Analyst forecasting bias: Comparing the U.S. and the Eurozone markets

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Abstract
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PURPOSE OF THE STUDY

The purpose of this paper is to study financial analysts working in the US and the Eurozone markets. I will study forecasting biases between sales and earnings. I will study whether forecasting biases are intentional and to what degree regulation policies can affect those forecasting biases.

DATA

I have obtained the data from I/B/E/S analyst database. I have included all stocks from New York Stock Exchange and Nasdaq to my sample from the US markets. I have included all stocks from Frankfurt and Paris stock exchanges to my sample from the Eurozone. Time period goes from final quarter of 1994 to first quarter of 2010. This research period is split to two in order to study the effect of the regulation changes in the US markets. The study uses quarterly and annual financial reports and forecasts data.

RESULTS

I find out that Regulation Federal Disclosure and Global Settlement have altered markets in the US. Forecasting errors are distributed to larger area but on average forecasting biases have become smaller. In the Eurozone markets there has not been any significant development or improvements during research period. Analysts are affected by their prior forecasting errors and they react differently to positive and negative news. There are also some hints that even though average forecasting biases have declined, some of the analysts buy additional information from the management with favorable forecasts.

KEYWORDS

forecasting, financial markets, earnings forecasts, analysts, forecasting bias, intentionally added bias

Aalto-yliopiston kauppakorkeakoulu

ANALYYTIKKOJEN ENNUSTEVIRHEET: VERTAILU YHDYSVALTOJEN JA EUROALUEEN MARKKINOISTA

TUTKIELMAN TAVOITTEET

Tutkimuksen tavoitteena on selvittää, miten analyytikkojen ennusteiden systemaattiset virheet ovat kehittyneet erilaisissa sääntely-ympäristöissä. Tavoitteena on valottaa, onko analyytikkojen tulos ja liikevaihto ennusteissa systemaattista virhettä sekä sen tahallisuutta. Lisäksi tutkin voidaanko lainsäädännöllä vaikuttaa analyytikkojen ennusteiden tarkkuuteen.

LÄHDEAINEISTO

Lähdeaineistona käytän analyytikkotietokanta I/B/E/S:ia. Euroalueelta olen valinnut kaikki yritykset Frankfurtin ja Pariisin pörsseistä otokseeni. Yhdysvalloista olen valinnut kaikki yritykset Nyse:stä ja Nasdaq:ista otokseeni. Tutkimusperiodi ulottuu vuoden 1994 viimeiseltä neljännekseltä vuoden 2010 ensimmäisen neljänneksen loppuun. Käytän tutkimuksessani vuosineljännes ennusteita sekä ennusteita koko vuodelle.

TULOKSET

Havaitsen, että Yhdysvalloissa rahoitusmarkkinat ovat muuttuneet sääntelyn tuloksena (Regulation Federal Disclosure ja Global Settlement). Ennustevirheiden jakauma on levinnyt, mutta keskimäärin ennustevirheet ovat pienentyneet. Euroalueen markkinoilla ei ole ollut minkäänsuuntaista merkittävää kehitystä tutkimusperiodin aikana. Aikaisemmat ennustevirheet vaikuttavat analyytikkojen ennusteiden tarkkuuteen kuten myös hyvät ja huonot uutiset. Löydän myös viitteitä siitä, että vaikka keskimääräiset ennustevirheet ovat pienentyneet, jotkin analyytikot "ostavat" lisätietoja liikkeenjohdolta liian positiivisilla ennusteilla.

AVAINSANAT

ennustaminen, rahoitusmarkkinat, tulosennusteet, analyytikot, ennustevirhe, tahallisesti lisätty virhe

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Summary

Analysts' forecasts and errors of those forecasts are widely studied topics in finance. There are several anomalies in forecasting errors for which analysts' forecasts are said to be biased. These biases can be related to behavioral mistakes the analysts make; or business relationship between the firm and the bank making forecasts; or analyst' career concerns or the biases might be intentionally added as a way of getting better quality information from the management. In the U.S. there have been several regulatory changes between 2000 and 2003 which were targeted to reduce incentive to intentionally add bias on forecasts and reveal hidden conflicts of interests. During same time there have not been anything similar happening in the Eurozone markets which could affect competitiveness of the Eurozone markets.

In this study I will study forecasting errors before and after the regulatory changes in the U.S. and in the Eurozone. My study reveals that forecasts in the U.S. markets have become increasingly accurate after regulatory changes. In earlier literature there have been studies about an effectiveness of the regulation changes and those new regulations have been found to improve information content of the markets. I will compare this improvement to the reality in the market without regulatory changes and study whether intentionally added biases have diminished.

I find out that the forecasts are less accurate in the Eurozone than in the U.S. markets. In the U.S. markets forecasting errors gradually get smaller and smaller when one gets closer to the release date of the financials. This kind of development cannot be seen in the Eurozone markets. After regulation changes there is significant increase in earnings forecasting errors in the U.S. markets. Same time variability of the earnings forecasting bias has increased. This is conflicting with some of the existing research but there are also supporting studies available. More importantly the difference between sales and earnings forecasts has gotten smaller. This implies that there is less intentionally added bias in order to please the management as my research hypothesis states. Altogether, the results hint that some analysts might add intentionally higher bias to their estimates in order to attain better quality information. The base bias has decreased. However, increase in coefficient for analysts' uncertainty shows that some analysts are still trading their unbiased forecasts for information. There are also some hints that even though average forecasting biases have declined, some of the analysts buy additional information from the management with favorable forecasts.

1. Introduction

1.1 Academic motivation

Financial markets and individuals working on them have been under scope of finance. Earlier markets were thought to be nearly perfect which led to efficient market hypothesis. It is taken granted that market value of the equity carries information about future prospects of the firm. In a short, market value of the firm can be divided in two parts: value of assets and potential future value. The value of assets can be easily found from the firm's balance sheet. The potential future value can be calculated as a difference between market value and the asset value. On average this valuation should be unbiased. Same way analysts' forecasts carry information. There will be uncertainty about this future value as long as we don't have magical crystal ball to forecast the future. The firms with large growth opportunities are usually called "growth" firms against more stable so called "value" firms. There is an information asymmetry between investors and the management of the firm. Here analysts can work as information intermediates that reduce this asymmetry. However, it is widely studied fact that analysts' forecasts are rarely unbiased. This paper will study analysts' forecasting bias between two different regulation environments and with two different variables which have different degree of incentive to add positive bias.

Earlier research has handled forecasting bias thoroughly and also opened our eyes for behavioral mistakes which might affect analysts' forecasting accuracy. Financial markets are now larger and there are more people following them than ever before. It would be easy to think that valuations would become more and more accurate with more people analyzing the markets. It would be interesting to know does this result a more efficient market. Unfortunately, as usually markets also give rise for different forms of conflicts of interest. Investors' major concern is to try to understand future and probabilities it holds. In this research I will try to find out how accurate analysts' future estimations are and have recent changes in the regulatory environment at the U.S. markets reduced conflicts of interest. I will concentrate to study information asymmetry between analysts and the firm management.

Analysts' ability to forecast accurately has been debated topic in academic literature. There are several studies find that analysts' forecasts are biased in the way that can be interpret from publicly available data. Explanations for this bias have been numerous. In this paper I'm planning to test forecasting bias evolution between the Eurozone and the U.S. markets and the

effectiveness of the regulatory changes. I will limit my study to sales and earnings forecasts on publicly traded companies in the markets in question.

1.2 Contribution to the literature

This paper will study analysts' forecasting biases on earnings and sales in two highly developed financial markets with different regulation environment (i.e. the U.S. markets and the Eurozone). I will study whether there are differences how forecasting biases have developed over time in these markets. In the U.S. markets there have been several regulation changes which have been targeted to even the playing ground and one of the scopes was to affect analysts' ability to get exclusive information. I will study forecasting biases for sales and earnings forecasts separately because it is possible that analysts' intentionally add bias to earnings forecasts more than sales forecasts. Therefore, sales and earnings forecasting biases might react differently to changes in regulation environment.

Earlier studies have found out that analysts' earnings forecasts are mostly upward biased. However, studies are controversial regarding how intentional this earnings forecasting bias is. Probably the truth is both. Partly the bias is intentional and partly unintentional (e.g. cognitive bias). I will follow the intentionally added bias strain of research presented by Lim (2001) and Mest and Plummer (2003) who suggests that analysts' positive bias is rational and intentionally added to forecasts in order to get better quality information from management. The idea is that analysts try to please the management to build their relation and gain access for better quality information. Therefore, analysts add positive bias on financial estimates which matter the most for the management. This would translate to larger bias on financial measure such as earnings compared to sales forecasts.

After implementation of the Regulation Fair Disclosure at the U.S. there have been controversial studies about its effectiveness. Some studies show that earnings forecasting biases have been reduced (e.g. de Jong and Apilado (2009)) and same time other studies argue that the biases have not changed at all. I will take account these regulation changes in my research and compare the U.S. markets before and after implementation of the regulations to the Eurozone markets. This way it will be possible to distinguish the true effect of regulation changes when development of the Eurozone markets is used as a reference point.

Earlier studies have examined analysts' forecasting bias thoroughly and yielded valuable information which has helped to reduce conflicts of the interest on financial markets. In the United States major regulation changes happened at the beginning of 21th century. Those changes aimed to reduce unequal treatment of investors and restrict major financial firms' ability to benefit from their information advantage. Those changes have been studied to some degree. My research will continue this strain from the literature and expand it by studying differences between two different regulation environments (i.e. the U.S. and the Eurozone) and by studying how forecasting biases evolve over time. I will study how regulation changes have affected the information asymmetry and the conflicts of interest. My study also contains much larger dataset than any of the earlier studies. I will also contribute to the literature by studying different levels of forecasting bias between the U.S. and the Eurozone markets. There have been arguments that compared to the U.S. the Eurozone markets are less efficient. This will in turn affect competitiveness of European financial markets and in the end, cost of the capital in the Eurozone equity markets.

1.3 Research problem

This study will try to answer several questions considering forecasting bias. I approach the problem from intentionally added bias viewpoint [i.e. Lim (2001), Mest and Plummer (2003), de Jong and Apilado (2009)]. I will start by researching whether analysts truly make bias on average. Many researchers have already found out that analysts do make on average over-optimistic forecasts. After judging the situation with biasness of the forecasts, I will continue to reveal more information of the phenomenon and study it in different markets and time periods.

I will try also find out have analysts intentionally added biases in their forecasts to please firm managers. There are two methods from literature which try to capture analysts' intentional biases. First, Mest and Plummer (2003) argued that analysts add larger bias for financial measures which are more important for management (e.g. earnings versus sales). Second, de Jong and Apilado (2009) argue that Regulation Fair Disclosure (Reg FD) has diminished analysts' need to please managers. They study biases before and after Reg FD. I will study those intentionally added biases with both frameworks and compare them. Because I don't believe that forecasting biases disappear in one night I will also study how those biases evolve over time and with evidences obtained from the United States and the Eurozone.

The final research problem in my study is to compare different regulation environments, namely the U.S. and the Eurozone. It has been argued that the Eurozone is less competitive in financial markets and the less effective regulation could be one of the reasons. The less effective regulation makes it harder for analysts to produce accurate estimates without inside information from management. Therefore, they would have greater incentive to upward bias their estimates. This in turn increases cost of capital for European firms. My regression model takes account several well-known anomalies which could potentially cause forecasting bias (e.g. estimate revision based on prior error, news effect, information availability and firm specific difficulty of forecasting). This is done in order to prevent different magnitude of biases just because markets' structure is different.

1.4 Scope and limitations of the study

Availability of good quality data is major limitation of my study. To get up-to-date company information for research the events should be manually picked from some news service. It would too much work to pick up all preliminary earnings/sales figures. For this I do not have sufficient resources. Therefore, I cannot get data between financial reporting periods. From analyst databases such as I/B/E/S it is possible to get analysts' estimates from different points of time but unfortunately firms own earnings guidance publications are not recorded in similar manner.

I/B/E/S reports in its basic set only consensus estimates. It will not be possible to examine individual analysts' forecasts. I/B/E/S is regarded as high quality source of earnings forecast data. Unfortunately it still has some holes in its data. Firms from the United States have exhaustive data available whereas the Eurozone data contains only major firms and even for them time series are short. I/B/E/S database contains wide coverage of earnings forecast data. It is major player in earnings forecasting industry and its data is considered to be high quality. For my research it provides sufficient number of observations from large sample of firms. However, I/B/E/S database has started to report sales forecasts much later and there are lots of companies with only earnings forecasts without sales estimates. This limits my sample of sales forecasts which might potentially reduce reliability and accuracy of the results of the study. This actually becomes problem only with the European companies. This is taken into the account when the results are discussed.

Most of the analysts revise their estimates towards end of the financial period. These revisions make forecasts more and more accurate. It could be possible that sufficiently close publication of the financial report analysts' forecast get closer and closer of being unbiased. Usually firms publish their own estimates and preliminary figures which guide analysts in making their estimates and at natural way reduce forecasting errors. However, I am interested in how analysts behave based on their prior forecasting bias and therefore forecast errors are observed just after prior release of actual figures. This prior forecasting error affects current period's forecasting accuracy. For quarterly and annual releases, I record my data with monthly intervals.

Because regulation changes have affected firms working in the United States, I will naturally pick up all companies from NYSE and Nasdaq to my sample. Earlier studies have mainly used the U.S. data and therefore my study can be compared to their findings. However, I'm also including companies outside the U.S. in order to compare magnitude of forecasting bias between different regulation environments (i.e. the Eurozone). Unfortunately, the data outside the U.S. in I/B/E/S database is limited and contains mainly the largest global firms. Therefore, foreign dataset might have less observations and quality of the data might be questionable.

1.5 Structure of the study

The Section 1 will serve as an introduction and motivation to my research. In the Section 2 I will shortly discuss previous literature available. Section 2 is divided to general discussion about forecasting on financial markets and to discussion about analysts' forecasting bias. Section 2 will also make a glance on changes in regulation environment and its possible implications on analysts' forecasts. After that I will gather evidences how analysts could deliver value to investors with their estimates and finally I will try to find evidences if analysts' forecasts and their biases matter on financial markets. The Section 3 contains my research questions and hypothesis which are used as guideline in my study. The Section 4 will contain description of my research framework, employed data and methodology. The Section 5 contains empirical results and analysis of the study. The final part, Section 6 concludes and summarizes my findings.

2. Literature review

2.1 About forecasting

Everybody tries to forecast future but not many of us do it for living. However, in financial markets there is a group of people who make their living by revealing shades of the future and that group is called equity analysts. As an example, with CAPM model it is possible to calculate expected rate of return for certain asset. CAPM model has been derived to Fama&French multifactor model [French (2003)] to better explain actual realized returns. In addition to CAPM based expected return model there are numerous other models. Time series do this poorly, for example Brown and Rozeff (1978) show that analyst forecasts are superior to time series models. Next, I will try to study how analysts' forecasts are born and what kind of errors they may contain.

Before going any further I will define what is meant by forecasting error and bias. Many forecasts are shown to contain positive or negative bias. Usually error is defined as following

$$FE_{i,t} = FC_{i,t} - AC_{i,t} \tag{1}$$

where $FE_{i,t}$ is forecast error for period t and firm i; $FC_{i,t}$ is forecast value for period t; and $AC_{i,t}$ is actual value of the financial measure for the period t. There are almost always forecasting errors occurring in variety of degrees. The forecasting error's distribution has non-zero standard deviation. If forecasts are biased on average, this is called as forecasting bias. Individual analysts make forecasting errors. When this happens on collective level it is called a forecasting bias. Biases can be found from numerous fields of finance and quite often those biases are positive as for example Fleming (1998) shows in his research that implied volatility from index options is upward biased estimator for realized volatility. Still those biased estimators carry some information and make market more efficient. Thus analysts' forecasts are known to be biased and I will next shortly summarize research done so far. Regardless of their biasedness analyst forecasts carry information and can beat time series methods. Almost 30 years later Laws and Thompson (2004) offered evidence about predictive power of the financial futures. They found out that forecasts based on future prices are superior to random walk and stochastic models. However, the results are not consistent for all futures and durations. In most of the cases futures give superior forecast to stochastic models. Still in the end, they conclude that interest and exchange rate markets are approximately efficient and

forecasts cannot be used to gain abnormal returns. However, they didn't study how forecasts based on futures perform against analyst forecasts. Later, I will return to this topic when I discuss whether analysts can deliver value for investors.

2.2 Analyst forecast bias

It is a widely accepted fact based on empirical research that analysts' forecasts of earnings have on average positive bias [Abarbanell (1991) and Stickel (1990)]. There are numerous different explanations for forecasting bias: (i) internal pressure on analysts to increase firm brokerage commissions, investment banking business and proprietary trading profits [Kirgman et.al. (2002)]; (ii) analysts unintentional cognitive bias [Kahneman and Tversky (1982, De Bondt and Thaler (1990) and Kahneman and Lovallo (1993)]; (iii) analysts' career incentives and herding [Hong and Kubik (2003)]; (iv) inability to efficiently use information [Abarbanell and Bernard (1992), Ali et.al. (1992) and Easterwood and Nutt (1999)]; (v) pressure from the management of the companies covered by analysts [Lim (2001) and Mest and Plummer (2003) among others]. Especially, Studies of Mest and Plummer (2003) and Lim (2001) are interesting concerning my study. They argue that positive bias on forecasts is rational and done with a purpose. Before going to different explanations of the positive bias let us think a moment in what kind of environment the analysts do their research and forecasts.

Earlier I already showed how forecasting errors and biases differ from each other. Now I will introduce a measure for accuracy of the forecasts. Mean squared error is a widely used measure for the accuracy. The forecast error can be divided to squared bias and variance of forecasting errors

$$MSE = bias^2 + Var \tag{2}$$

where MSE is mean squared error of the forecast; $bias^2$ is squared bias and the last term, Var, is variance of the forecast error. Therefore it could be possible to reduce mean squared error of the forecast by doing trade-off between unbiased estimates for reduced variance [Lim (2001)]. A livelihood of an analyst is dependent on accuracy of his forecasts. A good analyst is expected to provide accurate estimates for firm's earnings. However, accuracy and positive career development do not necessary go hand in hand as Hong and Kubik (2003) show. The optimal forecasts for career development are slightly overoptimistic.

Next, let us study other theories for overoptimistic forecasts. This forecasting bias appears irrational and it can be predicted from publicly available information [Lim (2001)]. For this reason, I will preview several explanations for this apparent positive bias. One possible explanation would be investment banking relationship with a firm and attempt to get more business to analyst's own bank. Michaely and Womack (1999) studied this relationship between forecast firm and the bank employing the analyst which could be source of conflict of interest. Underwriting investment bank prefers more positive earnings forecasts because it makes book building process easier and reduces risk of being underwriter. However, this kind of relationship can be only measurable near initial public offerings (IPO), seasonal equity offerings (SEO) or such kind of events.

Other explanation would be that young analysts whose career has just begun, will bias their estimates closer to consensus in order to prevent extreme mistakes which might result punishment. Laster, Bennet and Geoum (1996) and Scharfstein and Stein (1990) observed this kind of behavior that younger analysts may give forecast which are closer to consensus because of career concerns. For young analyst it may be risky to publish forecasts which are far from consensus and fail to capture reality. The idea is that small biases from consensus can be forgiven as well as a bit too optimistic forecasts. This would result forecasts to be too positive on average.

One line of research tries to explain the bias in terms of analysts' ability to process information. De Bondt and Thaler (1990) argue that analysts are likely to overreact to new information and create forecasts which are too extreme. This is especially true with positive information. With negative information relation is completely opposite. Negative information is not completely transferred to forecast and the forecast becomes too positive. Easterwood and Nutt (1999) found the same kind of relation based on their research that analysts underreacted to negative information and overreact to positive information. After negative information analysts tend to revise their forecasts too little and with positive information forecasts are revised too much. This would explain momentum effect of analysts' forecasts and positive bias on average.

Kini et.al. (2009) show how analysts' research portfolio could affect forecasting accuracy and bias. The research portfolios which consists country diversification have higher forecast accuracy. It seems that the relation between diversification style (country vs. sector) and forecast accuracy is context-specific. Internationally sector diversification increases accuracy

but inside U.S. it reduces accuracy. It could be that national markets (the U.S. markets) differ from international markets less than industries from each other. McNichols and O'Brien (1997) take a little different perspective to analysts' research portfolios and argue that positive bias may arise because analysts tend to choose companies for their portfolio based on their true opinion of those companies. Analysts tend to choose companies they like and have positive opinion. They also might censor their forecasts if their expectations are sufficiently low compared to their own earlier opinion. They will censor the lower tail of the distribution of forecasts. Also analysts are slow to change their forecasts when new adverse information comes up which creates upward bias.

Based on above research, overoptimism or positive bias seems mostly irrational (expect career concerns hypothesis). However, Lim (2001) attacks against this belief and argues that optimal forecasts from perspective of the analyst are optimistically biased. This is explained by the fact that managers prefer favorable forecasts and they are also the main source of non-public information for analysts. In order to reduce variability of forecasts and to attain information from managers, analysts should give forecasts that are positively biased. The analysts search acceptance of the management to be granted inside information which could potentially reduce their forecasting bias (see equation 2 for two sources of the forecasting error). In other words analysts seek to reduce their variance of estimation error and trade-off is intentionally added positive bias. This could increase their forecast accuracy if measured with mean squared error (MSE). Even after tightening of the regulation, managers are shown to favor analysts who give them favorable forecasts [Mayew (2008)].

Mest and Plummer (2003) continue above research of Lim (2001) about rational bias and find that positive bias is smaller for financial measures which are less important for managers. They propose that analysts have smaller incentive to upward bias their estimates for sales than for earnings forecasts because management has more interest on earnings forecasts. The reasoning is that management's compensation is more often linked to earnings based variables than sales based variables. Later on, de Jong and Apilado (2009) argue that greater reduction of earnings forecasting bias after implementation of Regulation Fair Disclosure (Reg FD) supports the theory of purposely added bias for enhanced information access.

There has already been earlier evidence on information access effect which links fine with findings of Lim (2001) and Mest and Plummer (2003). Mikhail et.al. (1997) showed that experience and firm-specific knowledge improve accuracy of the forecasts. However, there is

also evidence from Chen and Jiang (2006) that analysts tend to over-weight their firm-specific information and unintentionally create biased estimates because information is not effectively utilized.

2.3 Regulation and political changes

Recently, there have been several significant changes in regulation environment in the U.S. which have not yet been widely studied [see SEC (2000) and SEC (2003a)]. I will next shortly summarize the most important legal and regulation changes which are likely to have impact on analysts' production of forecasts. Earlier in the United States it has been possible for companies to grant conference calls for selected audience like analysts and institutional investors. This changed in October 2000 with Regulation Fair Disclosure (Reg FD) which effectively means that current investors and potential investors should be able to get information equally. Whenever any information is released from the firm it should available to everyone and not just selected analysts. This could potentially affect on the need for analysts to please management in order to get better quality information. However, Mayew (2008) shows that even after implementing Reg FD instead of granting information selectively to analysts the management favors analysts giving good forecasts, during conference calls by giving them more chances to ask questions.

Moreover, in 2003 there were two important changes in regulation environment in the U.S., i.e. the Regulation Analyst Certification [see SEC (2003b)] and the Global Settlement [see SEC (2003a)]. The purpose of the Regulation Analyst Certification is meant to reveal hidden conflicts of interest. Analysts are required to report their potential conflicts of interest and related monetary compensations. I assume that this could potentially reduce intentionally added bias on analysts' forecasts. The Global Settlement was an agreement between SEC, NYSE, Nasdaq and ten of the U.S. largest investment firms. The purpose was to reduce investment bankers' pressure on analysts to provide favorable forecasts for the management and to sanction for past misbehavior.

All those above regulation changes were implemented in order to reduce incentive to please management of the firms and to reveal hidden conflicts of interests. This should reduce positive bias of forecasts which is partly based on analysts' attempt to search managements favor. This effectively means that forecast biases should be different for period before 2000 from forecast biases after 2003. That is, there should be a difference in forecast errors if it is

assumed that firms have earlier used their information asymmetry for their own advantage and entered in malicious practices.

There have been several studies which try to estimate Reg FD's effect on financial markets [e.g. Gintschel and Markov (2004), Jackson and Madura (2007) and de Jong and Apilado (2009)]. Gintschel and Markov (2004) present early evidences that absolute price impact of analyst announcement is 28% lower than prior Reg FD. This price impact reduction has been even greater for growth firms which can be interpret as evidence that analysts have consciously added bias on their estimates. De Jong and Apilado (2009) show that earnings forecasts are still biased, but bias is less than before Reg FD. Their study difference between growth and value stocks and find out that reduction in bias is larger for growth stocks. They argue in lines of Lim (2001) that analysts have added bias in their estimates intentionally to build relationship with firm's management. After Reg FD those incentives are cut off and the results suggest that analysts did not misinterpret news signals from firm but consciously maintained good relationship with growth firm managers. The analysts consciously try to offset negative earnings surprises mainly for growth stocks and therefore to generate forecasts which are overoptimistic on average.

Barber et.al. (2001) show that analysts act as information intermediates between firm and markets. They process and deliver their insider information through earnings forecasts and buy/sell recommendations. Jackson and Madura (2007) argue that the amount of the insider information leaks has decreased significantly after implementation of Reg. FD. They argue that analyst announcements contain less information which is not already available in the market. This reduces price impact of the analyst announcements. Gintschel and Markov (2004) showed that Reg FD has reduced the difference (measured with price impact) between large brokerage houses and other brokerage houses and therefore leveled playing ground for new players. This can be interpreted so that investors believed that earlier different brokerage houses had different access to information about an analyzed firm.

Bagella et.al. (2007) study differences of analyst forecasting errors between U.S. and European markets. They show that forecasting errors are consistently higher for the Eurozone. However, forecasting biases have been getting smaller and smaller at the 90s. In both markets biases tend to converge when approaching the release date. They argue that the quality of information is lower in the Eurozone and this justifies higher forecasting bias. This could potentially increase the possibility for insider trading and reduce access of small shareholders

to financial markets. This could be one reason for weak international competitiveness of the Eurozone financial markets in attracting foreign capital and reduced access to cheap external financial sources for listed companies.

2.4 Added value of analyst forecasts

Analysts' forecasts can add value for investors. There are numerous cross-section studies in which analysts' forecasts are used to explain stock returns and studies in which possibility to generate abnormal returns with analysts' forecasts and recommendations is examined. Barber et.al. (2001) find out that acting based on stock recommendations can generate abnormal returns of four percent annually. However, in order to capture those profits daily portfolio rebalancing and quickly response to recommendation changes is required. With less frequent rebalancing abnormal returns diminish. It cannot be said that after transaction costs it would be possible to gain positive abnormal returns by following analysts' recommendations. In this aspect semi-strong form of market efficiency holds. For least favorable recommendations market price adjustment takes more time which creates asymmetry on market price reaction between favorable and less favorable forecasts.

Womack (1996) show in his research that a recommendation change causes initial stock price reaction. The reaction does not end there but there will also be momentum effect which differs for positive and negative recommendation changes. The momentum effect is longer (up to six months) and greater in order of magnitude for sell recommendations. Womack (1996) argues that scholars spend great time in analyzing analysts' earnings forecast even thought producing earnings forecast is secondary job for analysts. The main priority is always making timely buy/sell recommendations which require stock picking and timing skills. Analysts issue "buy" recommendations seven times more than "sell" recommendations. This shows that there is a "cost" for issuing a "sell" recommendation which is larger than for "buy" recommendation. Womack (1996) also finds that this effect is much stronger for small companies.

Porta (1996) shows that analysts' earnings estimates are too extreme. When stocks are sorted by expected growth rate, portfolios with low expected growth rate overperform those with higher expected growth rate. The event study grants evidence that market was initially overly pessimistic about the earnings of low expected earnings portfolio and over-optimistic about the earnings of high expected earnings portfolio. Low expected growth stocks have lower

volatility and betas than ones with higher expected growth. Furthermore, they perform significantly better during bear market. However, the returns of betting against analyst are about same magnitude than analysts' forecasting error.

Jegadeesh et.al. (2004) show that sell-side analysts generally recommend "glamour" stocks. They argue that analysts add value only when the stock has favorable quantitative characteristics, namely value stocks and momentum stocks. Analysts prefer growth and momentum stocks. On the other hand, analysts dislike firms with low trading volume, high earnings-per-price ratio, low capital expenditures, low long-term growth opportunities and low sales growth measures.

Hong et.al. (2000) have revealed several phenomena regarding analysts' forecasting bias: the firm size affects strength of momentum strategies; momentum strategies work better for stocks with low analyst coverage; and the effect of analyst coverage is larger for stocks which are past losers than past winners. They argue that their findings show that the firm-specific information diffuses slowly to investors. This is especially true for negative information. Analysts should be able to value firms objectively; still they fail to revise their earlier estimates based on new information.

In short, it seems clear that analysts' recommendations do have stock market effect even though it might be short lived. With momentum stocks analysts' forecasts could produce the most value for investors. Still sometimes it could be even reasonable to bet against analysts, but in that case potential investor should remember that forecasting errors have larger than zero variance and some risk exists. Some "glamour" stocks are much more closely followed than their peers. Those stocks will have larger analyst coverage and it should therefore reduce forecasting errors of the consensus forecast (ceteris paribus). However, those same stocks have characteristics that are liked by analysts which makes their forecasts overoptimistic.

2.5 Do forecasts really matter?

Now it has been noted that analysts' forecasts are accurate (measured with standard deviation of the forecasting error) but they are also biased. It has been discussed whether those forecasts are important for financial markets. However, Copeland (2002) argues that theories and teachings in academia matter little if at all for reality of the firms. Earnings, EPS growth, economic value added and their growth rates are uncorrelated with total return to shareholders.

He argues that actually the difference between expected and actual performance is significantly related to the total return to shareholders. Expectations' management is a tool for providing value to shareholders. He argues that the expectations of analysts and investors should be managed to be more in line with existing reality inside the firm. Copeland (2002) also clearly states that the management should manage expectations of the market and this can be done by announcements from the firm or affecting forecasts of the analysts. In other words, the management should have close relationship with analysts. This is usually seen as a relationship full of conflicts of interest. Formerly mentioned regulation changes have affected this relationship and guide its actions towards direct management of investors' expectations.

2.6 Literature summarized

There are lots of researches who try to explain this upward bias or overoptimism. Explanations range from behavioral biases to intentionally added bias and from career concerns to analysts picking stocks they like. Prior literature is consistent with the fact that analysts' forecasts are upward biased and this bias can be seen with publicly available information. The literature also is consistent that analysts' forecasts are superior to time-series and forecasts of the common people.

The very recent literature from Lim (2000) and Mest and Plummer (2003) have tried to explain the forecast bias as an intentionally added bias which makes it possible to get more accurate information from management. Recent study by de Jong and Apilado (2009) supports the theory of intentionally added bias. However, recently regulation has changed to direction which penalizes and forbids giving information to analysts selectively. At the same time, there has been a pressure in banking sector to make conflicts of interest more visible and reduce pressure on equity analysts. These topics are likely to affect analysts' forecasting behavior based on earlier research. However, it is still questionable do analysts' forecasts really matter in equity markets. There are lots of researches whether analysts' forecasts can earn abnormal returns after risk adjustment and the results are not uniform.

3. Research question and hypotheses

In short, my research tests the theory developed by Lim (2001) and Mest and Plummer (2003). They argue that analysts add bias to their forecasts in order to attain favor of the management and to get access to better quality information. This will improve analysts' forecasting accuracy by reducing forecasting error's standard deviation. The data they have used is prior year 2000 and after that there have been several changes in regulation environment which are likely to have an effect on analysts' need to add bias to their forecasts intentionally. After 2000 there should be less pressure for analysts to please management (e.g. Reg Analyst Certification and Global Settlement) and the management should have less possibilities to legally grant information selectively (e.g. Reg Fair Disclosure). The effectiveness of those regulatory changes has been studied for example by Heflin et.al. (2003) and Jackson and Madura (2007). Both of those studies argue that informational efficiency of the stock markets have improved. From earlier studies I draw several hypotheses for my study.

H1: The forecast bias will be greater for a variable which is more important for management (i.e. earnings). Earnings forecasts are keenly followed and they are likely to affect management's compensation. The bias should therefore be greater for earnings than sales forecasts.

Earnings forecasts are widely followed by market and they could affect expectations of the investors and therefore pricing of the asset. Management's compensation is more often linked to earnings or stock based measures than sales. Thus development of earnings is more important for a manager who maximizes his utility. For sales forecasts former relationship should be less solid. This was shown by Mest and Plummer (2003).

H2: Forecast bias will be greater for firms with higher level of information uncertainty. The size and variability of earnings (sales) forecasts are proxy for uncertainty and are related to difficulty of making accurate forecasts.

Information uncertainty affects forecast bias in two ways. First of all, it is easier to make more accurate forecasts in good information environment. However, if analysts are not in equal position and some analysts get additional information from management and in same time choose to add positive bias on their estimates, this results situation where analysts trade-off their unbiased estimates for enhance their information environment by adding intentionally

positive bias in their estimates. Standard deviation of the analysts' estimates should be good measure for information environment because it tells us how evenly different analysts are informed. I am assuming that with equal access to information the analysts' estimates should be closer to each other. In addition to standard deviation of the estimates, the size of the firm describes how much information is publicly available regardless of management's intentions and it therefore should represent overall information environment. It is easier to get more information from large companies than from small companies and thus there is less need for analysts to please management for information when information environment is already good. Therefore, my hypothesis is that size has negative effect on forecasting bias. This was also finding of Lim (2001). The standard deviation of the forecasts will have with same logic positive relation to forecasting bias.

H3: After changes in regulation environment, forecast bias should become smaller for financial measures which are more important for management. There will no longer be reason to add bias for earnings forecasts over sales forecasts thus reduction in forecasting bias should be greater for financial measure more important to the management.

After regulation changes earnings and sales forecasts should be in equal position. If the results still differ after regulation changes, it could mean that firms and analysts are still doing forbidden cooperation - or it is just harder to forecast earnings than sales [Kim and Prather-Kinsey (2010)]. Also, it could be rational for analysts to overreact good news when facing high earnings uncertainty [Gu and Xue (2007)]. Early studies from Heflin et.al. (2003) showed that at least price impact of the forecasts has been reduced after Reg FD.

H4: Analysts react differently to positive and negative information.

For example, Womack (1996) argued that analysts react slowly to new information and the momentum effect can be visible for a long time. Barber et.al. (2001) and Hong et.al. (2000) also argued for analysts' inefficient usage of information which creates the momentum effect. I will try to explain consensus forecasts' bias. I believe that analysts are professionals who know what they are doing and they make forecasts and their judgment errors are not related to their skills or experience. Of course, there may be some behavioral biases but still analysts do their forecast with best of their knowledge without descending into rolling a dice. However, I will not deny behavioral mistakes found from earlier research such as linking to Prospect theory [Ding et.al. (2004)]; and management use of framing to future plans after loss [Sedor (2002)].

H5: The Eurozone forecasting biases are larger compared to the U.S. markets due to less effective regulation and less analyst coverage.

The Eurozone has fragmentized regulation environment and less analyst coverage. This results that it is much harder for analysts to produce accurate estimates. Bagella et.al. (2007) compared Eurozone and U.S. markets and found out that earnings forecasting errors were significantly higher at Eurozone markets during their research period of 1990-2001.

Lim (2001) tried to explain forecast bias by variability of actual earnings. However, the method had problem that time-series for earlier earnings were always short and it was difficult to accept an idea that more than few years could explain nature of firm's current state. McNichols and O'Brien (1997) report that analysts tend to censor their extremely negative forecasts and thus effectively cut the lower part of the earnings distribution away. However, this would not cause changes between my study periods.

4. Data and methodology

4.1 Data

The data is obtained via Thomson ONE Banker interface from several databases. I use I/B/E/S database for analysts' quarterly and annual forecasts. It would have been possible to use First Call analysts' forecast database. However, Ramnath et.al. (2005) argue that I/B/E/S database is superior to other competing databases when measured by quality and amount of the data available. They show that quality of I/B/E/S data has increased since entry of First Call to the earnings forecast industry at early 1990s. In forecast industry after 1993 there are more analyst firms doing forecasts from wide range of firms. Earlier with I/B/E/S there has been reported a problem whether "special items" from the balance sheet are included in forecast and actual numbers [Philbrick and Ricks (1991)]. It seems that earlier the data in I/B/E/S database has been inconsistent in the treatment of special items. The special items are usually write-downs which happen almost solely in the fourth fiscal quarter. This is taken in to account when choosing time range for this research. The data prior 1993 will not be used and with this decision I will be able to obtain good quality data for this study. I will also

discuss this possible inconsistent treatment of "special items" later on when the results are analyzed.

I have obtained forecasts and actual figures at two levels: annually and quarterly. Earlier studies have used both datasets but they have been rarely used in the same study. However, there have been arguments that annual level data is higher quality than quarterly estimates data. These both kinds of data are recorded from the Eurozone and the U.S. markets. As I mentioned earlier, the one part of research question is to compare financial forecasting errors between different regulation environments and for this the U.S. and the Eurozone equity markets give magnificent opportunity. They both have highly developed financial markets and the firms in these markets which can be found from I/B/E/S database, are rather similar. The forecasts for earnings and sales are recorder 9 to 1 month prior to release of the financial measures.

From databases described above I have picked all NYSE and Nasdaq firms to my U.S. datasets. The data from the U.S. markets is high quality and the most of the firms have long time-series of forecasts available. To the Eurozone sample I have picked up all firms Frankfurt, Paris and Berlin stock exchanges. Majority of the forecasts in I/B/E/S database are produced by firms operating mainly in the U.S. markets. Because of this forecasts in Eurozone are available only for the largest companies and often at annual level. I also require my data to have at least two subsequently periods of forecasts (i.e. for annual forecasts this is two years and for quarterly forecasts two quarters) and actual figures available. I discard observations when stock price is below 5 dollars. Because when stock price is entered in divisor, the small values would add unnecessary fluctuation and error to my sample. Putting all above limitations together my sample sizes are much smaller than total available observations with forecasts and actual figures.

Furthermore, I use two different periods of the time-series data. The first period is from 1993 to 2000 and second period is from 2003 to 2010. The reason for this kind of different periods is that between 2000 and 2003 there were several changes in regulation environment which could potentially affect the results. Furthermore, I am interested to study whether the forecasting errors are from similar kind of population. For this reason the middle period is left out of regression analysis. After all, the research hypothesis suggests that possibility to acquire exclusive information about the firm explains level of the forecasting bias. The theory of Lim (2001) and Mest and Plummer (2003) would suggest that there are differences

between before and after regulation changes which affect availability of information. This division to subperiods is done for the dataset containing quarterly and annual data. For annual level data the first sample would be extremely small and regression results would be insignificant or weakly significant at the best case. However, it is possible to inspect mean and median biases for both subperiods even with the annual data.

Lim (2001) used quarterly data whereas Mest and Plummer (2003) used annual data. I will use both levels of the data in my study. With quarterly data it is possible to get 24 research periods of the feasible data from 1994Q4 to 2000Q4. The latter research period contains 28 periods of the quarterly data from 2003Q1 to 2010Q1. The quarters in the middle (9) are discarded from analysis because during that time there occurred changes in regulation environment (mainly in the U.S. markets) and the main interest here is the effects of those changes to forecasting efficiency. Table 1 shows graphically how those research periods are divided.

Table 1. Research period sample

Note: First 24 periods are from 1994Q4 to 2000Q4. This will become the first subsample. The latter subsample contains observations from 2003Q1 to 2010Q1 (28 periods). The observations in the middle are discarded when I am doing analysis with subsamples. Annual forecasts are from 1993 to 2000 and from 2003 to 2010.

Annual periods	Quarterly periods	
1993–2000	1994Q4–2000Q4	Prior regulation changes period
2001–2002	2001Q1–2002Q4	Discarded, because there were regulation changes during this period
2003–2010	2003Q1–2010Q1	After regulation changes period

For example, Mest and Plummer (2003) argued that analysts only purposely add bias to their estimates for financial figures that matter more for the firm management. This means that analysts have more incentive to add additional bias to earnings forecasts than sales forecasts. I will also study this relationship because it is strongly related to effectiveness of the market regulation. At informational inefficient markets analysts have much stronger incentive to add bias to their forecasts in order to attain more non-public information from the firm management. If the markets have developed to become more efficient, then forecasting bias between earnings and sales should decrease. Therefore, I will obtain both earnings forecast

and sales forecast data for my study. I will also approximate informational efficiency of the markets with standard deviation of the analysts' forecasts as a proxy. Table 2 summarizes different kinds of datasets I am using. All in all, I have 8 different datasets which are further divided at latter parts of my study.

Table 2. Summary of the different datasets

Note: The table shows how my eight different samples are constructed. The total number of samples is eight (2*2*2). There are earnings and sales forecast data for annual results and interim results. These sets are available both for the U.S. and the Eurozone markets.

	U.S.		Eurozone	
Annual data	Sales	Earnings	Sales	Earnings
Quarterly data	Sales	Earnings	Sales	Earnings

The rest of accounting items (i.e. earnings, sales, and total number of share outstanding) are obtained from Worldscope database which is the only available database with wide international coverage and exhaustive the U.S. data. For share price data I will also be using Worldscope database. Moreover, the Worldscope and I/B/E/S databases are readily available and the data from them can be easily imported to other statistical software.

Next, I will demonstrate how my sample size evolves and explain limitations which the data puts on my research. Total number of active companies in NYSE is 2,773 and in Nasdaq the number is about 3,800. Only fraction of them has entry in I/B/E/S database. Total number of companies in sample is 3,165. Theoretically, there could be 193,065 observations for interim data. However, from the U.S. markets I start with 43,848 earnings and 24,595 sales interim forecast observations. In the Eurozone markets I start with 3,961 earnings and 2,307 sales interim forecast observations. The difference between starting sample sizes is about ten-fold. With annual forecast observations the difference is much smaller. I start with 14,698 earnings and 10,516 sales forecast observations from the U.S. markets and with 7,762 earnings and 4,935 sales forecast observations from the Eurozone markets.

I will choose only companies with share value higher than 5 dollars to my sample. The share value is used in the divisor and with small values the results would be less accurate. I also exclude extreme forecasting error observations on 2.5% tail areas of the distribution. This is done in order to get rid of outliers and cases where it is unclear whether forecast and actual

values are correctly reported in the database. I also require that forecast error observations have at least one previous forecasting error available. Last, the sample is divided based on "good" and "bad" news (earnings/sales surprises). The observations are arranged based on previous forecasting bias (see equation 3 for calculation). The third of the observations from the highest end of the continuum are labeled to have encountered bad news. The lowest third of the observations from the lower end encountered good news. The middle third has data in which it is unclear whether there has been positive or negative surprise. This news impact is later on used to explain analysts' forecasting error. Figure 1 and Figure 2 show how the sample sizes evolve when restrictions are implemented.

Figure 1. Evolution of the sample, earnings

Note: The figure shows how different earnings samples are reduced to their final states which are later on used in the analysis. The left most pillars present the whole sample. Moving to the right is limitation to the observations with stock price over 5 dollars and next to that 2.5% percent tail-areas are removed from the sample. The news impact is restriction to have only observations which can be considered either good or bad news. Observations where information content is not clear are discarded. The final regression sample set is further reduced because some of the needed data items are missing.
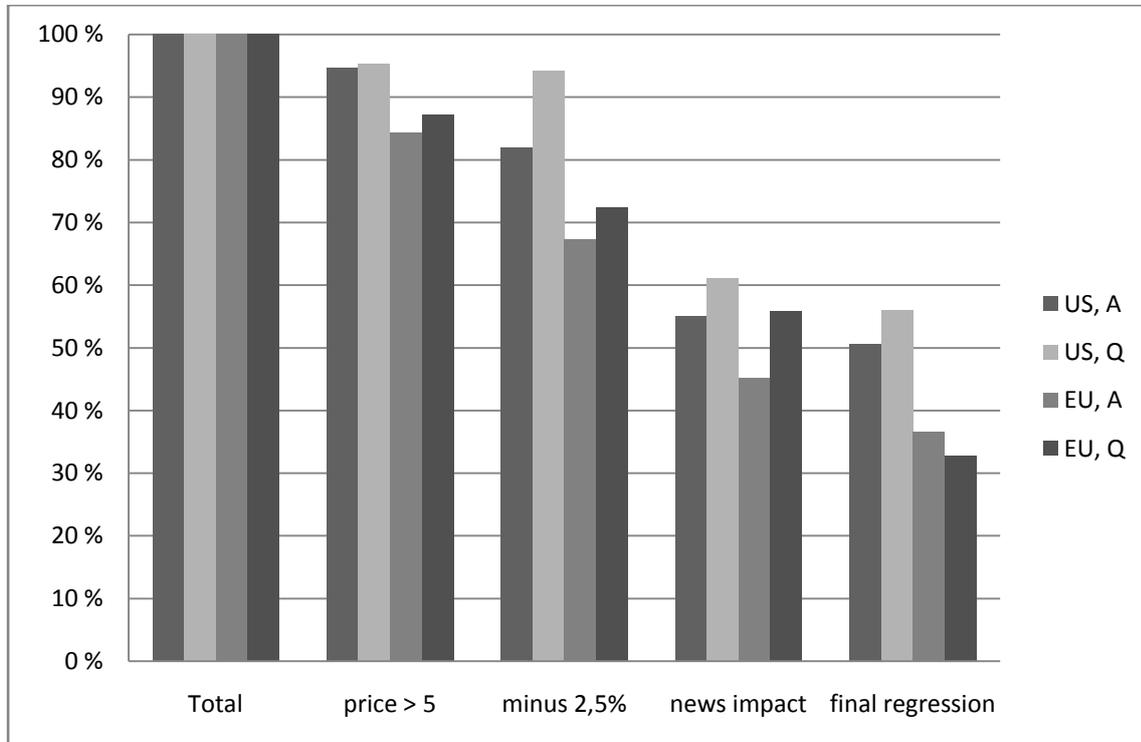
Figure 2. Evolution of the sample, sales

Note: The diagram is similar to Figure 1. The figure shows how different sales samples are reduced to their final states which are later on used in the analysis. The left most pillars present the whole sample. Moving to the right is limitation to the observations with stock price over 5 dollars and next to that 2.5% percent tail-areas are removed from the sample. The news impact is restriction to have only observations which can be considered either good or bad news. Observations where information content is not clear are discarded. The final regression sample set is further reduced because some of the needed data items are missing.
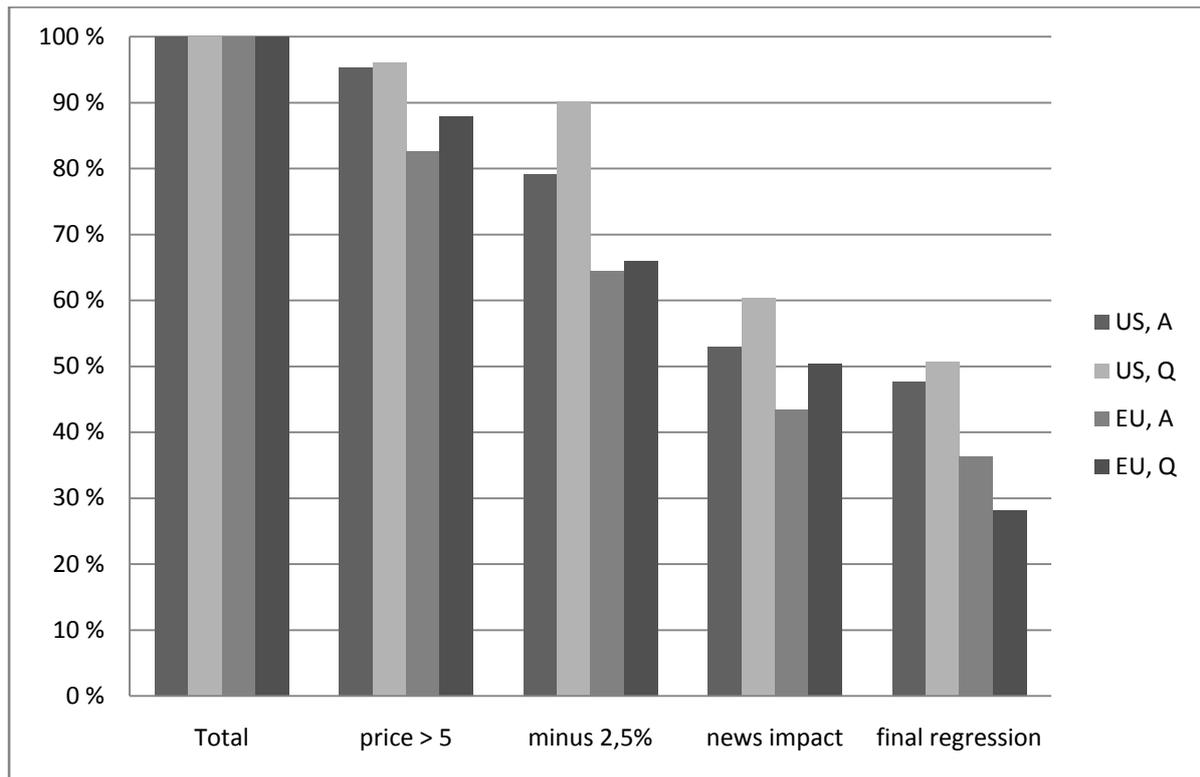

4.2 Regression model and variables

Next, I will explain how different variables are calculated and the reasons for choosing applied calculation method. First and the most important variable will be the forecasting error. The absolute forecasting error is depending on the size of a firm and there is huge variation in size of firms. Without any adjustment the size of the firm could easily affect the obtained results; for large firms $10 million error in forecast can be small but for smaller one it can be an enormous error. Therefore, in order to reduce heteroscedasticity Lim (2001) suggests calculating forecasts and forecasting errors as a percentage of the share price at the beginning of the quarter. I will employ same method and use the closing price at the beginning of the observation month in divisor. Following equation shows how this is done in practice

$$FE\% = \frac{FC_{i,t} - AC_{i,t}}{P_{i,t}} \hspace{4cm} (3)$$

where FE% is forecast error of consensus forecast as percentage of share price; FC is forecasted value; AC_i is actual value of the metric for the period; and P_i is a share price at the beginning of the forecasting quarter. The median forecast is taken as a consensus forecast as have been done in researches of Lim (2001) and Mest and Plummer (2003). Forecasts are generally offered in earnings-per-share format. For sales I have to first calculate sales-per-share ratio.

Second important variable is size of the firm as a proxy for information environment. Size is measured as logarithm of the market capitalization. There are two main reasons for use of market capitalization as a measure for the size instead of assets' value or book value of the equity. First, some industries are more capital intensive than others and balance sheet would not give unbiased estimate for firm's potential to generate profits for its owners. Second, I am using analysts' forecasts for earnings which are calculated after capital costs for debtholders. It would be possible to use total firm value instead of just market value of the equity. However, then capital structure would affect results because I would have one measure before costs on capital and other one after costs on capital. In addition, earlier research by Lim (2001) used analyst coverage as a measure for information environment. However, in this study I don't use analyst coverage as explaining variable because it has high correlation with size and would cause problems in regression. This could potentially cause coefficients for size and analyst coverage to be falsely interpreted as insignificant.

Third regressed variable is variance of prior earnings (sales) forecast. Earlier research done by Lim (2001) and Mest and Plummer (2003) has found out that variance of the earnings (sales) is barely significant and it might be possible to left out of the regression. Still it will be included in regression because most of the earlier researches have used it and theoretically it should affect difficulty of making accurate forecasts.

Figure 3. Contraction of the sample based on nature of the observed news impact

Note: forecasting errors are arranged in ascending order. The highest one third contains the observations in which analysts overestimated the financial results the most and this is interpret as that there are some bad news which were not available in the market. Similar way the lowest one third contains cases in which analysts were surprised by some good news and they underestimated the financial results. Based on this I give my observations two dummy variables *GoodNews* and *BadNews*.
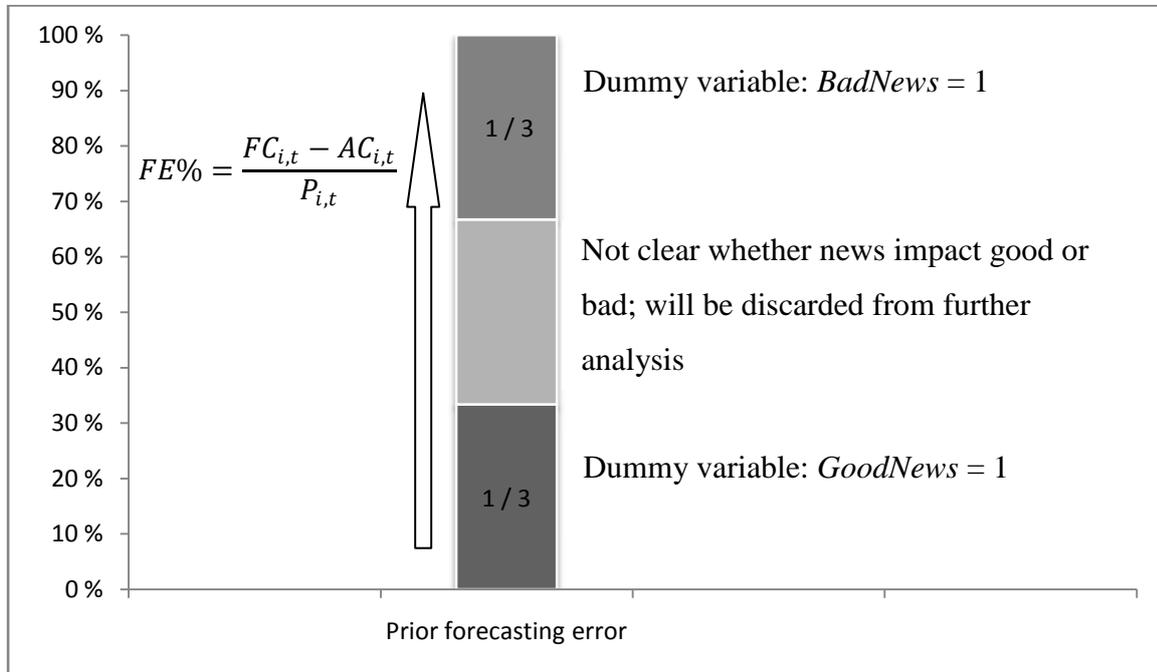
It has been pointed out that analysts respond differently to the most extreme positive and negative prior year forecast biases. For this reason I add dummy variables for clearly positive and negative forecast errors (e.g. earnings surprises or disappointments). The dummy variables are defined in following way. Forecast errors for current year earnings and sales are arranged based on prior year forecast error (see Figure 3). The bottom third (dark grey at bottom in Figure 3) consists the forecast errors of the cases where analysts' forecasts were too low and actual results were more positive than expected. This is considered good news and those observations are given 1 for *GoodNews* dummy variable. The top third (light grey at upmost in Figure 3) consists the forecast errors of the cases where actual results were disappoints compared to analysts' forecast. Those firms will receive 1 for *BadNews* dummy variable. The observations of the middle third (light grey at middle in Figure 3) are ones where prior year forecasts were fairly accurate and they cannot be categorized either to good nor bad news. In those cases analysts do not need to learn from prior errors and therefore those forecasts are not likely to have clear implications for the current forecasts. In order to make analysis more simply and the model easier to handle those observations are left out of

the regression analysis. Only bottom and top third of the observations are used for the regression analysis.

4.3 Model

My model has been developed based on findings of Lim (2001), Mest and Plummer (2003) and Kini et.al. (2009). Lim (2001) suggests that positive bias in analysts' forecasts is actually logical and describes information environment of the firm. For more accurate forecasts the analysts needs access to insider information which is only available from the management. They positively bias their estimates in order to gain better access to those resources. In the optimal situation their forecast accuracy increases even with added bias (see equation 2). However, public information amount differs from company to company. It is easier to get more information from large companies than from smaller ones (see hypothesis H2).

Mest and Plummer (2003) argued that analysts may positively bias their forecast but they add bias only to the values which matter to management. The earnings forecasts are more important to management than sales forecasts. This thinking rises from the idea that earnings forecasts are likely to have an effect on a stock price and thus have an effect on compensation of the management. First, I will study whether biases for sales and earnings forecasts are different. This is done by running two different regressions: one for earnings and other one for sales. The regressions are run separately for both time periods. The results are then tested whether they come from same population or are differences statistically significant.

Figure 4 shows how values are gathered from three different time points for an observation. Let us look how different time points are used in analysis through an example. At 2003Q1 I record forecast for 2003Q2. This forecast is used to measure prior forecast error for regression. At 2003Q2 I calculate analysts' forecast error after actual values are available. Same time I also record forecast for period 2003Q3. At 2003Q4 current forecast error is measured and this value is used in my regression as an explained variable. Other variables such as market capitalization and variance of the prior earnings are measured at 2003Q4 which is the point t in the Figure 4.

Figure 4. Graph of how data is gathered from different periods

Note: The prior forecasting error is needed for regression analysis and therefore there has to be time series data available at least at three time points. Analysts' consensus estimate is observed approximately one month prior release of the financial results. With actual financial measure and the observed consensus estimate it is possible to calculate forecasting error. In my regression model current forecasting error is explained by previous forecasting error and other variables. Two periods of forecasting errors are needed for observation to enter my sample.
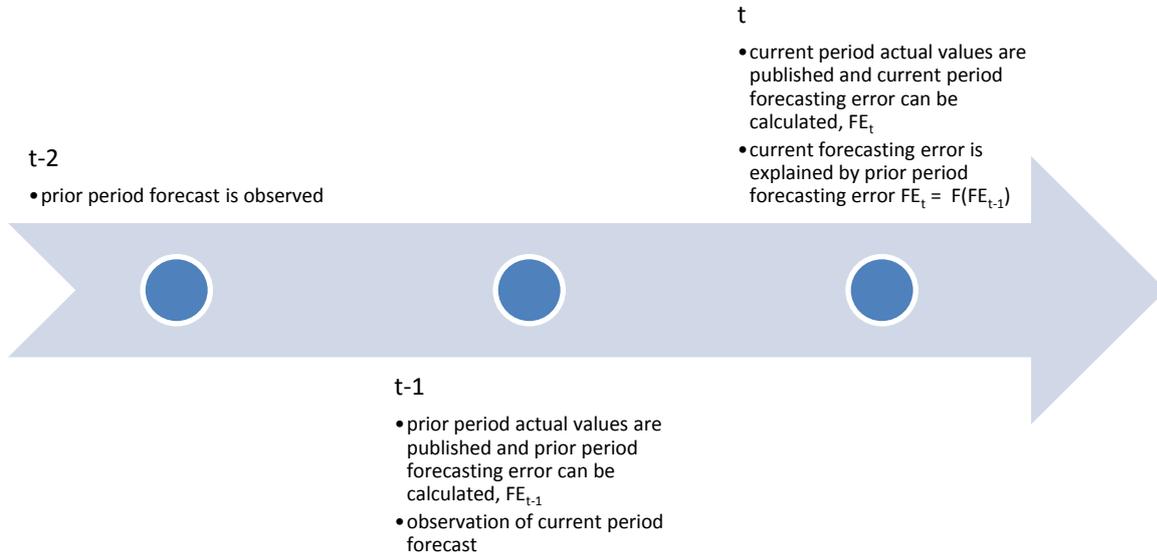
The forecast error is explained by market capitalization, previous forecasting error, and historical variability of sales/earnings forecasts. In empirical analysis I use multivariate regression model similar to the one used by Mest and Plummer (2003). I am using current quarter's forecast error as a dependent variable which is explained by prior quarter forecast error, news impact and variables that are proxy for the firm's informational uncertainty (i.e. market value of equity and variability of earnings/sales forecasts). The Equation 4 describes the model used to regress variables (earnings forecasting error and sales forecasting error). Following model is used separately for sales and earnings forecast errors at both quarter and annual level:

$$FE_{i,t} = \alpha_1 GoodNews_{i,t-1} + \alpha_2 BadNews_{i,t-1} + \alpha_3 GoodNews_{i,t-1} * FE_{i,t-1} +$$
$$\alpha_4 BadNews_{i,t-1} * FE_{i,t-1} + \alpha_5 MVE_{i,t-1} + \alpha_6 VAR_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

where $FE_{i,t}$ is the forecast error of the consensus forecast for the period t; $FE_{i,t-1}$ is forecast error for prior period (t -1); GoodNews$_{i,t-1}$ and BadNews$_{i,t-1}$ are dummy variables for the prior

period forecast surprise defined earlier (positive or negative); $MVE_{i,t-1}$ is the logarithm of the market value of the equity for firm is measured at the forecast date; and $VAR_{i,t}$ is historical variability of the sales or the earnings depending on which regression is in question. The forecast errors are calculated with equation 1.

Usually regression model contains a constant term. However, this model does not have the constant term because every single observation has either *GoodNews* or *BadNews* dummy value of one and thus intercept terms α_1 and α_2 can be considered as constants and they measure basic forecasting bias not related to any other factor in the model. If the intercept terms α_1 and α_2 are different from zero, this is indication that on average analysts' forecasts are biased. The positive value would mean that forecasts are on average too positive whereas negative intercept would mean that forecasts are biases downward.

The intercept α_3 is the $FE_{i,t-1}$ slope coefficient for *GoodNews* and α_4 is the $FE_{i,t-1}$ slope coefficient for *BadNews*. Always when these coefficients (α_3 and α_4) are different from zero the analysts are not fully adjusting their estimates to new information available. If they used information efficiently prior forecasting errors should not be related to current forecasting errors and coefficients would be statistically insignificant. If both coefficients are positive ($\alpha_3 > 0$ and $\alpha_4 > 0$), it would indicate that analysts underreact to forecast errors in the past. After good news analysts are still too negative whereas after bad news they their forecasts are too high. If both coefficients are negative ($\alpha_3 < 0$ and $\alpha_4 < 0$), it would mean that analysts generally overreact and forecast revision is too large. That is, after positive information forecasts are generally too high and after negative information forecasts tend to become too low. The negative value for α_3 and positive value for α_4 would be consistent with existing literature that analysts overreact to positive information and underreact to negative information. Hong et.al. (2000) show that stock price momentum effects are stronger and more persistent for poor performers, indicating that bad news diffuses more slowly than good news to the investing public.

Market value of equity (MVE) and variance of the past earnings/sales (VAR) are trying to capture information environment of the firm. For large firms there is more information available and forecasts should therefore be more accurate than with smaller firms. With larger companies there should be less information asymmetry between analysts. As the variability of the financial measure increases, the uncertainty around firm increases and the forecasting becomes increasingly difficult. I expected that the coefficient for MVE (α_5) will be negative,

which effectively means that there is less information uncertainty with large companies. I expect that the coefficient for VAR (α_6) is positive which is consistent with hypothesis that increased difficulty of making accurate forecasts increases forecasting bias. This can also be interpreted so that analysts will add more positive bias under high uncertainty to buy more information from the management. This will effectively be a test for hypothesis H2.

However, Engle and Granger (1987) show that traditional regression tests are inefficient and can lead to erroneous conclusions if time-series are non-stationary and follow unit root process. De Jong and Apilado (2009) argue that this is usually case with earnings series and therefore cointegration methods should be used. I am not using earnings or sales measures as such but rather I take difference between forecast and actual value. I make conservative assumption that expected value of forecast equal actual realized value. Thus the measure is integrated of order one which usually is enough to cure non-stationary time series problem.

5. Analysis and results

5.1 Descriptive results

As was already noted in previous section my data set consists of systematic forecasting errors which indicate that analysts produce biased estimates. However, it is yet to be finding out which factors affect that those biases and how those biases evolve over time in the U.S. and the Eurozone. I will first go through my findings about analysts' forecasting bias at general level. After that I will study evolution of the forecasting bias over the years and finally I will try to explain some of the reasons behind the forecasting biases with regression analysis. Figure 5 shows how annual average forecasting bias evolves from 1995 to beginning of 2010 in Eurozone. Euronext 100 index is used as approximation of the markets' development. The figure shows that there are clearly period when analysts' forecasts become less reliable and forecasting errors grow sharply. Other observation is that analysts' forecasts tend to become more volatile at times when direction of the market is turning. This seems to be truth in European markets. Figure 6 shows how forecasting bias has evolved from 1995 to 2010 in markets in the United States. My sample is combined from stocks in NYSE and Nasdaq. Therefore the figure contains indices for both of those exchanges. The very same conclusions

can be drawn from the figure: distribution of the forecasting error grows at the turning point of the markets; since year 1995 average forecasting errors have not changed much however their distribution has grown slightly. In both figures it seems that forecasting errors standard deviation grows much more when declining market starts to recover. Bagella et.al. (2007) showed that during stock market boom in 1997-2000 forecasting bias is relatively higher at the U.S. markets compared to the Eurozone. Usually stock market development is correlated with real economic development of the underlying firms. My observations that forecasting errors increase with changes in stock markets, is in line with findings of Chopra (1998). Standard deviation and accuracy of analysts' forecasts is affected by realized growth rates [Chopra (1998)]. Many studies have found out that analysts' forecasting errors are correlated with prior stock returns [e.g. Abarbanell and Bernard (1992) and Chan et.al. (1996)]. This makes analysts' forecasts inefficient and above figures (Figure 5 and Figure 6) show clearly that distribution of forecasting errors widens when stock market returns are suddenly changing. These results are true with forecasts targeting full financial year.

Next, I will study how forecasting biases have evolved for analysts' quarter forecasts. Figure 7 shows quarterly earnings forecasting biases in the U.S. markets over research period. In the U.S. markets forecasting errors make four large spikes which should be removed from Figure 7 in order to get clearer picture of how forecasting errors have truly developed over time. Those spikes are all located at the points when direction of the market has been changing (see Figure 6). Especially the spike at end of the year 2008 made analysts hugely overestimate the earnings of the firms. After excluding those observations from very special occasions we get Figure 8. There it is possible to see that there is a small rise in the level of the forecasting bias at 2000 at that point of time Regulation of Fair Disclosure was implemented. Williams and McGough (2000) argue that Reg. FD reduces information available and would lead to wider distribution of the forecasts and more surprises. From Figure 8 it seems that the forecast was true and analysts' estimates have become more volatile since year 2000. Figure 9 and Figure 10 are similar graphs for forecasting error evolution at the Eurozone markets. First of all it should be noted that there are a lots of more spikes. After removing those spikes as outliers there is not clear development visible. In the U.S. markets there were clear increase in the variability of the earnings forecasting errors and a slight increase in the mean forecasting error but in the Eurozone there has not been any single visible change. In the U.S. and the Eurozone markets level of forecasting errors seems to about similar when observed from the pictures.

From this I will conclude that there has been some kind of change at the beginning of the year in the U.S. markets. Similar kind of change is not visible in the Eurozone markets.

Figure 5. Analysts' forecasting bias in Europe compared to performance of the market index

Note: The figure shows average earnings forecasting biases and 90 percent confidence intervals for forecasting biases assuming that the distribution is normal. The data is from annual forecasting errors for the Eurozone. Euronext100 index is used as approximation of the underlying market's development. This index is only available since 2001. Left-hand side scale is for forecasting errors and right-hand side scale is for index values.
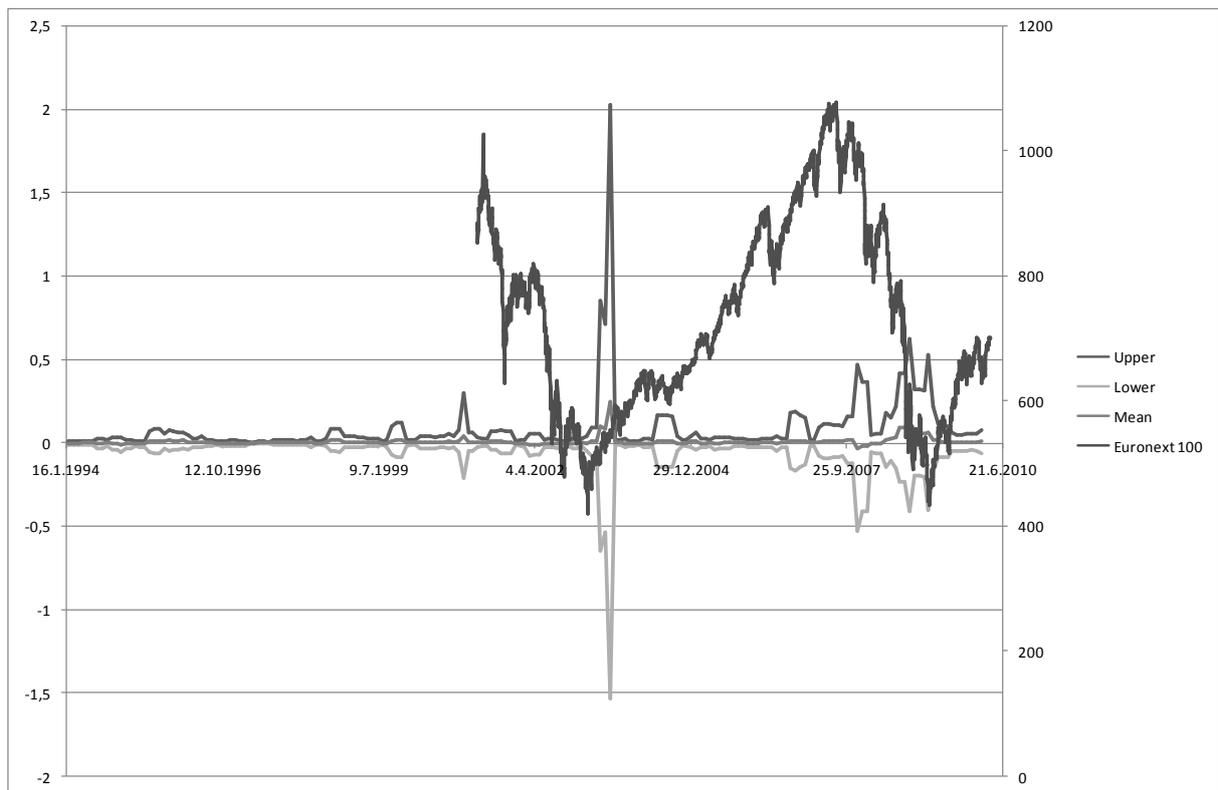
Figure 6. Forecasting bias in the U.S. compared to market indices

Note: The figure shows average earnings forecasting biases and 90 percent confidence intervals for forecasting biases assuming that the distribution is normal. Forecasting errors for firms in Nasdaq and NYSE are pooled together to make graphical presentation simpler. It can also be noted that Nasdaq and NYSE indices follow each other quite tightly and therefore this pooling method does not cause any significant loss of information. Left-hand side scale is for forecasting errors and right-hand side scale is for index values. The indices are standardized to start from value 100. This is done because indices cannot be shown in same scale.
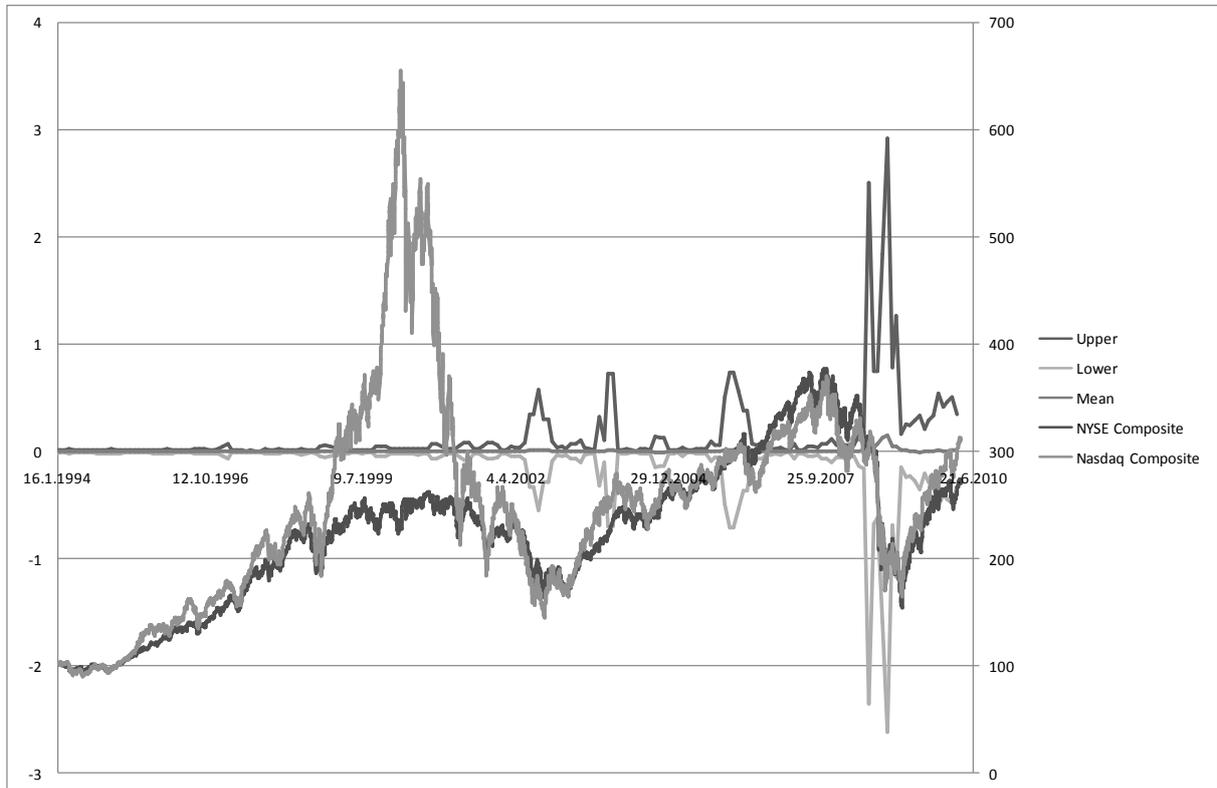
Figure 7. Quarterly forecasting error evolution over time, earnings, the U.S.

Note: The figure contains earnings forecasting errors for quarters in the U.S. markets. Five spikes make the figure harder to comprehend. Forecasting errors are calculated as percentage of stock price. The data in figure contains whole data sample even with outliers which are excluded from regression analysis.

Figure 8. Quarterly forecasting error evolution over time without outliers, earnings, the U.S.

Note: The figure contains earnings forecasting errors for quarters in the U.S. markets. The major spikes from Figure 7 are excluded in order to show forecasting bias evolution more in-depth. Those spikes are from periods Q3Y2002, Q4Y2003, Q1Y2006, Q3Y2008 and Q4Y2008. It can be seen that forecasting errors have become more volatile after year 2003.

Figure 9. Quarterly forecasting error evolution over time, earnings, the Eurozone

Note: The figure contains earnings forecasting errors for quarters in the Eurozone markets. Forecasting errors are calculated as percentage of stock price. There are far less observations for European firms compared to U.S. ones which might make forecasting error mean more volatile.
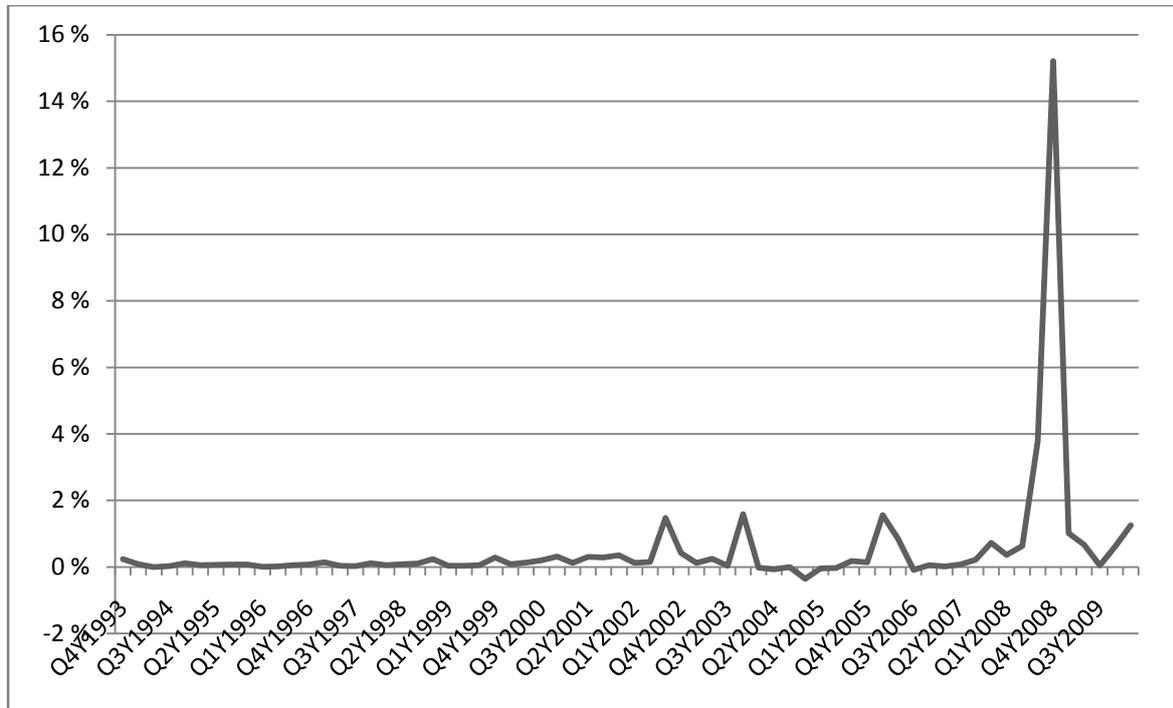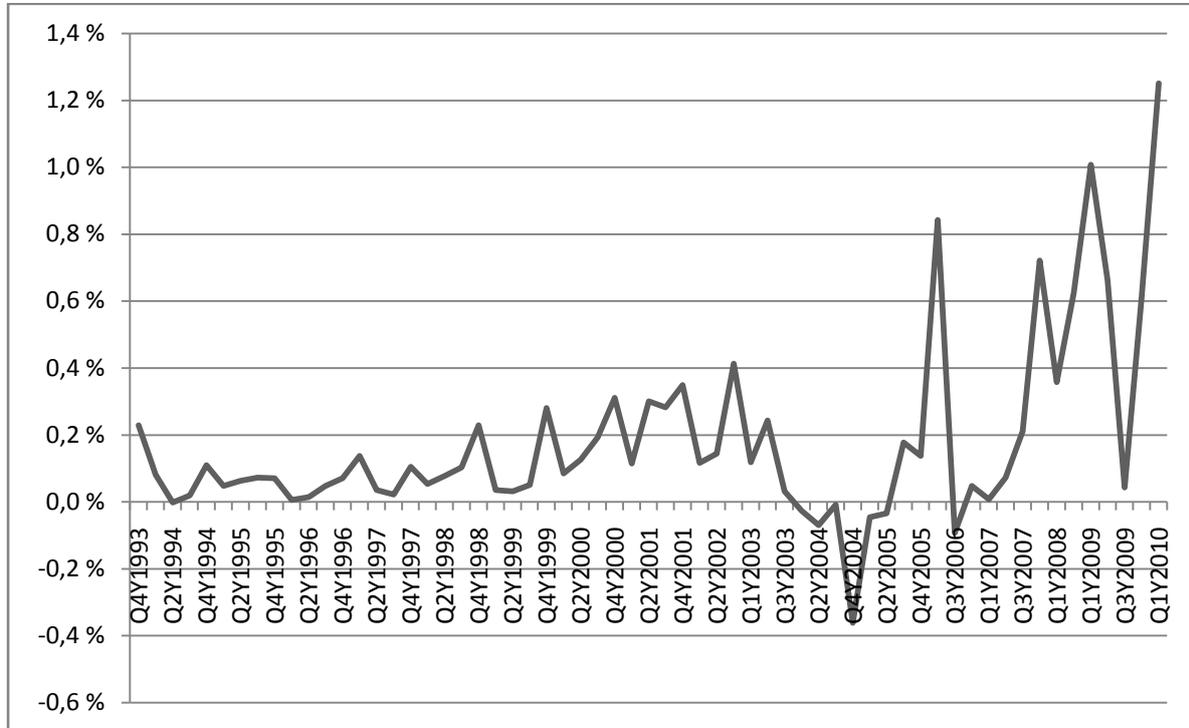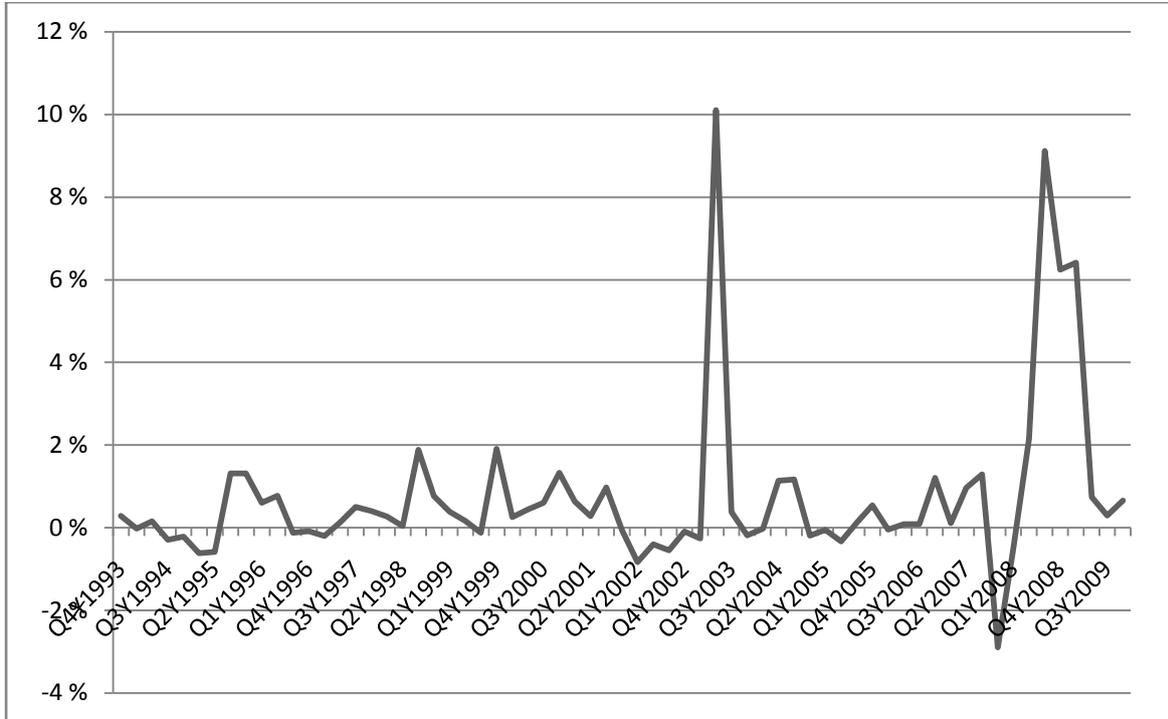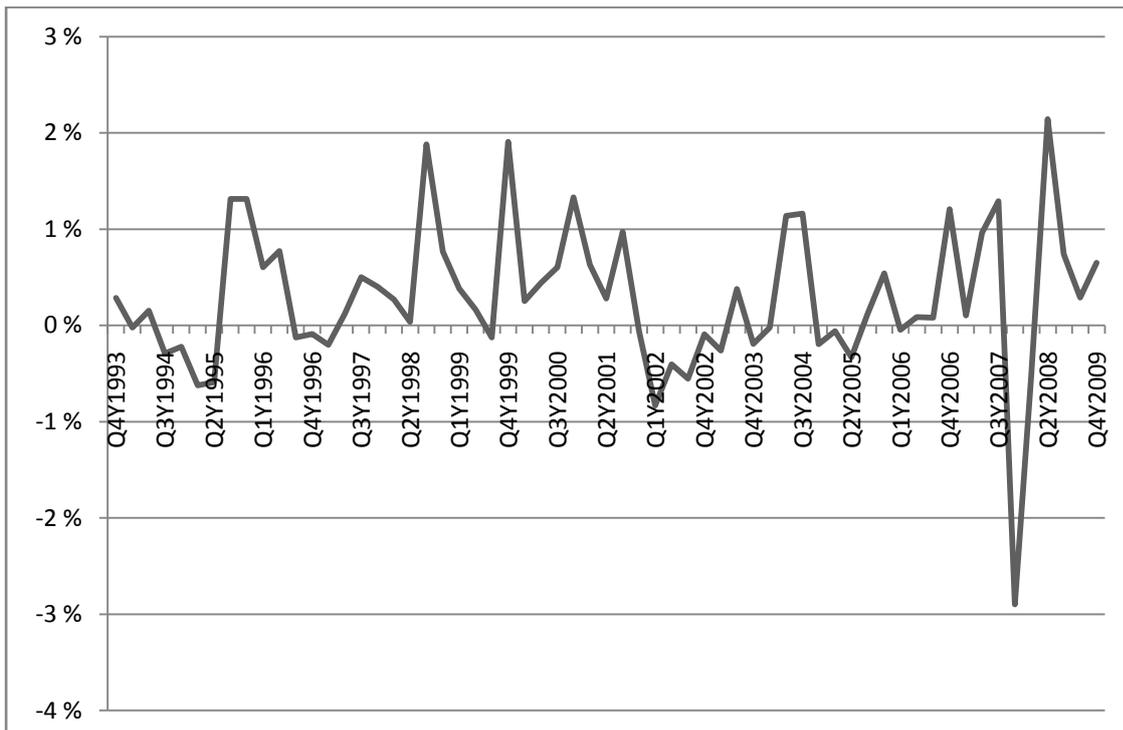

Figure 10. Quarterly forecasting error evolution over time without outliers, earnings, the Eurozone

Note: The figure contains earnings forecasting errors for quarters in the Eurozone markets. Forecasting errors are calculated as percentage of stock price. Extreme outliers excluded are from periods Q2Y2003, Q3Y2008, Q4Y2008 and Q1Y2009.

Analysts make forecast for interim and annual financial periods. It is widely held belief that analysts make more efforts to polish their annual forecasts than quarterly forecasts. After qualitative analysis of the forecasting biases let us take a look to real numbers behind the phenomena. Table 4 summarizes descriptive statistics for my annual level datasets for the U.S. and the Eurozone. Similarly Table 3 contains descriptive statistics for the quarter forecasts. Approximately, the amount of observations is twice as large in the U.S. compared to the Eurozone. That is understandable because most of the analysts producing estimates to I/B/E/S are from North American institutes and therefore they have more interests on their local firms. However, on average level differences in earnings and sales are quite small and even standard deviations are very close to each others. Therefore, I will judge that underlying firms are quite similar in both markets.

A quick glance on data shows that on average forecasting errors are larger for earnings estimates than sales estimates (see Table 4 and Table 3). It seems that errors on sales forecasts are less variable than errors on earnings forecasts. Standard deviations of the sales forecasting errors for sales estimates are larger than for earnings estimates. One simple explanation for this is that sales have naturally larger variability than earnings which are part of the sales. Even though sales estimates are harder to make (higher standard deviation), still they are on average more accurate than earnings estimates. The only exception is the hugely underestimated annual figures in the U.S. markets.

On average earnings estimates are 0.1 percent too large in the U.S. markets; whereas they are whopping 0.8 percent overoptimistic in the Eurozone markets. Quarterly estimates have lower quality because analysts use less time and resources for quarterly estimates. Therefore it is natural that forecasting biases for earnings are larger with quarterly data (0.5 percent in the U.S. and 1.4 percent in the Eurozone). However, in both markets for earnings and for sales median forecasting error is close to zero. This hints that forecasts could be potentially unbiased. Whenever mean and median are not equal it is clear that distribution is not normal. Abarbanell and Lehavy (2003) studied distribution of the forecasting errors and found out that two asymmetries; tail asymmetry (large number of extreme negative forecasting errors relative to extreme positive forecasting error); and middle asymmetry (large number of small positive forecasting errors relative to small negative forecasting errors). My annual dataset is mostly consistent with findings of Arabanell and Lehavy (2003). Gu and Wu (2003) argue that optimal forecast is the median instead of mean when underlying distribution is skewed. At annual level it seems to hold that the median is closer unbiased situation than the mean.

When comparing the forecasting biases between the U.S. and the Eurozone it is clear that the forecasting biases are consistently higher in the Eurozone markets. Once again only exception is the sales estimates in the U.S. This could only be due some very unusual situation under which analysts have encountered lots of positive surprises and failed to update their estimates to match the reality. It is likely that earnings forecasts are updated more often because they are likely to affect more stock markets. As in many earlier studies standard deviation of the earnings forecasting errors are smaller in the U.S. markets which implies that there are more public information available and higher analyst coverage. Another observation is that forecasting errors are slightly larger for interim reports (compare Table 4 and Table 3). Also standard deviations of the forecasting errors are larger at quarterly level. It has been argued that analysts use more effort on annual estimates than quarterly ones and my findings seem to support that idea.

Hypothesis 1 stated that forecasting bias would be larger for the financial variable more important for the management (namely earnings). This seems to be true based on results in Table 3 and Table 4. Hypothesis 5 stated that forecasting errors would be higher in the Eurozone markets. This is confirmed in Table 3 and Table 4. Later on we will see that this is due higher uncertainty and less developed regulation environment.

Table 3. Descriptive statistics, quarterly dataset

Note: The analysts' forecasts are recorded approximately one month before financial figures are published. The firms whose financial reporting periods are different from Jan-Mar, Apr-Jun, Jul-Sep and Oct-Dec are excluded from the sample. This reduces amount of firms especially in Europe where financial periods are less standardized. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	44263	105.6961	22.75380	374.3018
Earnings, EU	2896	178.7668	12.98095	603.5458
Sales, U.S.	24580	1785.288	484.0225	4840.837
Sales, EU	2294	3425.618	482.2510	7517.937
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	44263	0.005309	-0.005309	0.233362
Earnings, EU	2896	0.013670	0.000000	0.117098
Sales, U.S.	24580	0.003269	-0.000978	0.328576
Sales, EU	2294	0.008556	-0.002107	0.331176

Table 4. Descriptive statistics, annual dataset

Note: Descriptive statistics are for firms' actual reported earnings and sales at annual level but without outliers. An observation enters into the sample when it has analyst forecast and actual reported data available. However, observations which could be regarded outliers or cases where it is not clear whether data in database is correct or it is not clear what analysts' have tried to forecast, are excluded. I have excluded data from 5% tail-areas of the distribution and cases when stock price is below 5 dollars. I exclude the observations with low stock price because it will be then consistent with limitations implemented for data later on when I develop my regression models. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	13863	430.7045	95.36325	1504.484
Earnings, EU	6455	283.2252	17.32551	1176.139
Sales, U.S.	9766	5936.839	1622.335	17204.12
Sales, EU	4069	7166.216	491.9741	20305.61
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	13863	0.001218	-0.000310	0.016753
Earnings, EU	6455	0.008767	-0.000139	0.064202
Sales, U.S.	9766	-1.053283	-0.740367	1.021793
Sales, EU	4069	0.007328	-0.007294	0.374944

5.2 Evolution of the forecasting bias

In this section I will go through how forecasting biases have evolved in the markets under the research. It has been documented behavior that forecasts tend to converge nearer realized values when approaching the release date because more information becomes available. Figure 11 compares how the annual forecasting errors behave when release date comes closer. In the U.S. markets behavior is as expected and forecasting errors decrease. This could be because more information becomes available and there will be less uncertainty about time period still left before end of the financial year. At the Eurozone markets same kind of convergence process is not present. The data in Figure 11 is over my whole research period from 1995 to 2009 and therefore it cannot be that some kind of business cycle explanation would be possible because my data is extended over business cycle. Also it is not likely that those European companies do not have enough analyst coverage because they are mainly the largest companies in their markets. The only explanation I could come up is that data quality is weaker at the Eurozone markets and companies do not publish as much information about themselves as corresponding companies at the U.S. markets. This finding is in line with findings from Bagella et.al. (2007).

Figure 11 showed only summarized result of how forecasting biases converge over time. Now, I will move on to Figure 12 which present how those monthly forecasting errors have changed over years. There is only one period during which forecasting errors have been lower in the Eurozone than in the U.S. markets. This period is from 2004 to 2007. When comparing graphs in Figure 12 it becomes clear that forecasting errors are much more volatile in the Eurozone markets. This is the same finding as Bagella et.al. (2007) presented. The graphs also show that from two to three months prior to release of financial year results the Eurozone forecasts during research period never become superior to forecasts in the U.S. markets. Left side scales show that forecasts become more accurate but the earnings forecasts at the U.S. markets do it at much quicker pace. Still, positive news is that it seems that forecasting errors are developing more and more hand in hand between the U.S. and the Eurozone markets. This signals that the U.S. and the Eurozone markets are getting more integrated.

To this point I have mainly discussed about accuracy of the earnings and sales forecasts. In next step instead of studying levels of the forecast error, I concentrate on variability of the earnings forecast errors. Figure 13 and Figure 14 show development of forecasting error's standard deviation (the dispersion of the forecasting errors) for several years. In the U.S.

markets analysts become more and more to agreement on the level of the consensus estimate when approaching the release date. This is seen from negative slope in Figure 13. From same figure it can be seen that standard deviation of consensus forecasts becomes smaller and smaller over years. The results are similar even for the years not shown in the Figure 13. With the U.S. data year 2009 is surprise because standard deviation jumps to levels where is has not been before. This is probably due the turnaround in business cycle which increases forecasting errors. It also increases analysts' disagreement because some analysts were able to forecast the turn and some missed that one. Figure 14 tells us very different story than earlier Figure 13 about the U.S. markets. In the Eurozone markets there is not clear development towards agreement over months towards the release date. Also there is not same kind of development towards tighter forecast distribution visible. It seems that development of the forecasting error is random-walk or at least close of it. As noted earlier, average forecasting biases have started to move more together. However, the distribution of the forecasting bias has not converged which effectively means that the U.S. and the Eurozone markets still are very different from the viewpoint of analyst. This will be further studied when I next divide the study period to two sub-periods, 1994-2000 and 2003-2010.

Figure 11. Development of the forecasting bias when release date gets closer, annual dataset

Note: The figure is mean of the earnings forecasting errors over years from 1994 to 2009. Forecasting errors are mean forecasting errors. Forecasting errors are calculated 1 to 9 months prior release of the annual earnings. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).
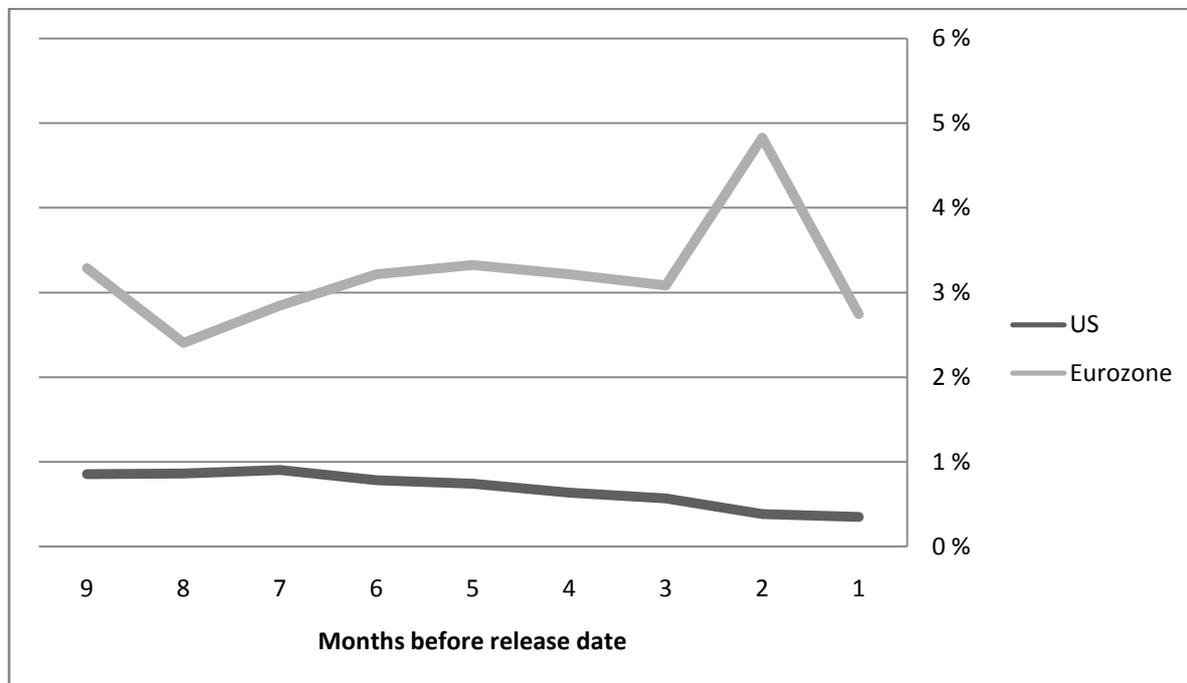
Figure 12. Forecasting bias evolution for earnings forecasts from 9 months to 1 month prior release date of the financial measure.

Note: The figure shows how forecasting errors have developed over years for certain months prior release of the annual earnings numbers. The figure contains only data from earnings forecasting errors because number of observations for individual month prior the release date for sales forecasts was quite a low. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

Figure 12 continues

7 months before the release date

6 months before the release date

5 months before the release date

4 months before the release date

3 months before the release date

2 months before the release date

1 month before the release date

Figure 13. Evolution of the standard deviation of the forecasting errors in the U.S.

Note: The figure standard deviations of the earnings forecasting errors in the U.S. markets. Only several years of the observations were chosen for this figure. The figure describes how the standard deviation of the forecasting error for earnings evolves from 9 to 1 month prior release of the annual figures. Tendency of the forecasting error's distribution to shrink when reaching the most recent year still exists even for years not presented here.

Figure 14. Evolution of the standard deviation of the forecasting errors in the Eurozone

Note: The figure standard deviations of the earnings forecasting errors in the Eurozone markets. The figure describes how the standard deviation of the forecasting error for earnings evolves from 9 to 1 month prior release of the annual figures.

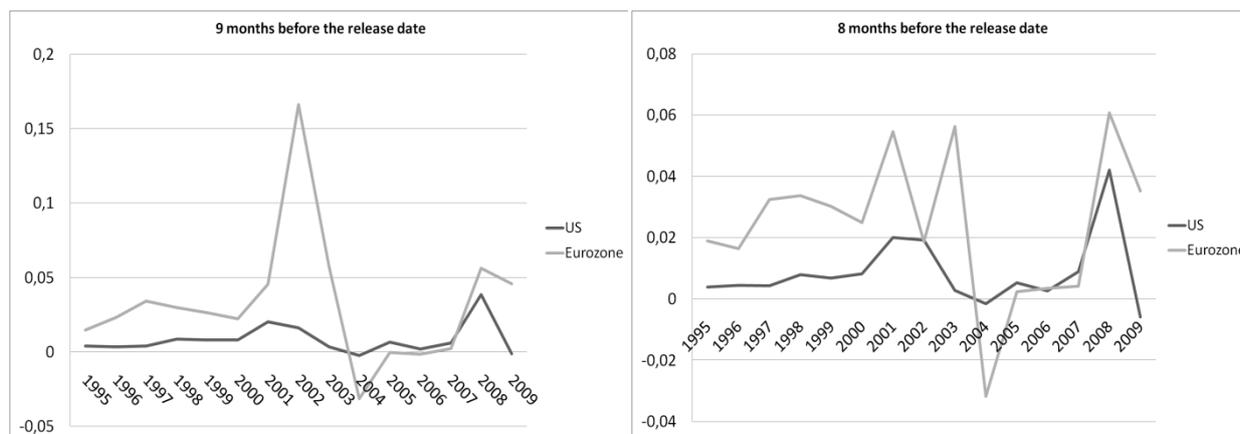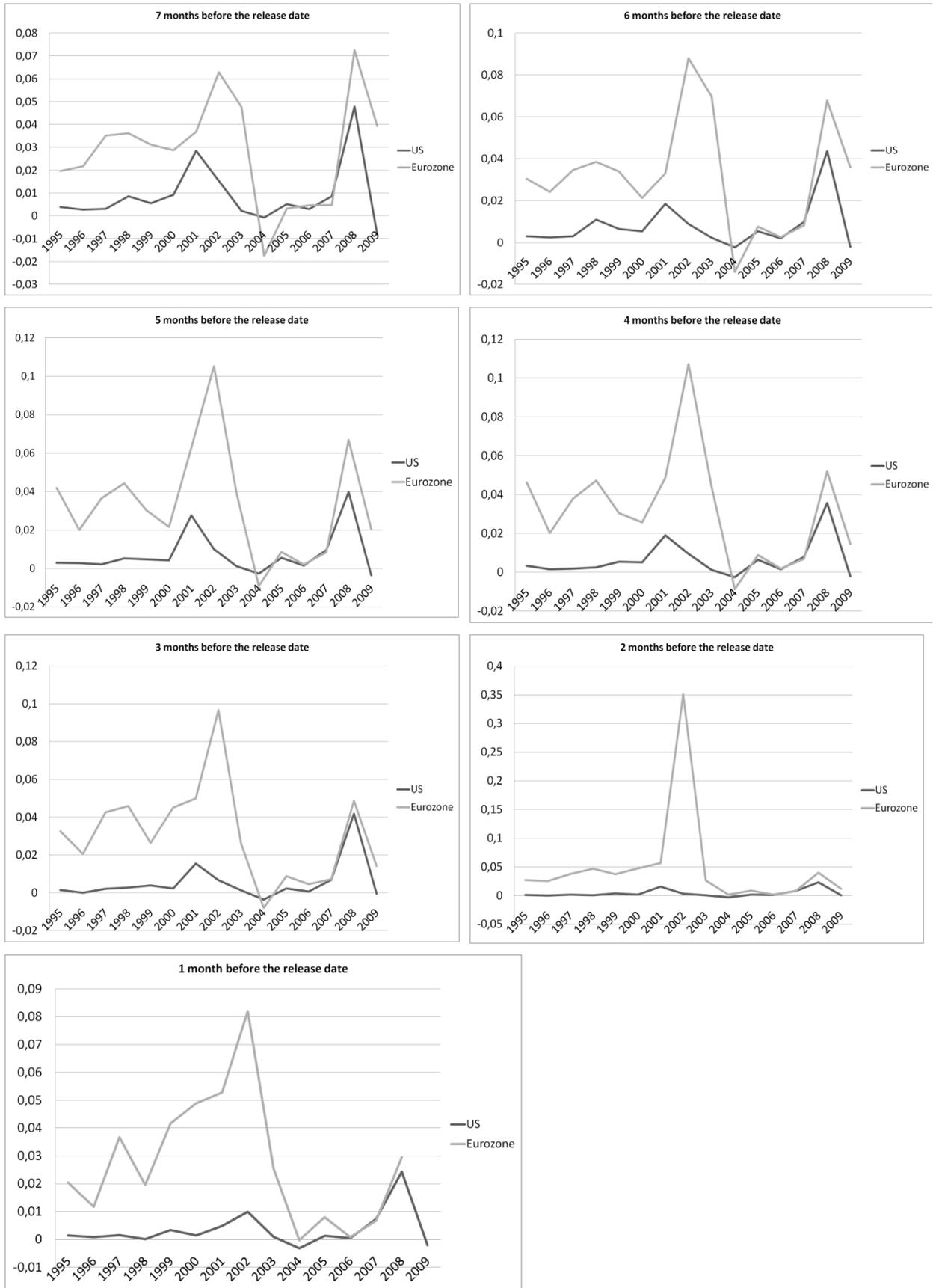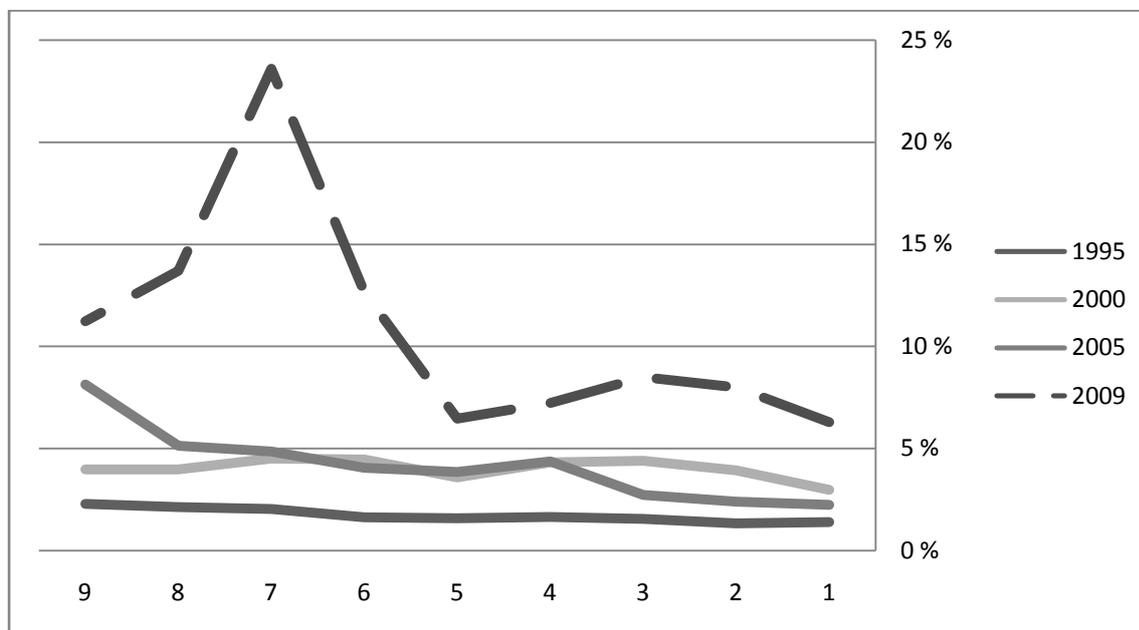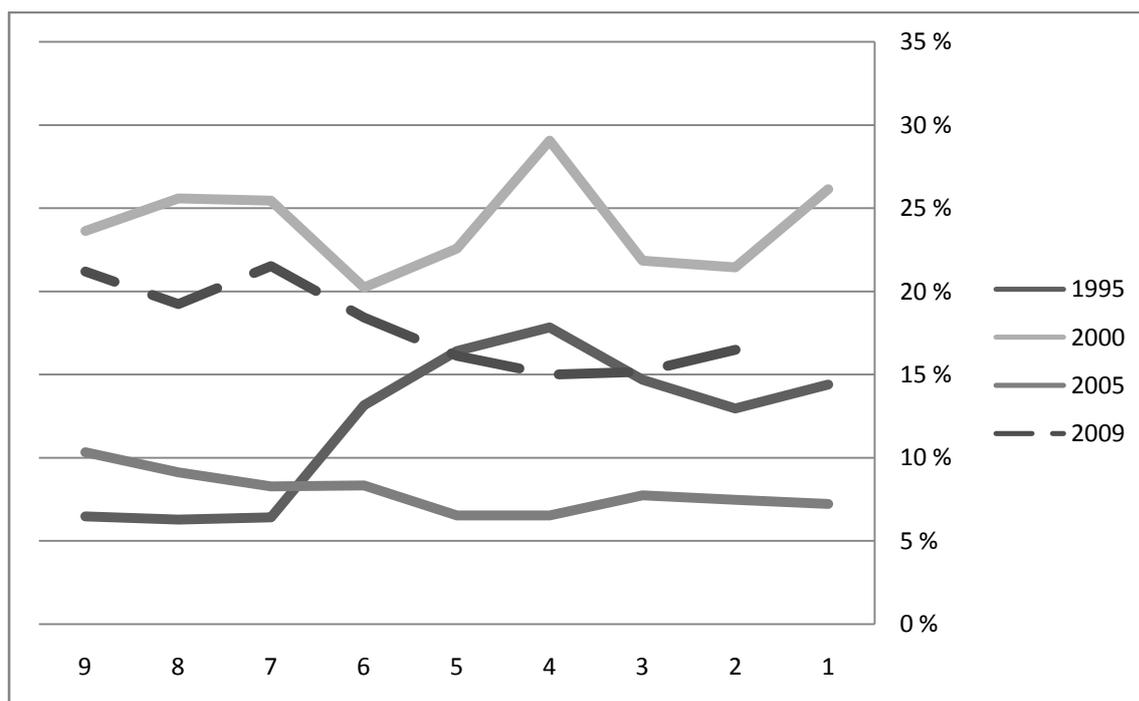Next, I will divide annual data to subperiods; 1995-2000 and 2003-2009. Between years 2000-2003 there were several regulation changes which are likely to have an effect on analysts forecasting. I have collected descriptive statistics of annual forecasts on Table 5 and Table 6. Let us remember that at latter period analysts in the U.S. no longer get additional information from the management which is not made already publicly available. Table 9 shows how mean forecasting biases have changed between periods. Judging from Table 9 the sales estimates have become increasingly accurate, whereas earnings forecasts have become less accurate. Four possible explanations come in mind: (1) analyst coverage has increased and made consensus forecasts more accurate; (2) analysts have improved their processing of information; (3) different part of the business cycle has changed difficulty of forecasting; or (4) regulation changes have affected purposely added bias on analysts' forecasts.

First explanation, the analyst coverage has surely increased but it should make forecasting markets more efficient in sales and earnings. Therefore, forecasting accuracy improvement should be similar to both variables. Table 9 shows that improvement in forecasting accuracy has been much greater with sales than earnings. Second explanation does not sound very reasonable. It states that analysts have changed and earlier they had little idea what they were doing. Third explanation clearly is not true if we look situation of the business cycle from Figure 5 and Figure 6. Clearly at earlier period there was less fluctuation than the latter period. In other words, it seems that it should be harder to make accurate forecasts at 2003-2009 periods. The fourth explanation states that regulation changes would affect forecasting accuracy to one direction or other. I argue that the difference of the change between earnings and sales forecasting errors could be used as approximation for the effectiveness of the regulation changes.

Same time earnings forecasts have become less accurate and their standard deviation of the forecasting error has increased. It is puzzling if we observe increasing accuracy in sales forecasts but loss of accuracy in earnings forecasts. It might be that earnings forecasts accuracy has depreciated because there are firms who are careful not to reveal additional information over publicly available information. Still after increase in forecasting error for earnings, the standard deviation has also increased. The analysts have to rely more on publicly available information. This information might be inaccurate sometimes and cause greater forecasting errors and standard deviation. But it does not explain why forecasting errors are

increasingly positive. Could it be that "price" of insider information from the management has increased and the analysts have to add more bias to their estimates in order to get access to management's information?

Table 7 and Table 8 present descriptive statistics for subperiods just like earlier with annual datasets. Here we have very interesting results. When measured with mean forecasting bias earnings forecasts have become less accurate both in the Eurozone and the U.S. markets. However, median forecasting errors are still close to zero. At the U.S. markets median and mean forecasting errors have moved to opposite directions thus making forecasting error distribution even more skewed. Earlier with the annual dataset and now with the quarterly dataset it seems that sales forecasts are continuously underestimated except in the Eurozone markets. In the Eurozone it is puzzling that on annual level sales estimates are underestimated but on interim level they are on average overestimated. With quarterly data I make same finding as Mest and Plummer (2003) that standard deviation of sales forecast errors are smaller compared to earnings forecast errors. Also absolute forecasting errors are with quarterly data in both time periods lower for sales. Mest and Plummer (2003) argued that those findings together show that analysts purposely add bias on their earnings estimates. The story is same with annual and quarterly datasets. The direction and the magnitude of the change can be seen from the Table 9.

Table 5. Descriptive statistics for subperiod 1995-2000, annual dataset

Note: Descriptive statistics are for firms' actual reported earnings and sales at annual level. An observation enters into the sample when it has analyst forecast and actual reported data available. The dataset is sliced to subperiod which consists time before Regulation Fair Disclosure and tightening of regulatory environment. The Table 5 contains data for financial years from 1995 to 2000. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	4964	312.0032	77.98189	880.0827
Earnings, EU	2284	205.6604	12.33623	1019.960
Sales, U.S.	1470	5757.610	1770.700	13891.01
Sales, EU	1063	7064.045	566.6685	20823.28
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	4964	0.000469	-0.000263	0.008335
Earnings, EU	2284	0.016276	0.001742	0.065286
Sales, U.S.	1470	-1.141772	-0.740966	1.218215
Sales, EU	1063	-5.385765	0.283997	30.31322

Table 6. Descriptive statistics for subperiod 2003-2009, annual dataset

Note: Descriptive statistics are for firms' actual reported earnings and sales at annual level. An observation enters into the sample when it has analyst forecast and actual reported data available. After year 2003 majority of regulation changes have been implemented (Regulation Fair Disclosure at 2000 and Global Settlement 2003) and the results of those regulation changes should have become visible. The Table 6 contains data for financial years from 2003 to 2009. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	7159	528.1505	113.5951	1855.881
Earnings, EU	3454	370.3809	24.14569	1323.993
Sales, U.S.	6876	6072.272	1578.960	18546.95
Sales, EU	2466	7480.447	491.3240	21164.71
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	7159	0.001168	-0.000400	0.020725
Earnings, EU	3454	0.001476	-0.001474	0.048110
Sales, U.S.	6876	-1.020815	-0.727958	0.972999
Sales, EU	2466	-4.392683	0.410622	24.94739

Table 7. Descriptive statistics for subperiod 1994-2000, quarterly dataset

Note: The analysts' forecasts are recorded approximately one month before financial figures are published. The firms whose financial reporting periods are different from Jan-Mar, Apr-Jun, Jul-Sep and Oct-Dec are excluded from the sample. This reduces amount of firms especially in Europe where financial periods are less standardized. Amount of Europe based firms drop dramatically because I/B/E/S mainly reports annual figures before year 2000 for European firms. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	15145	75.93581	17.23995	212.5783
Earnings, EU	449	47.76676	1.688600	158.7327
Sales, U.S.	1053	1420.323	494.0000	3833.277
Sales, EU	88	377.0035	26.09200	968.0036
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	15145	0.001031	-0.000131	0.021252
Earnings, EU	449	0.003110	0.000000	0.024408
Sales, U.S.	1053	0.004529	-0.000219	0.206744
Sales, EU	88	0.010540	-0.000479	0.133468

Table 8. Descriptive statistics for subperiod 2003-2009, quarterly data

Note: The analysts' forecasts are recorded approximately one month before financial figures are published. The firms whose financial reporting periods are different from Jan-Mar, Apr-Jun, Jul-Sep and Oct-Dec are excluded from the sample. This reduces amount of firms especially in Europe where financial periods are less standardized. Since financial year 2000 I/B/E/S has improved its international coverage and therefore the amounts of the observations from the Eurozone is much larger than with earlier time period 1994-2000. The difference between amounts of observations between U.S. and Europe reduces because there are a lot of more analysts covering also European stock markets. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity).

	N	Mean	Median	Std. dev.
Panel A: Actual reported values (in millions of dollars)				
Earnings, U.S.	24903	125.9069	27.00033	454.7825
Earnings, EU	2330	210.8299	22.04897	666.0453
Sales, U.S.	21968	1795.652	476.3730	4906.039
Sales, EU	2153	3630.503	544.6919	7712.084
Panel B: Percentage forecast errors (in millions of dollars)				
Earnings, U.S.	24903	0.008560	-0.000447	0.310173
Earnings, EU	2330	0.017089	0.000112	0.130160
Sales, U.S.	21968	0.002525	-0.001072	0.335161
Sales, EU	2153	0.009684	-0.002439	0.340758

Table 9. Forecasting accuracy percentage change from 1995-2000 to 2003-2009

Note: The table contains percentage changes in forecasting bias between the earlier and the latter periods. The changes are calculated with figures from Table 5, Table 6, Table 7 and Table 8 as (FE_period2-FE_period1)/FE_period1. Negative numbers mean that forecasting error has reduced.

	U.S.	Eurozone
Earnings, annual	+149%	-90.9%
Earnings, quarterly	+730%	+44.9%
Sales, annual	-10.6%	-18.4%
Sales, quarterly	-44%	-8%

Figure 15 and Figure 16 show average forecasting error for earnings and sales for Eurozone and U.S. markets arranged by financial quarter. There have been arguments that I/B/E/S might have inconsistent treatment of the so called special items of the income statement. These special items are usually write-downs and other non-cash flow items. Often those special items lower reported earnings and could possible cause over-estimation of the earnings. Following Figure 15 and Figure 16 study this potentiality. Sales forecasts should not contain this special items problem and therefore they can be used as comparison point. Sales forecasting errors in U.S. markets are effectively equal for 3rd and 4th financial quarters with sales but this equality does not hold with earnings. There is a sharp increase in over-optimism at 4th financial quarter this could be partly because of "special items" lower actual reported earnings and analysts have not prepared to forecast those earnings with special items included. In Eurozone sample there seems to be even decline in forecasting error magnitude and therefore I have admit that "special items" are not affecting my sample in great detail.

Figure 15. Quarterly forecasting bias of earnings for the U.S. and the Eurozone firms

Note: The figure contains mean quarterly earnings forecasting errors for the U.S. and the Eurozone firms over whole research period from 1994Q4 to 2010Q1. Possible outliers are still included as was done earlier. Horizontal-axis has fiscal quarters from first quarter (Jan-Mar) to fourth quarter (Oct-Dec). Fourth quarter might contain special items which are not treated consistently in I/B/E/S before year 2000. Forecasting errors are measured approximately one month prior release of the interim figures.
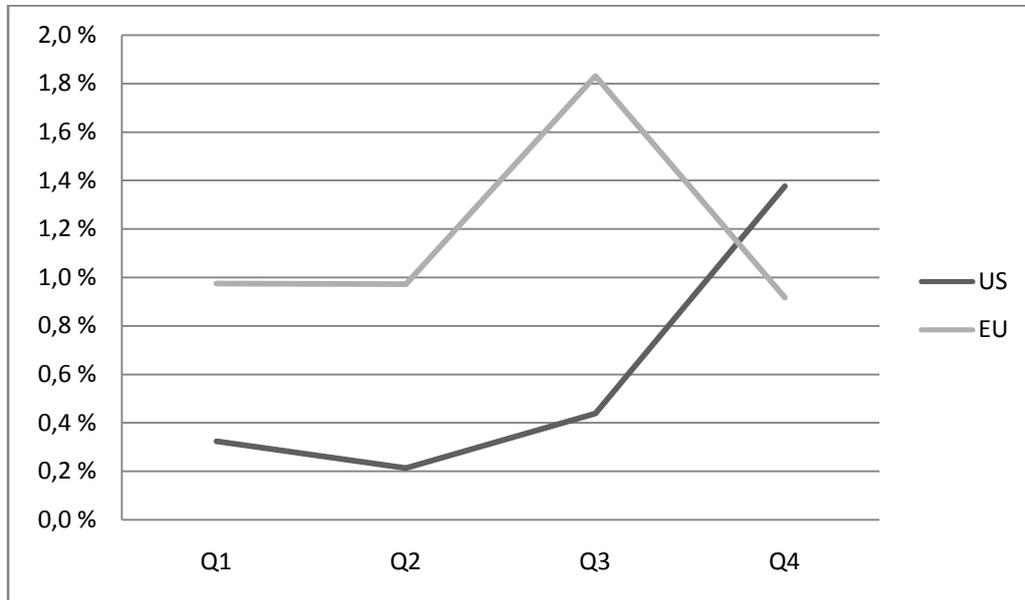
Figure 16. Quarterly forecasting bias of Sales for the U.S. and the Eurozone firms

Note: The figure contains mean quarterly sales forecasting errors for the U.S. and the Eurozone firms over whole research period from 1994Q4 to 2010Q1. Mean forecasting biases for quarter as percentage of stock price are calculated as weighted average. Weights used are number of observations for certain quarter in certain year. The forecasting errors are calculated approximately one month prior release of the financial figures for quarter.
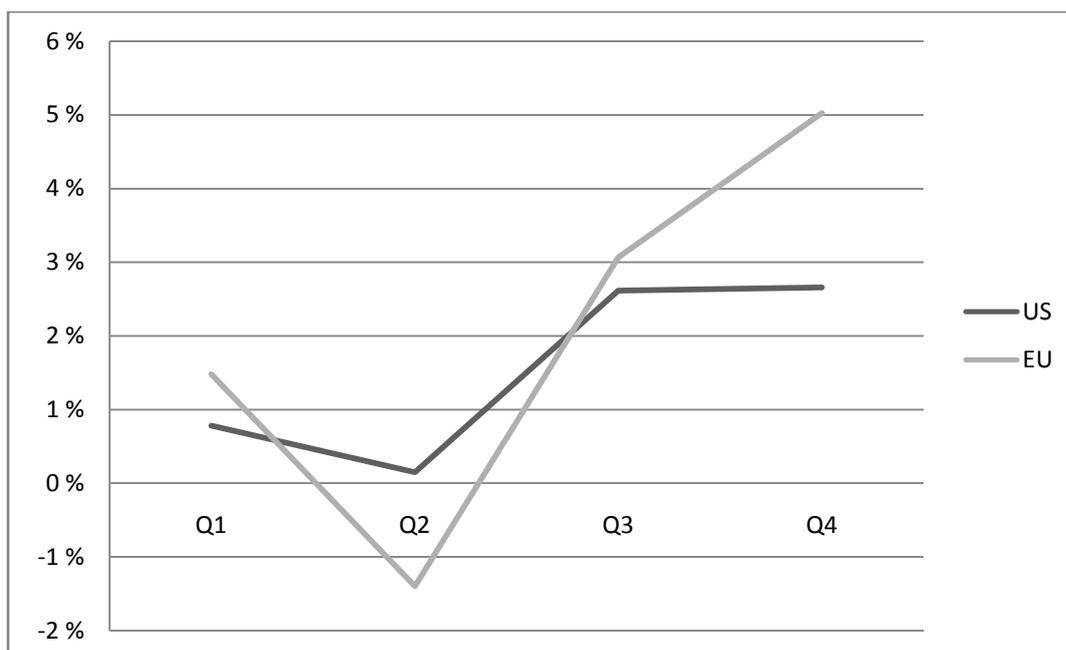
5.3 Regression analysis

I will answer rest of the research questions with regression analysis. I will incorporate several well-known sources of forecasting bias to my regression equation. It is very close to one used by Mest and Plummer (2003). However, I have discarded analyst coverage variable because there is high autocorrelation between analyst coverage and market capitalization of the firm. Those potential sources of analysts' forecasting bias have to be controlled in order to reveal true relationships from the data. Instead of I will be using analysts' forecasts standard deviation. See equation 4 for regression function.

Table 10 contains regression results for earnings forecast errors obtained from quarterly and annual datasets. Several notes from the results should be made. There is positive bias (intercept term) in every sample regardless of the prior forecasting error and news impact. The degree of the prior forecasting bias is statistically significant and the coefficients (α_3 and α_4) are different for negative and positive news impact. The analysts therefore react differently to positive and negative surprises and furthermore they are slow to revise their forecast. The size of the firm has negative effect to forecasting bias as expected because there is more information available about larger firms. The standard deviation of earlier forecasts has mostly significant positive coefficient. This is surprising because it means that larger the analysts opinions dispersion is, larger will be average forecasting bias. I will analyze these intercepts and coefficients again later on when I divide my sample to two periods 1994-2000 and 2003-2009.

From Table 10 we can see that intercept terms (α_1 and α_2) for prior good and bad news are positive. This shows an average level of forecasting bias before any other variable taken in the account. Forecasting bias is positive in the Eurozone and the U.S. markets from both annual and interim datasets. Positive earnings surprises earlier affect forecasting accuracy. Forecasting bias is larger in the Eurozone and the U.S. markets with quarterly data which is as expected. With annual forecasts analysts have over half of a year time adjust their estimates to correct mistakes made earlier. Whereas with interim estimates have to be done in two months. Also analysts use more energy to their annual estimates than to forecast interim reports. At quarterly level at the U.S. markets good news intercept is insignificant and at Eurozone markets good and bad news intercepts are insignificant at interim level. The intercept for prior bad news is significant in the U.S. markets.

Slope coefficients for prior forecasting error (α_3 and α_4) are positive or insignificant both in the Eurozone and the U.S. markets. This means that analysts are reacting over-conservatively to their prior forecasting errors. After good news estimates are still too pessimistic and after poor performance (bad news) analysts estimates are too high. Also intercept terms and slope coefficients are all higher at the Eurozone markets. It seems that analysts are more affected by biases on European markets and produce consensus forecasts less efficiently.

Market capitalization (α_5) of the equity has as expected negative sign. There is more information available from large firms and therefore forecasts are more accurate for larger firms. It seems that standard deviation of the forecasts is good indicator of the information uncertainty. Its coefficient (α_6) is significant for all datasets expect annual dataset from the Eurozone. It also has expected positive sign which indicates that under larger information uncertainty forecasts become more positively biased.

Table 11 show regression results for sales forecasting errors. With sales forecasting errors the results are quite different from ones obtained from earnings forecasts. First of all sales have negative intercept terms (α_1 and α_2) regardless of the prior year surprises at annual level. Still at interim level only negative sales surprises have significant intercept term in the U.S. markets and this intercept term is positive. At annual level all slope coefficients are statistically highly significant and positive. Slope coefficients (α_3 and α_4) are also higher for annual level forecast errors which is puzzling because final analyst consensus forecasts are recorded only one month before the end of the financial year. When comparing prior sales surprises on two different markets, there is one interesting finding that in the U.S. markets analysts are less likely to be affected by good news than in the Eurozone. Otherwise slope coefficients (α_3 and α_4) in the U.S. and the Eurozone are quite close each others at annual level. Very surprising result is that coefficients for market capitalization (α_5) are highly positive. This could be cognitive bias among analysts that large, well-known and successful companies could generate excessively sales growth.

One of the several differences between the U.S. and the Eurozone markets is how forecast variability affects the accuracy of the sales forecasts. In Europe the factor (α_6) is insignificant. Still in the U.S. larger uncertainty about sales (i.e. higher standard deviation between forecasts) reduces average forecasting bias. Standard deviation of the forecasts is used as proxy for information environment. With high information uncertainty standard deviation should be high and when there is ample information available standard deviation of forecasts

should be smaller. It is also very surprising that with sales analysts' forecast dispersion has negative effect whereas with earnings forecasts it has positive effect. High informational uncertainty should not have effect on forecasting bias but just widen the distribution of the forecasting errors. The positive coefficient in analysts' forecasts dispersion variable might indicate that under high uncertainty some analysts are ready to sacrifice their unbiased forecasts to attain information from the firm's management.

Table 12 contains regression results for earnings forecasting errors for subperiods. In the U.S. markets all statistically significant intercepts and coefficients have gotten closer to zero at latter time period 2003-2010. It could indicate that the U.S. earnings forecasts have become more efficient since implementation of the regulation changes (i.e. Regulation Fair Disclosure and Global Settlement). Comparison to the Eurozone is difficult with data from Table 12 because none of the figures are statistically significant in earlier period and on latter period there are only two significant values (slope for bad news α_4 and standard deviation of forecasts α_6). The measure for uncertainty (α_6 forecasts' standard deviation) has increased which hints that some analysts are compensating tightened regulation by buying information with larger positive bias. However, it is still possible to compare those results to the results from the U.S. markets. The slope coefficient (α_4) for bad news is 2.5 times higher and standard deviation of forecasts is almost 100 times higher in the Eurozone markets.

Table 13 contains regression results of forecasts errors for sales for subperiods. At earlier period there are very few observations in both market areas. It would affect how statistically significant the results will be. In the U.S. markets for period 1994-2000 there is only one statistically significant value which is positive slope coefficient (α_3) for prior good news. However, latter time period (2003-2010) yields the results which are all statistically significant. Intercept term (α_1) in the U.S. markets after good news is negative which makes sales forecasts very different from earnings forecasts. Same time, after bad news intercept term (α_2) is clearly positive. The slope coefficient (α_3) for bad news is only one third of the corresponding slope coefficient for good news (α_4). It seems that after weak performance (bad news) analysts think that the firm will improve its sales more than is realistic and after good performance (good news) they are likely to keep their estimates too low and be pessimistic about future growth. At least sales forecasting error hints to this kind of direction. In the Eurozone markets once again the only significant value, slope coefficient for prior bad news is twice as high as corresponding term for the U.S. markets.

Table 14 shows final results of Chow-test for similarity of the subperiods. For earnings it seems clear that something has happened between 1994-2000 and 2003-2010 periods. The same regression intercept and coefficient terms should not be used anymore and I can argue that regulation has affected some characteristics of the U.S. markets. The Eurozone sample is of course much smaller but still Chow-test confirms that there has not been any significant change between time periods. For sales difference between sample sizes is extremely large which makes Chow-test unreliable and therefore sales forecasting errors will not be tested.

Table 10. Regression of analysts' forecast errors on prior period forecast errors and informational uncertainty variables

Note: The above number is the coefficient value from regression equation and the lower value in brackets is a t-value for the significance of the above value. The percentage forecast errors are calculated with Equation 3 ([Forecast − Actual] / Market value of the equity). The values market with * are significant at 1 percent level. The values market with ** are significant at 5 percent level.

Financial variable	Sample size	Intercept: Goodnews, α_1	Intercept: Badnews, α_2	FE: Goodnews, α_3	FE: Badnews, α_4	MKT, α_5	Sted.dev. of forecasts, α_6	Adjusted R^2
Earnings, U.S., Quarterly	24549	0.000323 (1.23)	0.002292 (8.80)*	0.090483 (15.24)*	0.028083 (8.88)*	-0.000183 (-5.56)*	4.68e-5 (3.37)*	0.044
Earnings, EU, Quarterly	969	0.001815 (0.53)	0.002666 (0.80)	0.251281 (3.02)*	0.457550 (10.05)*	-0.000107 (-0.027)	0.003193 (2.46)**	0.147
Earnings, U.S., Annual	7439	0.002535 (2.36)**	0.004909 (4.54)*	0.047119 (2.14)**	-0.016031 (-1.42)	-0.000311 (-2.29)**	9.66e-5 (3.30)*	0.008
Earnings, EU, Annual	2839	0.029503 (5.78)*	0.028897 (6.18)*	0.055542 (1.05)	0.123868 (3.98)*	-0.003419 (-5.27)*	8.41e-7 (0.42)	0.018

Table 11. Regression of analysts' forecast errors for sales on prior period forecast errors and informational uncertainty variables, annual and quarterly datasets

Note: The above number is the coefficient value from regression equation and the lower value in brackets is a t-value for the significance of the above value. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity). The values market with * are significant at 1 percent level. values market with ** are significant at 5 percent level.

Financial variable	Sample size	Intercept: Goodnews, $\alpha1$	Intercept: Badnews, $\alpha2$	FE: Goodnews, $\alpha3$	FE: Badnews, $\alpha4$	MKT, $\alpha5$	Sted.dev. of forecasts, $\alpha6$	Adjusted R^2
Sales, Annually, U.S.	5007	-3.923298 (-24.33)*	-2.146525 (-10.77)*	0.177496 (28.58)*	0.887847 (2.69)*	0.246592 (12.02)*	-75.96636 (-3.74)*	0.344
Sales, Annually, EU	1790	-8.297268 (-6.09)*	-5.173839 (-3.49)*	0.808811 (53.27)*	0.704926 (10.01)*	0.887388 (4.46)*	-304.8383 (-1.50)	0.676
Sales, Quarterly, U.S.	12457	0.004307 (1.46)	0.014172 (4.77)*	0.332557 (32.10)*	0.137554 (16.70)*	-0.001055 (-2.87)*	5.467859 (3.34)*	0.140
Sales, Quarterly, EU	650	0.002671 (0.14)	0.015624 (0.90)	-0.124371 (-1.76)***	0.222367 (3.50)*	-0.001808 (-0.85)	-5.853735 (-0.96)	0.028

Table 12. Regression of analysts' forecast errors for earnings on prior period forecast errors and informational uncertainty variables for subperiods 1994-2000 and 2003-2009

Note: The above number is the coefficient value from regression equation and the lower value in brackets is a t-value for the significance of the above value. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity). The values market with * are significant at 1 percent level. values market with ** are significant at 5 percent level.

Financial variable	Sample size	Intercept: Goodnews, $\alpha1$	Intercept: Badnews, $\alpha2$	FE: Goodnews, $\alpha3$	FE: Badnews, $\alpha4$	MKT, $\alpha5$	Sted.dev. of forecasts, $\alpha6$	Adjusted R^2
Earnings, 1994-2000, U.S.	7162	0.000673 (1.87)***	0.001478 (4.07)*	0.217672 (9.11)*	0.159452 (8.01)*	-0.000128 (-2.82)*	-2.33e-5 (-0.87)	0.058113
Earnings, 2003-2009, U.S.	13388	0.000195 (0.44)	0.001191 (2.74)*	0.209882 (13.91)*	0.180548 (13.64)*	-0.000119 (-2.24)**	3.78e-5 (2.15)**	0.060787
Earnings, 1994-2000, EU	153	-0.002497 (-1.16)	-0.001246 (-0.64)	0.017488 (0.09)	0.182486 (1.07)	0.000298 (1.16)	-0.000647 (-0.14)	0.018
Earnings, 2003-2009, EU	648	0.004184 (1.18)	0.006102 (1.51)	0.083519 (0.89)	0.435578 (7.45)*	-0.000603 (-1.35)	0.003628 (3.47)*	0.136

Table 13. Regression of analysts' forecast errors for sales on prior period forecast errors and informational uncertainty variables for subperiods 1994-2000 and 2003-2009

Note: above number is the coefficient value from regression equation and the lower value in brackets is a t-value for the significance of the above value. The percentage forecast errors are calculated with Equation 3 ([Forecast – Actual] / Market value of the equity). The values market with * are significant at 1 percent level. values market with ** are significant at 5 percent level.For sales forecast errors in Eurozone my quarterly sample is too small (<100) to make feasible regression.

Financial variable	Sample size	Intercept: Goodnews, $\alpha1$	Intercept: Badnews, $\alpha2$	FE: Goodnews, $\alpha3$	FE: Badnews, $\alpha4$	MKT, $\alpha5$	Sted.dev. of forecasts, $\alpha6$	Adjusted R^2
Sales, 1994-2000, U.S.	226	-0.004978 (-0.21)	0.005337 (0.22)	0.563157 (4.96)*	-0.077890 (-0.75)	0.000972 (0.34)	20.58531 (0.88)	0.153
Sales, 2003-2009, U.S.	17862	-0.003031 (-3.60)*	0.007117 (8.83)*	0.320523 (34.83)*	0.138355 (20.13)*	-0.000143 (-2.14)**	4.016262 (3.16)*	0.125
Sales, 1994-2000, EU	-	-	-	-	-	-	-	-
Sales, 2003-2009, EU	535	-0.020720 (-1.18)	-0.021182 (-1.25)	0.090394 (1.22)	0.323708 (3.52)*	0.001817 (0.93)	-7.051667 (-1.52)	0.034

Table 14. Chow-test for analysts' forecasting bias for earnings on subperiods 1994-2000 and 2003-2009

Note: The table contains Chow-test results for the similarity of the samples between subsamples. I have used annual earnings forecasting errors because sizes of these samples are fairly close each other. The difference in size for quarterly data to effectively use for Chow-test is too large.

	RSS1	RSS2	TSS	F-test statistics
earnings, U.S.	0,183455401	0,986523629	1,171034013	3,170267024 (0.4%)
earnings, Eurozone	0,005642909	0,291140671	0,297614901	0,36834526 (89.9%)

6. Conclusions

There definitely has happened a change in the U.S. markets after implementation of new regulation (i.e. Reg FD). Forecasting errors for earnings are now much more volatile than earlier. However, some well-known biases' effects have become weaker. This effectively means that analyst get less non-public information from management. This increases volatility of the forecasting errors. At same time the convergence of analysts' forecasts is much stronger than earlier which means that analysts having same kind of information available tend to end to similar conclusions. This has made information environment more equal for analysts and investors. There are differences at which level forecasting errors are recorded: annually or quarterly. At annual level forecasting bias starts from higher level but it is affected less by prior earnings surprises and the company size reduces the bias more strongly. Annual level forecasts become more accurate over time which is quite natural because more data becomes available and quite a large part of the earnings/sales are already known at the very end of the financial year. With interim forecasts this is not the case because every interim forecasts are recorded at the time when there is still one third of the time period still to come (about one month prior the release of the interim reports) whereas with annual forecasts there is only about one tenth of the time period yet to come.

Same kind of development has not happened in the Eurozone markets. The U.S. markets have become informational more efficient whereas the Eurozone markets have remained the same which surely has implications on effectiveness of the capital markets and costs of raising financing for the firms. Almost every single variable's coefficient form regression analysis is

larger in the Eurozone markets than the U.S. markets. There are several very worrisome observations to notice: for example analysts' estimates do not converge at the Eurozone markets which shows that information asymmetry is not reduced and that there are analysts and investors with knowledge which is not available to all other analysts and investors; and it seems that analysts' in the Eurozone markets are more affected by their prior forecasting errors than their counterparts at the U.S. markets. There has been significant development in the U.S. markets which has made that market more competitive and same time the Eurozone has been lost its competitiveness. This might become hindrance for firms located in the Eurozone markets and raise their cost of capital. I compared sales and earnings forecasts in order to find out does analysts' forecasts contain purposely added bias.

Further research will be needed in order to evaluate if investors compensate this difference in the level of information content of the analysts' forecasts in some way or another. It would be interesting to measure whether analysts produce value equally between markets with their recommendations. This study answered to the question whether there are differences between the U.S. and the Eurozone markets in terms of analysts' accuracy. This study also revealed how analysts' forecasts and forecasting errors are related to some well-known biases. More importantly I also tested whether regulation changes at the U.S. markets have improved the information asymmetry and whether has those changes spilled to other highly developed financial markets (i.e. the Eurozone markets).

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