table 4, I gain a clear view of the practical meaning of the above conclusion. The intercept (alpha) provides an estimate of the expected quarterly abnormal return for the low age quintile which is 2.9% for positive news, 1.76% for no new and -0.38% for negative surprises. Combining this information with the coefficient of the age, I calculated the annualized abnormal return for low and high uncertainty portfolios for each of the three surprises.

Table 5 Annualized Abnormal Return for Low and High Uncertainty Portfolios for each kind of surprise

Portfolios	Positive Surprise	Negative Surprise	Zero Surprise
Low uncertainty	11.6%	-1.52%	7.04%
High uncertainty	8.4%	-11.2%	-0.8%

The primary outcome of the above table is that the annualized return differential of low and high uncertainty portfolios is -3.2% and -9.68% for positive and negative surprises respectively providing clear evidence to the asymmetric response of growth stock returns to negative earnings surprise.

6.2.2 Determinants of earnings surprises

Tables 6 and 7, report the results of the regression setting the absolute forecast errors as the dependent variable and the explanatory variables of industry, country, size, and coverage in the right side of the equation. I repeat the regression for the four forecast horizons and the two subperiods. The estimated coefficient shows a negative and highly statistically significant relation between absolute forecast error and size across the four forecast horizons but slightly larger in magnitude from 2008 to 2018. As previously documented, the bigger the coverage of the firm the smaller the absolute forecast error which can be revealed by the negative coefficients of this variable across all the horizons and periods excluding horizon 2, 3 and 4 in period 1 where the coefficients are also negative but lack of statistical significance.

Hereby I am focusing on the differences of analysts' forecasts among the industries. Starting with the first period 2004-2007, I cannot form a clear conclusion about the differences between industries compared to the manufacturing sector as the coefficients are not keeping their statistical significance in the four forecast horizons. However, I can safely claim that Retail Trade has a more negative influence on the analyst' forecasts compared to manufacturing by 10.7% in horizon 1. Also, the absolute forecast errors are smaller in Construction and Transportation, but they are significant only in two horizons. In the second period, the results are more precise and more meaningful. Services, Transportation and Agriculture sectors have a negative and highly significant coefficient almost in all horizons while Mining and Wholesale Trade have high in magnitude and significant positive coefficients (+10.3% and +4.2% respectively) in Horizon 1 compared Manufacturing sector. The new evidence is the Finance, Insurance, and Real Estate, which has coefficients of -2.3% and -4.3% (significant at 1% confidence interval) at horizon 3 and 4 respectively. This result is in the same line with the descriptive evidence.

Moving to the country variable, we cannot see significant differences between the countries at least for the first period. The coefficients indicate that only Norway has higher absolute forecast errors than Germany (reference point) in all the horizons (coefficient in the 1st horizon is 7.6%) indicate the difference in the magnitude of absolute forecast error among these countries. Conversely, only France and Sweden seem to have significant negative coefficients in three of the four horizons whereas the United Kingdom and Spain have large negative coefficients (-16.8% and -8.9%) but only horizon 1 and 2 respectively. The evidence in period 2 (2008-2018) is more apparent and can be easily interpreted. Norway follows the same pattern as before with positive coefficients, and the same is also true for Hungary, Finland, and Italy. Other countries like Greece and Portugal also have positive and significant coefficients but only in three or two horizons. Czech Republic, France, Switzerland, and the Netherlands have significant negative coefficients compared to Germany almost in all the horizons. As expected, the intercept gets smaller as approaching the realized EPS indicating that accuracy is higher in the shorter horizon.

Table 6 OLS regression of Absolute Forecast Errors on country, industry, coverage and size for the four horizons before realized EPS, period 2004-2007

Coefficients		Estimated Parameters			
Forecast Horizon		1-90	91-180	181-270	271-360
Intercept	α	0.290***	0.336***	0.305***	0.301***
Industries					
Agriculture, Forestry, Fishing	$\beta_{1,1}$				
Mining	$\beta_{1,2}$	0.01	0.039	0.048	-0.011
Construction	$\beta_{1,3}$	-0.036	-0.063	-0.149**	-0.206*
Transportation & Public Utilities	$\beta_{1,5}$	-0.015	-0.038*	-0.043	-0.105**
Wholesale Trade	$\beta_{1,6}$	0.03	0.003	0.049	0.134
Retail Trade	$\beta_{1,7}$	-0.107***	-0.137***	-0.220***	-0.235**
Finance, Insurance, Real Estate	$\beta_{1,8}$	0.012	-0.008	0.001	-0.086
Services	$\beta_{1,9}$	-0.016	-0.024	-0.054**	-0.053
Public Administration	$\beta_{1,10}$	0.005	0.055	0.224***	-0.286
Countries					
Austria	$\beta_{2,1}$	-0.1	-0.077	-0.03	0.087
Belgium	$\beta_{2,2}$	-0.004	-0.108	0.148	0.181
Cyprus	$\beta_{2,3}$	-0.103	0.086	0.22	0.306
Czech Republic	$\beta_{2,4}$				
Denmark	$\beta_{2,5}$	-0.080*	-0.06	-0.029	0.069
Estonia	$\beta_{2,6}$				
Finland	$\beta_{2,7}$	0.016	-0.016	0.012	0.012
France	$\beta_{2,8}$	-0.111***	-0.138***	-0.072	-0.155*
Germany	$\beta_{2,9}$				
Greece	$\beta_{2,10}$				
Hungary	$\beta_{2,11}$				
Ireland	$\beta_{2,12}$				
Italy	$\beta_{2,13}$	-0.108	-0.046	0.059	-0.066
Luxembourg	$\beta_{2,14}$	-0.075	-0.076	-0.245	-0.115
Netherlands	$\beta_{2,15}$	-0.033	-0.046	0.023	0.079
Norway	$\beta_{2,16}$	0.076***	0.115***	0.097***	0.160**
Poland	$\beta_{2,17}$				
Portugal	$\beta_{2,18}$				
Slovenia	$\beta_{2,19}$				
Spain	$\beta_{2,20}$	-0.089*	-0.099**	-0.056	-0.112
Sweden	$\beta_{2,21}$	-0.051**	-0.040*	0.036	0.102**
Switzerland	$\beta_{2,22}$	-0.037	-0.057*	0.017	0.063
United Kingdom	$\beta_{2,23}$	-0.168***	-0.152***	0.041	-0.052
Coverage	β_3	-0.017*	-0.003	-0.003	0
Size	β_4	-0.012**	-0.020***	-0.017**	-0.017
Adjusted R^2		5.46%	7.28%	4.67%	5.55%
Observations		1,946	1,870	913	336

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1%

Table 7 OLS regression of Absolute Forecast Errors on country, industry, coverage and size for the four horizons before realized EPS, period 2008-2018

Coefficients		Estimated Parameters			
Forecast Horizon		1-90	91-180	181-270	271-360
Intercept	α	0.299***	0.344***	0.338***	0.368***
Industries					
Agriculture, Forestry, Fishing	$\beta_{1,1}$	-0.052*	-0.047*	-0.047	-0.099***
Mining	$\beta_{1,2}$	0.103***	0.088***	0.092***	0.103***
Construction	$\beta_{1,3}$	0.037***	-0.004	0.01	0.015
Transportation & Public Utilities	$\beta_{1,5}$	-0.020***	-0.016**	-0.021**	-0.014
Wholesale Trade	$\beta_{1,6}$	0.042***	0.037***	0.048***	0.062***
Retail Trade	$\beta_{1,7}$	0	-0.005	-0.02	-0.063***
Finance, Insurance, Real Estate	$\beta_{1,8}$	0.007	-0.004	-0.023***	-0.043***
Services	$\beta_{1,9}$	-0.041***	-0.063***	-0.061***	-0.078***
Public Administration	$\beta_{1,10}$	0.021	0.004	0.014	0.048**
Countries					
Austria	$\beta_{2,1}$	0.045**	0.037**	-0.027	-0.091***
Belgium	$\beta_{2,2}$	-0.018	-0.038	-0.029	-0.036
Cyprus	$\beta_{2,3}$	-0.027	0.029	0.018	-0.068
Czech Republic	$\beta_{2,4}$	-0.108***	-0.118***	-0.123***	-0.135
Denmark	$\beta_{2,5}$	0.007	-0.013	-0.025**	-0.027
Estonia	$\beta_{2,6}$				
Finland	$\beta_{2,7}$	0.054***	0.018**	0.016*	-0.009
France	$\beta_{2,8}$	-0.043***	-0.045***	-0.071***	-0.099***
Germany	$\beta_{2,9}$				
Greece	$\beta_{2,10}$	0.079	0.204***	0.196***	0.336***
Hungary	$\beta_{2,11}$	0.152***	0.082**	0.102**	0.335***
Ireland	$\beta_{2,12}$	-0.013	-0.024	-0.079*	-0.114*
Italy	$\beta_{2,13}$	0.035*	0.073***	0.061**	0.083***
Luxembourg	$\beta_{2,14}$	-0.021	-0.007	0.039	0.04
Netherlands	$\beta_{2,15}$	-0.016	-0.045***	-0.035**	-0.053***
Norway	$\beta_{2,16}$	0.096***	0.106***	0.086***	0.077***
Poland	$\beta_{2,17}$	-0.05	-0.075*	-0.055	-0.144
Portugal	$\beta_{2,18}$	0.071**	0.052*	0.03	0.004
Slovenia	$\beta_{2,19}$				
Spain	$\beta_{2,20}$	-0.02	-0.031**	-0.031*	-0.023
Sweden	$\beta_{2,21}$	0.004	0	-0.018**	-0.003
Switzerland	$\beta_{2,22}$	-0.023**	-0.019*	-0.029**	-0.016
United Kingdom	$\beta_{2,23}$	-0.013	-0.002	-0.012	-0.019
Coverage	β_3	-0.036***	-0.031***	-0.028***	-0.019***
Size	β_4	-0.014***	-0.019***	-0.014***	-0.022***
Adjusted R^2		7.48%	7.34%	6.90%	9.19%
Observations		13,376	15,433	10,235	5,931

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1%

Tables 8 and 9 report the result of the regressions using the forecast error as the dependent variable. Starting with the relation of the forecast bias and the number of analysts following the firm, I observe a negative association in period 1 which indicate that the bigger the coverage, the larger the optimism in forecasting (more negative FE) being significant only in the first two horizons. In the second period, someone could observe a completely different situation. The coverage is positively associated with pessimism in forecast bias with a highly significant positive coefficient ranging from 1.1% in horizon 1 to 1.4% in horizon 3. Turning our research towards the size characteristics of the firm, we can observe a different pattern in the two periods. The years 2004-2007 analysts seem to have low expectations about the future performance of the stocks, so it was easy for companies to beat these forecasts (significant positive coefficients across the three horizons) whereas in period 2 (2008-2018) size variable has a low in magnitude positive and significant coefficient only in horizon 1.

The estimated industry coefficients measure the differences between the forecasts of one industry as compared to the reference point, which is the manufacturing sector. Using the sample of the first period only the coefficients of Finance, Insurance and Real Estate are significantly positive across the first two horizons showing that analysts underestimate the performance of companies belong to that sector compared to manufacturing. Conversely, the coefficients of Mining and Public Administration are negatively significant, revealing that analysts overestimate forecasts in this period. The years 2008-2018, the pattern is the same and more pronounced for Finance, but additionally, someone could say that analysts also exceed their predictions in Mining, Transportation and Retail Trade (negative coefficients).

In a country level, I cannot form safe statements about the differences of one country compared to Germany as the coefficients lack statistical significance by forecast horizon. The only countries with statistically significant results in two out of the four horizons are Spain and the UK where we can see a positive relationship between this country and optimism in analysts' forecasts and Luxemburg with positive coefficients. The second period (2008-2018) allowed me to form more conclusions. Countries like Cyprus, Finland, Italy, Norway, Sweden, and the United Kingdom seem to host more optimist analysts at least in two of the four horizons whereas only Belgium and Luxemburg tend to have positive coefficients compared to Germany.

Table 8 OLS regression of Forecast Errors on country, industry, coverage and size for the four horizons before realized EPS, period 2004-2007

Coefficients		Estimated Parameters			
Forecast Horizon		1-90	91-180	181-270	271-360
Intercept	α	-0.071*	-0.021	-0.007	0.125
Industries					
Agriculture, Forestry, Fishing	$\beta_{1,1}$				
Mining	$\beta_{1,2}$	-0.159***	-0.256***	-0.443***	-0.441
Construction	$\beta_{1,3}$	0.026	0.038	0.063	0.095
Transportation & Public Utilities	$\beta_{1,5}$	0.033	0.028	0.061	0.049
Wholesale Trade	$\beta_{1,6}$	0.081*	-0.053	-0.109	-0.340***
Retail Trade	$\beta_{1,7}$	0.034	0.017	0.06	0.009
Finance, Insurance, Real Estate	$\beta_{1,8}$	0.060**	0.095***	0.039	0.111
Services	$\beta_{1,9}$	-0.004	0.016	-0.001	-0.039
Public Administration	$\beta_{1,10}$	-0.250***	-0.310***	-0.574***	-0.317
Countries					
Austria	$\beta_{2,1}$	-0.043	-0.086	0.032	-0.114
Belgium	$\beta_{2,2}$	-0.054	0.118	0.065	0.355
Cyprus	$\beta_{2,3}$	0.025	-0.137	-0.089	-0.182
Czech Republic	$\beta_{2,4}$				
Denmark	$\beta_{2,5}$	0.037	0.059	0.08	0.018
Estonia	$\beta_{2,6}$				
Finland	$\beta_{2,7}$	0.048	0.024	-0.015	-0.091
France	$\beta_{2,8}$	0.01	-0.061	-0.043	0.008
Germany	$\beta_{2,9}$				
Greece	$\beta_{2,10}$	0.01			
Hungary	$\beta_{2,11}$				
Ireland	$\beta_{2,12}$				
Italy	$\beta_{2,13}$	-0.009	-0.149	-0.220*	0.079
Luxembourg	$\beta_{2,14}$	0.065	0.451***	0.460**	0.489
Netherlands	$\beta_{2,15}$	-0.035	-0.041	-0.04	-0.147*
Norway	$\beta_{2,16}$	0.007	-0.009	0.114**	0.154
Poland	$\beta_{2,17}$				
Portugal	$\beta_{2,18}$				
Slovenia	$\beta_{2,19}$				
Spain	$\beta_{2,20}$	-0.094	-0.146**	-0.167*	-0.155
Sweden	$\beta_{2,21}$	-0.032	-0.044	-0.055	-0.019
Switzerland	$\beta_{2,22}$	-0.001	0.016	0.104	0.243
United Kingdom	$\beta_{2,23}$	0.022	-0.028	-0.220**	-0.297**
Coverage	β_3	-0.031**	-0.048***	-0.026	-0.041
Size	β_4	0.030***	0.022**	0.015	-0.002
Adjusted R^2		2.12%	3.32%	5.00%	6.62%
Observations		1,946	1,870	913	336

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1%

Table 9 OLS regression of Forecast Errors on country, industry, coverage and size for the four horizons before realized EPS, period 2008-2018

Coefficients		Estimated Parameters			
Forecast Horizon		1-90	91-180	181-270	271-360
Intercept	α	-0.035***	-0.052***	-0.036**	-0.029
Industries					
Agriculture, Forestry, Fishing	$\beta_{1,1}$	0.002	0.087**	0.026	0.033
Mining	$\beta_{1,2}$	-0.016	-0.006	-0.066***	-0.093***
Construction	$\beta_{1,3}$	-0.02	0.013	0.032	0.11
Transportation & Public Utilities	$\beta_{1,5}$	-0.023**	-0.030***	-0.001	-0.022
Wholesale Trade	$\beta_{1,6}$	0.025	0.019	0.04	0.056*
Retail Trade	$\beta_{1,7}$	-0.077***	-0.106***	-0.121***	-0.101***
Finance, Insurance, Real Estate	$\beta_{1,8}$	0.028***	0.040***	0.039***	0.050***
Services	$\beta_{1,9}$	-0.029***	-0.015	-0.019	-0.022
Public Administration	$\beta_{1,10}$	-0.018	-0.039	-0.052*	-0.100***
Countries					
Austria	$\beta_{2,1}$	-0.057**	-0.036	-0.02	0.042
Belgium	$\beta_{2,2}$	0.073**	0.084**	0.038	0.021
Cyprus	$\beta_{2,3}$	-0.001	-0.121***	-0.115***	-0.169***
Czech Republic	$\beta_{2,4}$	0.02	0.02	0.027	0.037
Denmark	$\beta_{2,5}$	-0.011	-0.004	0.016	0.03
Estonia	$\beta_{2,6}$				
Finland	$\beta_{2,7}$	-0.027**	-0.026**	-0.030**	-0.026
France	$\beta_{2,8}$	0.029*	0	0.008	-0.006
Germany	$\beta_{2,9}$				
Greece	$\beta_{2,10}$	-0.029	0.044	0.11	0.565***
Hungary	$\beta_{2,11}$	0.112*	0.003	-0.095	-0.326
Ireland	$\beta_{2,12}$	0.043	0.093**	-0.039	-0.081
Italy	$\beta_{2,13}$	-0.044	-0.098***	-0.109***	-0.031
Luxembourg	$\beta_{2,14}$	0.173***	0.228***	0.274***	0.338***
Netherlands	$\beta_{2,15}$	0.018	0.006	-0.022	-0.017
Norway	$\beta_{2,16}$	-0.064***	-0.077***	-0.039***	-0.017
Poland	$\beta_{2,17}$	0.067	0.022	-0.058	0.126
Portugal	$\beta_{2,18}$	-0.008	-0.03	0.009	0.021
Slovenia	$\beta_{2,19}$				
Spain	$\beta_{2,20}$	0.014	-0.001	-0.003	-0.021
Sweden	$\beta_{2,21}$	-0.019*	-0.023**	-0.001	0.009
Switzerland	$\beta_{2,22}$	0.013	0.003	-0.013	-0.071**
United Kingdom	$\beta_{2,23}$	-0.008	-0.060***	-0.066***	-0.109***
Coverage	β_3	0.011***	0.013***	0.014**	0.01
Size	β_4	0.006*	0.005	-0.005	-0.005
Adjusted R^2		1.20%	1.45%	1.38%	2.64%
Observations		13,376	15,433	10,235	5,931

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1%

7 Conclusion

In this thesis, I approached the growth/value phenomenon from a learning perspective. I proved that the return differential between these two kinds of stocks could be attributed to the uncertainty level about the mean profitability of firms. As the uncertainty proxy, I used the age of the company. The sensitivity of abnormal returns to earnings surprises varies as a function of the uncertainty with young firms being more sensitive to earnings announcements than low uncertainty/old firms. Finally, I showed that bad earnings surprises have a higher magnitude on abnormal returns than the good earnings surprises on high uncertainty/young firms, and this asymmetry tends to decrease as the company is aging. After reporting that uncertainty can explain the MB effect, I proceeded to the next level of my analysis showing how uncertainty can affect the forecast accuracy considering that investors rely on these predictions. Using several proxies of uncertainty like coverage, size, industry, country and testing my results into two periods (before and after the crisis) across four forecast horizons, I showed their power in generating accurate forecasts. Size and coverage have a negative relationship with forecast errors that are caused mainly due to information disclosure, while the accuracy varies among the industries. Specific industries like Mining, Trading, or Manufacturing have more negative forecast errors while Finance produces positive and more stable forecasts. The performance of countries fluctuates as a function of the examined period with the countries being involved in crisis having the biggest errors. As a general view, we could say that during the crisis, the analysts produce more inaccurate forecasts and are more optimistic in their analysis. Finally, the accuracy tends to get higher as we are approaching the earnings announcement date.

The present research is subjected to several limitations that should be taken into consideration when evaluating the results and can be changed in future studies. Starting with the event study, I excluded from my sample any mergers and acquisitions during the examined period as these events can have a major impact on stock return. However, a future researcher can also consider other events like the initial public offering (IPO) of the company that also has an impact on stock returns and eliminate them from the sample. Additionally, as a benchmark for my market return, I created a sized matched portfolio and used the market model for generating the abnormal returns. Future studies could use another index (where the stock is listed) and another model like CAPM, Fama-French multifactor model, etc. Moving to the first empirical part, I used the last median forecast, which is closest to the EPS announcement as this is the most accurate according to our results. However, it would be interesting for future researchers to use also other forecast horizons and instead of age to use different proxies of uncertainty like the coverage or the size of the firm. Regarding the time period (2000-2018), the number of estimates for the European countries before 2004 was too low and many of them were eliminated after my restrictions so the first period includes the forecasts from 2004 to 2007. Turning our attention towards the second empirical part of this analysis, the variable "coverage" is an approximation for the number of analysts that cover the firm and provide their estimation to IBES. However, some analysts do not associate with this database, or their estimates were excluded from the Summary History of IBES as outliers, so using the Detailed History of IBES instead of the Summary can provide a better approach. Furthermore, the current study could be repeated in other countries and using different periods. As a final remark for further research, I would recommend to include also interaction terms between my independent variables to study how the firm size or the coverage vary among the industries or countries.

8 Appendix

8.1 Robustness checks

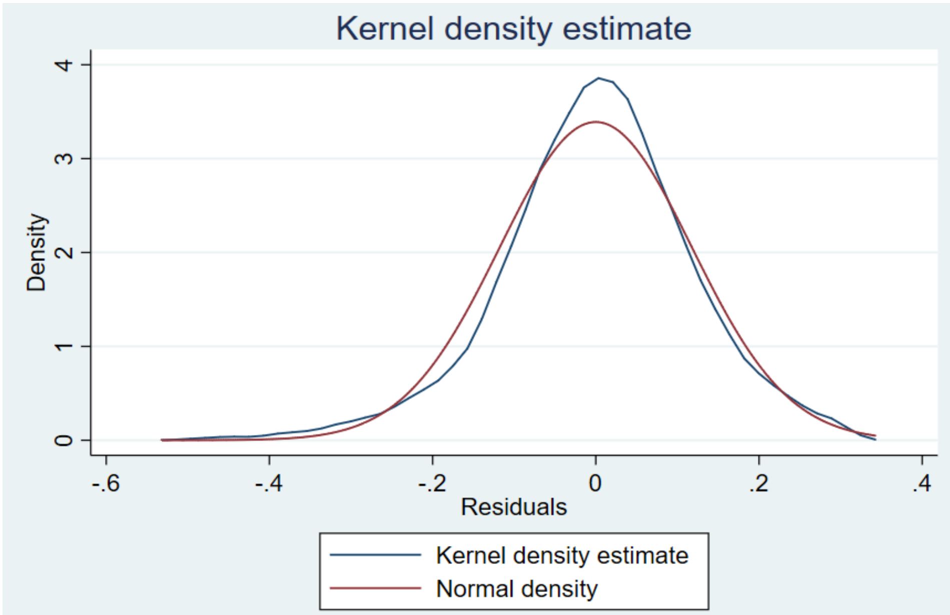

Figure 13 Normality test: Kernel plot

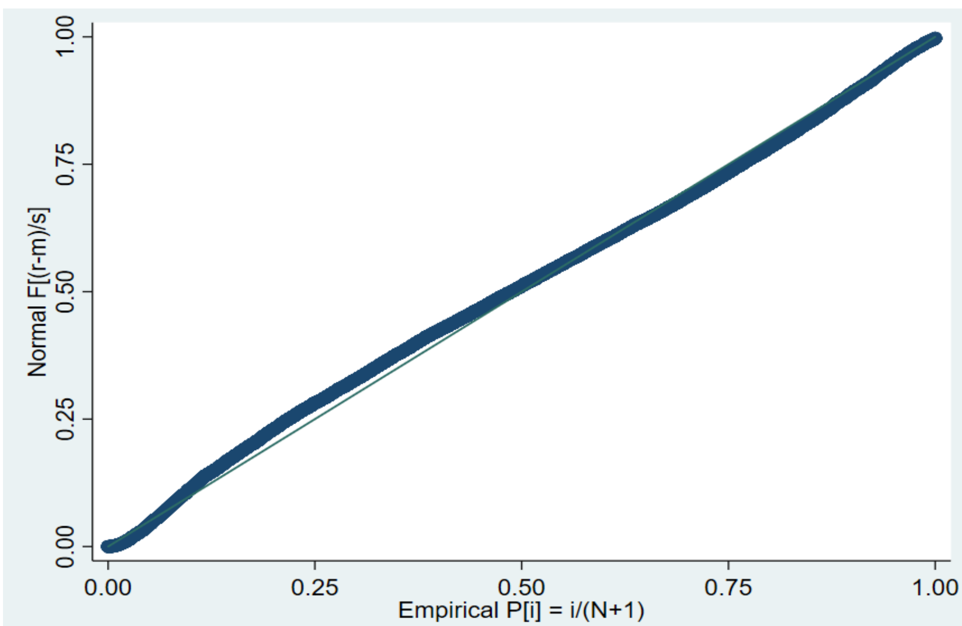

Figure 14 Normality test: standardized normal probability plot

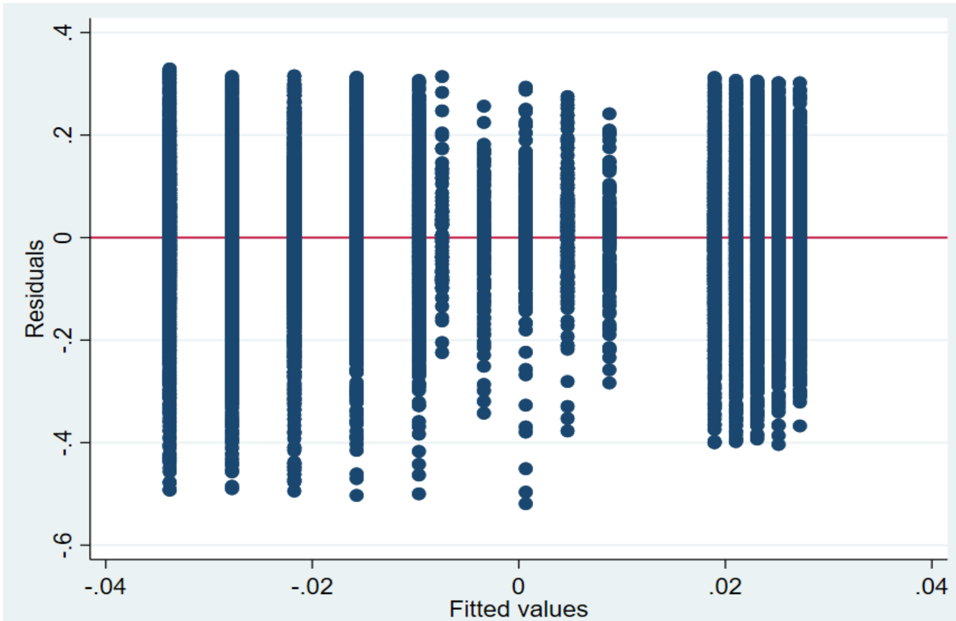

Figure 15 Heteroskedasticity plot

8.2 Distribution of Forecasts

Table 10 Distribution of forecast among industries and countries in period 2004-2007

Countries/Industries	2	3	4	5	6	7	8	9	10	Total
Austria		27		17						**44**
Belgium		1	27					1		**29**
Cyprus				15						**15**
Denmark		38	37					15		**90**
Finland	54	26	1590		6	42	373	199	103	**2393**
France		23	25				98			**146**
Germany		68	355		23		108	21		**575**
Italy			33							**33**
Luxembourg				16						**16**
Netherlands		31	133				29	40		**233**
Norway		36	299	62	15		80	32		**524**
Spain		9	25				31	1		**66**
Sweden	30	121	378	2		36	38	77		**682**
Switzerland		12	131				12	2		**157**
United Kingdom			54					8		**62**
Total	**84**	**392**	**3087**	**112**	**44**	**78**	**769**	**396**	**103**	**5065**

Table 11 Distribution of forecast among industries and countries in period 2008-2018

Countries/Industries	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Austria		12	118	213	146				28		**517**
Belgium			76	108			7		72		**263**
Cyprus					336						**336**
Czech Republic			122								**122**
Denmark			521	1487				93	467		**2568**
Finland		403	732	7481		83	217	1638	922	684	**12160**
France			303	821	17			278	41	26	**1486**
Germany		43	702	3395		292	87	969	287	108	**5883**
Greece			43	29				1			**73**
Hungary			94								**94**
Ireland				109					48		**157**
Italy			119	296	5				11		**431**
Luxembourg				7	307						**314**
Netherlands			316	1012			26	123	63		**1540**
Norway	247		773	2533	1626	234	24	504	388	111	**6440**
Poland			55	2	23						**80**
Portugal			3	249			2		3		**257**
Spain		8	336	269			92	208	83		**996**
Sweden		701	1330	4356	170		327	634	826		**8344**
Switzerland			285	1002			11	293	216		**1807**
United Kingdom			38	763	218				88		**1107**
Total	**247**	**1167**	**5966**	**24132**	**2848**	**609**	**793**	**4741**	**3543**	**929**	**44975**

1-Agriculture, Forestry, Fishing 2-Mining 3-Construction 4-Manufacturing 5-Transportation & Public Utilities

6-Wholesale Trade 7-Retail Trade 8-Finance, Insurance, Real Estate 9-Services 10-Public Administration

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