INFORMATION PROCESSING IN FINANCIAL MARKETS – THREE ESSAYS ON EQUITY ANALYSTS

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Contents

Chapter 2 is based on Hess, Kreutzmann, and Pucker (2013), The Good, The Bad, and The Lucky: Projected Earnings Accuracy and Profitability of Stock Recommendations, working paper. Chapter 3 is based on Hess, Kretzmann, Maaz, and Pucker (2013), Sell Side Recommendations during Booms and Busts, working paper. Chapter 4 is based on Orbe and Pucker (2013), Do Aggregate Company Outlooks have Macroeconomic Content?, working paper.

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Chapter 1 – Introduction

Equity analysts play a crucial role in financial markets. Stocks covered by analysts account for more than 95% of U.S. market capitalization (Barber et al. (2001)). Initiation of analyst coverage leads to a boost in stock price of about 5% (Demiroglu and Ryngaert (2010)). Furthermore, investors rely on equity analysts to make investment decisions. The issuance of "Buy" or "Sell" recommendations is associated with a significant stock price reaction in the direction of the recommendation (Womack (1996)). Equity analysts are frequently featured in media outlets such as The Wall Street Journal, which also conducts a yearly survey for the "Best on the Street" analyst. However, since the late 1990s the relevance of analysts has been controversially discussed with a particular focus on analyst conflict of interests (SEC (2002)). Several regulations have been passed since then to mitigate such conflicts.

Security prices of covered firms cannot fully reflect all available information, because if they would, those who commit resources to obtain information would not be compensated. An "equilibrium degree of disequilibrium" is the necessary condition for efficient markets (Grossman and Stiglitz (1980)). Against this backdrop, the relevance of equity analyst in financial markets becomes apparent. Analysts are incented to facilitate profit opportunities for investors by discovering private information. Moreover, their rationale to exist depends on the issuance of research reports that are considered relevant by investors. It is therefore a fruitful research opportunity to explore the information content of analyst outputs, i.e., stock recommendations and earnings forecasts, in greater detail.

This thesis covers three broad research questions: The first paper (chapter 2) "The Good, The Bad, and The Lucky: Projected Earnings Accuracy and Profitability of Stock Recommendations" explores cross-sectional differences among analysts regarding the accuracy of their earnings forecasts and the investment value of their stock recommendations. It focuses on the question whether some analysts add more value in the investment decision process than others and how these analysts can be identified. The second paper (chapter 3) "Sell Side Recommendations during Booms and Busts" switches the focus from the cross-section to the time series. It examines the profitability of analyst stock recommendations across the business cycle. In particular, it studies how the information content of stock recommendations as well as the initial investor reaction depend on the business cycle. The third paper (chapter 4) "Do Aggregate Company Outlooks have Macroeconomic Content?" addresses the question whether aggregated analyst forecasts have predictive power for overall economic developments. The major difference to the previous two chapters is that analyst outputs are studied on an aggregated basis to analyze their macroeconomic content. A new application of analyst recommendations is proposed which mimics a survey among analysts about the overall future development of all companies covered by them.

Chapter 2 explores ability differences among equity analysts. Loh and Mian (2006) show that more accurate analyst earnings forecasts lead to superior firm valuations and in turn to more profitable stock recommendations. Their study is based on a one-dimensional sorting of analysts in terms of their ex post realized earnings accuracy, i.e., they examine the contemporaneous relationship between earnings accuracy and recommendation profitability. Analyst skill variables that have been used for in-sample analyses of earnings accuracy such as the experience of the analyst (e.g., Hilary and Hsu (2013)) are neglected. We argue that this approach cannot differentiate between skill and luck. Some earnings forecasts might simply be more accurate because of randomness. For example, an analyst who is always overly pessimistic will be relatively more accurate when a recession strikes. Following this analyst's recommendations is probably not a good advice, since the demonstrated higher accuracy is based on luck and not on skill. The distinction between luck and skill is very important as earlier studies show that there is little persistency in ex-post rankings of analysts both regarding their earnings accuracy as well as their recommendation profitability. For example, Hall and Tacon (2010) demonstrate that last year's rank tables of earnings accuracy or recommendation profitability do not predict recommendation profitability in the next period.

Our study makes several contributions to the literature. First, we develop a new framework which allows to distinguish between able and lucky analysts, i.e., whether an analyst produces superior outputs due to skill or due to luck, by combining the input–output analysis of Loh and Mian (2006) with the forecast accuracy literature (e.g., Bae, Stulz, and Tan (2008)). In contrast to Loh and Mian (2006), our framework is based on ex ante available information and in is implementable from an investor's perspective. We project out-of-sample analyst earnings accuracy to ex ante identify analysts who produce superior earnings estimates, i.e., analysts with superior knowledge of fundamentals. We find that the distinction between able and lucky analysts is essential. In addition to analyst past performance, investors must take into account analyst skill measures, i.e., look beyond the track record. The track record of an analyst is not sufficient to determine whether an analyst will issue profitable stock recommendations and accurate earnings forecasts in the future. Only able analysts with superior skill measures and a good track record also have high projected earnings accuracy that translates into higher future recommendation profitability. In contrast, recommendations of lucky analysts with a good track record but low skill measures do not have any investment value. These results also explain why the trading strategy suggested by Hall and Tacon (2010) is not profitable since it is based on analyst track records only. Our analysis indicates that the challenging task for investors is to identify and disregard the investment advice of lucky analysts, i.e., analysts that seem to be able just because they delivered a good result last year while in fact they are not.

Second, we find a pronounced heterogeneity among analysts in terms of their recommendation performance and earnings accuracy. Only some analysts add value in the investment decision process. There is a strong difference between able analysts who produce substantial investment value and their unable counterparts whose recommendations actually do not add any value. Our study differs fundamentally to previous studies which identify a link between individual analyst ability measures such as experience and the market impact in an event-study setting (e.g., Sorescu and Subrahmanyam (2006)). We simultaneously combine several analyst characteristics and optimally weight them based on a rolling regression framework to maximize their predictive power. Due to this approach, we find a significantly more pronounced heterogeneity which renders the majority of analyst recommendations worthless. Also, in contrast to an event study design, we use an investor-oriented calendar time approach which allows more informative conjectures about the investment value of recommendations, e.g., in terms of transaction costs. Our findings are of particular relevance for mutual fund managers, since previous literature suggests that mutual fund managers are not capable to differentiate between good and bad sell side research (Busse, Green, and Jegadeesh (2012)). We find that the higher excess return of recommendations by able analysts is not simply caused by a reputation effect. The higher overall return of these recommendations is not driven by the immediate announcement return during the first trading days after the recommendations are issued. Instead, the higher returns materialize over a longer time window of several months. This suggests that able analysts can identify those stocks that outperform the market over a longer period, supposedly because the respective companies repeatedly release “good news”.

Our study contributes to the literature in several ways. We extend the career concerns literature (e.g., Hong and Kubik (2003)) by showing that track records alone are insufficient to reduce information asymmetries in principal-agent relationships, because they can be heavily influenced by lucky outcomes. Our results suggest that analyst promotion and demotion decisions by brokers should be based on a combination of objectively measureable analyst skill attributes and the track record, in particular, if the investment value for clients is of primary concern. From the subset of analysts with a good track record, only those with high skill measures issue profitable stock recommendations and more accurate earnings forecasts in the future. Our study shifts the focus from the career concerns of analysts (e.g., does an analyst with a better track record move to a more prestigious broker?) to the investment value for their clients. A fruitful opportunity for further research is an examination of the career outcomes of lucky analysts. For example, it would be interesting to study to what extent lucky outcomes in terms of earnings forecasts lead to unjustified outcomes on the labor market. The career concerns of lucky analysts over a longer time period might be of particular interest, e.g., are lucky analysts also demoted after not fulfilling initial employer expectations?

Furthermore, our results have important implications for studies using analyst outputs as surrogates for market expectations. Based on our framework, we find that analysts with a significant advantage in forecasting earnings can be identified ex ante. This implies that equity valuation models to estimate the implied cost of capital of a firm (e.g., Gebhardt, Lee, and Swaminathan (2001)) could be improved by using only earnings forecasts of able analysts.

We also present evidence on the rationale of analyst herding. Less skilled analysts perform best if their recommendations coincide with those of skilled analysts. In fact, they only produce investment value if they do not disagree with their more skilled peers. This strongly suggests that unable analysts should have an incentive to mimic more able colleagues. The herding literature so far has produced mixed results. While some studies suggest that analysts tend to follow each other (e.g., Jegadeesh and Kim (2010)), others find that there is also a tendency to anti-herd (e.g., Bernhardt, Campello, and Kutsoati (2006)). However, little attempt has been made to distinguish between more or less skilled analysts and to see whether one group is following the other. Our results suggest that differences in skills may be a driver of (rational) herding behavior.

Our study also complements literature on analyst rankings. Star analysts ranked high in the two most well-known analyst rankings, the "Best on the Street" ranking by the Wall Street Journal and the "All-American Research Team" ranking by Institutional Investor, do not outperform their peers in the year after becoming stars (Emery and Li (2009)). Our results imply that these rankings could be improved by using other criteria, since they do not have out-of-sample investment value for investors. More generally, our study provides a framework for other studies dealing with records that are influenced by lucky outcomes, e.g., studies on mutual fund or CEO performance, in how to differentiate between luck and skill.

Chapter 3 switches the focus from the cross-section to the time series, i.e., we analyze time-specific differences in respect to the information content of analyst recommendations and the investor reaction. It is the first study to examine analyst recommendations against the backdrop of the business cycle. We extend the literature which studies the importance of the business cycle for information processing on capital markets. For example, Boyd, Hu, and Jagannathan (2005) and Beber and Brandt (2010) find that investors process the same information differently depending on the business cycle. We contribute to this literature by showing that the information content of sell side research as well as the reaction of investors to this research is fundamentally different in expansions and recessions. In recessions, investors react significantly stronger to analyst recommendations, i.e., the price impact of recommendations is significantly higher. This finding suggests that sell side research is more valuable for investors in bad times. However, contrary to this notion, we find that "Buy" recommendations on average do not have long-term investment value in recessions. Investors strongly overreact to positively recommended stocks in recessions, indicating that investors overestimate the unique information set of analysts (Grossman and Stiglitz (1980)) in economic downturns. These findings supplement the results from chapter 2. In addition to cross-sectional differences in recommendation profitability (e.g., Hess, Kreutzmann, and Pucker (2012)), we also detect time dependent price formation patterns. While the results in chapter 2 point out that only some analysts add value for investors, the results in chapter 3 show that analysts on average even destroy value in recessions in terms of the long-term investment value of their “Buy” recommendations.

We also contribute to the literature on recommendation profitability (e.g., Barber et al. (2001)) by showing that recommendation profitability is correlated with the business cycle. Therefore, it is important to control for the effects of macroeconomic fluctuations when assessing analysts’ stock recommendations. Specifically, we find that for “Buy” recommendations the initial excess return on the first four trading days is 0.67% higher in recessions than in expansions. For upgraded stocks, the difference is with 1.05% even larger. For “Sell” recommendations the initial excess return in recessions is 0.9% lower than in expansions respectively 1.26% lower for downgraded stocks. Over a longer time horizon, “Buy” recommendations generate positive excess returns of 0.38% over six months after the recommendation issuance (excluding the recommendation announcement day) in an expansion, but negative excess returns of -1.60% in recessions. This return difference of 1.98% is similar for upgraded stocks. “Sell” recommendations generate an additional negative excess return of -2.83% in recessions compared to -2.02% in expansions after the recommendation announcement day.

Moreover, we contribute to previous literature on systematic biases (e.g., Jegadeesh et al. (2004)). We find that analysts favor “glamour” stocks during recessions and expansions. The preference of analysts for “glamour” stocks is even slightly higher in recessions. The underlying economic rationale for this bias is questionable, since Lakonishok, Shleifer, and Vishny (1994) show that returns of growth stocks are lower in comparison to those of value stocks in recessions. Analyst recommendations are not fully in line with quantitative investment signals, particularly in economic downturns.

Chapter 4 of this thesis is based on the working paper "Do Aggregate Company Outlooks have Macroeconomic Content?". This paper explores the information content of aggregated stock recommendations for macroeconomic developments. The underlying economic rationale of our study is the fact that the U.S. economy consists to a substantial extent of firms listed on the stock market. About one-third of all employees in the U.S. private business sector work at publicly traded companies (Davis (2006)). We therefore hypothesize that the development of the overall economy is significantly related to the development of firms listed on the stock market. As a measure for expected firm developments we use analyst stock recommendations. Equity analysts collect and process information at the firm level for publicly traded companies. Besides public macroeconomic-, industry- and company-specific content their information set should also comprise non-public company-specific information (Grossman and Stiglitz (1980)). Our central research question is whether aggregated analyst recommendations as a measure for the overall economic outlook of firms have predictive power for macroeconomic developments. We thereby follow the notion that the economy as a whole is the sum of all its individual parts.

This paper contributes to the literature in several ways. First, we show that aggregated analyst outputs contain predictive power for future macroeconomic developments of about one year. The information content of aggregated analyst outputs is supplementary to well-established macroeconomic predictors such as the Leading Economic Indicator, the equity risk premium, the dividend yield, the default spread, the term spread, and the 3-month T-Bill rate. Therefore, aggregated analyst recommendations are useful for macroeconomic forecasts which are substantial to guide monetary policy decisions or federal tax cuts to stimulate economic growth.

Second, our results provide a link between the studies of Howe, Unlu, and Yan (2009) and Stock and Watson (1998). Stock and Watson (1998) show that the stock market leads the real economy, while Howe, Unlu, and Yan (2009) provide evidence that aggregate analyst recommendations predict the overall stock market. Our results fill the missing link between both studies, since we find that aggregate analyst recommendations also predict the real economy. We provide evidence that changes in expectations about future firm performance rationally (i.e., correct on average) determine asset values before overall economic activity changes. Therefore, our results provide a potential explanation for the old Wall Street saying that the stock market leads the economy.

Third, we contribute to the literature on the information content of equity analyst outputs. We provide additional evidence that equity analysts provide useful information as intermediaries between firms and investors. Analyst outputs contain predictive power for macroeconomic developments. Implicitly or explicitly analysts anticipate macroeconomic developments when collecting information about the firms they cover. This finding supports the argument that the resources spent by information intermediaries are rewarded in terms of an information advantage.

Chapter 2 – The Good, The Bad, and The Lucky: Projected Earnings Accuracy and Profitability of Stock Recommendations

2.1 Introduction

Estimates about future company earnings are crucial to make stock investments. Firms that beat earnings expectations usually experience a significant stock price increase, while firms that fall short of earnings expectations can be severely punished by investors. Consequently, earnings forecasts are a central input for sell side analysts when making stock recommendations. More accurate earnings forecasts lead to superior firm valuations and in turn to more profitable stock recommendations. In this study, we analyze whether investors can identify ex ante more profitable stock recommendations when following analysts with higher projected earnings accuracy, i.e., analysts with superior knowledge of fundamentals.

Most closely related to our research are the studies of Loh and Mian (2006) and Hall and Tacon (2010). Loh and Mian (2006) indicate a link between the accuracy of earnings projections and the profitability of recommendations. They show that following the recommendations of analysts who issue the most accurate earnings forecasts yields significant excess returns. This is plausible, because earnings forecasts and recommendations should be related, at least contemporaneously. However, the trading strategy suggested by Loh and Mian (2006) involves a look-ahead bias. To implement such a strategy investors would need to know in advance which analysts will have issued the most accurate earnings forecasts at the end of a given period. Hall and Tacon (2010) avoid this look-ahead bias and propose an implementable trading strategy focused on past performance, i.e., to follow only those analysts who have issued the most accurate earnings forecasts and/or the most profitable recommendations for the last period. Interestingly, their trading strategy does not yield excess returns.

Our interpretation of these conflicting results is that following analysts' recommendations based on analysts' past earnings track records alone does not adequately differentiate between analysts that have been lucky and analysts that are more able. In every period there may be some analysts whose earnings projections hit the target best just because some unforeseeable events happened. For example, an analyst who is always overly pessimistic will be relatively more accurate when a recession strikes. However, following this analyst's recommendations next year is probably not a good advice, since the demonstrated higher accuracy was based on pure chance and not skill.

We project out-of-sample the firm-specific annual earnings accuracy of analysts to ex ante identify analysts who produce superior earnings estimates. When forecasting analyst earnings accuracy, we only include information that is available ex ante. We therefore avoid the look-ahead bias from Loh and Mian (2006). Since past earnings accuracy does not sufficiently forecast future accuracy (Hall and Tacon (2010)), our forecast model additionally uses analyst skill proxies that have shown explanatory power for earnings accuracy in-sample. For example, we use the experience of the analyst (e.g., Clement and Tse (2005), Hilary and Hsu (2013)) and the size of the broker the analyst is working for (e.g., Malloy (2005), Bae, Stulz, and Tan (2008)). A similar overall approach, albeit in a different field of research, is used by Boyer, Mitton, and Vorkink (2010) when identifying stocks with high idiosyncratic skewness: Since lagged skewness alone does not adequately forecast skewness, the authors use additional predictive variables.

First, we document that investors actually can profit from the contemporaneous link between earnings accuracy and the recommendation profitability in the 1994 to 2010 time period. We rank analysts according to their projected earnings accuracy and define analysts with high projected earnings accuracy as "able" and analysts with low projected earnings accuracy as "unable". Using an implementable trading strategy, we find that the recommendations of able analysts generate significant positive excess returns of 5.17% p.a. for the long portfolio and

7.57% p.a. for the long-minus-short portfolio, while the recommendations of unable analysts do not generate significant excess returns. Our findings suggest that only able analysts add value in the investment process. Investors must filter out the value-adding investment advice from sell side analysts to realize excess returns. In terms of transaction cost the critical threshold for the long portfolio is 1.53% per round-trip transaction. The market capitalization of the average stock covered by able analysts is with $8.4 billion relatively high therefore making it likely that investors can profit from able analysts even after accounting for transaction costs.

Second, we define analysts as "lucky" if they have issued relatively more accurate earnings forecasts in the past, but are projected to issue relatively less accurate earnings forecasts in the future (i.e., a good track record, but low projected earnings accuracy). We find that recommendations of lucky analysts do not yield positive excess returns. Only analysts who have a good track record and high projected earnings accuracy due to their superior skill measures issue profitable recommendations. Our results suggest that investors must take into account the skills of analysts in addition to their past performance, i.e., look beyond their track record. This result also explains why the trading strategy of Hall and Tacon (2010) does not yield excess returns. The track record of an analyst is not sufficient to determine whether the analyst will issue profitable stock recommendations in the future. Investors must combine the track record with analyst skill measures to differentiate between able and lucky analysts. Only analysts with high skill proxies and a good track record also have a high projected earnings accuracy that translates into higher future recommendation profitability.

Third, we observe significant differences in the profitability of individual stock recommendations issued by able, unable, and lucky analysts. Specifically, we evaluate the excess returns of recommendations if we hold a recommended stock until the corresponding earnings have been announced, until the point in time when the superior (versus inferior) forecasting ability materializes in a projected smaller (versus larger) surprise. We find that especially “Strong Buy” and “Buy” recommendations of able analysts earn significantly higher returns than “Strong Buy” and “Buy” recommendations of unable or lucky analysts. This result indicates that able analysts can identify undervalued stocks.

Fourth, we find that the higher excess return of the “Strong Buy” and “Buy” recommendations of able analysts is not simply caused by a reputation effect, this means that the higher overall return of these recommendations is not driven by the immediate announcement return during the first trading days after the recommendations are issued. Instead, the higher returns materialize over a longer time window of several months. This suggests that able analysts can identify those stocks that outperform the market over a longer period, supposedly because these companies repeatedly release “good news”. Our results can be interpreted as evidence that stock recommendations from able analysts add value in the investment decision process.

Finally, when comparing the ex-post realized earnings accuracy among analysts in the projected accuracy quintiles, we find statistically and economically significant differences: the price-scaled absolute forecast error of able analysts is only half as large as the error of unable or lucky analyst (0.91% compared to 2.02% and 1.97%, respectively). In terms of absolute dollar values able analysts are about $0.21 more accurate. Assuming an average Price-to-Earnings ratio of 10, this advantage would translate into a stock valuation that is about 9% more accurate (based on a median stock price of $21 in our sample). These results suggest that the lower forecast error of able analysts also translates into higher recommendation profitability.

Overall, our study provides evidence that the heterogeneity in analysts’ skill can be exploited by investors. To achieve excess returns, investors should only follow a subset of analysts with favorable characteristics. These analysts can be identified ex ante based on their projected future earnings accuracy. However, investors should not rely on analysts’ track records alone, since track records are not very informative on a stand-alone basis. Only when combined with skill measures track records have predictive value out-of-sample.

Our study contributes to the literature in several ways. We extent the analyst career concerns literature (e.g., Hong and Kubik (2003)) by showing that track records alone are not sufficient to reduce information asymmetries in principal-agent relationships, since they can be heavily influenced by lucky outcomes. We shift the focus from the career concerns of analysts, i.e., does an analyst with a better track record move to a more prestigious broker, to the investment value for the clients. Interestingly, the two most well-known analyst rankings, the "Best on the Street" ranking by the Wall Street Journal and the "All-American Research Team" ranking by Institutional Investor, do not have any significant investment value (Emery and Li (2009)). Our results suggest that analyst rankings as well as promotion and demotion decisions by brokers should be based on a combination of objectively measureable analyst skill attributes and the track record, in particular if the investment value for clients is the primary concern. From the subset of analysts with a good track record, only those with high skill measures issue profitable stock recommendations and more accurate earnings forecasts in the future. Our research is also of interest for studies that deal with track records which are potentially influenced by lucky outcomes, e.g., when analyzing mutual fund or CEO performance. Furthermore, our findings are of particular relevance to mutual fund managers, since they are not able to differentiate between good and bad sell side research (Busse, Green, and Jegadeesh (2012)). In addition, our results have implications for studies using analysts' outputs as surrogates for market expectations. As an example, equity valuation models based on discounted expected cash flows or (residual) earnings would be improved by using only superior forecasts, thereby reducing measurement error.[1]

[1] For example, the quality of estimated risk premia implied in stock prices is presumably strongly affected by the quality of earnings forecasts (see, e.g., Bestelmeyer, Breunsbach, and Hess (2011)).

The remainder of this paper is organized as follows. Section 2.2 introduces the research design. Section 2.3 describes the data and explains the empirical approach in detail. Section 2.4 presents the empirical results. Finally, section 2.5 concludes the paper.

2.2 Research Design

Our main research question is whether analysts who issue more profitable stock recommendations can be identified ex ante when forecasting their earnings accuracy. Hence, we predict the forecast accuracy of an analyst at the point in time when she provides her earnings forecast. Our approach is distinct from previous studies as we avoid a look-ahead bias. Furthermore, the predictive accuracy model incorporates several ability proxies to differentiate among analysts. Our approach comprises three steps:

In the first step, we project out-of-sample the accuracy of annual earnings forecasts based on two different information sets: the first information set, I_{TRACK}, incorporates exclusively the analysts' past earnings accuracy (her "track record"). We consider both the firm–specific track record and the track record over all companies covered by the analyst and use track records over the preceding one and two years. The second information set used for forecasting, I_{FULL}, includes I_{TRACK} and additionally the information set I_{SKILL} which consists of characteristics approximating analyst skill, such as her experience or her working environment. While these characteristics may not directly measure ability they are at least thought to be highly correlated with an analyst's ability to generate accurate forecasts or her effort in doing so. Although both I_{TRACK} and I_{SKILL} provide imperfect proxies for the ability of an analyst to generate accurate forecasts, the distinction is crucial because the two are differently affected by noise. For example, an inexperienced analyst may have had luck last year, but luck is by definition not persistent. Then I_{TRACK} would erroneously signal a high ability while I_{SKILL} would not. Nevertheless, there may be two equally experienced analysts but one of them can better play out her experience and provide persistently more accurate forecasts. In this case, I_{TRACK} provides additional useful information. Hence, looking at both I_{TRACK} and I_{SKILL} together, i.e., at I_{FULL}, provides a better assessment of an analyst's true ability.

In the second step, we classify analysts based on their projected earnings accuracy. We define an analyst with high (low) projected accuracy according to I_{FULL} as able (unable). In a separate analysis, we rank analysts by independently sorting according to I_{TRACK} and I_{FULL} to differentiate between analysts who have high past earnings accuracy and high projected earnings accuracy and analysts who have high past earnings accuracy and low projected earnings accuracy, i.e., lucky analysts. Lucky analysts appear to be able based on their past earnings accuracy, although they are unable according to their skill measures.

In the third step, we analyze the recommendation profitability of able, unable and lucky analysts separately. We use two different evaluation procedures: a trading strategy and an event-study design.

2.3 Data and Methodology

2.3.1 Data

We use two analyst outputs: (1) annual earnings forecasts and the corresponding actual earnings from the Institutional Brokers Estimate System (I/B/E/S) and (2) stock recommendations by individual analysts also from I/B/E/S. Daily stock returns and daily market capitalizations come from The Center for Research in Security Prices (CRSP). To calculate excess returns we use daily Fama and French and momentum factors provided by Kenneth R. French's website.[2] We retrieve equity book values of individual companies from Compustat to calculate daily excess returns according to Daniel et al. (1997). Our sample

[2] See Fama and French (1993) and Carhart (1997). The factors are retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

starts in 1994, since recommendations in I/B/E/S are only available beginning in late 1993. Our final sample of recommendations covers the 1994 to 2010 time period.

We retrieve individual analysts' annual earnings forecasts from the I/B/E/S unadjusted detail files. We use earnings forecasts issued from January 1993 to December 2010 and we readjust the earnings following the recommendation of Wharton Research Data Services (WRDS).[3] We keep the forecasts issued in 1993, since we classify analysts beginning in January 1994 based on the accuracy model covering the previous twelve months t-12. We apply the following filters to the data set: (1) we drop all firms that cannot be matched with CRSP, since stock returns are required for the trading strategy. (2) we only keep analysts in the sample that do not remain anonymous, since otherwise the characteristics of the analysts cannot be calculated for the accuracy model. (3) In line with the I/B/E/S guidelines, we use primary earnings until 1997 and diluted earnings from 1998 on. (4) we drop all observations which are issued more than two years before the earnings report date. (5) To control for obvious data errors, we drop all forecasts with a share price scaled forecast error above 25% (e.g., Loh and Mian (2006)). (6) We only keep firm years for which at least two analysts issue earnings forecasts, since the analyst characteristics are standardized relatively to other analysts issuing forecasts in the same firm year (e.g., Clement and Tse (2005)). (7) In line with previous studies (e.g., Hillary and Hsu (2013)) we only keep the last forecast issued by an analyst in the fiscal year in the regression analysis. We obtain a total of 709,450 earnings forecasts.

We use the following filters for the stock recommendations: (8) we drop analysts that remain anonymous in I/B/E/S, since these analysts cannot be classified according to their characteristics. (9) In order to control for data errors we keep only one recommendation if more than one recommendation with the same rating, for the same firm, by the same analyst

[3] Specifically, we follow "Method 3" suggested by Robinson and Glushkov (2006) which perhaps is "the most reliable and accurate way of joining Unadjusted Detail History and Actuals".

on the same day has been issued. Our final sample consists of 331,121 stock recommendations. For convenience, the data filters and the corresponding number of observations for the annual earnings forecasts and the stock recommendations are summarized in Table 2.8 in Appendix 2 B.

2.3.2 Projected Earnings Accuracy

In the first step, we project the accuracy of earnings forecasts out-of-sample based on two different information sets I_{FULL} and I_{TRACK}. The out-of-sample projection is based on analyst- and forecast characteristics that have shown explanatory power for earnings accuracy in-sample: BROKER_SIZE, the size of the broker the analyst is working for, (e.g., Bae, Stulz, and Tan (2008)), FOR_FREQUENCY, the frequency with which the analyst issues earnings forecasts (e.g., Clement and Tse (2005)), FIRM_EXPERIENCE, the number of years the analyst has covered the firm (e.g., Hilary and Hsu (2013)), GEN_EXPERIENCE, the overall number of years the analyst has covered firms (e.g., Sonney (2009)), COMPANIES, the number of companies the analyst covers (e.g., Clement and Tse (2005)), INDUSTRIES, the number of industries the analyst covers (e.g., Clement and Tse (2005)), BOLD, the distance between the analyst's forecast and the consensus forecast (e.g., Hilary and Hsu (2013)), LAG_ACCURACY, the analyst's earnings accuracy from the previous fiscal year for the firm (e.g., Clement and Tse (2005)), GEN_ACCURACY, the analyst's earnings accuracy from the previous fiscal year for all firms he covered (e.g., Brown and Mohammad (2010)), DAYS_ELAPSED, the time elapsed since the last forecast issued by any analyst covering the firm (e.g., Clement and Tse (2005)), and FOR_HORIZON, the number of days between the forecast date and the fiscal year end (e.g., Malloy (2005)).[4]

We use a rolling regression in order to avoid a look-ahead bias. The regressions are performed at the end of each month during the sample period 1/1994 to 12/2010. Hence, we

[4] See Appendix 2 A for a more detailed description of the variables.

run 204 regressions. The rolling time window of these regressions covers the previous 12 months before the month in which the earnings forecast was published. We produce out-of-sample predictions of earnings accuracy based on the estimated analyst characteristics parameters from the rolling regression along with the observable characteristics at the time the earnings forecast is issued. Hence, we only use information available at the point in time when an analyst provides her earnings forecast. The rolling regression approach has the advantage that it can account for non-stable relationships between characteristics and earnings accuracy. For example, broker size and firm-specific experience lose their explanatory power for earnings accuracy after Regulation FD in 2000 (Findlay and Mathew (2006)).

As an example, consider how the accuracy is projected for an earnings forecast that was issued in August 2006 for a firm with a fiscal year ending in December 2006: If an analyst issues an earnings forecast in August of 2006, the firm-specific characteristics of the analyst and the forecast are calculated for August of 2006. The earnings accuracy (for the fiscal year end) is projected by combining the analyst's characteristics of August 2006 with the coefficients of the regression covering the August of 2005 to July of 2006 time period. When projecting the accuracy of the earnings forecast we separately use the two different information sets, e.g., only past earnings accuracy I_{TRACK} or I_{FULL} which combines I_{TRACK} and analyst skill measures I_{SKILL}. Since the reported earnings must be known to calculate earnings accuracy, in the regression we include only annual earnings forecasts for which the actuals have been already reported. The characteristics used for the out-of-sample projection of earnings accuracy can be classified into two information sets:

I_{SKILL}: Includes seven proxies for analyst skill, including the size of the broker the analyst is working for (BROKER_SIZE), the frequency with which the analyst issues earnings forecasts (FOR_FREQUENCY), the amount of time the analyst has covered the firm in the past (FIRM_EXPERIENCE), the amount of time the analyst has overall covered firms

(GEN_EXPERIENCE), the number of companies the analyst covers (COMPANIES), the number of industries the analyst covers (INDUSTRIES), and the deviation of the earnings forecast from the consensus (BOLD).

I_{TRACK}: Includes two proxies for the track record, including the analyst's earnings accuracy from the previous fiscal year for the same firm (LAG_ACCURACY) and the analyst's earnings accuracy from the previous fiscal year for all firms covered (GEN_ACCURACY).

Additionally, we control for two forecast characteristics, including the time elapsed since the last forecast issued by any analyst covering the firm (DAYS_ELAPSED) and the horizon of the forecast (FOR_HORIZON).

We separately analyze two different information sets I_{TRACK} and I_{FULL}. When we evaluate the power of past performance (I_{TRACK}) for projecting earnings accuracy, we only include the track record and the forecast characteristics into the rolling regression. In contrast, I_{FULL} additionally includes the analyst skill proxies (I_{SKILL}). Below, the case for the entire information set, I_{FULL}, is shown (coefficients 1–7 account for the information set I_{SKILL}, coefficients 8–9 for I_{TRACK}, and 10–11 for the forecast control variables):

$$\begin{aligned} ACCURACY_{ijt\text{-}1} = {} & \alpha_0 + \alpha_1 BROKER\_SIZE_{ijt\text{-}1} + \alpha_2 FOR\_FREQUENCY_{ijt\text{-}1} \\ & + \alpha_3 FIRM\_EXPERIENCE_{ijt\text{-}1} + \alpha_4 GEN\_EXPERIENCE_{jt\text{-}1} \\ & + \alpha_5 COMPANIES_{ijt\text{-}1} + \alpha_6 INDUSTRIES_{ijt\text{-}1} + \alpha_7 BOLD_{jt\text{-}1} \\ & + \alpha_8 LAG\_ACCURACY_{ijt\text{-}1} + \alpha_9 GEN\_ACCURACY_{ijt\text{-}1} \\ & + \alpha_{10} DAYS\_ELAPSED_{ijt\text{-}1} + \alpha_{11} FOR\_HORIZON_{ijt\text{-}1} + \varepsilon_{ijt\text{-}1} \end{aligned} \tag{2.1}$$

In line with previous studies, the characteristics and earnings accuracy are standardized relatively to other analysts to control for time- and firm-specific effects.[5] A characteristic of

[5] See, for example, Clement and Tse (2005), Herrmann and Thomas (2005), and Dechow and You (2012). Our results are similar, albeit weaker, when we standardize the variables according to Hong and Kubik (2003), i.e., ranking the analysts according to $\text{Score}_{\text{ijt-1}} = 100 - \left[\frac{\text{Rank-1}}{\text{Number of Analysts}_{jt} - 1} \right] \cdot 100$. For example, if a stock is followed by three analysts, the most accurate analyst, the mean analyst, and the least accurate analyst are assigned a score of 100, 50, and 0, respectively. The problem with this ranking is that the absolute differences between the analyst characteristics, e.g., in terms of the forecast error, are not taken into account.

analyst i (respectively of the forecast) for company j in time t-1 as explanatory variable is defined as:

$$CHARACTERISTIC_{ijt\text{-}1} = \frac{RAW\_CHARACTERISTIC_{ijt\text{-}1} - RAW\_CHARACTERISTIC\min_{jt\text{-}1}}{RAW\_CHARACTERISTIC\max_{jt\text{-}1} - RAW\_CHARACTERISTIC\min_{jt\text{-}1}} \qquad (2.2)$$

Analogously, the accuracy of the earnings forecasts is standardized relatively to other analysts who issued earnings forecasts in the same period t-1 for the same company j:

$$ACCURACY_{ijt-1} = \frac{AFE\max_{jt-1} - AFE_{ijt-1}}{AFE\max_{jt-1} - AFE\min_{jt-1}} \qquad (2.3)$$

The results of the OLS rolling regression where I_{FULL} is used as the information set are shown in Table 2.1:

Table 2.1: Summary Statistics of the Rolling Regression

This table shows the summary statistics of the OLS rolling regression (with White-corrected standard errors) performed in the 12/1993 to 11/2010 time period. The regression analysis is performed monthly covering the respective previous twelve months. The definitions of the characteristics can be found in Appendix 2 A. Column 2 shows the coefficient's arithmetic mean. Column 3 shows the percentage of the coefficients that are positive, column 4 shows the standard deviation of the coefficients, column 5 shows the average absolute t-value, column 6 and 7 show the minimum respectively the maximum value of the coefficients.

				Average # of obs.		22,774
				Average R^2		0.327
Characteristic	Average Coeff.	% of Coeff. > 0	Standard Dev. of Coeff.	Avg. abs. t-value	Min. Coeff.	Max. Coeff.
BROKER_SIZE	-0.007	26.5	0.013	2.36	-0.031	0.017
FOR_FREQUENCY	0.066	100.0	0.027	8.59	0.012	0.104
FIRM_EXPERIENCE	-0.011	23.0	0.014	1.97	-0.052	0.013
GEN_EXPERIENCE	0.008	77.5	0.011	1.40	-0.012	0.790
COMPANIES	0.002	56.4	0.013	1.57	-0.028	0.024
INDUSTRIES	-0.019	5.9	0.013	3.00	-0.040	0.020
BOLD	-0.082	4.9	0.061	7.86	-0.209	0.004
LAG_ACCURACY	0.082	100.0	0.018	10.39	0.027	0.115
GEN_ACCURACY	0.103	100.0	0.032	6.22	0.049	0.170
DAYS_ELAPSED	-0.063	0.0	0.021	5.96	-0.101	-0.013
FOR_HORIZON	-0.740	0.0	0.064	65.94	-0.844	-0.588
constant	0.699	100.0	0.052	50.30	0.585	0.790

On average we use 22,774 observations in each of the 204 regressions. Overall, the results are in line with other studies such as Clement and Tse (2005). We find differences in respect to broker size (BROKER_SIZE) and the number of companies covered (COMPANIES), since these characteristics do not have a time-stable impact on earnings accuracy. Also, in contrast to Clement and Tse (2005), we find that firm experience (FIRM_EXPERIENCE) has overall a negative impact on earnings accuracy. Regulatory changes are possible reasons for changes in the relationship between characteristics and earnings accuracy. The advantage of our rolling regression approach is that it incorporates such non-stable relationships. Determining the influence of the characteristics only once, e.g., at the beginning of the sample period, would not be sufficient to capture this effect.

Next, we produce one-step-ahead forecasts of earnings accuracy based I_{SKILL} and I_{TRACK}. The characteristics of the analysts and forecasts are standardized relative to the annual earnings forecasts made in the respective previous 12 months. The one-step-ahead projection based on I_{FULL} is given by

$$\begin{aligned} \widehat{INTRINSIC\_ACCURACY}_{ijt} = {} & \widehat{\alpha}_0 + \widehat{\alpha}_1 BROKER\_SIZE_{ijt} + \widehat{\alpha}_2 FOR\_FREQUENCY_{ijt} \\ & + \widehat{\alpha}_3 FIRM\_EXPERIENCE_{ijt} + \widehat{\alpha}_4 GEN\_EXPERIENCE_{ijt} \\ & + \widehat{\alpha}_5 COMPANIES_{ijt} + \widehat{\alpha}_6 INDUSTRIES_{ijt\text{-}1} + \widehat{\alpha}_7 BOLD_{ijt} \\ & + \widehat{\alpha}_8 LAG\_ACCURACY_{ijt} \widehat{+ \alpha_9} GEN\_ACCURACY_{ijt}, \end{aligned} \tag{2.4}$$

where $\widehat{\alpha}_i$ are the coefficients obtained from the rolling regression. We do not include the forecast characteristics in the projection, because the forecast horizon and the time elapsed since the last forecast are not intrinsic characteristics of the analyst. For example, an analyst issuing a forecast two months before the end of the fiscal year is very likely to be more accurate than an analyst issuing a forecast six months before the end of the fiscal year, even if the latter analyst has superior forecast abilities. We focus on the forecast ability of an analyst, estimated only on the basis of an analyst's skill proxies and her track record.

2.3.3 Identification of Able, Unable and Lucky Analysts

In a second step, we use the projected intrinsic accuracy to identify able, unable and lucky analysts. Specifically, we rank analysts according to their projected intrinsic accuracy

(Equation (2.4)). The ranking is conducted monthly during the period from 1994 to 2010. In line with previous studies (e.g., Loh and Mian (2006)) we use quintiles for discriminating between analysts. The classification is firm-specific. This implies that an analyst may be simultaneously classified as able for one company and unable for another company, e.g., because he has covered one of the two companies longer and therefore has a better understanding of the company fundamentals respectively is more connected within the firm. The quintiles for the analyst classification are calculated market-wide, i.e., all analysts classified in a given month are compared across firms. Analyst characteristics are standardized to control for firm- and time-specific effects. The advantage of this approach is that we do not require at least five analysts issuing an earnings forecast for the same firm in a given month. The firm-specific classification is effective until the firm's (for which the forecast is issued) fiscal year report date or until the classification changes. For example, an analyst could be classified as neither able nor unable according to her first earnings forecast for a given firm but as able according to the second earnings forecast made by her for the same firm year (e.g., because she has moved to a different broker in between).

We monthly classify analysts as able (unable) if they belong to the upper (lower) intrinsic accuracy quintile according to information set I_{FULL}, i.e., we incorporate all available analyst information according to our model. Next, we sort analysts independently according to their past earnings accuracy (I_{TRACK}) and their past earnings accuracy and skill proxies combined (I_{FULL}) in order to differentiate between the lucky winners and the able winners of the earnings game. We use one-year and two-year earnings track records.[6]

We classify analysts as lucky if they belong to the upper two intrinsic accuracy quintiles in terms of I_{TRACK} and to the lowest intrinsic accuracy quintile in terms of I_{FULL}. This implies

[6] In the case of the two-year track record the information set I_{FULL} incorporates the two-year track record as well.

that lucky analysts have a superior earnings track record, but are unable according to their skill proxies.[7]

Table 2.2 reports summary statistics for the final sample of stock recommendations we obtain after linking analysts' earnings forecasts and recommendations. The sample covers the 1994 to 2010 time period and consists of 331,121 recommendations. 50,602 recommendations come from analysts classified as able, 86,466 recommendations from unable, and 10,161 recommendations from lucky analyst. As a remainder, the same amount of analysts is classified as able and unable based on their projected earnings accuracy. Therefore, the numbers indicate that unable analysts are more active in issuing stock recommendations. Table 2.2 also shows that able analysts on average cover stocks with a market capitalization above the mean of the covered stocks, while unable and lucky analysts cover stocks with a smaller market capitalization:

[7] Technically, we identify analysts with a high projected earnings accuracy based on only their past earnings accuracy. However, only analysts with high past earnings accuracy can have high projected earnings accuracy according to equation (2.4).

Table 2.2: Summary Statistics for the Stock Recommendations

This table provides the number of recommendations issued, the number of stocks covered, and the number of analysts for each year in the 1994 to 2010 sample period. The last row gives the average market capitalization (USD in thousands) of the covered stocks (on the day the recommendations are issued). Lucky analysts are classified based on their one-year track record.

	All Analysts			Able Analysts			Unable Analysts			Lucky Analysts		
Year	Recs	Stocks	Analysts	Recs	Stocks	Analysts	Recs	Stocks	Analysts	Recs	Stocks	Analysts
1994	15,063	2,539	1,594	2,532	393	228	3,902	778	501	308	261	206
1995	14,896	2,640	1,756	2,339	374	253	3,948	853	502	152	125	112
1996	12,741	2,585	1,888	1,906	345	252	3,495	835	615	253	220	189
1997	9,289	2,475	1,750	1,577	422	289	2,352	722	500	67	61	63
1998	16,860	2,959	2,534	2,327	387	337	4,988	1,019	792	244	214	195
1999	19,384	3,165	2,753	2,731	428	317	5,335	1,045	843	1,015	691	644
2000	17,024	2,878	2,680	2,192	343	310	4,662	975	821	440	361	339
2001	18,319	2,793	2,563	2,590	473	310	6,224	1,005	1,086	1,226	759	686
2002	29,756	2,928	2,698	4,658	505	335	8,218	924	914	1,371	797	661
2003	24,452	2,868	2,674	3,533	433	358	6,583	906	887	484	367	307
2004	21,239	2,855	2,822	2,998	373	358	5,748	1,006	846	543	423	357
2005	19,659	3,045	2,836	3,175	376	424	4,813	1,004	741	539	425	391
2006	20,522	3,166	2,856	3,448	474	467	4,628	926	719	688	531	495
2007	21,876	3,184	2,897	3,757	465	434	4,820	901	760	887	612	563
2008	25,150	3,257	2,895	3,898	421	362	5,969	1,031	822	708	540	486
2009	23,345	2,982	2,725	3,505	403	343	5,742	935	804	600	451	431
2010	21,546	2,923	2,910	3,436	406	454	5,039	900	765	636	498	461
Total	331,121	49,242	42,831	50,602	7,021	5,831	86,466	15,765	12,918	10,161	7,336	6,586
MC Ø		8,432,402			9,279,443			6,241,638			7,240,515	

Table 2.3 reports the summary statistics for the mean analyst characteristics. Able analysts issue significantly more earnings forecasts for the firms they cover, cover less industries, deviate less from the consensus forecast, and have issued significantly more accurate forecasts in the previous year. The characteristics of the unable and lucky analysts are very similar with exception of the past earnings accuracy, since lucky analysts are defined as analysts with high past earnings accuracy and low skill.

Table 2.3: Summary Statistics for the Analyst Characteristics

This table reports summary statistics for the analyst characteristics. Lucky analysts are classified based on their one-year track record. Panel A shows the unstandardized analyst characteristics. Forecast Frequency is the number of forecasts issued by the analyst in the firm year. Boldness is the absolute deviation in dollar from the 90-day consensus on the day the forecast is issued. Lagged Accuracy is the price-scaled absolute forecast error for the same firm in the last fiscal year. General Accuracy is the price-scaled absolute forecast error over all firms in the last year. The second part of the table shows the standardized analyst characteristics. The definitions of the standardized analyst characteristics can be found in Appendix 2 A.

	All Analysts	Able (Q5)	Q4	Q3	Q2	Unable (Q1)	Lucky
Broker Size (# analysts)	53.82	52.70	54.95	55.33	55.00	51.63	57.69
Forecast Frequency (#)	4.74	7.39	5.83	4.76	3.87	3.19	3.05
Firm Experience (years)	3.61	3.99	3.94	3.66	3.37	3.34	2.77
General Experience	7.32	7.66	7.59	7.35	7.09	7.12	6.51
# of covered Companies	15.72	15.53	16.16	15.92	15.83	15.29	13.84
# of covered Industries	3.85	3.46	3.74	3.86	3.96	4.03	3.89
Boldness ($)	0.17	0.09	0.12	0.14	0.18	0.25	0.39
Lagged Accuracy (%)	0.72	0.32	0.38	0.48	0.65	1.41	0.30
General Accuracy (%)	0.74	0.51	0.59	0.66	0.74	1.04	0.45
BROKER_SIZE	0.38	0.36	0.38	0.38	0.39	0.39	0.42
FOR_FREQUENCY	0.43	0.73	0.54	0.42	0.34	0.28	0.22
FIRM_EXPERIENCE	0.38	0.42	0.40	0.37	0.34	0.37	0.27
GEN_EXPERIENCE	0.40	0.42	0.41	0.39	0.38	0.40	0.34
COMPANIES	0.39	0.39	0.40	0.39	0.39	0.39	0.38
INDUSTRIES	0.35	0.27	0.32	0.34	0.36	0.40	0.42
BOLD	0.28	0.13	0.17	0.22	0.30	0.46	0.64
LAG_ACCURACY	0.81	0.95	0.93	0.89	0.83	0.57	0.97
GEN_ACCURACY	0.81	0.88	0.86	0.84	0.81	0.72	0.91

The mean analyst characteristics should be interpreted carefully, however, since we use a dynamic model. While past accuracy and forecast frequency have a stable impact on earnings accuracy, the impact of the other characteristics varies over time and in some cases even reverses. For example, able analysts tend to cover a relatively small amount of companies in the 1994 to 1997 time period, while they cover significantly more companies in the 2006 to 2010 period (unreported results). Our model accounts for such non-stable relationships.

2.3.4 Profitability of Recommendations

2.3.4.1 Trading Strategy

We analyze the profitability of recommendations issued by able, unable, and lucky analysts. In order to facilitate a comparison to previous studies, we perform a trading strategy similar to Loh and Mian (2006) and Barber et al. (2001), however, using only ex ante information, i.e., making the trading strategy implementable. Following Loh and Mian (2006), we calculate the consensus recommendation of a stock based on the recommendations issued in the corresponding previous six months. We perform the trading strategy separately according to our classification of analysts, i.e., we separately analyze the profitability of able, unable, and lucky analysts.

A single recommendation A assumes values between 1 and 5, where a rating of 1 reflects a "Strong Buy" recommendation, 2 a "Buy", 3 a "Hold", 4 a "Sell", and 5 a "Strong Sell", respectively. For example, if one "Strong Buy" recommendation and one "Buy" recommendation have been issued within the previous six months for firm j, the current consensus recommendation for firm j would be 1.5 for the six-month consensus calculation period:

$$\overline{A}_{j\tau-1} = 1/n_{j\tau-1} \sum_{i=1}^{n_{j\tau-1}} A_{ij\tau-1} \tag{2.5}$$

Based to the consensus recommendation, we assign each stock on the following trading day (1) to the long portfolio if $\overline{A}_{j\tau-1} \leq 1.5$ (implying that the consensus recommendation is at least between "Strong Buy" and "Buy")[8] or (2) to the short portfolio if $\overline{A}_{j\tau-1} > 2.5$. The portfolio classifications follow Barber et al. (2006) and Loh and Mian (2006). Also in line

[8] Using a consensus recommendation of $\overline{A}_{j\tau-1} \leq 2$ for the long portfolio yields the same overall conclusions.

with previous studies we buy (sell) a stock at the opening price of the following trading day after announcement in order to avoid trading before the recommendation was available.

The stocks assigned to the long portfolio or short portfolio ρ are weighted according to market capitalization on the prior trading day. $x_{j\tau-1}$ is the market value of equity for firm j at the close of trading on date $\tau-1$ divided by the aggregate market capitalization of all firms in portfolio ρ at the close of trading on that date. $R_{j\tau}$ is the return of firm j's common stock on date τ and $n_{\rho\tau-1}$ is the number of firms in portfolio ρ at the close of trading on day $\tau-1$:

$$R_{\rho\tau} = \sum_{j=1}^{n_{\rho\tau-1}} x_{j\tau-1} R_{j\tau} \tag{2.6}$$

The daily excess returns of the long- and short portfolio are calculated according to Carhart's (1997) four-factor-model:

$$R_{\rho\tau} - rf_{\tau} = \alpha_{\rho} + \beta_{\rho}(Rm - rf_{\tau}) + s_{\rho}SMB_{\tau} + h_{\rho}HML_{\tau} + m_{\rho}UMD_{\tau} + \varepsilon_{\rho\tau} \tag{2.7}$$

To calculate portfolio turnover we follow Barber et al. (2001). First, we calculate the hypothetical weight $G_{j\tau-1}$ for each stock j in portfolio ρ at the end of the trading day $\tau-1$, i.e., the weight if the portfolio would not have been rebalanced:

$$G_{j\tau} = \frac{x_{j\tau-1}(1+R_{j\tau})}{\sum_{j=1}^{n_{\rho\tau-1}} x_{j\tau-1}(1+R_{j\tau})} \tag{2.8}$$

Next, the hypothetical weight $G_{j\tau}$ is compared to stock's j actual weight $F_{j\tau}$ in the portfolio at the end of trading day τ. Finally, the daily portfolio turnover $U_{j\tau}$ is calculated as the sum of the potential decreases in weights for all stocks j on date τ:

$$U_{j\tau} = \sum_{j=1}^{n_{\rho\tau}} \max\{G_{j\tau} - F_{j\tau}, 0\} \tag{2.9}$$

The annual portfolio turnover is calculated as the daily portfolio turnover U_{jT} times the number of trading days in the year.

2.3.4.2 Event-Study

We also address the profitability of recommendations issued by able, unable, and lucky analysts with an event-study design (e.g., Womack (1996)). We analyze the extent to which differences in returns are due to the forecasting skills of the analysts: does the market react differently to the recommendations of an able analyst compared to the recommendations of an unable analyst? When does the return of the recommendation materialize? For example, investors may primarily follow the recommendations of able analysts. If the excess returns associated with recommendations can be attributed to such a reputation effect, we expect a strong post announcement effect, e.g., a large positive return immediately after an able analyst has issued a "Strong Buy" recommendation and only average returns thereafter. Hence, we would expect that the vast majority of the excess return associated with a recommendation is realized immediately after the recommendation was issued. We analyze recommendations levels as well as recommendation changes.[9]

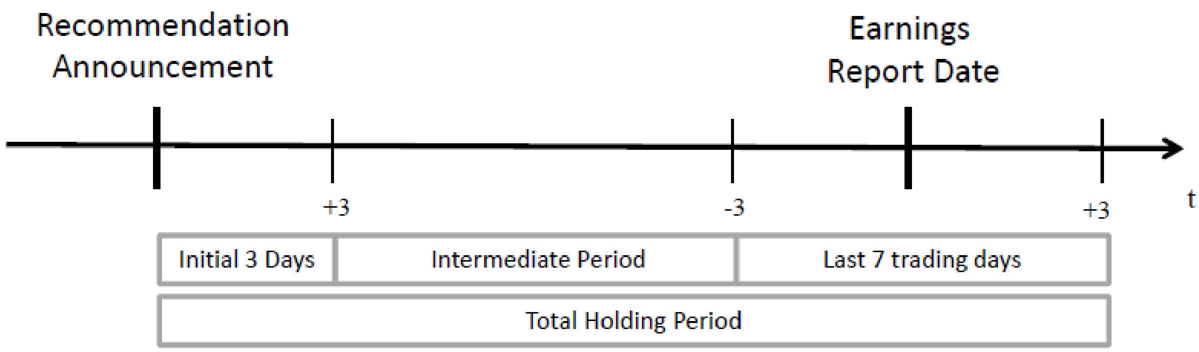
For the five level recommendation categories ("Strong Buy" to "Strong Sell") we analyze the excess returns if the single recommendations were followed. Since an analyst is classified based on an earnings forecast made prior to the recommendation in the firm year, we hold the recommendation until the earnings report date of the respective stock plus three trading days. Therefore, we hold a recommended stock until the corresponding earnings have been announced (plus three trading days), i.e., until the point in time when the superior (versus inferior) forecasting ability has materialized in a smaller (versus larger) surprise. Analogously to the trading strategy we follow a stock beginning one trading day after the recommendation announcement, i.e., we do not include the return on the first trading day. We separate the

[9] Recommendations changes contain more predictive power than recommendation levels (e.g., Jegadeesh, Kim, Krische, and Lee (2004)).

entire recommendation holding period which spans from one trading day after recommendations announcement to the earnings report date plus three trading days, into three different time windows:

Figure 2.1: Holding Periods of Individual Recommendations

This figure shows the respective holding periods that are analyzed in the event study. We separate the total holding period spanning from the first trading day after announcement (not including the announcement day) to three trading days after the earnings report date into three time windows: (1) The time window covering the first three trading days after recommendation announcement (not including the excess return on the announcement day), (2) the intermediate time window spanning from three trading days after announcement to three trading days before earnings report date, and (3) the excess return from three trading days before until three trading days after the earnings report date. Note that the three time windows combined are equal to the total holding period.



(1) The initial three trading days after the recommendation announcement (not including the recommendation announcement day), (2) the intermediate time window between three trading days after recommendation announcement and three trading days before the earnings report date, and (3) the time window spanning three trading days before until three trading days after the earnings announcement. The total holding period return is equal to the three time windows combined.

We also analyze recommendations changes and assign recommendations to either a "Buy portfolio" or "Sell portfolio" as outlined by Cohen, Frazzini, and Malloy (2010). The "Buy portfolio" consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates her coverage with a "Strong Buy" or "Buy" recommendation. The short portfolio consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates her coverage with a "Hold", "Sell" or "Strong Sell" recommendation. We do not include the return of the recommendation announcement day in the analysis. A stock is held in the portfolio until the earnings have been announced plus three trading days as long as the recommendation is not revised before the earnings announcement day. If a recommendation is revised before the earnings announcement we hold the underlying stock one additional day after the revision in our portfolio.

We calculate daily excess returns for firm i on trading day t according to Daniel et al. (1997) as shown in Equation 2.10. From each stock's raw return we subtract the return on a value-weighted portfolio of all CRSP firms in the same size, (industry-adjusted) market-to-book ratio and one-year momentum quintile. We use the Fama and French 48-industry classification and update the 125 characteristic portfolios at the end of June of each year:

$$ER_{it} = Raw\_Return_{it} - DGTW\_Benchmark\_Return_{it} \tag{2.10}$$

The cumulative adjusted returns (CAR) are calculated for the three event windows specified above. To control for outliers the mean returns are winsorized at the 99% level:

$$CAR_{itT} = \sum_{t=t}^{T} ER_{it} \tag{2.11}$$

2.4 Results

2.4.1 Results of the Trading Strategy

The results of the trading strategy are reported in Table 2.4. Panel A shows a strong heterogeneity in respect to recommendation profitability of the long portfolio: the returns decrease monotonically from Q5 to Q1. The long portfolio based on able analysts' stock recommendations generates significant positive excess returns of 5.17% p.a. in the 1994 to 2010 sample period, while the Q4 portfolio generates significant excess returns of 3.13% p.a. In contrast, the portfolio based on unable analysts' stock recommendations and the portfolios in the remaining two quintiles Q3 and Q2 generate no excess returns. The return difference between the able and unable analysts of 5.99% p.a. is statistically and economically highly significant.

Table 2.4: Trading Strategy – Information Set I_{FULL}

This table shows the results of the trading strategy in the 1994 to 2010 time period for analysts classified according to information set I_{FULL}. Panel A shows the annualized four-factor excess returns for all quintiles for the Long Portfolio, the Short Portfolio, and the Long-Short Portfolio. Panel B shows the summary statistics for the portfolios of the able and unable analysts. Columns 1 to 4 show the coefficient estimates of equation (2.6) for the market excess return (Rm-rf), the size portfolio (SMB), the book-to-market portfolio (HML), and the momentum portfolio UMD). Column 5 shows the adjusted R^2 from the regression performed in Equation (2.6), column 6 shows the average daily number of firms in the respective portfolio, and column 7 shows the annual portfolio turnover in % from Equation (2.8). The t-statistics are shown in parentheses below the estimates. The significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Panel A: Ability Quintiles according to Information Set I_{FULL}

	Able (Q5)	Q4	Q3	Q2	Unable (Q1)	Q5 - Q1
Long	5.17%***	3.13%**	0.93%	0.18%	-0.78%	5.99%***
	(3.03)	(2.17)	(0.67)	(0.13)	(-0.55)	(2.67)
Short	-2.24%	-1.35%	-0.96%	-1.81%	-0.05%	-2.19%
	(-1.49)	(-1.05)	(-0.74)	(-1.48)	(-0.04)	(-1.13)
Long-Short	7.57%***	4.54%**	1.90%	2.02%	-0.73%	8.36%***
	(3.11)	(2.16)	(0.92)	(0.97)	(-0.35)	(2.56)

Panel B: Summary Statistics for the Portfolios of the Able and Unable Analysts

	Rm-rf	SMB	HML	UMD	Adj. R^2	# of Firms	Annual Turnover (%)
Long							
Able (Q5)	1.06***	-0.11***	-0.18***	-0.021	0.91	172.0	338.0%
	(112.95)	(-5.82)	(-9.27)	(-1.61)			
Unable (Q1)	1.05***	-0.043*	-0.15***	0.12***	0.92	284.0	270.7%
	(107.44)	(-2.36)	(-10.73)	(13.27)			
Short							
Able (Q5)	0.966***	-0.115***	0.128**	-0.086***	0.91	345.5	266.9%
	(133.97)	(-6.48)	(7.25)	(-6.73)			
Unable (Q1)	0.992***	-0.0862***	0.207***	-0.0476***	0.94	559.9	226.8%
	(146.59)	(-6.42)	(13.24)	(-4.79)			
Long-Short							
Able (Q5)	0.098***	0.008	-0.309***	0.066***	0.16	517.5	604.9%
	(7.68)	(0.27)	(-12.02)	(3.88)			
Unable (Q1)	0.0540***	0.0435	-0.354***	0.168***	0.27	843.9	497.5%
	(3.81)	(1.59)	(-14.55)	(10.98)			

Our results imply that investors should only follow stock recommendations of analysts with superior characteristics. Investors must filter out the profitable recommendations to realize excess returns.

Table 2.4 Panel A also shows that there is very limited heterogeneity among analysts in respect to recommendation profitability of the short portfolio. None of the five analyst quintiles issue profitable recommendations. Interestingly, Cohen, Frazzini, and Malloy (2010) come to a similar result when differentiating between analysts in respect to their school ties: buy recommendations on school-tied stocks outperform buy recommendations on non-tied stocks, while sell recommendations do not. We find that able analysts only have an advantage in identifying undervalued stocks.

Combining the long and the short portfolio leads to significant excess returns of 7.57% p.a. when following only able analysts respectively to a return of 4.54% p.a. when following only the analysts in the fourth quintile. The long-minus-short portfolios of the remaining three analyst quintiles are not profitable. The return difference between the able and unable analysts of 8.36% p.a. is both economically and statistically significant. Overall, these findings indicate that it is crucial for investors to differentiate among analysts based on their projected earnings accuracy. Able analysts issue profitable recommendations and, therefore, add value in the investment decision process.

A related question is the impact of transaction costs, i.e., are the returns of the trading strategy economically significant after accounting for the costs of trading the securities? The annual turnover of the long portfolio of able analysts is 338% p.a. Therefore, the net return after transaction costs would be positive up to round-trip transaction costs of around 1.53% (5.17%/3.38). The respective threshold round-trip costs for the short portfolio are around 0.84% and 1.23% for the long-short portfolio. Since the average stock covered by the analyst has a relatively high market capitalization of around $8.4 billion (Table 2.2), the average round-trip transaction cost, at least for the long portfolio, are most likely lower than the thresholds. It should also be noted that the annual turnover of the portfolios is high, because we use daily rebalancing. The trading strategy employed here is not optimized in terms of transaction costs. Nevertheless, our results indicate that the net return, at least for the long portfolio, is very likely still economically significant after accounting for transaction costs.

In a separate analysis we address the question whether the past earnings track record of an analyst is sufficient to forecast stock recommendation profitability. We examine analysts with a superior track record, i.e., analysts who belong to the upper two accuracy quintiles in terms of I_{TRACK}. As a remainder, I_{TRACK} comprises the firm-specific and the general track record (over all covered firms) of an analyst. We independently sort analysts based on their track record and on the information set including the track record and analyst skill proxies (I_{FULL}). Table 2.5 shows the intersection of analysts that belong to the upper two accuracy quintiles in terms of their past earnings accuracy and the ability quintiles analyzed in Table 2.4. The results are shown for one-year and two-year track records. The results reveal that the earnings track record, i.e., information set I_{TRACK}, is not sufficient to ex ante identify the analysts who issue more profitable recommendations. From the group of analysts with a superior track record, analysts in the upper ability quintile issue profitable recommendations in the long portfolio for the one-year and two-year track record period. The returns are 3.72% p.a. for the one-year track record and 4.94% p.a. for the two-year track record. Furthermore, analysts in the fourth ability quintile issue profitable stock recommendations for the one-year track record period that yield 3.65% p.a. The stock recommendations in the long portfolio of the remaining analysts are not profitable. The portfolios based on recommendations of lucky analysts even generate negative (albeit statistically insignificant) excess returns. The short portfolio generates significant excess returns for the third and fourth ability quintile when looking at the one-year track record. The long-short portfolio is significant for the upper three quintiles when looking at the one year track record, but only significant for the upper quintile for the two-year track record.

Table 2.5: Trading Strategy – Lucky Analysts

This table shows the results of the trading strategy in the 1994 to 2010 time period for analysts that belong to the upper two quintiles according to I_{TRACK}. The analysts are independently sorted according to information set I_{FULL}. The table shows the annualized four-factor excess returns for all quintiles for the Long Portfolio, the Short Portfolio, and the Long-Short Portfolio. We use one-year and two-year earnings track records. The t-statistics are shown in parentheses below the estimates. The significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

	Track Record	Q5	Q4	Q3	Q2	Lucky (Q1)	Q5 - Q1
Long	1-year	3.72%*	3.65%**	0.67%	-0.39%	-5.81%	10.12%**
		(1.86)	(2.07)	(0.36)	(-0.17)	(-1.55)	(2.22)
Short		-2.38%	-2.64%*	-3.84%**	-0.90%	-2.60%	0.23%
		(-1.45)	(-1.69)	(-2.35)	(-0.55)	(-0.96)	(0.07)
Long-Short		6.25%**	6.46%***	4.68%*	0.65	-3.29	9.87%*
		(2.23)	(2.61)	(1.81)	(0.22)	(-0.71)	(1.74)
Long	2-year	4.94%**	0.44%	1.37%	1.68%	-2.07%	7.16%
		(2.43)	(0.21)	(0.61)	(0.52)	(-0.46)	(1.40)
Short		-0.37%	-1.50%	-0.24%	-2.43%	-4.69%	4.53%
		(-0.20)	(-0.85)	(-0.14)	(-1.23)	(-1.48)	(1.20)
Long-Short		5.48%**	2.03%	1.43%	4.21%	2.67%	2.73%
		(1.96)	(0.73)	(0.48)	(1.05)	(0.48)	(0.44)

Our findings explain why the trading strategy proposed by Hall and Tacon (2010) does not yield excess returns, since following all analysts only based on their good track record is not sufficient to differentiate between able and lucky analysts. Analysts who issue more profitable recommendations in the future cannot be identified based on a one-dimensional evaluation of their record without taking into account other ability proxies. From the analysts with high past earnings accuracy only those with high projected earnings accuracy issue profitable stock recommendations in the next period. On a stand-alone basis past earnings accuracy is not sufficient in order to identify able analysts. Following the winners of last year's earnings game does not translate into more profitable stock recommendations in the following year, because only some of those analysts are expected to also issue accurate earnings forecasts in the future. The skill of an analyst must be scrutinized in addition to her track record. Some analysts appear to be able based on their track record, while in fact they are unable, i.e., they do not have higher forecast skills.

2.4.2 Results of the Event-Study

Next, we analyze which returns an investor can expect on average if individual recommendations provided by an able, unable, or lucky analysts were followed in an event-study setting. We analyze different holding periods to address possible reasons for differences in the profitability of the recommendations of able, unable, and lucky analysts: does the market react differently to the recommendations of an able analyst compared to the recommendations of an unable analyst? When does the excess return of the recommendation materialize? The results are reported in Table 2.6. Note that the returns are not annualized and that analogously to the trading strategy we do not include the stock return on the first trading day. The mean excess returns implicitly assume equally-weighted portfolios. We lose about 11.3% of observations due to the required DGTW matching criteria of CRSP with Compustat.

Table 2.6: Profitability of Individual Stock Recommendations and Upgrades /Downgrades

This table shows the profitability of single stock recommendations and Buy/Sell portfolios (following Cohen, Frazzini, and Malloy (2010)) for able, unable, and lucky analysts. The respective event windows are displayed in Figure 2.1. Column 1 shows the number of recommendations. Column 2 shows the average number of trading days until the earnings report date (for single recommendations) respectively until the earnings report or revision (Buy and Sell portfolios). Column 3 shows the mean DGTW excess return in the total holding period. Column 4 shows the mean DGTW excess return on the first three trading days after recommendation announcement (not including the announcement day). Column 5 shows the mean DGTW excess return between three trading days after recommendation announcement and three trading days before the earnings for the respective stock are reported or revision (Buy and Sell portfolios). Column 6 shows the mean excess return from three trading days before the earnings announcement until three trading days after the earnings announcement (for Buy/Sell portfolios only if they are not revised before). Column 7 shows the mean DGTW excess return on the announcement day (not included in the total holding period). Panel B shows the differences in mean DGTW excess returns between able and unable respectively between able and lucky analyst. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Panel A: Able, Unable, and Lucky Analysts

Rec Category	No. of Rec 1	Holding Days 2	Total Holding Period Return 3	Initial Three Days 4	Intermediate Return 5	Return around Earn. Report 6	Return First Day 7
				Able Analysts			
Strong Buy	10,427	169.0	2.04%***	0.34%***	1.33%***	0.36%***	1.30%***
Buy	12,985	164.1	2.34%***	0.09%**	2.03%***	0.26%***	0.60%***
Hold	18,878	170.1	0.95%***	-0.21%***	1.14%***	0.07%	-1.06%***
Sell	2,203	177.9	-1.68%**	-0.39%***	-0.74%	-0.32%	-1.65%***
Strong Sell	1,270	183.5	-3.51%***	-0.46%***	-2.29%	-0.69%***	-1.72%***
Buy PF	21,614	111.0	3.40%***	0.86%***	1.11%***	0.36%***	1.15%***
Sell PF	21,276	115.3	1.58%***	0.13%***	0.41%*	0.06%	-1.38%***
				Unable Analysts			
Strong Buy	17,428	222.1	0.49%	0.44%***	0.01%	0.15%**	1.13%***
Buy	22,231	215.5	0.52%	0.07%**	0.44%	0.09%	0.39%***
Hold	30,372	223.4	-0.41%	-0.30%***	-0.05%	-0.03%	-1.25%***
Sell	3,594	235.1	-1.99%***	-0.55%***	-0.93%	-0.45%***	-1.81%***
Strong Sell	1,854	222.8	-2.76%***	-0.67%***	-1.34%	-0.45%**	-1.71%***
Buy PF	36,499	145.8	2.11%***	0.88%***	-0.32%	0.12%*	0.89%***
Sell PF	34,631	151.0	-0.16%	0.05%	-1.18%***	-0.09%	-1.50%***
				Lucky Analysts (1-year track record)			
Strong Buy	2,007	289.1	0.42%	0.50%***	0.24%	-0.10%	1.27%***
Buy	2,675	266.2	0.75%	0.20%**	0.73%	-0.13%	0.51%***
Hold	3,704	251.8	0.11%	-0.28%***	0.78%	-0.19%	-1.71%***
Sell	455	263.1	-3.35%	-0.74%***	-1.96%	-0.68%	-2.25%***
Strong Sell	221	279.0	-1.50%	-1.10%***	-1.22%	0.66%	-3.09%***
Buy PF	4,452	199.9	2.03%***	0.63%***	0.26%	-0.25%	1.05%***
Sell PF	4,203	174.8	0.46%	-0.14%	-0.28%	-0.24%	-2.07%***

Table 2.6: (continued)

Panel B: Differences in Return

Rec Category	ΔNo. of Rec	ΔHolding Days	ΔTotal Hold. Period Return	ΔInitial Three Days	ΔIntermediate Return	ΔReturn around Earn. Report	ΔReturn First Day
	1	2	3	4	5	6	7
Able Analysts – Unable Analysts							
Strong Buy	-7,001	-53.1	1.55%***	-0.09%	1.32%**	0.20%*	0.17%***
Buy	-9,246	-51.4	1.82%***	0.01%	1.60%***	0.17%	0.21%***
Hold	-11,494	-53.3	1.36%***	0.10%**	1.19%***	0.09%	0.20%***
Sell	-1,391	-57.2	0.32%	0.15%	0.19%	0.13%	0.16%
Strong Sell	-584	-39.3	-0.75%	0.21%	-0.95%	-0.24%	-0.01%
Buy PF	-14,885	-34.8	1.29%***	-0.02%	1.43%***	0.24**%	0.25%***
Sell PF	-13,355	-35.7	1.73%***	0.07%	1.59%***	0.15%	0.12%***
Able Analysts – Lucky Analysts (1-year track record)							
Strong Buy	8,420	-120.1	1.73%**	-0.11%	1.48%**	0.29%*	0.07%
Buy	10,310	-102.1	1.27%**	-0.14%**	1.31%**	0.11%	0.12%*
Hold	15,174	-81.7	0.18%	-0.03%	0.14%	-0.07%	0.36%***
Sell	1,748	-85.2	0.40%	0.11%	0.70%	-0.29%	0.49%***
Strong Sell	1,049	-95.5	-1.74%	0.36%	-1.53%	-0.98%**	0.80%***
Buy PF	17,162	-88.9	1.36%**	0.24%**	0.85%	0.61%***	0.09%
Sell PF	17,073	-59.5	1.11%*	0.27%**	0.69%	0.30%	0.69%***

Table 2.6 shows the results for the recommendation levels (i.e., “Strong Buy” to “Strong Sell”) as well as for upgrades and downgrades according to the portfolio definitions of Cohen, Frazzini, and Malloy (2010). With respect to the recommendation levels the results in Panel A show that able analysts issue profitable recommendations for all recommendation categories if the recommendations are held from the trading day after the announcement until three trading days after the report date. “Strong Buy”, “Buy”, and “Hold” recommendations earn positive excess returns, while “Sell” and “Strong Sell” recommendations earn negative excess returns. In contrast, “Strong Buy”, “Buy”, and “Hold” recommendations by unable or lucky analysts do not yield excess returns. “Sell” and “Strong Sell” recommendations by unable analysts also yield negative excess returns. Lucky analysts do not issue recommendations in any category that are profitable. The differences in excess returns between analysts are shown in Table 2.6 Panel B: “Strong Buy” recommendations of able analysts earn 1.55% (1.73%) more excess return than “Strong Buy” recommendations of unable (lucky) analysts. The differences in returns cannot be attributed to differences in the holding period, since the length of the holding period is even significantly lower for the able

analysts' recommendations. Also, "Buy" recommendations of able analysts are 1.82% (1.27%) more profitable than those of unable (lucky) analyst. The "Hold" recommendations of able analysts outperform those of unable analysts by 1.36%. For the "Sell" and "Strong Sell" recommendations there is no significant difference in returns between able and unable, respectively able and lucky analysts. The findings are in line with the results of the trading strategy: Able analysts issue significantly more profitable recommendations, but only in the upper recommendation categories.

Panel A also shows that across all analysts the excess return on the recommendation announcement day is economically significant. The average absolute announcement day return over all categories and analysts is about 1.4%. Panel B, however, points out that there is no economically significant difference in return on the announcement day across all recommendation categories between able and unable or able and lucky analysts. Recommendations from able analysts do not have a stronger market impact on the recommendation announcement day in terms of an economically significantly higher return. Similarly, the cumulative excess return on the three trading days following the announcement day shows that in general there is a post-announcement drift, i.e., the stock return follows the direction of the announcement day. For example, the average "Strong Buy" recommendation of an able analyst generates 0.34% of excess return on the three trading days following the announcement day. However, the results in Panel B also show that there is no economically significant difference in excess return between able, unable, and lucky analysts on the first three trading days after the announcement day. This finding indicates that the differences in excess returns in the total holding period are in general not due to a reputation effect, i.e., market participants do not just blindly follow able analysts whatever they recommend.

The majority of the return difference of the "Strong Buy" and "Buy" recommendations is realized over a longer time window, i.e., in the intermediate time period, indicating that able analysts have stock picking ability. One plausible explanation is that the "Strong Buy" and

"Buy" recommendations of able analysts earn higher returns, because able analysts anticipate the trend of the underlying stock due to their better knowledge of future earnings. Interestingly, the return difference around the earnings report date is relatively small. This indicates that investors anticipate positive or negative earnings news before the release.

Overall, the results show that able analysts are superior to unable and lucky analysts in identifying undervalued stocks, as indicated by the higher performance of the "Strong Buy" and "Buy" recommendations. The higher excess returns, however, are not generated in the first trading days after the recommendation announcement, but rather over a longer time window. The higher returns of "Strong Buy" and "Buy" recommendations are in line with the results of the long portfolio of the trading strategy. A noticeably difference are the returns of the lower recommendation categories, e.g., we find excess returns for "Sell" recommendations of able analysts. As a reminder we do not find excess returns for the short portfolio of the trading strategy. This difference can be attributed to using an event-study approach instead of a calendar-time approach, using equally-weighted returns instead of value-weighted returns, and using DGTW excess returns instead of Fama and French excess returns. Taking into account both the results from the event-study and the trading strategy shows that "Sell" and "Strong Sell" recommendations might earn excess returns when using an event-study, but not when using a calendar-time approach which mimics an investor following the recommendations. In contrast, "Strong Buy" and "Buy" recommendations are also profitable when using a calendar-time approach with value-weighting.

Table 2.6 also shows the results of the event study when using the "Buy portfolio" and "Sell portfolio" definitions of Cohen, Frazzini, and Malloy (2010). The mean return of recommendations from able analysts assigned to the "Buy porfolio" is 1.29% higher in comparison to unable analysts when holding the recommendations until they are revised or until the earnings for the underlying stock are announced plus three trading days (again, the returns are not annualized). The return difference between able and lucky analysts is 1.36%.

Recommendations assigned to the “Sell porfolio” of unable analysts earn significantly lower returns than recommendations by able analysts. This result is driven mainly by the significantly lower return of “Hold” recommendations from unable analysts (as shown in Table 2.6). The direction of the return, however, is not in line with the recommendation to hold the stock, i.e., the excess return can only be generated when short-selling instead of holding the underlying stock.

2.4.3 Differences in Ex Post Realized Accuracy

A crucial question is whether able analysts also issue more accurate annual earnings forecasts, i.e., whether the ex ante classification of analysts translates into a higher ex post realized earnings accuracy. The results for the earnings accuracy of the last forecast issued by the analyst in the fiscal year are shown in Table 2.7. We find that the absolute forecast error scaled by price (AFEP) and the standardized ACCURACY increase monotonously from Q5 to Q1. Overall, our findings suggest that able analysts have a significant advantage in predicting earnings. Their forecast error is about 50% lower. The AFEP of able analysts is 0.91%, while the AFEP of unable and lucky analysts is 2.02% and 1.97%, respectively. The high past earnings accuracy of lucky analysts does not translate into higher future forecast accuracy. In terms of absolute dollar values able analysts are about $0.21 more accurate based on a median stock price of $21 in our sample. Assuming an average Price-to-Earnings ratio of 10, this advantage would translate into a firm valuation that is about 9% more accurate ([10-$21/($2.1+$0.21)]/10). The results imply that the lower forecast errors of able analysts translate into superior firm valuations and in turn into more profitable stock recommendations. Superior knowledge of company fundamentals also yields value-adding investment advice.

Table 2.7: Differences in Ex Post Realized Earnings Accuracy

This table shows the ex post realized accuracy for analysts that are ex ante classified according to I_{FULL} and the one-year I_{TRACK} information set. The table reports the absolute forecast error (AFE) scaled by price in % and the standardized earnings accuracy variable ACCURACY. Panel A shows the results according to information set I_{FULL}. Panel B shows the results for the analysts that belong to the upper two quintiles according to I_{TRACK} which are independently sorted according to information set I_{FULL}. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Panel A: Ex Post Accuracy Quintiles according to Information Set IFULL

	Able (Q5)	Q4	Q3	Q2	Unable (Q1)	Q5 - Q1
AFE scaled by Price (%)						
Mean	0.91%	1.00%	1.19%	1.44%	2.02%	-1.10%***
Median	0.20%	0.20%	0.26%	0.34%	0.56%	
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	
Maximum	24.95%	25.00%	24.96%	24.89%	25.00%	
ACCURACY						
Mean	0.80	0.78	0.74	0.69	0.60	0.20***
Median	0.93	0.91	0.88	0.84	0.72	
Minimum	0.00	0.00	0.00	0.00	0.00	
Maximum	1.00	1.00	1.00	1.00	1.00	

Panel B: Ex Post Accuracy Quintiles according to Information Set ITRACK (1 year)

	Q5	Q4	Q3	Q2	Lucky (Q1)	Q5 - Q1
AFE scaled by Price (%)						
Mean	0.88%	0.96%	1.24%	1.46%	1.97%	-0.93%***
Median	0.20%	0.19%	0.24%	0.32%	0.48%	
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	
Maximum	24.50%	25.00%	24.70%	24.89%	24.84%	
ACCURACY						
Mean	0.81	0.79	0.75	0.70	0.66	0.16***
Median	0.93	0.92	0.89	0.86	0.82	
Minimum	0.00	0.00	0.00	0.00	0.00	
Maximum	1.00	1.00	1.00	1.00	1.00	

The values of the forecast errors and the difference in forecast errors between the upper and the lower quintile are in line with the results of Loh and Mian (2006). In their study, when differentiating between analysts based on ex-post realized earnings accuracy, analysts in the most accurate quintile have an AFEP of 0.756%, while analysts in the least accurate quintile have an AFEP of 2.199%. This implies that our ex-ante classification of analysts works remarkably well, since the forecast errors are only slightly higher (lower) for the able (unable) analysts. Contrary to Brown (2001) and Brown and Mohd (2003) we find that analyst characteristics can be used to identify economically significant more accurate earnings forecasters out-of-sample.

2.5 Conclusion

We find a pronounced heterogeneity in the information processing abilities of analysts that can be identified ex ante. Able analysts add value in the investment decision process. In contrast, unable analysts' recommendations are generally not worth following. Our results imply that certain analysts have the ability to discriminate between over- and undervalued stocks. Therefore it pays for investors to filter out the superior investment advice from the large number of recommendations provided by analysts. Differentiating between able and unable analysts is challenging, because there are lucky analysts, i.e., analysts that seem to be able just because they delivered a good result last year, while in fact they are not. Our approach enables us to look beyond the track record of an analyst, since we do not base our assessment on historical performance alone, but also on the skills and working environment. Our findings contribute to previous literature on analyst career concerns. We find that track records on a stand-alone basis are not applicable in order to reduce information asymmetries in principal-agent relationships, since they can be heavily influenced by lucky outcomes. We find that judging analysts on past outcomes alone leads to suboptimal investment decisions by investors and to unjustified promotion and demotion decisions by employers.

More generally, our results allow for conjectures concerning the broad literature of performance and compensation evaluation, e.g., for mutual funds or CEOs. Identifying the more skilled information processors provides a promising approach for other fields of research, in particular, if their results depend on the quality of analysts' forecasts, e.g., studies using analysts' outputs to capture the expectations of market participants. Furthermore, equity valuation models based on discounted expected cash flows or (residual) earnings, or estimates of intrinsic cost of capital could profit from using only the forecasts of (ex ante identifiable) superior information processors.

Chapter 3 – Sell Side Recommendations during Booms and Busts

3.1 Introduction

The importance of the business cycle for information processing on capital markets has been pointed out by several studies: For example, Veronesi (1999) shows that the reaction of prices to news tends to be stronger in good economic times than in bad economic times. Boyd, Hu, and Jagannathan (2005) and Beber and Brandt (2010) find that investors process the same information differently depending on the business cycle. One of the main information sources for equity investors are sell side analysts who provide recommendations for the covered stocks. Changes in stock recommendations are on average associated with significant stock price reactions. In this paper, we analyze the relationship between analysts' stock recommendations and general macroeconomic conditions. To the best of our knowledge we are the first to study this link.

Related research has studied the performance of stock recommendations during the Dot-com bubble in 2000 and 2001 (Barber et al. (2003)). However, economic fluctuations are not necessarily convergent to movements on equity markets. For example, there is a negative correlation between per capita GDP growth and real equity returns in the 1900-2002 time period (Ritter (2005)). Furthermore, bull and bear markets are to some extent arbitrary demarcations whereas expansions and recessions are marked "officially" by economic dating committees (e.g., the National Bureau of Economic Research (NBER)) or economic activity indices (e.g., the Chicago Fed National Activity Index (CFNAI)).

It appears reasonable to assume that the work of stock analysts is affected by economic conditions. In their role as market intermediaries financial analysts gather, analyze, and disseminate information which investors regard as a valuable allocation advice. Such advice comprises a comparison of the current and the expected market valuation of a firm and culminates in a stock recommendation that informs investors about potential mispricings. Today's forecast of tomorrow's price depends, among other factors, on the expected earnings (respectively cash flows) and the cost of capital. As capital markets and the real economy are closely interlinked, both, corporate earnings and interest rates are affected by aggregate economic fluctuations. An economic slowdown usually impairs the company's value, e.g., when expected growth rates are lowered. Changed company outlooks demand adjustments in valuation which must also lead to revised recommendations.

We analyze stock recommendations against the backdrop of general economic activity. We address two main research questions: First, we analyze the performance of sell side recommendations over the business cycle, i.e., whether there is a difference in stock recommendation profitability between recessions and expansions? Stock returns and the business cycle are linked, for example, Chordia and Shivakumar (2002) find that momentum strategies earn positive returns in expansions, but negative returns in recessions. Second, we analyze the characteristics of the stocks that are recommended by analysts: For example, do analysts recommend stocks with similar characteristics over the business cycle? Or do they have preferences for, e.g., "value" stocks in recessions and "glamour" stocks in expansions?

First, we show that recommendations affect stock prices differently contingent on the business cycle. The initial price impact is significantly stronger in recessions.[10] For example, an upgraded stock yields excess returns of 2.41% in the first three trading days after recommendation issuance during an expansion, but 3.45% in a recession. The difference of 1.05% is both statistically and economically significant. Also, downgraded stocks yield excess returns of -2.34% in the first three trading days after recommendations issuance during

[10] We calculate excess returns according to Daniel, Grinblatt, Titman, and Wermers (1997). Stocks are matched in terms of size, market-to-book ratios, and one-year momentum and are divided in 125 portfolios. Therefore, excess returns indicate an outperformance over the peer-group of stocks with similar characteristics.

an expansion, but -4.42% in a recession. This difference of -1.26% is statistically and economically significant as well.

Interestingly, analyzing the price reaction of recommended stocks over a longer time horizon reveals a different picture: In recession, "Buy"[11] recommendations generate negative excess returns during the 6-month window[12] after recommendation issuance. Hence, these "Buy" recommendations have no long-term investment value in recessions, i.e., investors would be better off to sell the recommended stocks after the recommendation announcement day. In expansions, we find that "Buy" recommendations have positive long-term investment value. After the initial positive price reaction, the recommended stocks generate positive excess returns. We also find that the market reaction is in line with the recommendation in both expansions and recessions for "Sell" recommendations, i.e., the stocks underperform their peer-group.

Second, we analyze the characteristics of the recommended stocks. We show that analysts' preferences towards the recommended firms are consistent over the business cycle, since analysts favor "glamour" over "value" stocks in both expansions and recessions. The documented bias in analysts' recommendations for "glamour" stocks (Jegadeesh et al. (2004)) is sustained in recessions. However, the underlying economic rationale for this bias is questionable, since e.g., Lakonishok, Shleifer, and Vishny (1994) show that returns of growth stocks are lower in comparison to those of value stocks in recessions.

Our results are robust in the post Regulation Fair Disclosure (Reg FD) time period, to the business cycle classification according to both NBER and CFNAI, and to mean and median returns. Also, our results are not driven by analyst herding.

[11] We follow Cohen, Frazzini, and Malloy (2010) in the classification of recommendations. The "Buy" portfolio consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates her coverage with a "Strong Buy or "Buy" recommendation.
[12] The post-recommendation drift lasts up to six months (Womack (1996)).

Prior research on the relation between business cycle on analysts is limited. Welch (2000) documents increased recommendation herding for bullish markets but not for contracting markets. Richards, Benjamin, and Strawser (1977) and Richardson, Teoh, and Wysocki (1999) show that EPS forecasts issued during booms tend to be overly optimistic while forecasts issued during busts are less optimistic. Lee, O'Brien, and Sivaramakrishnan (2008) observe a similar pattern in five-year earnings growth forecasts, Dhole, Mishra, and Sivaramakrishnan (2010) in managers' outlooks and Spiwoks, Gubaydullina, and Hein (2011) in interest rate forecasts. As a counterexample, Dreman, and Berry (1995) study EPS forecasts but do not find any differences in optimism between expansions and recessions. As far as firm characteristics are concerned, research has so far solely focused on stock market trends and the extent to which they influence analysts' recommendations. Barber et al. (2003) find that analysts keep favoring growth stocks despite their poor performance during stock market busts.

Overall, our study documents that controlling for business cycle effects is important when analyzing financial analysts. Our results indicate that the information content and the information processing of stock recommendations differ fundamentally between expansions and recessions. Investors react significantly stronger to all recommendations in recessions, i.e., the price impact of stock recommendations is significantly higher in recessions. However, while "Sell" recommendations issued in recessions generate negative excess returns over a longer time window, "Buy" recommendations do not have long-term investment value in recessions. These results point out that in recessions analysts are generally too optimistic with regard to the stocks they recommend as a "Buy". Analysts favor "glamour" stocks during recessions and expansions. But these recommended "glamour" stocks are worth following only in expansions. At the same time investors strongly overreact to the positively recommended stocks in recessions, indicating that investors overestimate the investment value of "Buy" recommendations in economic downturns.

The remainder of this paper is structured as follows: Section 3.2 describes the data, section 3.3 describes the research approach and the results, section 3.4 presents various robustness checks and finally, section 3.5 concludes.

3.2 Data

Analyst recommendations are obtained from the Institutional Brokers' Estimate System (I/B/E/S) database. Our sample includes observations from January 1994 to December 2010. Stock data are obtained from the Center for Research in Security Prices (CRSP) database. Company financial data are retrieved from the Compustat database. The total data sample captures two recessions of unequal duration and severity and three expansions. Recessions account for a smaller fraction of the sample time. The total duration of expansions is 173 months compared to only 26 months of recession. Resulting from that, the combined expansion panel contains approximately 390,000 observations compared to 60,000 in recessions.

Table 3.1: Distribution of Recommendations

This table presents the combined distribution of initial recommendations and revisions thereof as obtained from the I/B/E/S database from January 1994 until December 2010. Relative frequencies refer to the distribution of recommendations within the respective time frame. The consensus is calculated as the arithmetic mean of all recommendations under the standard classification in which a strong buy recommendation is coded as "1", buy as "2" etc.

Start/End	Exp. 01/1994	Rec. 03/2001	Exp. 12/2001	Rec. 12/2007	Exp. 07/2009	Total Exp.	Total Rec.	Total Sample
	02/2001	11/2001	11/2007	06/2009	12/2010			
Duration (months)	85	8	71	18	15	171	26	197
N (observations)	189,609	16,927	164,221	43,287	36,772	390,602	60,214	450,816
Rel. Frequency (%)								
(1) Strong Buy	29.67	25.41	20.02	19.00	22.12	24.86	20.95	24.36
(2) Buy	36.00	37.56	26.54	23.13	26.13	31.11	27.02	30.59
(3) Hold	30.89	34.23	44.06	46.25	43.48	37.64	42.84	38.31
(4) Sell	1.83	1.77	6.51	7.25	5.55	4.15	5.73	4.36
(5) Strong Sell	1.61	1.04	2.87	4.38	2.55	2.23	3.46	2.39
Consensus	2.10	2.15	2.46	2.55	2.40	2.28	2.44	2.30

(The distinction of recessions and expansions is based on the NBER statistics.)

The two most prominent business cycle classification schemes are the demarcations of expansions and recessions by the National Bureau of Economic Research (NBER)[13] and the Chicago Fed National Activity Index (CFNAI).[14] Both classifications are used in this study.[15] Unlike other classification schemes, the NBER does not employ simplistic rules such as two quarters of declining GDP in a row to mark recessions. Instead they follow their less formal definition of a recession as a "significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales" (National Bureau of Economic Research (2011)). It is important to note that the NBER is not available in real time, i.e., the business cycle classification is determined with a (substantial) time lag. Additionally, the three months moving average of the CFNAI is employed for robustness checks. Published with a smaller time lag and based on formal quantitative rules about coincident economic activity, it is available as more recent information for decision making. It comprises 85 monthly indicators of national economic activity from the fields of production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. The index is constructed in such a way that it has a mean value of zero with a standard deviation equal to one. This construction is straightforward in the way that a positive value corresponds to growth above trend and vice versa.

The divergent approach of both indices becomes apparent in Figure 3.1 which displays the official NBER dated recessions and the course of the three months moving average CFNAI. The CFNAI has two important thresholds for the determination of recessions: First, the likelihood that a recession has begun increases if the index falls below -0.7 after a period of

[13] The NBER classification is retrieved from the NBER site http://www.nber.org/cycles.html.

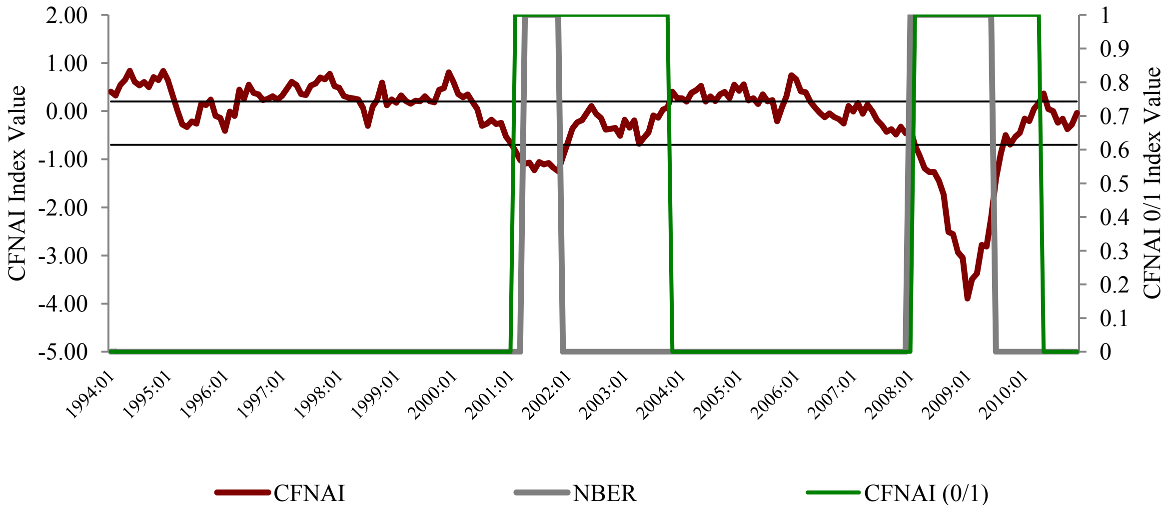
[14] The CFNAI is retrieved from the Federal Reserve of Chicago http://www.chicagofed.org/webpages/research/data/cfnai/current_data.cfm.

[15] The NBER classification is used as the default classification. The results for the CFNAI classification are discussed in section 3.4 (Table 3.8).

economic expansion. Second, the likelihood that a recession has ended increases if the index outperforms +0.2 after a period of economic contraction.

Figure 3.1: Comparison of NBER and CFNAI Dated Recessions

This figure displays the three months moving average CFNAI in its continuous classification as well as in the binary (0/1) version, whereby 0 stands for expansion and 1 for recession. The latter one can be directly compared to the NBER classification. The horizontal bars pertain to the left vertical axis and display the +0.2 and -0.7 point thresholds.



As it can be seen in Figure 3.1, the CFNAI was able to detect both recessions which have occurred in the time between 1994 and 2010. Coming from an expansion, this is indicated by the index falling below the -0.7 threshold which in turn sets the binary CFNAI to the value of 1. This fact needs to be considered in the context of the release time. Although the actual dates of the beginnings and endings of recessions are published with a substantial delay by the NBER committee, the CFNAI provides a good early warning system. However, the CFNAI has a broader definition of recessions in comparison to the NBER which leads to marked recessions that are larger. Both CFNAI dated recessions, starting in 2001 and in late 2008, account for more than twice the time span indicated by the NBER recessions.

3.3 Research Design & Results

3.3.1 Event Returns and the Price Formation Process

We conduct an event-study to analyze the profitability of recommendations depending on the business cycle. We calculate daily excess returns for firm i on trading day t according to Daniel et al. (1997) ("DGTW") as shown in Equation 3.1. From each stock's raw return we subtract the return on a value-weighted portfolio of all CRSP firms in the same size, (industry-adjusted) market-to-book ratio, and one-year momentum quintile. We use the Fama and French 48-industry classification and update the 125 characteristic portfolios at the end of July of each year. A positive DGTW excess return implies an outperformance over stocks in the peer-group with similar size, market-to-book, and one-year momentum characteristics.

$$\text{Excess\_Return}_{it} = \text{Raw\_Return}_{it} - \text{DGTW\_Benchmark\_Return}_{it} \tag{3.1}$$

We analyze the DGTW excess returns on the recommendation announcement day ("0"), in the first four trading days ("0–3"), in the first month, in the first three months, and up to six months. If a recommendation is revised, we drop the stock from our portfolio after holding it one additional trading day. The cumulative adjusted returns (CAR) are calculated for the event windows specified below:

$$\text{CAR}_{itT} = \sum_{t=t}^{T} \text{Excess\_Return}_{it} \tag{3.2}$$

There is evidence that stocks already move before the recommendation is officially announced (Stickel (1995)). However, the general idea of correctly using stock recommendations implies that one's observation period starts with the official publication date, hence we use t = 0. Moreover, the fraction of price change that occurs before the recommendation publication is rather small. We use t up to 6 months / 126 trading days as Womack (1996) finds related market reactions for up to that period.

We focus on recommendation changes rather than recommendation levels, since changes have higher predictive power for subsequent price changes than levels (e.g., Jegadeesh et al. (2004)). Recommendations are assigned to either a “Buy” portfolio or “Sell” portfolio as outlined by Cohen, Frazzini, and Malloy (2010). The “Buy” portfolio consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a “Strong Buy” or “Buy” recommendation. The “Sell” portfolio consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a “Hold”, “Sell” or “Strong Sell” recommendation. Furthermore, in accordance with Cohen, Frazzini, and Malloy (2010) we analyze the performance of upgraded and downgraded stocks separately.

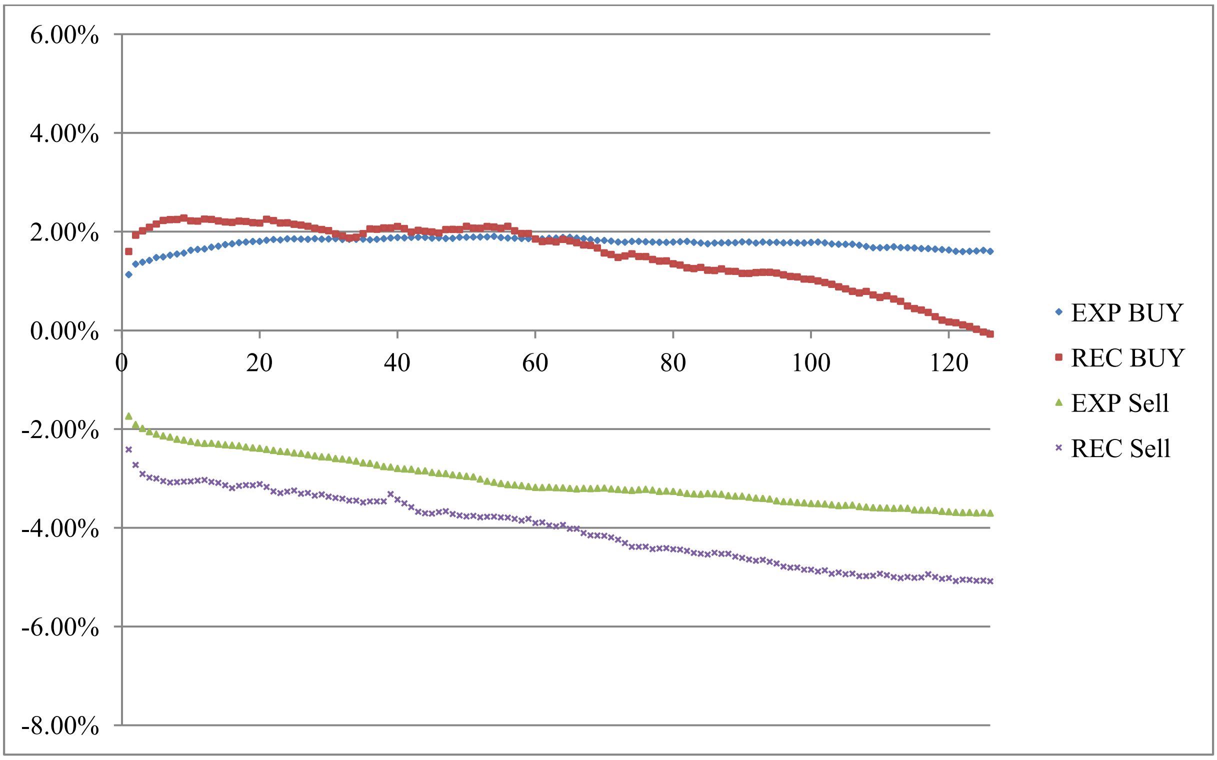
The recommendations are defined according to recessions and expansions by the business cycle stage at which they are announced, i.e., a recommendation which is issued during the last month of a recession is considered to belong to the recession. After calculating excess returns for recommendations issued in expansions and recommendations issued in recessions we compare the two to assess differences.

Figure 3.2 and Figure 3.3 display differences in the initial market reaction to the recommendations announcement and in the subsequent price formation pattern between expansions and recessions. The numeric results are shown in Table 3.2. Figure 3.2 shows that stocks in the “Buy” portfolio have a significant stronger market impact in recessions than in expansions. The difference is 0.67% in the first four trading days (“0–3”) including the recommendation announcement day. Figure 3.3 shows that for the subsample of upgraded stocks the difference is with 1.05% even larger. Also, the stock market reaction to recommendations in the “Sell” portfolio respectively downgraded stocks is significantly stronger in recession: Stocks in the “Sell” portfolio underperform their DGTW peer group by -0.9% in the first four trading days, while downgraded stocks underperform by -1.26%.

Overall, the initial stock market reaction to analysts' recommendations is significantly stronger in recessions in all analyzed recommendation categories. This difference is both statistically and economically significant.

Figure 3.2: Event Study: Buy and Sell Portfolio in Expansion and Recession (NBER)

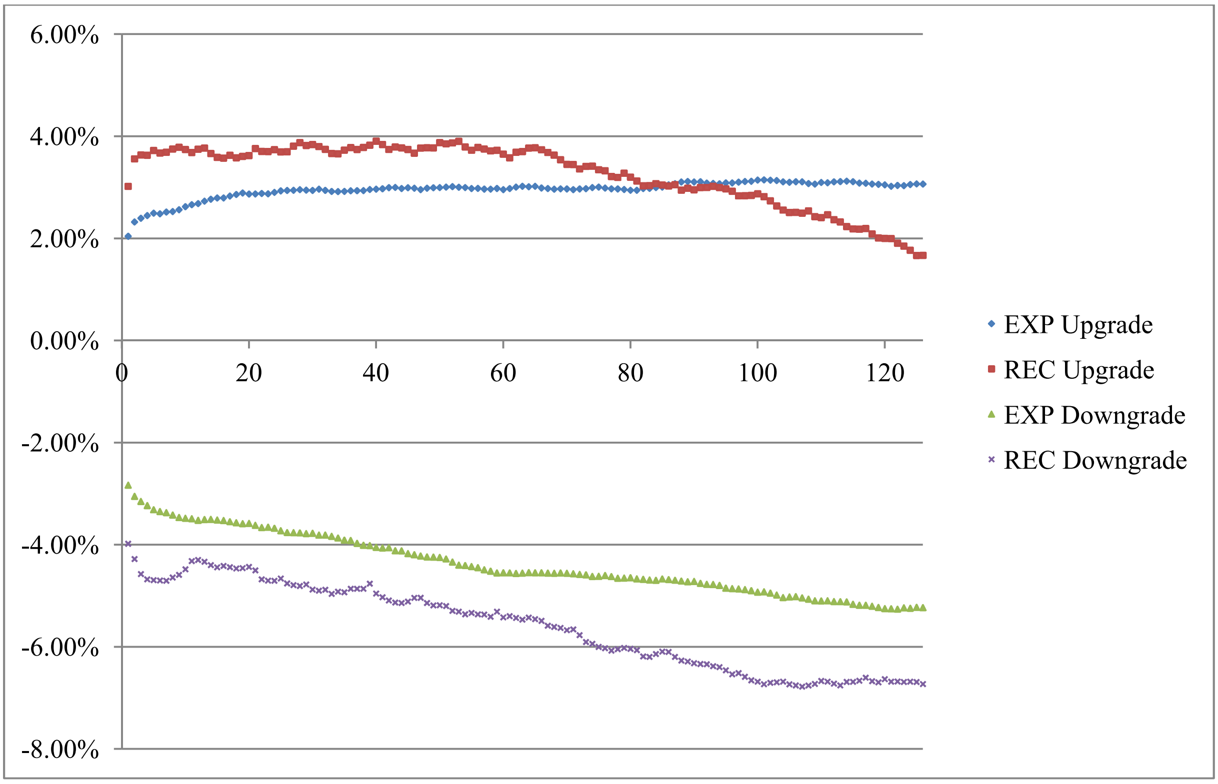
This figure shows the cumulated excess returns from the recommendation announcement day up to 126 trading days, i.e., 6 calendar months, later. The ordinate indicates the DGTW (1997) excess return. The abscissa indicates days elapsed since the recommendation was announced with written trading day values. The sample period is from January 1994 to December 2010 using revisions announced during NBER-designated expansions (EXP) and recessions (REC). The individual curves stand for the performance of the Buy and the Short portfolio in expansions and recessions.



However, the reaction over a longer horizon, i.e., the price formation pattern, is different for the "Buy" portfolio and the "Sell" portfolio respectively for the subsample of upgraded and downgraded stocks: In a recession stocks in the "Sell" portfolio follow the initial market reaction, i.e., stocks generate negative excess returns. In line with the initial market reaction, the market reaction over the following 6 months is stronger in recessions. For example, stocks in the "Sell" portfolio generate an additional negative excess return of -2.83% in a recession in comparison to -2.02% in expansions after the recommendation announcement day. This indicates that "Sell" recommendations have higher investment value in recessions in comparison to expansions.

Figure 3.3: Event Study: Upgrades and Downgrades Portfolio in Expansion and Recession (NBER)

This figure shows the cumulated excess returns from the recommendation announcement day up to 126 trading days, i.e., 6 calendar months, later. The ordinate indicates the DGTW (1997) excess return. The abscissa indicates days elapsed since the recommendation was announced with written trading day values. The sample period is from January 1994 to December 2010 using revisions announced during NBER-designated expansions (EXP) and recessions (REC). The individual curves stand for the performance of the Upgrade and the Downgrade portfolio in expansions and recessions.



In contrast, stocks in the "Buy" portfolio generate positive excess returns of 0.38% over six month after recommendation issuance excluding the recommendation announcement day in an expansion, but negative excess returns of -1.60% in recessions. This return difference of 1.98% is similar for upgraded stocks. Our results indicate that recommended stocks have a positive long-term investment value over six months in expansions, but a negative one in recessions. Investors would be better off to sell the recommended stocks in recessions after the announcement day, indicating that investors overreact in their initial market reaction.

Table 3.2: Event Study: Excess returns according to DGTW (1997) (NBER)

This table presents the results of the event-study for the total sample period 01/1994–12/2010. The event-returns are shown for expansions and recessions according to the NBER classification. The excess returns are calculated according to DGTW (1997). The portfolio classifications follow Cohen, Frazzini, and Malloy (2010). The "Buy portfolio" consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Strong Buy or "Buy" recommendation. The "Sell portfolio" consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Hold", "Sell" or "Strong Sell" recommendation. The upgraded and downgraded stocks are shown separately. The excess returns are shown for the announcement day (Day "0"), the first 3 trading days, 1 month, 3 months, 6 months and 6 months excluding the announcement day. If recommendations are revised during the holding period, the stocks remain in the portfolio till the revision plus one trading day. A t-test is performed to evaluate whether the excess returns are significantly different from zero. *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively.

Trading days	Sample	Recommendation Classification (Mean Returns)			
	NBER	Buy-PF	Sell-PF	Upgrade	Downgrade
0					
	Exp	1.24%***	-1.51%***	2.13%***	-2.34%***
	Rec	1.83%***	-1.93%***	3.11%***	-2.89%***
	Rec-Exp	0.60%***	-0.42%***	0.98%***	-0.55%***
0 - 3					
	Exp	1.41%***	-2.12%***	2.41%***	-3.16%***
	Rec	2.08%***	-3.03%***	3.45%***	-4.42%***
	Rec-Exp	0.67%***	-0.90%***	1.05%***	-1.26%***
1 month					
	Exp	1.28%***	-2.37%***	2.53%***	-3.65%***
	Rec	1.59%***	-3.03%***	3.38%***	-4.58%***
	Rec-Exp	0.31%**	-0.65%***	0.85%***	-0.93%***
3 months					
	Exp	1.53%***	-3.07%***	2.82%***	-4.43%***
	Rec	1.48%***	-3.86%***	3.48%***	-5.47%***
	Rec-Exp	-0.05%	-0.79%***	0.66%**	-1.04%***
6 months					
	Exp	1.62%***	-3.74%***	3.05%***	-5.26%***
	Rec	0.20%	-5.03%***	2.02%***	-6.75%***
	Rec-Exp	-1.42%***	-1.29%***	-1.03%***	-1.49%***
6 months (ex Day 0)					
	Exp	0.38%***	-2.02%***	0.92%***	-2.63%***
	Rec	-1.60%***	-2.83%***	-1.00%**	-3.38%***
	Rec-Exp	-1.98%***	-0.81%***	-1.92%***	-0.75%**

(The distinction of recessions and expansions is based on the NBER statistics.)

Overall, our results point out that the information content and the stock market reaction to the recommendations is very different in respect to the business cycle. In recessions, the initial market reaction is significantly stronger for both the “Buy” and the “Sell” portfolio. However, the stronger reaction is only in line with the long-term investment value of the recommendations for the “Sell” portfolio. Stocks in the “Buy” portfolio generate negative excess returns after the recommendation announcement day over six months. This finding indicates that investors overreact to positive recommendations in recessions, since in fact analysts overestimate the long-term performance of the stocks. Stocks that are recommended to buy during recessions perform very poorly in the long run, i.e., they do not generate excess returns. This finding points out that analysts are positively biased in terms of the expected performance of “Buy” recommendations during recessions.

3.3.2 Analyst Preferences Towards Firms

Next, we analyze whether analysts change their preferences toward firm characteristics dependent on the business cycle. For example, do analysts favor growth stocks in expansions and value stocks in recessions or are they consistent in their preferences? Economic fluctuations impact corporate earnings, cash flows and therefore valuations. Hence, we expect rational analysts to alter their recommendations according to the business cycle not only in such a way that they issue less optimistic recommendations, but that they also align to preferable stock and company characteristics. We expect revisions to reflect the adaptive ability of analysts the most, because revisions are richer in new data and have shown to add more value to investment decisions (Jegadeesh et al. (2004)).

Economic fluctuations affect the expectations of market participants about firms’ earnings and the business climate in general. As firms differ on various dimensions, we also suspect expectations of investors and financial analysts to be subject to changing conditions. Important distinguishing factors among others are: the size and industry affiliation of a firm, the current market valuation in comparison to book earnings or valuation, and the past success and growth of a company.

The methodology of our analysis is based on the following research questions to gain insight into the sources of the predictive power of financial analysts and about potential biases and their consequences for investors.

(I) What preferences for company characteristics are revealed through stock recommendations?

(II) Do analysts change their preferences contingent on the business cycle?

(III) Are the preference structure and its alteration in line with empirical research about the relation between firm characteristics and future excess returns?

A straight–forward way to detect what stock characteristics analysts favor consists in the calculation of means (or medians) of particular financial figures, e.g., the market capitalization (as a proxy for the size) and a subsequent comparison across business cycles. However, this approach does not enable precise comparisons of absolute figures. Both recessions occur in the second half of the sample. Between 1994 and 2010 stock prices (and thereby market capitalizations) have increased substantially. Hence, despite the sharp decline in prices during recessions, average values are still higher than during the relatively big time–span of expansion before.

Table 3.3: Company Financials across Business Cycles

This table displays financial data of firms across expansions and recessions according to the recommendation category. Values are calculated on the basis of data which was winsorized at the top and bottom quintiles. Prices are obtained from the CRSP database on a daily basis. The market capitalization of firms is calculated as the number of shares outstanding multiplied by the share price (in thousand USD). The definitions of ratios are given in the body of this chapter.

	N		Price ($)		Market Cap. ($)		MB		PE	
	Exp.	Rec.	Exp.	Rec.	Exp.	Rec.	Exp.	Rec.	Exp.	Rec.
(1) Strong Buy	97,667	12,134	35.41	52.71	4,260,457	5,371,954	3.49	3.01	17.59	13.69
(2) Buy	122,244	15,652	36.38	39.44	4,643,797	5,674,206	3.42	3.07	17.23	13.97
(3) Hold	147,899	24,815	40.25	41.55	4,717,733	4,884,081	2.96	2.52	16.24	12.65
(4) Sell	16,322	3,318	36.90	22.93	4,467,955	4,389,518	2.54	2.11	13.74	10.64
(5) Strong Sell	8,758	2,007	40.36	23.23	4,303,041	5,123,125	2.76	2.24	13.88	10.96
Mean/Total	392,890	57,926	37.71	41.61	4,561,436	5,179,729	3.21	2.74	16.73	13.05

(The distinction of recessions and expansions is based on the NBER statistics.)

However, relative metrics can be compared. As expected, we find the market-to-book and price-earnings ratio to be higher in times of economic expansion. On average, the market-to-book ratio (price-earnings ratio) is 3.21 (16.73) during expansions and 2.74 (13.05) in recessions. These results could be expected from times of declining stock prices. Though, firms which receive the most favorable recommendations according to the I/B/E/S classification score substantially higher on these valuation multiples than those with negative recommendations. In expansions a "Strong Buy" recommendation averages 17.59 compared to 13.88 for a "Strong Sell" on the price-earnings ratio. The same pattern is found for recessions. It indicates a tilt towards stocks which have higher growth opportunities respectively stocks with a higher market valuation. Arguably, this preference is in conflict with capital market research which documents higher returns for stocks that score low on these ratios (Fama and French (1998)).

In order to control for the general effect of the business cycle on financial metrics two complementary approaches are used in the following to enable a reliable line-up of firm characteristics across cycles: First, a comparison of decile ranks of firm fundamentals is employed. Table 3.3 displays the deciles of average momentum statistics to which recommendations and revisions pertain in order to determine the extent to which analysts discriminate their recommendations based on the past performance of stocks. In addition, it is accounted for size, value, and growth specific preferences across business cycles. The second approach for the investigation of analysts' preferences, displayed in Table 3.4, deals with quantitative investment signals which have been subject to extensive research in the past indicating a nexus with future returns (see Jegadeesh et al. (2004)). The correlation between recommendation/revision categories and the criteria described below is investigated. Subsequently, if a correlation above 0.10 is found the actual is compared to the normative direction (of sign) of the correlation with future returns that was found in prior studies. The decile rank comparison and the correlation analysis are somewhat similar as to their contribution to the question about the analysts' preference structure. Though, the latter method gives insight to whether analysts consider and align their recommendations to commonly accepted investment signals in general and in changing economies or if they simply ignore them.

The stock characteristics ratios used for this study are defined in the following. For all definitions listed subsequently *q, m, d* are defined as the quarter, month, or day of a recommendation/revision announcement for the firm *i*. Company financial data pertains to the end of the respective quarter, whereas prices pertain to the day on which a recommendation is published.

Sales growth is calculated as the rolling sum of sales for the preceding two and four quarters:

$$SG2=\frac{\sum_{i=0}^{1}\mathrm{Sales}_{q-i}}{\sum_{i=0}^{1}\mathrm{Sales}_{q-2-i}} \tag{3.3}$$

The market-to-book ratio is calculated as the market value of a stock over the book value of common equity:

$$MB=\frac{\mathrm{Price}_d \times \mathrm{Shares\ outstanding}_d}{\mathrm{Book\ value\ of\ common\ equity}_q} \tag{3.4}$$

The price-earnings ratio is computed as the price of the stock divided by the rolling sum of the EPS for the preceding four quarters (EPS_q = Earnings per share before extraordinary items):

$$PE=\frac{\mathrm{Price}_d}{\sum_{i=0}^{3}\mathrm{EPS}_{q-i}} \tag{3.5}$$

The price momentum for the periods of 3, 6, 12, and 18 months is calculated as the product of monthly stock returns less the product of the monthly returns on the CRSP Value Weighted Index.

$$\begin{aligned} PM18_m = & \{[\prod_{m-18}^{m-1}(1+\text{monthly return}_i)]-1\} \\ & -\{[\prod_{m-18}^{m-1}(1+\text{monthly return}^{CRSP\text{-}VW})]-1\} \end{aligned} \tag{3.6}$$

The size of a firm is calculated as the natural logarithm of the market capitalization.

$$SIZE=\ln\,(Price_d \times Shares\ outstanding_d) \tag{3.7}$$

In short, our empirical results reveal that analysts show a persistent preference for relatively expensive large cap growth stocks which have performed well in the past. This preference is significantly stronger in recessions. We discover a monotonic decrease in decile ranks on the 3 and 18 months price momentum in recessions and expansions. Both, recommendations and revisions display such a pattern. In line with prior studies, this indicates that analysts favor stocks that have performed well in the past. However, the degree of discrimination, which is measured by the spread between strong buy and strong sell, is lower for the 3 months momentum (0.41 and 0.55) compared to the 18 months momentum (1.37 and 1.38) in both economic states.

Table 3.4: Test for Analyst Preferences

This table displays past returns, value, growth, and size characteristics of firms for recommendations (panel A and C) and revisions (panel B and D). Average decile ranks are calculated for each recommendation or revision category according to the business cycle. The bottom 10% of all observations within a specific characteristic group are assigned the rank "1". Whereas the top 10% group receives the rank "10". Accordingly, ranks above "5" can be interpreted as exceeding the median. The bottom row of each panel table presents the spread between the most favorable and the most unfavorable recommendation level. It reveals the degree to which analysts discriminate their assessments. Panel A and B report ranks for returns during the 3 and 18 months before the recommendation announcement ("PM"). Panel C and D report ranks for the sales growth during the previous 4 quarters before the announcement ("SG4"), the size of a firm ("SIZE"), and its market-to-book ratio at the time the recommendation was published ("MB"). All t-statistics pertain to the null-hypothesis that the mean respective rank is equal in expansion and recession.

Panel A: Price Momentum (Recommendations)

	N		PM3			PM18		
	Exp.	Rec.	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat
(1) Strong Buy	91,261	11,929	5.68	5.73	-1.91	6.23	6.53	-10.94
(2) Buy	114,023	15,403	5.66	5.60	2.29	6.03	6.38	-14.27
(3) Hold	142,070	24,658	5.39	5.36	1.14	5.46	5.71	-12.86
(4) Sell	16,007	3,307	5.21	5.27	-1.01	4.88	5.14	-4.79
(5) Strong Sell	8,415	2,002	5.27	5.18	1.17	4.85	5.16	-4.16
Spread (1) - (5)			0.41	0.55		1.37	1.38	

Panel C: Value, Growth, and Size (Recommendations)

N		SG4			SIZE			MB		
Exp.	Rec.	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat
75,201	10,564	6.19	6.39	-7.06	6.74	6.99	-10.68	6.23	6.51	-10.60
94,069	13,864	6.09	6.33	-9.40	6.90	7.20	-14.60	6.15	6.47	-14.06
119,050	21,981	5.74	5.95	-10.26	7.01	6.92	5.39	5.79	5.92	-7.03
13,610	2,901	5.36	5.49	-2.29	6.89	6.86	0.54	5.31	5.36	-0.93
6,978	1,793	5.28	5.77	-6.37	6.75	6.81	-0.97	5.42	5.48	-0.84
		0.91	0.62		-0.01	0.18		0.81	1.02	

Panel B: Price Momentum (Revisions)

	N		PM3			PM18		
To ...	Exp.	Rec.	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat
(1) Strong Buy	38,946	5,843	5.60	5.79	-4.72	6.02	6.49	-11.86
(2) Buy	47,977	6,504	5.57	5.54	0.68	5.82	6.25	-11.80
(3) Hold	68,945	12,502	5.42	5.37	1.66	5.47	5.68	-7.67
(4) Sell	9,537	1,978	5.24	5.31	-0.92	4.87	5.18	-4.50
(5) Strong Sell	5,552	1,508	5.33	5.24	1.04	4.82	5.18	-4.26
Spread (1) - (5)			0.28	0.55		1.21	1.31	
Upgrade	77,545	12,439	5.52	5.62	-3.54	5.73	6.16	-15.62
Downgrade	93,412	15,896	5.46	5.38	3.30	5.56	5.73	-6.97

Panel D: Value, Growth, and Size (Revisions)

N		SG4			SIZE			MB		
Exp.	Rec.	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat	Exp.	Rec.	t-stat
33,553	5,286	5.91	6.25	-8.29	7.12	7.22	-3.07	6.19	6.49	-8.19
41,174	5,970	5.85	6.15	-7.55	7.17	7.31	-4.60	6.02	6.34	-9.07
59,251	11,286	5.73	5.97	-8.23	6.92	6.84	3.11	5.79	5.87	-3.00
8,126	1,724	5.37	5.58	-2.77	6.81	6.73	1.35	5.28	5.30	-0.36
4,712	1,380	5.20	5.72	-5.97	6.72	6.76	-0.55	5.36	5.43	-0.78
		0.71	0.53		0.40	0.46		0.83	1.07	
66,520	11,266	5.66	5.95	-10.14	7.17	7.20	-1.44	5.96	6.18	-8.26
80,296	14,380	5.86	6.09	-9.07	6.90	6.87	1.38	5.86	5.94	-3.38

(The distinction of recessions and expansions is based on the NBER statistics.)

Analysts seem to consider rather the longer term performance of stocks than the short term performance. Surprisingly, the spread statistics are slightly lower for revisions. One could have expected analysts to discriminate across stocks even more rigorously when changing their expectations which seems not to be the case.

The overall finding for the 18 months momentum measure is that for all types of recommendations decile ranks are significantly higher in recessions. Stocks which are revised to “Strong Buy” are on average in the 6.49 decile during recessions and in the 6.02 decile in expansions. Analogously, “Strong Sell” revisions pertain to stocks of the 5.18 decile in recessions and to the 4.82 decile in expansions. Thus, the preference for high momentum stocks is even more pronounced during recessions.

As far as the size of firms is concerned, we discover a general preference for larger companies in expansions and recessions (exceeding the 6.9 decile on average). Furthermore, analysts appear to take sales growth into consideration when issuing recommendations. They discriminate substantially across categories (e.g., 6.19 for “Strong Buy” vs. 5.28 for “Strong Sell” during expansions) and weigh growth stronger during recessions (6.25 vs. 5.91 for revisions to “Strong Buy”). Besides that, analysts favor stocks with rather high market-to-book valuation metrics. Commonly, such stocks are popular investment choices whose prices are driven by the magnitude of investors. Again, this is revealed even more explicitly during recessions where a “Strong Buy” recommendation is located at the 6.51 decile in contrast to a “Sell” one at the 5.36 decile. Noticeably, there is no consistent monotonic pattern anymore as to the order from positive to negative recommendations and revisions. Combined with their favor for past winners, the analysts’ preference does not seem to be vastly different from so called naïve trading strategies.

In sum, analysts reveal a preference for growth and momentum stocks and even exaggerate that during recessions. However, the benefit of such liking is questionable. Analysts do not only favor stocks that have performed well in the past but they also exaggerate that favor during economically dull times. One could argue that analysts rely more heavily on quantitative characteristics instead of their qualitative idiosyncratic knowledge when markets are not in good shape. Since decile ranks are significantly different for expansions and recessions and persistent over time, it appears unlikely that the preference reinforcement is just random.

3.3.4 Quantitative Investment Signals

The preceding section reveals that analysts alter their preferences contingent on the business cycle in such a way that during recessions they amplify their likings for momentum and growth. The following section investigates the appropriateness of such likings. In sum, the preference structure of analysts and its alterations are in line with empirical research about the relation between firm characteristics and future excess returns as to momentum but not in the case of their favor for growth stocks.

The results shown below confirm the findings of the decile comparison: The correlation between the price momentum variables and the absolute recommendation/revision level is negative which means that a high recommendation number (e.g., “Strong Sell” which is coded as 5 in I/B/E/S notation) by tendency is associated with a relatively low momentum and vice versa. On average, the 18 months price momentum reveals the strongest correlation with analyst recommendations. Further, the correlation is stronger in recessions (-29.03%) than during expansions (-16.36%). As indicated by the consistence of the normative direction and the actual direction, analysts' preference for past high performers is in line with empirical findings that prove this to coincide with future abnormal returns (the algebraic sign of the normative direction equals the actual direction).

Table 3.5: Analyst Preferences and Investment Signals

This table presents Spearman rank correlation coefficients between the continuous explanatory variable and consensus analyst recommendations. In the first column five investment signals are listed (price momentum comprises four temporal variations, sales growth has two temporal variations). The correlation between these variables and the recommendations level (1) to (5) is reported in columns three and four. The normative direction refers to the expected algebraic sign among both as to future returns. The actual direction is derived from the time weighted correlation coefficient (not tabulated) across recession and expansions and reported if it exceeds 10%. Otherwise it is displayed as "?". *, **, and *** indicate statistical significance at the 10, 5, and 1%-level respectively. The statistics pertain to the null-hypothesis that the mean correlation coefficient in expansion and recession is equal (i.e., that their difference is equal to zero). T-values are obtained via the Fisher r-to-z transformation.

Explanatory Variable	Normative Direction	Correlation		Actual Direction
		Exp.	Rec.	
Price Momentum Variables				
PM18	-	-16.36%***	-29.03%***	-
PM12	-	-16.48%***	-25.40%***	-
PM6	-	-12.76%***	-18.08%***	-
PM3	-	-8.31%***	-11.54%***	?
Value vs. Growth Variables				
SG4	+	-15.63%	-14.91%	-
SG2	+	-13.45%	-13.25%	-
MB	+	-14.76%***	-20.23%***	-
PE	+	-7.45%***	-10.08%***	?
Size	+	4.46%***	-5.87%***	?

(The distinction of recessions and expansions is based on the NBER statistics.)

In contrast to that, we document a discrepancy between what sign of correlation (positive/negative) was expected and what was actually found to exist in the following cases: Companies whose revenues face rather strong growth rates and whose stocks account for relatively high market-to-book and price-earnings ratios are considered as growth stocks (Fama and French (1998)). Empirical analyses have uncovered a negative relation of these aspects with future returns which should translate into a positive relationship with the magnitude of recommendations (i.e., higher rating scores). However, our results reveal a negative correlation for four quarters sales growth of -15.63 % and -14.91% respectively in expansion and recession which signifies that more positive recommendations (with smaller absolute values) are issued for firms which grow at relatively high levels.

The same discrepancy is found for the market-to-book and price-earnings ratios. However, the correlation found under the latter metric is of a small magnitude (only -7.45%) and needs to be interpreted with some caution. The same applies for the size metric. In general, all correlation coefficients are found to be significantly different at the 1% level during expansions and recessions except the sales growth metrics. According to Jegadeesh et al. (2004) analysts prefer firms high in operating performance. High market-to-book firms are generally higher in RoE and expected to grow at faster rates in the future. One could infer that analysts recognize and actively consider investment signals (which appears just logical in light of today's extensive quantitative components of stock research) and in doubt weigh operating performance higher if the respective indicator is in a normative vs. actual conflict (Jegadeesh et al. (2004)). Generally speaking, analysts' preferences are not fully in line with empirical indications. Thus, their contribution to investors might be questioned. However, analysts' preference structure varies systematically across the business cycle.

3.4 Robustness Checks

3.4.1 Regulation FD, Median Returns, and CFNAI Business Cycle Classification

Regulation Fair Disclosure (Reg FD) became effective on October, 23rd, 2000. Its goal was to prevent selective disclosure of material nonpublic information to investors and financial intermediaries such as stock analysts. As stated by the U.S. Securities and Exchange Commission (2000) "the practice of selective disclosure leads to a loss of investor confidence in the integrity of our capital markets. Investors who see a security's price change dramatically and only later are given access to the information responsible for that move rightly question whether they are on a level playing field with market insiders." Recent findings indicate that Reg FD was successful in generating a more equal information environment for security analysts. For example, Cohen, Frazzini, and Malloy (2010) find that analysts generate more profitable stocks recommendations when they have an educational link to the company. However, the higher profitability almost diminished after Reg FD.

Table 3.6: Event Study: Excess returns according to DGTW (1997) after Reg FD

This table presents the results of the event-study for the period 11/2000-12/2010 after Regulation Fair Disclose (Reg FD). The event-returns are shown for expansions and recessions according to the NBER classification. The excess returns are calculated according to DGTW (1997). The portfolio classifications follow Cohen, Frazzini, and Malloy (2010). The "Buy portfolio" consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Strong Buy or "Buy" recommendation. The "Sell portfolio" consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Hold", "Sell" or "Strong Sell" recommendation. The upgraded and downgraded stocks are shown separately. The excess returns are shown for the announcement day (Day "0"), the first 3 trading days, 1 month, 3 months, 6 months and 6 months excluding the announcement day. If recommendations are revised during the holding period, the stocks remain in the portfolio till the revision plus one trading day. A t-test is performed to evaluate whether the excess returns are significantly different from zero. *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively.

Trading days	Sample	Recommendation Classification (Mean Returns)			
	NBER	Buy-PF	Sell-PF	Upgrade	Downgrade
0					
	Exp	1.54%***	-1.48%***	2.55%***	-2.48%***
	Rec	1.83%***	-1.93%***	3.11%***	-2.89%***
	Rec-Exp	0.29%***	-0.45%***	0.56%***	-0.40%***
0 - 3					
	Exp	1.75%***	-2.09%***	2.81%***	-3.34%***
	Rec	2.08%***	-3.03%***	3.45%***	-4.42%***
	Rec-Exp	0.32%***	-0.94%***	0.65%***	-1.08%***
1 month					
	Exp	1.81%***	-2.17%***	3.23%***	-3.56%***
	Rec	1.59%***	-3.03%***	3.38%***	-4.58%***
	Rec-Exp	0.32%**	-1.27%***	0.96%***	-1.41%***
3 months					
	Exp	1.83%***	-2.67%***	3.22%***	-4.18%***
	Rec	1.48%***	-3.86%***	3.48%***	-5.47%***
	Rec-Exp	-0.49%**	-1.34%***	-0.23%	-1.52%***
6 months					
	Exp	1.76%***	-3.04%***	3.20%***	-4.61%***
	Rec	0.20%	-5.03%***	2.02%***	-6.75%***
	Rec-Exp	-1.47%***	-1.99%***	-1.11%***	-2.14%***
6 months (ex Day 0)					
	Exp	0.19%*	-1.28%***	0.62%***	-1.71%***
	Rec	-1.60%***	-2.83%***	-1.00%**	-3.38%***
	Rec-Exp	1.79%***	1.55%***	1.63%***	1.67%***

(The distinction of recessions and expansions is based on the NBER statistics.)

Table 3.7: Event Study: Excess returns according to DGTW (1997) Medians

This table presents the results of the event-study for the total sample period 01/1994-12/2010. The median event-returns are shown for expansions and recessions according to the NBER classification. The median excess returns are calculated according to DGTW (1997). The portfolio classifications follow Cohen, Frazzini, and Malloy (2010). The "Buy portfolio" consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Strong Buy or "Buy" recommendation. The "Sell portfolio" consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a "Hold", "Sell" or "Strong Sell" recommendation. The upgraded and downgraded stocks are shown separately. The excess returns are shown for the announcement day (Day "0"), the first 3 trading days, 1 month, 3 months, 6 months and 6 months excluding the announcement day. If recommendations are revised during the holding period, the stocks remain in the portfolio till the revision plus one trading day.

Trading days	Sample	Recommendation Classification (Median Returns)			
	NBER	Buy-PF	Sell-PF	Upgrade	Downgrade
0					
	Exp	0.53%	-0.61%	0.99%	-1.05%
	Rec	0.88%	-1.10%	1.70%	-1.82%
	Rec-Exp	0.35%	-0.49%	0.71%	-0.77%
0 - 3					
	Exp	0.81%	-1.11%	1.39%	-1.73%
	Rec	1.28%	-1.97%	2.30%	-2.92%
	Rec-Exp	0.47%	-0.86%	0.91%	-1.19%
1 month					
	Exp	0.79%	-1.90%	1.54%	-2.84%
	Rec	0.79%	-2.98%	1.85%	-4.01%
	Rec-Exp	0.00%	-1.08%	0.31%	-1.17%
3 months					
	Exp	0.19%	-2.95%	1.13%	-3.97%
	Rec	-0.15%	-4.66%	1.14%	-5.76%
	Rec-Exp	-0.33%	-1.71%	0.01%	-1.79%
6 months					
	Exp	-0.54%	-3.87%	0.60%	-4.98%
	Rec	-1.48%	-5.57%	0.12%	-6.26%
	Rec-Exp	-0.94%	-1.70%	-0.48%	-1.28%
6 months (ex Day 0)					
	Exp	-1.07%	-3.26%	-0.39%	-3.93%
	Rec	-2.36%	-4.47%	-1.58%	-4.44%
	Rec-Exp	-1.29%	-1.21%	-1.19%	-0.51%

(The distinction of recessions and expansions is based on the NBER statistics.)

Since Reg FD had a significant impact on the information content of analysts' stock recommendations we conduct a robustness check by using only recommendations issued from 11/2000 to 12/2010. The results are shown in Table 3.6. Next, to check the robustness against outliers we calculate median returns. The results are shown in Table 3.7. Table 3.7 shows the results when using median returns. For all portfolio classifications and holding periods the general direction is in line with the mean results. Using median returns does change the picture, i.e., our main results are not driven by outliers.

Furthermore, we use the CFNAI business cycle definition instead of the NBER business cycle definition. According to the Federal Reserve of Chicago a value of the CFNAI moving average over 3 months below -0.7 indicates “an increasing likelihood that a recession has begun”. A value is above +0.2 indicates a “significant likelihood that a recession has ended”.[16] Table 3.8 shows the results of the event-study when using the CFNAI business cycle classification.

Table 3.8: Event Study: Excess returns according to DGTW (1997) (CFNAI)

This table presents the results of the event-study for the total sample period 01/1994-12/2010. The event-returns are shown for expansions and recessions according to the CFNAI classification. The excess returns are calculated according to DGTW (1997). The portfolio classifications follow Cohen, Frazzini, and Malloy (2010). The “Buy portfolio” consists of all upgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a “Strong Buy or “Buy” recommendation. The “Sell portfolio” consists of all downgraded stocks and stocks for which the analyst initiates, resumes or reiterates the coverage with a “Hold”, “Sell” or “Strong Sell” recommendation. The upgraded and downgraded stocks are shown separately. The excess returns are shown for the announcement day (Day “0”), the first 3 trading days, 1 month, 3 months, 6 months and 6 months excluding the announcement day. If recommendations are revised during the holding period, the stocks remain in the portfolio till the revision plus one trading day. A t-test is performed to evaluate whether the excess returns are significantly different from zero. *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively.

Trading days	Sample	Recommendation Classification (Mean Returns)			
	CFNAI	Buy-PF	Sell-PF	Upgrade	Downgrade
0					
	Exp	1.21%***	-1.49%***	2.04%***	-2.26%***
	Rec	1.53%***	-1.72%***	2.74%***	-2.69%***
	Rec-Exp	0.31%***	-0.22%***	0.70%***	-0.43%***
0 - 3					
	Exp	1.39%***	-2.09%***	2.28%***	-3.05%***
	Rec	1.74%***	-2.56%***	3.10%***	-3.86%***
	Rec-Exp	0.35%***	-0.47%***	0.81%***	-0.80%***
1 month					
	Exp	1.23%***	-2.47%***	2.23%***	-3.71%***

[16] As a remainder, the recessions and expansions according to NBER and the CFNAI are shown in Figure 3.1.

	Rec	1.53%***	-2.47%***	3.50%***	-3.92%***
	Rec-Exp	0.29%***	0.00%	1.27%***	-0.21%
3 months					
	Exp	1.54%***	-3.27%***	2.61%***	-4.57%***
	Rec	1.49%***	-3.02%***	3.53%***	-4.58%***
	Rec-Exp	-0.05%	0.25%*	0.93%***	-0.01%
6 months					
	Exp	1.71%***	-4.14%***	2.89%***	-5.65%***
	Rec	0.84%***	-3.58%***	2.93%***	-5.18%***
	Rec-Exp	-0.88%***	0.56%***	0.04%	0.47%*
6 months (ex Day 0)					
	Exp	0.49%***	-2.40%***	0.84%***	-3.03%***
	Rec	-0.67%***	-1.69%***	0.26%	-2.22%***
	Rec-Exp	1.16%***	-0.70%***	0.58%**	-0.82%**

(The distinction of recessions and expansions is based on the CFNAI statistics.)

Table 3.8 shows that the results are robust to the CFNAI business cycle definition.

3.4.2 Herding Behavior[17]

The arguably most prominent bias in analyst recommendations is herding. Observed herding behavior might be caused by independent similar information processing or mutual imitation. In so far that recessions are marked by a more volatile economic situation and thus more divergent information, it would be plausible that there is less herding due to the first explanation. With regard to the second case, the situation does not seem to be intuitively clear: As in general, analysts might either herd to be on the safe side or anti-herd to stand out from the crowd. A recession might only strengthen this pattern. In recessions and their more volatile market environment an analyst might have the desire not to be entirely wrong, or if so, at least not to be the only one. Thus, an analyst would herd more. On the other hand, it might be that under these circumstances the employer is more forgiving and she could therefore try a risky approach. Summarizing this reasoning, a different intensity of herding could be expected during recessions compared to expansions.

[17] Departing from other analyses in this paper, we include observations starting from October 1993 until December 2010.

As a foundation for our herding study we use the Jegadeesh and Kim (2010) approach. Their model assumes that investors recognize herding and, ceteris paribus, react less to herders. They construct a model which controls for sensible other influences and assume that the remaining differences of event excess returns can at least partially be attributed to investors' different behavior towards herders versus non-herders. Our approach employs the basic regression

$$ER^{i}(t,T)=a_{T-t}+b_{T-t}*I_{multi}+c_{T-t}*I_{single} \\ +d_{T-t}*(New\_rec_{i,j,t}-Con\_rec_{i,t-1})+\varepsilon_{i,j,t,T} \tag{3.8}$$

Where

I_{multi} = +1 if the revision increases the numerical I/B/E/S recommendation level[18] (i.e., a downgrade) by at least two labels

= -1 if the revision decreases the numerical I/B/E/S recommendation level (i.e., an upgrade) by at least two labels

I_{single} = +1 if the revision increases the numerical I/B/E/S recommendation level by exactly one label

= -1 if the revision decreases the numerical I/B/E/S recommendation level by exactly one label

$New\_rec_{i,j,t}$ is the new recommendation level of analyst *j* for stock *i* on day *t*, after revision. $Con\_rec_{i,t-1}$ is the consensus recommendation of all active recommendations (except of analyst *j*) about stock *i* one day before the revision. It is calculated as an arithmetic mean without weights using the I/B/E/S recommendation level codes.

[18] Recommendation level codes are such, that the lower the better. We keep these values while Jegadeesh/Kim (2010) redefine the level codes and thus obtain opposing signs.

The excess returns are expected to be influenced by the recommendation revisions' direction and intensity. If in addition there is a significant non-zero coefficient for the deviation from consensus ($New\_rec_{i,j,t}$ - $Con\_rec_{i,j,t-1}$) then this means that the market participants assume one kind of herding behavior. The mere fact that one strays from the consensus would then lead to a more intense market reaction. Using the I/B/E/S recommendation codes a negative d stands for assumed regular herding behavior, while a positive d signifies an underlying anti-herding assumption. That would be the case when the market reaction rewards a move to consensus because supposedly the analysts' information force him/her to do so, while his/her natural tendency would be rather to issue a divergent recommendation.

The data is prepared according to Jegadeesh and Kim (2010). However, we employ linear regressions instead of Fama-MacBeth regressions.

Table 3.9: Herding: Expansions versus Recessions (NBER)

This table presents the regression estimates for

$$ER^i(t,T) = a_{T-t} + b_{T-t} * I_{multi} + c_{T-t} * I_{single} + d_{T-t} * (New\_rec_{i,j,t} - Con\_rec_{i,j,t-1}) + \varepsilon_{i,j,t,T}$$

where I_{multi} is 1 (-1) for a multi-step revision upwards (downwards) in I/B/E/S recommendations codes with lower values indicating better recommendations. I_{single} is correspondingly defined for single-step revisions. $New\_rec_{i,j,t}$ - $Con\_rec_{i,j,t-1}$ is the new revision's deviation from the consensus level of active recommendations for the same company. Each T-t-period excess return is estimated for the complete sample and then individually for the sub-samples of expansive and recessive business cycle phases, as defined by NBER (Panel A) and CFNAI (Panel B, see next page). A Wald test is performed to compare the coefficients for *deviation from consensus* of expansions and recessions for equality, i.e., the null hypothesis is that the coefficients are the same. *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively. Significance is only indicated for *deviation from consensus* for the sake of clarity. All other coefficients are significant at the 1%-level. The sample period is from October 1993 to December 2010. "t-stat" abbreviates t-statistic.

Days since revision	(Sub-) Sample	N	I_multi (= 1 or -1, multi level) Coef. (%)	t-stat	I_single (= 1 or -1, single level) Coef. (%)	t-stat	*Deviation from consensus* Coef. (%)	t-stat
			Panel A: NBER					
0	Complete	107,068	-2.26	-40.86	-2.27	-62.77	-0.64***	-19.85
	Exp	92,160	-2.10	-35.80	-2.15	-56.73	-0.66***	-19.24
	Rec	14,908	-3.15	-19.61	-3.07	-27.21	-0.54***	-5.74
	Exp-Rec (P > χ^2)						(0.25)	
1	Complete	107,060	-2.63	-42.58	-2.59	-64.38	-0.71***	-19.83
	Exp	92,154	-2.44	-37.43	-2.44	-57.97	-0.72***	-18.83
	Rec	14,906	-3.64	-20.23	-3.60	-28.50	-0.68***	-6.50
	Exp-Rec (P > χ^2)						(0.77)	
2	Complete	107,042	-2.76	-42.28	-2.69	-63.12	-0.72***	-18.87
	Exp	92,141	-2.56	-37.27	-2.54	-57.23	-0.73***	-18.14
	Rec	14,901	-3.88	-19.77	-3.73	-27.08	-0.67***	-5.83
	Exp-Rec (P > χ^2)						(0.63)	
21	Complete	106,478	-3.09	-27.88	-3.22	-44.44	-0.80***	-12.40
	Exp	91,624	-2.97	-25.70	-3.10	-41.52	-0.83***	-12.24
	Rec	14,854	-3.73	-10.87	-3.96	-16.44	-0.68***	-3.42
	Exp-Rec (P > χ^2)						(0.51)	
42	Complete	105,378	-3.21	-21.04	-3.45	-34.64	-0.91***	-10.15
	Exp	90,618	-3.11	-19.53	-3.31	-32.29	-0.98***	-10.52
	Rec	14,760	-3.78	-7.95	-4.29	-12.89	-0.54*	-1.95
	Exp-Rec (P > χ^2)						(0.14)	
126	Complete	101,003	-3.55	-13.21	-3.83	-21.91	-1.17***	-7.49
	Exp	86,605	-3.41	-12.00	-3.60	-19.71	-1.39***	-8.40
	Rec	14,398	-4.27	-5.47	-5.09	-9.32	-0.12	-0.26
	Exp-Rec (P > χ^2)						(0.02)**	

Table 3.9: continued

Days since revision	(Sub-) Sample	N	*I_multi* (= 1 or -1, multi level) Coef. (%)	t-stat	*I_single* (= 1 or -1, single level) Coef. (%)	t-stat	*Deviation from consensus* Coef. (%)	t-stat
				Panel B: CFNAI				
0	Complete	107,068	-2.26	-40.86	-2.27	-62.77	-0.64***	-19.85
	Exp	71,169	-1.88	-30.10	-2.06	-50.79	-0.59***	-16.20
	Rec	35,899	-3.02	-27.74	-2.70	-37.55	-0.74***	-11.67
	Exp-Rec (P > ?²)						(0.06)*	
1	Complete	107,060	-2.63	-42.58	-2.59	-64.38	-0.71***	-19.83
	Exp	71,164	-2.20	-31.62	-2.32	-51.46	-0.65***	-15.96
	Rec	35,896	-3.47	-28.65	-3.14	-39.27	-0.84***	-11.89
	Exp-Rec (P > ?²)						(0.03)**	
2	Complete	107,042	-2.76	-42.28	-2.69	-63.12	-0.72***	-18.87
	Exp	71,151	-2.30	-31.40	-2.40	-50.38	-0.66***	-15.43
	Rec	35,891	-3.67	-28.43	-3.29	-38.63	-0.83***	-11.06
	Exp-Rec (P > ?²)						(0.06)*	
21	Complete	106,478	-3.09	-27.88	-3.22	-44.44	-0.80***	-12.40
	Exp	70,656	-2.68	-21.08	-2.96	-35.88	-0.78***	-10.57
	Rec	35,822	-3.92	-18.36	-3.78	-26.79	-0.84***	-6.74
	Exp-Rec (P > ?²)						(0.70)	
42	Complete	105,378	-3.21	-21.04	-3.45	-34.64	-0.91***	-10.15
	Exp	69,725	-2.82	-15.97	-3.22	-28.04	-0.94***	-9.07
	Rec	35,653	-4.01	-13.89	-4.01	-21.05	-0.84***	-5.01
	Exp-Rec (P > ?²)						(0.64)	
126	Complete	101,003	-3.55	-13.21	-3.83	-21.91	-1.17***	-7.49
	Exp	66,093	-3.07	-9.45	-3.59	-17.12	-1.49***	-7.85
	Rec	34,910	-4.62	-9.78	-4.58	-14.70	-0.59**	-2.15
	Exp-Rec (P > ?²)						(0.01)**	

In order to test the impact of herding we analyze the coefficients for deviation from consensus. Within the NBER classification (Panel A), the difference between expansions and recessions is only significant for 126 trading days. The coefficient for recessions alone, however, is not significant anymore for that time period. This is most probably due to noise which is successively introduced in all coefficients in longer time periods and which should be even higher in volatile recessions. Moreover, as the shorter durations do not show any significant differences, this result for that duration can be considered meaningless. All other differences are insignificant at the 10%-level.

The CFNAI classifications (Panel B of Table 3.9) show a surprisingly different picture. While the difference is insignificant, the NBER differentiation still indicates that the magnitude of herding might be less in recessions. In the CFNAI results the coefficient is just the opposite: bigger for recessions, not smaller. This difference is even significant in the short and long run (albeit not in the medium term). The CFNAI is released monthly and therefore corresponds better to what analysts and other market participants actually know at the time of their decision making. Therefore, there might be some kind of herding effect, after all. CFNAI more easily proclaims a recession than NBER. Essentially the CFNAI recessions consist of the NBER recessions plus some fringe months at the beginning and end of NBER-recessions. It might be that market participants subdivide the business cycle into at least four stages instead of two. And just during the transition phases form expansion to recession and from recession to expansion (covered by CFNAI), there might be more herding taking place. But there might also be a problem of the model. Maybe the consensus recommendation is just too old and as the market is volatile describes a situation which is not valid anymore, so that a new recommendation which takes into account the current situation can easily beat the odds.

Summarizing, there is no difference in herding behavior between recessions and expansions. This finding is in line with Lin, Chen, and Chen (2011) but contrary to Welch (2000).

3.5 Conclusion

We show that it is crucial to control for the effects of macroeconomic fluctuations when assessing analysts' stock recommendations. Dependent on the business cycle we find significantly different price formation patterns after recommendations have been issued. In addition to analyst characteristics (e.g., Hess, Kreutzmann, and Pucker (2012)), economic activity is an important determinant of the profitability of stock recommendations.

Our study shows that in recessions analysts are too optimistic with regard to the stocks they suggest as a "Buy". Such recommendations do not have long-term investment value. Interestingly, our results indicate that investors are not aware of this severe bias. In recessions, the initial market reaction to "Buy" recommendations is even stronger than in expansions.

This finding points out that the information content and the information processing of stock recommendations differ dependent on the business cycle. The unique information set of analysts (Grossman and Stiglitz (1980)) is assumed to be more valuable in recessions by market participants. However, analysts only issue profitable "Sell" recommendations in recessions, while "Buy" recommendations do not generate excess returns.

A plausible explanation for the difference in profitability is attributable to the nature of the stocks that are recommended: We show that analysts favor "glamour" over "value" stocks in recessions and expansions. However, the bias for glamour stocks does not pay off in terms of long-term investment value: The glamour stocks that are recommended to buy only generate excess returns in expansions. In recessions, analysts overestimate their investment value.

Chapter 4 – Do Aggregate Company Outlooks have Macroeconomic Content?

4.1 Introduction

The state determination of the economy and the prediction of future macroeconomic developments are essential for many purposes, e.g., to guide monetary policy decisions or decisions about federal tax cuts to stimulate economic growth. In this context coincident and leading macroeconomic indicators play an important role. Economic agents rely on them to gauge how the economy is doing and how it will likely do in the future. To measure economic activity these indicators incorporate a wide information set of macroeconomic variables, such as industrial production and capital market related measures, such as interest rate spreads and stock returns. Company expectations as a valuable source of information to forecast overall economic activity, however, are not directly included. To a substantial extent the economy consists of firms listed on the stock market. About one-third of all employees in the U.S. private business sector work at publicly traded companies (Davis (2006)). Therefore, the development of the overall economy is significantly related to the development of these firms as a whole. In this paper we show that aggregated company outlooks predict overall economic activity, i.e., combined forecasts of individual parts of the economy predict the entire economy. As a proxy for individual company level outlooks we use analysts' stock recommendations, since analysts have direct access to company specific information and therefore their information set is arguably the best available proxy for company specific forecasts.

At the firm level, company managers must make various decisions that are of great importance for the company such as investment decisions, financing decisions, employment decisions etc. Moreover, managers plan their actions ahead by setting specific goals. For example, the decision of managers to lay off a significant amount of the company's workforce in the next couple of months to cut expenses is a crucial decision for the future development of the company. Nevertheless, decisions at the firm-level are ceteris paribus not important for the overall economy. However, aggregated projected layoffs over all companies, which in sum constitute a significant amount of the entire economy, are basically a crucial input to forecast future employment figures. The same argumentation holds for other company specific information such as orders, production, and capacity utilization. Every company outlook includes growth perspectives and therefore information whether the management assumes a more optimistic or pessimistic development of the company over the next months and years. Consequently, aggregated expectations over all companies contain predictive power for future macroeconomic developments.

Observing and predicting the entire economy is similar to observing all companies in the economy simultaneously and aggregating these observations. Unfortunately, we cannot observe managers' expectations directly and a survey of all companies is unfeasible for several reasons (e.g., cost, timing etc.). However, stock analysts collect and process all kinds of information at the firm level for publicly traded companies. Besides public macroeconomic-, industry- and company-specific content their information sets should also comprise non-public company-specific information (Grossman and Stiglitz (1980)). By attending analysts' conferences, management meetings, and telephone conferences, stock analysts develop a sound understanding of the company's business and its future performance. Due to their extensive company knowledge their information set is arguably the best available proxy measure for company specific outlooks. In addition to public company information it presumably contains company-specific information that is not public knowledge. Analysts issue stock recommendations that indicate a general direction of the development of the underlying company: A positive recommendation suggests in general a relatively positive development, while a negative recommendation suggests in general a relatively negative development. We show that aggregating these signals over all companies listed on the stock market allows conclusions about the overall economy.

The existing literature provides support for our new approach to combine macroeconomic developments with stock analysts' outputs. Previous literature indicates that analyst recommendations have predictive power for stock returns on a firm-level, i.e., analysts possess a unique company specific information set. Womack (1996) shows that recommendations lead to a significant post-announcement drift up to 6 months. Barber et al. (2001) demonstrate that a trading strategy based on recommendations yields significant excess returns before transaction costs. Howe et al. (2009) find that aggregated recommendations predict future excess returns on a market level. Stock returns in turn have predictive power for macroeconomic activity. Stock and Watson (1998) provide evidence that the stock market leads the real economy. Consequently, it is reasonable to analyze the predictive power of analysts' recommendations for macroeconomic developments. If analysts' outputs can forecast stock market developments and the stock market anticipates macroeconomic developments, then analysts' recommendations should also contain predictive power for the real economy.

To the best of our knowledge, we provide the first study to show this link. To do so we use monthly changes in aggregated analysts' recommendations as a proxy for changes in aggregated company outlooks. We evaluate the predictive power of company outlook changes for future macroeconomic developments by using a regression framework in which we analyze the relation of recommendation changes to changes in a broad measure of economic activity. Our results provide evidence that aggregated company outlooks have predictive power for future macroeconomic developments of about one year. Our results remain valid when we control for other well-known macroeconomic predictors, such as the term-spread and the dividend yield. We find that the predictive power of aggregated company outlooks is not included in the Leading Economic Indicator (LEI) – which specifically has been developed to forecast economic activity – and other well-known macroeconomic predictors.

Overall, we show that aggregated company outlooks are an important macroeconomic variable that has been overlooked so far when forecasting economic developments. This result might be especially of interest to agencies which release economic indicators as well as to investors who might incorporate this information to form better expectations of upcoming overall economic activity. Our results also suggest that analysts implicitly or explicitly anticipate macroeconomic developments when processing information in their stock recommendations. The change in the aggregated monthly consensus has predictive power for the upcoming economic development up to about one year. Indicating that analysts have first-hand information about the individual firms they cover, our findings therefore also support the theoretical notion that analysts play an important role as financial intermediaries (Grossman and Stiglitz (1980)). Moreover, our results indicate a link between previous studies: Stock and Watson (1998) show that the stock market leads the real economy, while Howe et al. (2009) provide evidence that aggregated analysts' recommendations predict the overall stock market. Our results fill the missing link between both studies, since we find that aggregated analysts' recommendations also predict the real economy. We provide evidence that changes in expectations about future firm performance rationally (i.e., correct on average) determine asset values before overall economic activity changes. Therefore, our results provide a potential explanation, why the stock market leads the real economy.

The remainder of the paper is organized as follows. In Section 4.2, we introduce the research design. Section 4.3 describes the data. Section 4.4 discusses the empirical results. Finally, section 4.5 concludes.

4.2 Research Design

We consider the following general model to forecast overall macroeconomic activity:

$$\text{Economic Activity}_{t,t+\tau} = \alpha + \beta \cdot \text{Aggregated Company Outlooks}_t + \varepsilon_t. \qquad (4.1)$$

Unfortunately, company outlooks cannot be observed directly. We argue that assessments of analysts who cover the companies and therefore process company expectations are a good proxy for company outlooks. Sell side analysts aggregate a vast amount of information on the company level in their role as information intermediaries on financial markets. Since analysts possess a first-hand information set about the covered companies, it is straightforward to approximate companies' expectations with analysts' outputs. Our approach is supported by the theoretical notion that analysts' outputs should contain more than just public knowledge (Grossmann and Stiglitz (1980)).

However, since analysts issue two key outputs, namely earnings per share (EPS) forecasts and stock recommendations, the proxy measure's choice should be carefully considered. We decide to focus on stock recommendations[19] for the following reasons. First, revisions of earnings forecasts might be based on stale information, while revisions of stock recommendations are not (Jegadeesh and Kim (2010)). Second, recommendations contain more information than earnings forecasts. A recommendation reflects the upcoming yearly earnings, as well as all future earnings, the payout ratios and discount rates. Therefore, to determine the value of a company the analyst needs interest rates, risk premiums and growth expectations as inputs in addition to EPS forecasts. These are basically the same information the company manager has to consider when making investment decisions for the firm. Consequently, solely using EPS forecasts is not sufficient because a substantial proportion of

[19] As an alternative measure, we analyze the predictive content of changes in aggregate earnings forecasts. The results are discussed in section 4.4.

the information would be neglected. Third, a measure with "natural" boundaries is preferred to identify significant expectation changes.[20] While small changes of EPS forecasts might be due to minor changes in expectations, a recommendation revision is the result of major changes and therefore it is a clear interpretable signal that the companies' prospects changed significantly. Fourth, it is desirable to have a proxy measure undistorted by the impact of accounting policies and accounting standard changes. A company is easily able to influence, to a certain degree, their earnings per share by applying the accounting standards in different ways ("earnings management"). Therefore, analysts have to adjust their earnings forecasts even without a change in the underlying fundamentals. Moreover, our model would receive an incorrect signal if accounting standards are changed and as a consequence thereof all EPS forecasts change without fundamental reason, e.g., when stock option compensation is treated differently from an accounting perspective. Fifth, we avoid a "forecast horizon problem", since recommendations are always valid for a certain future time period (usually up to one year if not revised) independent of the point in time of the fiscal year they are issued. In contrast, the forecast horizon of EPS forecasts is determined by the end of a firm's fiscal year. For example, an earnings forecast issued on October 1st, for a firm with a fiscal year end at December 31st, has a forecast horizon of three months. An earnings forecast for the same firm issued one month later would have a forecast horizon of two months. Recommendations are easier to compare and to aggregate, since they are based on expectations for stable forecast periods. Following these considerations our main proxy measure for company outlooks are analysts' recommendations.

We are aware of the fact that analysts' recommendations might be biased, for instance that they are overoptimistic.[21] However, assuming that their incentive-driven overoptimism is

[20] In I/B/E/S all recommendations are coded as integers between 1 ("Strong Buy") to 5 ("Strong Sell").
[21] See for instance Jegadeesh et al. (2004).

constant over time this does not constitute a problem. Since we use recommendation changes, the positive bias cancels out.

Our dependent variable in Equation 4.1, the measure for economic activity, is the 3-month moving average of the Chicago Fed National Activity Index (CFNAI) and the 3-month average of its four components.[22] Based on the methodology of Stock and Watson (1999b) the index is a weighted average of 85 macroeconomic series from four categories: 23 series from production and income, 24 series from employment, unemployment, and hours, 15 series from personal consumption and housing, and 23 series from sales, orders, and inventories. The four categories' contributions are for (1) Production and Income (PI) about 33%, (2) Employment, Unemployment, and Hours (EUH) 32%, (3) Personal Consumption and Housing (CH) 14% and (4) Sales, Orders and Inventories (SOI) 21%. The CFNAI is a "single summary measure of a common factor" (Federal Reserve Bank of Chicago (2012)) in these series which is released monthly. It is constructed to have an average value of zero and a standard deviation of one. A positive value of the CFNAI implies economic growth above the historical trend, while a negative value corresponds to growth below the trend. The three-month-moving-average of the CFNAI has desirable properties concerning the state determination of the economy. Compared to other measures, such as the GDP, the timely availability of the CFNAI provides valuable information about the state of the economy almost in real time on a monthly basis.[23]

Our analysis proceeds in 4 steps. First, for each month we calculate the consensus of stock recommendations issued in the respective month. In contrast to Howe et al. (2009), we solely use recommendations issued in the respective month and not all recommendations outstanding in the respective month to remove stale recommendations and to focus solely on the most recent information. In a second step, to measure the changes of managers'

[22] For information on the CFNAI see www.chicagofed.org/webpages/research/data/cfnai/current_data.cfm.
[23] For a quality evaluation of the CFNAI see for instance Evans et al. (2002).

expectations we calculate the monthly change of the consensus ($rec\_consensus_t$) in month t Δrec_t. We define the monthly consensus change in month t as:

$$\Delta rec_t = \frac{rec\_consensus_t \text{-} rec\_consensus_{t-1}}{rec\_consensus_{t-1}} \tag{4.2}$$

The monthly consensus change in t is the percentage change in the consensus of all stock recommendations issued in month t compared to month t-1. In the third step we quantify the in month t unknown upcoming change of the economic indicator ($\Delta CFNAI$) between t and $t+\tau\left(\tau = 1,...,T\right)$ for different future time periods. Finally, in the fourth step, we perform a regression of the change of the economic indicator on the recommendation change, several lags of the dependent variable and various controls as specified in Equation 4.3:

$$\Delta CFNAI_{t,t+\tau} = \alpha + \beta_1 \cdot \Delta rec_t + \sum_{n=2}^{N} \beta_n \cdot control\,variable_t^n + \varepsilon_t,\ \forall\,\tau = 1,...,T \tag{4.3}$$

where all variables are specified as previously described and ε_t denotes the error term.

We estimate the model in different settings. First, we estimate the predictive power of a recommendation change for the future CFNAI development alone. In a second setting, to control for other common variables which possess macroeconomic prediction power, we specifically control for changes in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable. Third, we analyze the predictive power of the recommendation change for the four CFNAI components (IP, EUH, CH, and SOI) separately. Fourth, we only use stock recommendations issued for S&P 500 firms. Fifth, as an alternative measure for company outlooks, we evaluate the predictive power of changes in aggregate earnings forecasts.

4.3 Data

Table 4.1: Summary Statistics

This table reports the abbreviations, units as well as summary statistics, i.e., the mean (μ), standard deviation (σ), as well as minimum and maximum values of our set of variables. These include the Chicago Fed National Activity Index (CFNAI) and the changes of the respective CFNAI components Production and Income (PI), Employment, Unemployment and Hours (EUH), Personal Consumption and Housing (CH), and Sales, Orders, and Inventories (SOI), the Recommendation Change, the recommendation change if only companies in the S&P 500 are considered (Reco. Change (S&P 500)), the Leading Economic Indicator (LEI), monthly market excess returns calculated as the difference of the monthly market index return and the monthly risk-free rate including all NYSE, AMEX and NASDAQ firms (Market Excess Return), the Dividend Yield, the Default Spread (calculated as the difference between Moody's Baa corporate bond yield and the 10-year Treasury constant maturity rate), the 3-months T-Bill rate, the Term Spread (calculated as the difference between the 10-year Treasury constant maturity rate and the 3-month T-Bill rate), as well as the number of submitted recommendations (monthly Recommendations).

Variable	Abbr.	Unit	μ	σ	Min	Max
CFNAI		Change	-0.0023	0.2293	-1.0074	0.6226
CFNAI IP		Change	0.0003	0.1245	-0.5467	0.3333
CFNAI EUH		Change	-0.0008	0.0775	-0.2934	0.2576
CFNAI CH		Change	-0.0020	0.0211	-0.1058	0.0845
CFNAI SOI		Change	0.0003	0.0323	-0.1046	0.1433
Recommendation Change	Δrec	% Change	0.0002	0.0241	-0.0733	0.0629
Reco. Change (S&P 500)	$\Delta rec^{S\&P500}$	% Change	0.0000	0.1109	-0.3456	0.4194
Leading Economic Indicator	LEI	% Change	0.0022	0.0053	-0.0147	0.0154
Market Excess Return	mex	% Change	0.41	4.67	-18.54	11.04
Dividend Yield	divy	%	1.87	0.53	1.11	3.60
Default Spread	defs	%	2.31	0.89	1.29	6.01
3-months T-Bill rate	3mtb	%	3.46	1.87	0.03	6.17
Term Spread	tes	%	1.64	1.18	-0.53	3.70
Monthly Recommendations		#	2572	644	1812	7709

Our sample ranges from January 1994 to March 2010. Table 4.1 shows means (μ), standard deviations (σ) as well as minimal and maximal values of the variables used in the analysis. We apply the Phillips–Perron test to verify that the time series data do not contain a unit-root and we do not find evidence for non-stationarity.[24]

We obtain vintage data (whenever available) for the CFNAI and its four components[25] from the Federal Reserve Bank of Chicago to adequately describe the available information about

[24] Results are reported in Appendix 4 A.
[25] We use the 3-month moving average of the CFNAI and its components.

the state of the economy at every single point of time.[26] Figure 4.1 shows the CFNAI development from January 1994 to March 2010.

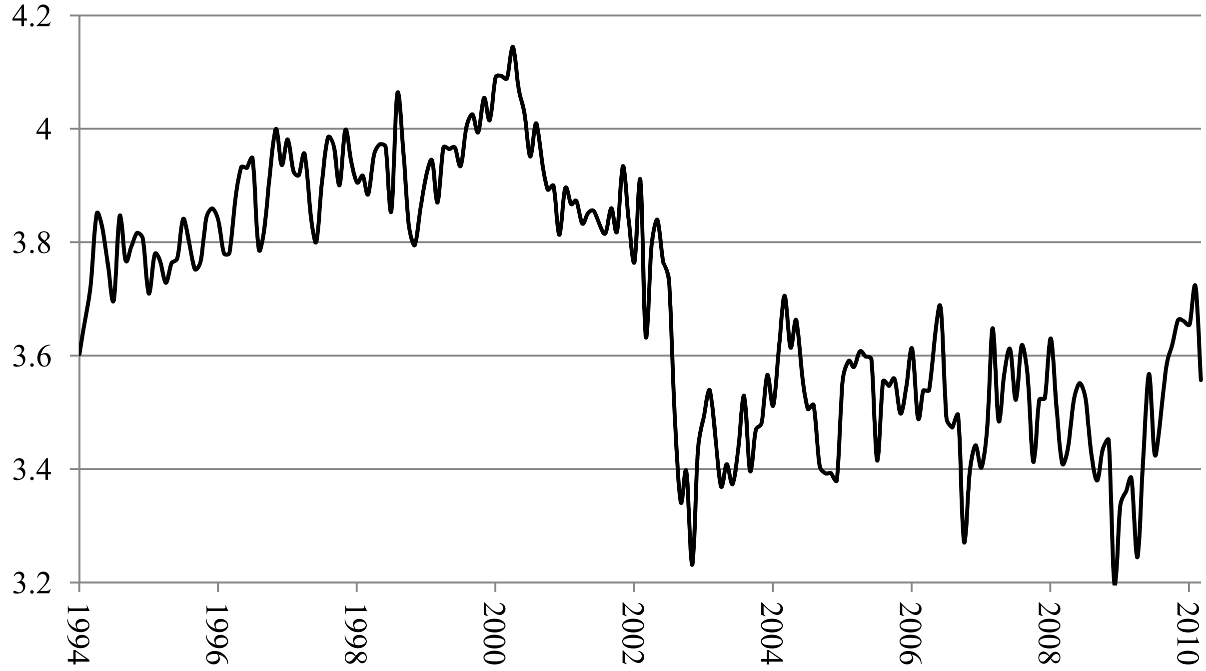
Figure 4.1: CFNAI Development

Analyst recommendations are obtained from the Institutional Brokers' Estimate System (I/B/E/S). We use the following filters for the recommendations: (1) we only keep recommendations for US-American firms to be consistent with the CFNAI measure, and (2) we drop 696 recommendations from our sample in order to control for obvious data base errors.[27] Our final sample consists of 499,571 stock recommendations.

We calculate the monthly aggregated mean analyst recommendation with the recommendations issued in the respective month. On average we consider 2,575 recommendations issued per month. Figure 4.2 visualizes the aggregated analyst recommendations from January 1994 to March 2010.

[26] Federal Reserve Bank of Chicago (2012).
[27] Specifically, we drop recommendations that have been issued by the same analyst from the same broker on the same day for the same firm with the same rating.

Figure 4.2: Average Consensus Recommendation



In the I/B/E/S database the recommendations are coded as follows: 1= “Strong Buy”, 2 = “Buy”, 3 = “Hold”, 4 = “Sell”, and 5 = “Strong Sell”. In line with previous literature (e.g., Jegadeesh and Kim (2010)) we reverse the ratings to facilitate a more intuitive interpretation. A “Strong Buy” receives the values of 5, a “Buy” a value of 4, a “Hold” a value of 3, a “Sel”l a value of 2, and a “Strong Sell” a value of 1. Therefore, a higher consensus recommendation implies a more optimistic analyst outlook. Figure 4.2 illustrates that the overall recommendation level varies significantly in the analyzed 1994 to 2010 time period. Jagadeesh and Kim (2010) point out that the mean recommendation level dropped significantly in 2002 when analysts were alleged of being overly optimistic by the New York State Attorney General’s office.

Data about the Leading Economic Index are obtained from Reuters. Monthly market excess returns are calculated by using the difference of the monthly market index return and the monthly risk-free rate including all NYSE, AMEX and NASDAQ firms. We obtain the data for monthly market excess returns from the website of Kenneth French.[28] We retrieve the monthly dividend yield from the homepage of Robert Shiller.[29] The 3-month T-Bill rate, the default spread (calculated as the difference between Moody's Baa corporate bond yield and the 10-year Treasury constant maturity rate), and the term spread (calculated as the difference between the 10-year Treasury constant maturity rate and the 3-month T-Bill rate) are obtained from the Federal Reserve Bank of St. Louis (2011).

4.4 Results

Table 4.2 shows the results of the univariate regression of the recommendation change on the upcoming CFNAI development. The column "Base Model" shows coefficient estimates of the model without any control variables. The results provide strong evidence that aggregate company level information has economic content. The aggregated stock recommendations have predictive power for the upcoming economic activity up to 7 months. Improving company outlooks, i.e., better recommendations ($\Delta rec > 0$) imply positive changes of overall economic activity as measured by CFNAI changes.

[28] French (2011).
[29] Shiller (2011).

Table 4.2: CFNAI Developments and Changing Company Outlooks

This table reports results from the following model:

$$\Delta CFNAI_{t,t+\tau} = \alpha + \beta_1 \cdot \Delta rec_t + \sum_{n=2}^{N} \beta_n \cdot control\,variable_t^n + \varepsilon_t, \quad \forall\, \tau = 1,...,T\,,$$

where the "Base Model" β is estimated without control variables and the "Control Model" β is estimated with control for changes in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable. Inference is based on Newey-West Standard Errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

	Base Model	Control Model
Horizon	β_1	β_1
1	2.250***	2.042**
2	2.879***	2.635**
3	2.981**	3.294***
4	2.207*	2.557**
5	2.233*	2.651*
6	2.564*	2.720*
7	3.102**	3.539**
8	2.005	2.610
9	2.516	2.848*
10	1.934	2.469
11	1.276	2.953*
12	1.192	2.066

In a second setting ("Control Model"), we control for well-established macroeconomic variables as discussed in Section 4.2 to ensure that our measure is not just a summary measure of well-known variables which possess macroeconomic prediction power. We use changes in the Leading Economic Indicator (Δlei),[30] market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable as control variables. The correlation matrix between the CFNAI changes and the control variables can be found in Appendix 4 B.

When controlling for macroeconomic variables that are well-known predictors of economic activity the aggregated recommendation change is still significant. Except for the 1- and 2-

[30] The LEI combines 10 single series with predictive power.

months horizons the coefficients are even larger. The coefficients of the aggregated recommendation change predict the upcoming 1-month to 11-months changes of economic activity. The results show that our measure contains unique information not captured in the 4 macroeconomic control variables as well as in the LEI, which was specifically designed to predict economic activity. While the control variables contain information about growth (LEI and dividend yield), risk premiums (market excess returns and default spreads) as well as interest rates (3-months T-Bill rate and term spread) our results suggest that aggregate company outlooks contain even more information about the development of the economy.

The results are economically significant. For example, the coefficient for the 1-month forward CFNAI change is 2.042, while the standard deviation of the recommendation change is 0.0241. Therefore, a one standard deviation increase in the recommendation change suggests a change in the CFNAI for the upcoming month of 0.05. This is relatively high since the CFNAI has by construction a mean of zero and a standard deviation of one.

Next, we analyze the predictive power of the recommendation change for the four individual CFNAI components. (1) Production and Income (PI) contributes about 33%, (2) Employment, Unemployment, and Hours (EUH) 32%, (3) Personal Consumption and Housing (CH) 14%, and (4) Sales, Orders and Inventories (SOI) 21% to the CFNAI.[31] We use the same control variables as for the analysis of the whole CFNAI. The results are reported in Table 4.3.

[31] The weights are readjusted monthly. The shifts in weights are rather small, see Federal Reserve Bank of Chicago (2012b).

Table 4.3: CFNAI Components Development and Changing Company Outlooks

This table reports results from the following model:

$$\Delta CFNAI\_COMPONENT_{t,t+\tau} = \alpha + \beta_1 \cdot \Delta rec_t + \sum_{n=2}^{N} \beta_n \cdot control\,variable_t^n + \varepsilon_t, \quad \forall \tau = 1,...,T,$$

where the "Control Model" β for the respective CFNAI Components Production and Income (PI), Employment, Unemployment and Hours (EUH), Personal Consumption and Housing (CH), and Sales, Orders, and Inventories (SOI) is estimated with control for changes in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable. Inference is based on Newey-West Standard Errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

	Control Model PI	Control Model EUH	Control Model CH	Control Model SOI
Horizon	β_1	β_1	β_1	β_1
1	1.084**	0.121	0.118*	-0.0118
2	1.814***	0.341	0.121	0.0841
3	2.063***	0.967**	0.179	0.1255
4	1.112*	0.911**	0.102	0.228**
5	1.034	1.197**	0.222	0.1541
6	1.533**	1.051**	0.202	0.237**
7	2.142***	1.099***	0.239	0.202*
8	1.349**	1.055*	0.153	0.218*
9	1.083	0.950*	0.201	0.261**
10	0.864	1.209**	0.215	0.248**
11	1.499**	1.220**	0.177	0.260**
12	0.918	1.280**	0.114	0.157

The results show that the predictive power of the recommendation change varies drastically for the four CFNAI components. The size of the coefficients is directly comparable. We find moderate predictive power for PI and EUH, relatively low predictive power for the SOI component, and no predictive power for CH. These results correspond to the weights of the individual series in the CFNAI and therefore to the relative importance for economic activity. Changes in company outlooks have less predictive power for individual measures of economic activity than for the CFNAI as an aggregate measure of economic activity.

To further evaluate the properties of aggregated company outlooks we restrict the sample to firms listed on the S&P 500. We again perform the previous analysis, however, the aggregated recommendation change is calculated only for S&P 500 firms. Using only outlooks of a part of the entire economy the number of observed companies decreases and consequently the number of issued stock recommendations also declines to an average of 552 recommendations per months compared to 2,575 recommendations in the base case where the entire economy is considered. The results are shown in Table 4.4.

Table 4.4: CFNAI Development and Changing Company Outlooks S&P 500 only

This table reports results from the following model:

$$\Delta CFNAI_{t,t+\tau} = \alpha + \beta_1 \cdot \Delta rec_t^{S\&P500} + \sum_{n=2}^{N} \beta_n \cdot control\,variable_t^n + \varepsilon_t, \quad \forall\, \tau = 1,...,T,$$

where the "Base Model" β is estimated without control variables and the "Control Model" β is estimated with control for changes in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable. Only S&P 500 firms are considered in the consensus recommendation calculation. Inference is based on Newey-West Standard Errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Horizon	Base Model β_1	Control Model β_1
1	1.655**	1.755**
2	1.709**	2.177**
3	1.454	2.430**
4	1.202	2.313**
5	1.695*	2.774**
6	1.914*	2.963**
7	1.916	3.151**
8	0.896	2.342*
9	0.651	1.942
10	1.411	2.713**
11	0.467	2.764**
12	0.907	2.727**

The results point out that our general results are somewhat weaker when using only the firms listed on the S&P 500. The aggregated recommendation change predicts economic activity up to 11 months ("Control Model").[32] The coefficient is smaller for 8 out of 12 months. The results indicate that using outputs from a larger sample leads to more predictive power than using only outlooks of companies listed in the S&P 500. However, since the largest publicly traded companies are included in the S&P 500 the economic difference is rather small.

Overall, our results show that aggregated company outlooks proxied by aggregated stock recommendations are an important macroeconomic predictor. The information set included in the aggregated company outlooks is not reflected in other established macroeconomic variables making it a valuable predictor for macroeconomic developments.

Next, we analyze aggregated company outlooks proxied by aggregated earnings forecasts as an alternative measure for company outlooks. Each month we calculate the median earnings per share forecast based on earnings forecasts issued in the respective month. In order to control for different forecast horizons we calculate the median earnings per share forecast separately for forecasts with a forecast horizon of less or equal to 3 months, less or equal to 6 months, less or equal to 12 months and greater than 12 months. Since earnings per share forecasts show seasonal patterns we calculate the monthly change in the earnings forecasts relatively to the aggregate median earnings forecast twelve months ago. Finally, we apply the Baxter-King filter[33] with a minimum period of oscillation of 18 and a maximum oscillation period of 96 corresponding to monthly date. The calculation of the monthly change in aggregated earnings per share forecasts is shown below:

$$\Delta EPS_t = \frac{Median\_EPS_{t,Horizon} - Median\_EPS_{t-12,Horizon}}{Median\_EPS_{t-12,Horizon}} \tag{4.4}$$

Estimation results are shown in Table 4.5:

[32] Results for the 12-month horizon should be handled with care due to non-stationarity issues according to the Phillips–Perron test.
[33] Baxter and King (1999).

Table 4.5: CFNAI Developments and Changing Median Earnings Forecasts

This table reports results from the following model:

$$\Delta CFNAI_{t,t+\tau} = \alpha + \beta_1 \cdot \Delta EPS_t + \sum_{n=2}^{N} \beta_n \cdot control\,variable_t^n + \varepsilon_t, \quad \forall \tau = 1,...,T,$$

where the "Control Model" β is estimated with the respective EPS change (horizon is equal to 3 months, 6 months, 12 months and above 12 months) and controlling for changes in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), 3-month T-Bill rate (3mtb), and three lags of the dependent variable. Inference is based on Newey-West Standard Errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

	Control Model EPS 3 months	Control Model EPS 6 months	Control Model EPS 12 months	Control Model EPS > 12 months
Horizon	β_1	β_1	β_1	β_1
1	0.0004	-0.0002	0.0003	0.0007
2	0.0034	-0.0001	-0.0002	0.0000
3	0.0054	0.0003	-0.0005	-0.0003
4	0.0040	0.0003	-0.0005	-0.0002
5	-0.0008	0.0004	-0.0007	-0.0006
6	0.0001	0.0002	-0.0028	-0.0008
7	-0.0044	0.0008	-0.0031	-0.0015
8	0.0024	0.0005	-0.0028	-0.0007
9	-0.0019	0.0006	-0.0003	-0.0014
10	-0.0006	-0.0002	-0.0004	-0.0012
11	-0.0048	-0.0002	0.0001	-0.0027
12	0.0018	-0.0010	0.0011	-0.0031

We do not find any predictive power for the CFNAI in companies' aggregated earnings per share forecasts. This result is in line with the disadvantages of earnings forecasts discussed in Section 4.2. Most prominently, recommendations contain a larger information set than just an one period earnings forecasts. They basically include earnings forecasts for several years as well as interest rate assumptions and risk premium forecasts. Additionally, earnings forecasts might be based on stale information. Consequently, our results lend support to the notion that more forward-looking information, as included in recommendation changes, is required if one attempts to forecast future macroeconomic developments.

4.5 Conclusion

Combining individual company outlooks and macroeconomic developments is a new approach to exploit publicly available, but neglected, information. Our results show that the aggregation of these outlooks has predictive power for future macroeconomic developments of about one year. Due to their strong performance, changing company outlooks might be a promising predictor for different applications, especially in the area of now-casting and mid-term forecasting, e.g., for economic agencies. As shown, our measure contains information content not inherent in well-established macroeconomic predictors. Therefore it seems mandatory to use company outlooks as a control variable in models which could be influenced by macroeconomic developments.

Our results also provide a potential explanation for the old Wall Street saying that the stock market leads the economy. Recommendation changes basically mirror expectation changes of well informed market participants. We document that these changes lead overall macroeconomic conditions. Assuming that the stock market incorporates these new expectations, the overall stock market must lead the real economy. Thus far there is no study showing this direct link.

Furthermore, we provide further evidence that analysts provide a unique information set on financial markets and play an important role as financial intermediaries. Analysts implicitly or explicitly anticipate macroeconomic developments when processing information in their stock recommendations. Our findings therefore also support the theoretical notion that analysts play an important role as financial intermediaries on financial markets.

References

Bae, Kee-Hong; Stulz, René; Tan, Hongping (2008): Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts, in: Journal of Financial Economics, Vol. 88, pp. 581 – 606.

Barber, Brad; Lehavy, Reuven; McNichols, Maureen; Trueman, Brett (2001): Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns, in: Journal of Finance, Vol. 56, pp. 531–563.

Barber, Brad; Lehavy, Reuven; McNichols, Maureen; Trueman, Brett (2003): Reassessing the Return to Analysts' Stock Recommendations, in: Financial Analysts Journal, Vol. 59, pp. 88 – 94.

Baxter, Marianne; King, Robert G. (1999): Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series, in: The Review of Economics and Statistics, Vol. 81, pp. 575 – 593

Beber, Alessandro; Brandt, Michael W. (2010): When It Cannot Get Better or Worse: The Asymmetric Impact of Good and Bad News on Bond Returns in Expansions and Recessions, in: Review of Financial Studies, Vol. 14, pp. 119 – 155.

Bernhardt, Dan; Campello, Murillo; Kutsoati, Edward (2006): Who herds?, in: Journal of Financial Economics, Vol. 80, pp. 657–675.

Bestelmeyer, Georg; Breunsbach, Miriam; Hess, Dieter (2011): Expected Risk Premium Dynamics Across the Business Cycle and the Stock Market's Response to Macroeconomic News, Working Paper, University of Cologne.

Boyd, John H.; Hu, Jian; Jagannathan, Ravi (2005): The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks, in: Journal of Finance, Vol. 60, pp. 649-672.

Boyer, Brian; Mitton, Todd; Vorkink, Keith (2010): Expected Idiosyncratic Skewness, in: Review of Financial Studies, Vol. 23, pp. 169 – 202.

Brown, Lawrence D. (2001): How Important Is Past Analyst Forecast Accuracy?, in: Financial Analysts Journal, Vol. 57, pp. 44 – 49.

Brown, Lawrence D.; Mohammad, Emad (2003): The Predictive Value of Analyst Characteristics in: Journal of Accounting, Auditing and Finance, Vol. 18, pp. 625 – 648.

Brown, Lawrence D.; Mohammad, Emad (2010): Is Analyst Earnings Forecast Ability Only Firm Specific?, in: Contemporary Accounting Research, Vol. 27, pp. 727 – 750.

Busse, Jeffrey A.; Green Clifton T.; Jegadeesh, Narasimhan (2012): Buy-Side Trades and Sell-Side Recommendations, Interactions and Information Content, in: Journal of Financial Markets, Vol. 15, pp. 207 – 232.

Carhart, Mark M. (1997): On persistence in mutual fund performance, in: Journal of Finance, Vol. 52, pp. 57 – 82.

Chordia, Tarun; Shivakumar, Lakshmanan (2002): Momentum, Business Cycle, and Time-varying Expected Returns, in: Journal of Finance, Vol. 57, pp. 985 – 1019.

Clement, Michael B.; Tse, Senyo Y. (2005): Financial Analyst Characteristics and Herding Behavior in Forecasting in: Journal of Finance, Vol. 60, pp. 307 – 341.

Cohen, Lauren; Frazzini, Andrea; Malloy, Christopher (2010): Sell–Side School Ties, in: Journal of Finance, Vol. 65, pp. 409 – 1437.

Daniel, Kent; Grinblatt, Mark; Titman, Sheridan; Wermers, Russ (1997): Measuring mutual fund performance with characteristic-based benchmarks, in: Journal of Finance Vol. 52, pp. 1035 – 1058.

Davis, Steven J. (2006): Publicly Traded Versus Privately Held Firms. Capital Ideas, Chicago GSB: http://www.chicagobooth.edu/capideas/sep06/4.aspx.

Dechow, Patracia M.; You, Haifeng (2012): Analysts' Motives for Rounding EPS Forecasts, in: The Accounting Review, Vol.87, pp. 1939 – 1966.

Demiroglu, Cem; Ryngaert, Michael (2010): The First Analyst Coverage of Neglected Stocks, in: Financial Management, Vol. 39, pp. 555 – 584.

Dhole, Sandip; Mishra, Sagarika; Sivaramakrishnan, Konduru (2010): On the Cross-Sectional Determinants of Management Forecast Bias, in: Fourth Indian School of Business Accounting Research Conference, http://www.isb.edu/AccountingResearchConference/File/OntheCross-SectionalSandip%20DholeAug.pdf.

Dreman, David N.; Berry, Michael A. (1995): Analyst Forecasting Errors and Their Implications for Security Analysis, in: Financial Analysts Journal, Vol. 51, pp. 30 – 41.

Emery, Douglas R.; Li, Xi (2009): Are the Wall Street Analyst Rankings Popularity Contests in: Journal of Financial and Quantitative Analysis, Vol. 44, pp. 411 – 437.

Evans, Charles l.; Liu, Chin Te; Pham-Kanter, Genevieve (2002): The 2001 recession and the Chicago Fed National Activity Index: Identifying business turning points, in: Economic Perspectives, Federal Reserve Bank of Chicago, Issue Q III, pp. 26 – 43.

Fama, Eugene F.; French Kenneth R. (1993): Common risk factors in the returns on stocks and bonds, in: Journal of Financial Economics, Vol.33, pp. 3 – 56.

Fama, Eugene F.; French, Kenneth R. (1998): Value versus Growth: The International Evidence, in: The Journal of Finance, Vol. 53, pp. 1975 – 1999.

Federal Reserve Bank of Chicago (2012): http://www.chicagofed.org/webpages/publications/cfnai/index.cfm.

Federal Reserve Bank of Chicago (2012): www.chicagofed.org/webpages/research/data/cfnai/current_data.cfm.

FRED (2011): http://research.stlouisfed.org/.

French, Kenneth (2011): http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Findlay, Scott; Mathew, Prem G. (2006): An Examination of the Differential Impact of Regulation FD on Analysts' Forecast Accuracy, in: Financial Review, Vol. 41, pp. 9 – 31.

Gebhardt, William R.; Lee, Charles M.; Swaminathan, Bhaskaran (2001): Toward an Implied Cost of Capital, in: Journal of Accounting Research, Vol. 39, pp. 135-176.

Grossman, Sanford J.; Stiglitz, Joseph E. (1980): On the Impossibility of Informationally Efficient markets, in: American Economic Review, Vol. 70, pp. 393 – 408.

Hall, Jason L.; Tacon, Paul B. (2010): Forecast Accuracy and Stock Recommendations, in: Journal of Contemporary Accounting and Economics, Vol. 6, pp. 18 – 33.

Herrmann, Don; Thomas, Wayne B. (2005): Rounding of Analyst Forecasts, in: The Accounting Review, Vol. 80, pp. 805 – 823.

Hess, Dieter; Kreutzmann, Daniel; Pucker, Oliver (2012): The Good, the Bad, and the Lucky: Projected Earnings Accuracy and Profitability of Stock Recommendations, Working Paper, University of Cologne.

Hilary, Gilles, Hsu, Charles Y. (2013): Analyst Forecast Consistency, in: Journal of Finance, Vol. 68, pp. 271 – 298.

Hong, Harrison; Kubik, Jeffrey D. (2003): Analyzing the analysts: Career concerns and biased earnings forecasts, in: Journal of Finance, Vol. 58, pp. 313 – 352.

Howe, John S.; Unlu, Emre; Yan, Xuemin (2009): The Predictive Content of Aggregate Analyst Recommendations, in: Journal of Accounting Research, Vol. 47, pp. 799 – 821.

Jegadeesh, Narasimhan; Kim, Joonghyuk; Krische, Susan D.; Lee, Charles M. C. (2004): Analyzing the Analysts: When do Recommendations Add Value?, in: Journal of Finance, Vol. 59, pp. 1083 – 1124.

Jegadeesh, Narasimhan; Kim, Woojin (2010): Do Analysts Herd? An Analysis of Recommendations and Market Reactions, in: Review of Financial Studies, Vol. 23, pp. 901 – 937.

Lakonishok, Josef; Shleifer, Andrei; Vishny, Robert W. (1994): Contrarian Investment, Extrapolation, and Risk, in: Journal of Finance, Vol. 49, pp. 1541 – 1578.

Lee, Byunghwan; O'Brien, John; Sivaramakrishnan, Konduru (2008): An Analysis of Financial Analysts' Optimism in Long-term Growth Forecasts, in: Journal of Behavioral Finance, Vol. 9, pp. 171 – 184.

Lin, Wen-Yi; Chen, Po-Jung; Chen, Sheng-Syan (2011): Stock characteristics and herding in financial analyst recommendations, in: Applied Financial Economics, Vol. 21, pp. 317 – 331.

Loh, Roger; Mian, Mujtaba (2006): Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?, in: Journal of Financial Economics, Vol. 80, pp. 455 – 483.

Malloy, Christopher J. (2005): The Geography of Equity Analysis, in: Journal of Finance, Vol. 60, pp. 719 – 750.

National Bureau of Economic Research (2011): History of the NBER, http://www.nber.org/info.html.

Richards, Malcolm R.; Benjamin, James J.; Strawser, Robert H. (1977): An Examination of the Accuracy of Earnings Forecasts, in: Financial Management, Vol. 6, pp. 78 – 86.

Richardson, Scott A.; Teoh, Siew Hong; Wysocki, Peter D. (1999): Tracking Analysts' Forecasts over the Annual Earnings Horizon: Are Analysts' Forecasts Optimistic or Pessimistic?, Working Paper.

Ritter, Jay R. (2005): Economic growth and equity returns, in: Pacific-Basin Finance Journal, Vol. 13, pp. 489 – 503.

Robinson, David; Glushkov, Denys (2006): A Note on IBES Unadjusted Data, Wharton Research Data Service, https://wrds-web.wharton.upenn.edu/wrds/.

Shiller, Robert (2011): Online Data, http://www.econ.yale.edu/~shiller/data.htm.

Sonney, Frédéric (2009): Financial Analysts' Performance: Sector Versus Country Specialization, in: Review of Financial Studies, Vol. 22, pp. 2087 – 2131.

Sorescu, Sorin; Subrahmanyam, Avanidhar (2006): The Cross Section of Analyst Recommendations, in: Journal of Financial and Quantitative Analysis, Vol. 41, pp. 139 – 168.

Spiwoks, Markus; Gubaydullina, Zulia; Hein, Oliver (2011): Trapped in the Here and Now – New Insights into Financial Market Analyst Behavior, in: Wolfsburg Working Papers, http://www.ostfalia.de/export/sites/default/de/w/download/WWP-11-01.pdf.

Stickel, Scott E. (1995): The Anatomy of the Performance of Buy and Sell Recommendations, in: Financial Analysts Journal, Vol. 51, pp. 25 – 39.

Stock, James H.; Watson, Mark W. (1998): Business Cycle Fluctuations in U.S. Macroeconomic Time Series, in: NBER Working Paper No. 6528.

Stock, James H.; Watson, Mark W. (1999): Forecasting Inflation, in: Journal of Monetary Economics, Vol. 44, pp. 293 – 335.

U.S. Securities and Exchange Commission (2000): Final Rule: Selective Disclosure and Insider Trading, http://www.sec.gov/rules/final/33-7881.htm.

U.S. Securities and Exchange Commission (2002): Analysts Conflicts of Interest: Taking Steps to Remove Bias, http://www.sec.gov/news/speech/spch559.htm.

Veronesi, Pietro (1999): Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model, in: Review of Financial Studies, Vol. 12, pp. 975 – 1007.

Welch, Ivo (2000): Herding among security analysts, in: Journal of Financial Economics, Vol. 58, pp. 369 – 396.

Womack, Kent L. (1996): Do Brokerage Analysts' Recommendations Have Investment Value?, in: Journal of Finance, Vol. 51, pp. 137 – 167.

Appendix to Chapter 2

Appendix 2 A:

Definitions of the analyst and forecast characteristics:

$ACCURACY_{ijt-1}$ - a measure of analyst i's forecast accuracy for firm j in year t-1. It is calculated as the maximum absolute forecast error for analysts who follow firm j in year t-1 minus the absolute forecast error of analyst i following firm j in year t-1, with this difference scaled by the range of absolute forecast errors for analysts following firm j in year t-1;

$BROKER\_SIZE_{ijt-1}$ - a measure of the analyst's broker size. It is calculated as the number of analysts employed by the broker employing analyst i following firm j in year t-1 minus the minimum number of analysts employed by following firm j in year t-1, with this difference scaled by the range of brokerage size for analysts brokers for analysts following firm j in year t-1;

$FOR\_FREQUENCY_{ijt-1}$ - a measure of analyst i's forecast frequency for firm j. It is calculated as the number of firm j forecasts made by analyst i following firm j in year t-1 minus the minimum number of firm j forecasts for analysts following firm j in year t-1, with this difference scaled by the range of number of firm j forecasts issued by analysts following firm j in year t-1;

$FIRM\_EXPERIENCE_{ijt-1}$ - a measure of analyst i's firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year t-1 minus the minimum number of years of firm-specific experience for analysts following firm j in year t-1, with this difference scaled by the range of years of firms-specific experience for analysts following firm j in year t-1;

$GEN\_EXPERIENCE_{ijt-1}$ - a measure of analyst i's general experience, It is calculated as the number of years of experience for analyst i following firm j in year t-1 minus the minimum number of years of experience for analysts following firm j in year t-1, with this difference scaled by the range of years of experience for analysts following firm j in year t-1.

$COMPANIES_{ijt-1}$ - a measure of the number of companies analyst i follows in year t-1. It is calculated as the number of companies followed by analyst i following firm j in year t-1 minus the minimum number of companies followed by analysts who follow firm j in year t-1, with this difference scaled by the range in the number of companies followed by analysts following firm j in year t-1;

$INDUSTRIES_{ijt-1}$ - a measure of the number of industries analyst i follows in year t-1. It is calculated as the number of industries covered by analyst i following firm j in year t-1 minus the minimum number of industries followed by analysts who follow firm j in year t-1, with this difference scaled by the range in the number of industries followed by analysts following firm j in year t-1.

$Bold_{ijt}$ - is a measure for the boldness of analyst i's forecast for firm j in year t-1. It is calculated as the absolute distance of analyst's i forecast from the 90 day consensus issued of all analysts following firm j in year t-1 minus the minimum absolute distance for analysts who follow firm j in year t-1, with this difference scaled by the range in absolute distances for analysts following firm j in year t-1.

$LAG\_ACCURACY_{ijt-1}$ - a measure of analyst i's past forecast accuracy for firm j. It is calculated as the earnings accuracy for analyst i following firm j in year t – 1 minus the minimum earnings accuracy by analysts who followed firm j in year t-1, with this difference scaled by the range in the earnings accuracy for analysts following firm j in year t-1.

$GEN\_ACCURACY_{ijt-1}$ - a measure of analyst i's general past forecast accuracy for all firms j covered by this analyst. The general past forecast accuracy is calculated as the mean of all values for $LAG\_ACCURACY_{ijt-1}$ by analyst i following firms j in year t – 1 minus the minimum general past forecast accuracy by analysts who followed firm j in year t-1, with this difference scaled by the range in the general past forecast accuracy for analysts following firm j in year t-1.

$DAYS\_ELAPSED_{ijt-1}$ - a measure of the days elapsed since the last forecast by any analyst following firm j in year t-1. It is calculated as the days between analyst i's forecast of firm j's earnings in year t-1 and the most recent preceding forecast of firm j's earnings by any analyst, minus the minimum number of days between two adjacent forecasts of firm j's earnings by any two analysts in year t-1, with this difference scaled by the range of days between two adjacent forecasts of firm j's earnings in year t-1;

$FOR\_HORIZON_{ijt-1}$ - a measure of the time from the forecast date to the end of the fiscal period. It is calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm j in year t-1 minus the minimum forecast horizon for analysts who follow firm j in year t-1, with this difference scaled by the range of forecast horizons for analysts following firm j in t-1.

Appendix 2 B:

Table 2.8: Data Filters

This table shows the filters used to obtain the sample along with the respective number of observations. Panel A shows the filters for the annual Earnings forecasts from I/B/E/S. Panel B shows the filters for the stock recommendations from I/B/E/S.

Panel A: Earnings Forecasts		# Obs.
	Annual earnings forecasts issued from 01/1993 to 12/2010	4,842,117
1	Firms that can be matched with CRSP	4,363,659
2	Analysts that do not remain anonymous in I/B/E/S	4,308,471
3	Forecasts until 1997 for primary earnings, from 1998 on for diluted earnings	4,002,822
4	Forecasts issued not more than two years before the report date	3,541,759
5	Forecasts with a price-scaled forecast error below 25%	3,488,074
6	At least two analysts issue forecasts for the firm-year	3,462,808
7	Forecasts which are the last earnings forecast by the analyst in the fiscal year	709,450

Panel B: Stock Recommendations		
	Recommendations issued between 1/1994 to 12/2010 for U.S. Firms	524,059
8	Analysts that do not remain anonymous in I/B/E/S	507,596
9	Recommendations that are not issued with the same rating on the same day for the same firm by the same analyst	506,882
10	Recommendations that can be classified according to the accuracy model	331,121

Appendix to Chapter 4

Appendix 4 A: Stationarity Tests of the CFNAI Change and its Components

Table 4.6: Stationarity Tests of the CFNAI Change and its Components

This table reports Phillips-Perron $\tau - \text{test}$ statistics using the corresponding MacKinnon approximated p-values for the forward looking CFNAI change (CFNAI F), historical CFNAI changes (CFNAI H), and the changes of the respective CFNAI components Production and Income (PI), Employment, Unemployment, and Hours (EUH), Personal Consumption and Housing (CH), and Sales, Orders, and Inventories (SOI). *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Horizon	CFNAI F	CFNAI H	CFNAI PI	CFNAI EUH	CFNAI CH	CFNAI SOI
1	-12.601***	-12.601***	-13.499***	-11.267***	-10.983***	-16.450***
2	-6.178***	-6.178***	-7.146***	-5.325***	-5.618***	-7.614***
3	-5.922***	-5.922***	-6.921***	-5.586***	-5.535***	-7.785***
4	-4.786***	-4.786***	-5.282***	-4.736***	-4.684***	-6.454***
5	-4.597***	-4.597***	-5.227***	-4.620***	-4.450***	-5.760***
6	-4.266***	-4.266***	-5.047***	-4.195***	-4.084***	-5.953***
7	-3.948***	-3.948***	-4.611***	-3.952***	-3.711***	-5.167***
8	-3.447***	-3.447***	-4.247***	-3.662***	-3.411**	-4.934***
9	-3.044**	-3.044**	-4.022***	-3.512***	-3.134**	-4.677***
10	-2.663*	-2.663*	-4.044***	-3.379**	-2.904***	-4.320***
11	-2.633*	-2.633*	-3.882***	-3.240**	-2.648*	-4.488***
12	-2.205	-2.205	-3.828***	-3.146**	-2.477	-4.074***

Appendix 4 B: Correlation Matrix

Table 4.7: Correlation Matrix

This table reports the correlations coefficients between the 12 forward looking CFNAI changes (CFNAI1 to CFNAI12), the recommendation change (Δrec), the change in the Leading Economic Indicator (Δlei), market excess returns (mex), dividend yield (divy), default spread (defs), term spread (tes), and the 3-month T-Bill rate (3mtb).

	CFNAI																		
	1	2	3	4	5	6	7	8	9	10	11	12	Δrec	Δlei	mex	divy	defs	3mtb	tes
CFNAI1	1.00																		
CFNAI2	0.72	1.00																	
CFNAI3	0.65	0.85	1.00																
CFNAI4	0.45	0.72	0.88	1.00															
CFNAI5	0.44	0.59	0.78	0.91	1.00														
CFNAI6	0.39	0.55	0.67	0.83	0.93	1.00													
CFNAI7	0.35	0.50	0.63	0.73	0.86	0.94	1.00												
CFNAI8	0.27	0.43	0.56	0.68	0.77	0.87	0.94	1.00											
CFNAI9	0.23	0.34	0.49	0.60	0.71	0.79	0.89	0.95	1.00										
CFNAI10	0.22	0.31	0.42	0.54	0.65	0.74	0.81	0.90	0.95	1.00									
CFNAI11	0.20	0.29	0.39	0.48	0.59	0.69	0.77	0.83	0.91	0.96	1.00								
CFNAI12	0.19	0.28	0.37	0.45	0.54	0.64	0.72	0.79	0.85	0.92	0.96	1.00							
Δrec	0.22	0.20	0.13	0.07	0.08	0.08	0.09	0.05	0.05	0.05	0.07	0.04	1.00						
Δlei	0.32	0.48	0.34	0.31	0.22	0.23	0.21	0.19	0.14	0.12	0.08	0.08	0.08	1.00					
mex	0.16	0.23	0.34	0.30	0.21	0.12	0.10	0.10	0.05	0.02	-0.02	-0.03	-0.12	0.28	1.00				
divy	-0.08	-0.10	-0.07	-0.01	0.06	0.11	0.14	0.17	0.20	0.22	0.24	0.26	0.01	-0.15	-0.08	1.00			
defs	-0.08	-0.07	-0.01	0.07	0.15	0.22	0.26	0.31	0.36	0.41	0.44	0.47	-0.08	-0.20	-0.27	0.17	1.00		
3mtb	-0.04	-0.07	-0.10	-0.14	-0.17	-0.20	-0.22	-0.25	-0.27	-0.29	-0.31	-0.33	0.03	-0.09	0.13	-0.15	-0.68	1.00	
tes	0.08	0.09	0.09	0.10	0.12	0.13	0.15	0.18	0.20	0.21	0.22	0.25	-0.01	0.25	-0.08	0.31	0.39	-0.76	1.00