Sell-side analyst recommendations and stock returns: An investor-oriented approach

Master Thesis

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ABSTRACT

Using Bloomberg firm-level data for the period 2000 - 2015 for the US, Japan, and 16 European countries, I find no support for the prediction that a trading strategy that goes long in a portfolio of high consensus recommendation level/upward revised stocks and short in a portfolio of low consensus recommendation level/downward revised stocks yields positive risk-adjusted returns. In a second analysis, I look deeper into a possible profitable combination of a value strategy and analyst recommendations. Even though a long-short portfolio of stocks double-sorted on book-to-market value and analyst recommendations earns significant alphas only for the extreme portfolios, these returns seem not to be robust to all used asset-pricing models. Although the existence of a profitable trading strategy in a reasonably investable universe using analyst recommendations remains an unresolved question, this thesis provides valuable insights concerning the value of analyst recommendations for both practitioners and financial academics.

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Preface and Acknowledgements

Before you lies the master thesis "Sell-side analyst recommendations and stock returns: An investor-oriented approach", which I have been writing between November 2015 and July 2016. This thesis is submitted as a final part of the master Economics & Business, specialisation Financial Economics, at Erasmus University in Rotterdam.

First and foremost, I would like to thank Mr. Maurizio Montone for his excellent guidance and support during the thesis process. I have learned a lot from his intuition and excitement about the field of behavioral finance and doing research in general. My grateful thanks also to Hans Betlem and Martijn Kleinbussink from IBS Capital Management in Amsterdam, who have provided me with their Bloomberg terminal for many hours in the last eight months.

To my parents, brother, sister, and my boyfriend: Thank you for your great support and motivation, enduring my periods of stress, and listening to all of my brainstorming.

I hope you enjoy your reading.

Fleur Bloemen

Rotterdam, July 4th, 2016

1. Introduction

The goal of this thesis is to investigate whether investors can earn abnormal stock returns when they follow a trading strategy based on sell-side analyst recommendations. Since the 1930's, researchers have been exploring this topic. Nevertheless, the literature is still divided in its opinion whether following analysts' advice is valuable for investors after accounting for transaction costs. According to the Efficient Market Hypothesis (EMH) (Fama, 1970), sell-side analysts would not be able to add any value since any information they have should already be incorporated in market prices (Jegadeesh and Kim, 2006). Outperforming the market through investing in stocks that are selected by 'experts' or market timing should not be possible. However, fortunes are spent on security analysis in the billion-dollar investment industry, so at least some firms and some clients believe that they can use these recommendations to earn superior returns. James Montier states in his book that people tend to blindly follow authority (The little book of behavioral investing, 2010). Especially retail investors see analysts as experts in their fields and as a result, they become authority figures. When investors consider sell-side analysts as experts, they can over rely on them: if, in their eyes, analysts possess unique skills in constructing their recommendations, they can add value.

While using international Bloomberg firm-level data for the period 2000 – 2015 to assess whether analyst recommendations have predictive value in the cross-section of stock returns, this thesis contributes to the market efficiency debate. The financial market cannot be considered to be semi-strong efficient when it is possible to profit from trading strategies based on public information that should already have been incorporated into stock prices. To the best of my knowledge, most studies concerning the relation between analyst recommendation and return have a focus on data for the United States for the period up to 2002. Though Jegadeesh and Kim (2006) study this topic from a more international perspective by studying the Group of Seven (G7) industrialized countries for the period between 1993 and 2002, I contribute to research by examining the value of analyst recommendations in a broader perspective for a more recent time period. Using data for the period between 2000 and 2015, I examine whether investors can earn abnormal profits using trading strategies based on analyst recommendations. To ensure replicability of the trading strategies, I use quarterly rebalancing and I only consider firms which are at least covered by 5 analysts and which have a market capitalization larger than 3 billion. I believe this thesis adds to existing literature by providing a more complete picture of the possible benefit analysts can offer.

Moreover, this thesis adds to the literature on the objectivity of analysts. Prior literature states that sell-side analysts can have several incentives to give positively biased recommendations.

Most analysts work for investment banks that have several sources of profit. Their actions could possibly influence the profits of other departments and these conflicts of interest could affect their judgment about firms. For instance, analysts could avoid giving a negative recommendation about a firm that they cover, because this could have a negative impact on the relationship that their investment bank has with this particular firm.

Following Barber et al. (2001), I take a more investor-oriented approach compared to other related studies. I consider calendar-time trading strategies, which are possible to implement in practice. The idea is to construct portfolios of stocks and test whether these portfolios exhibit excess returns that common risk factors from the literature do not capture. As Barber et al. (2001) and Jegadeesh and Kim (2006) point out in their studies, an event time analysis does not measure the profits stemming from an implementable investment strategy while a calendar-time trading strategy does. An event study is only able to investigate whether it would be possible to design potential profitable trading strategies, but it does not provide evidence on the exact amount of possible gross abnormal returns that could be earned (excluding transaction costs) (Barber et al. 2001).

As a first analysis, I perform several trading strategies based on analysts' consensus (mean) recommendation levels as well as recommendation revisions for 16 European countries[1], the US, and Japan. While using quarterly rebalancing and measuring the returns on a monthly basis, the results indicate that both trading strategies based on recommendation levels and recommendation revisions do not earn excess returns while constructing long-short portfolios. Using some model specifications, the alpha on a long-short portfolio is negative, which speaks to an overreaction story. When noise traders overreact to signals they receive from 'experts' (sell-side analysts), stocks with a buy recommendation become overpriced and stocks with a sell recommendation become underpriced. When investors rebalance quarterly, they are likely to capture the reversed price drift resulting from the overreaction, which explains the negative alpha on a long-short portfolio.

Moreover, I look into the optimism bias of analysts by assessing the ratio of sell versus buy recommendations and find that for all countries, the number of sell recommendations is considerably lower than the number of buy or hold recommendations. However, following the burst of the IT-Bubble, the introduction of the Regulation Fair Disclosure by the SEC in October 2000, and the implementation of the NASD rule 2711 in 2002, the buy-sell ratio has decreased sharply between 2000 and 2002. Confirming previous research, the frequency of sell recommendations is the lowest in the United States.

[1] Based on the developed markets database of Kenneth French: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom

As a second analysis, I investigate the impact of analyst recommendation changes, as a determinant of noise trader sentiment, on different investment styles (when double-sorting according to a value strategy). Following DeLong et al. (1990), who identify investor sentiment as trading beliefs that are not justified by the facts at hand (Baker and Wurgler, 2006), trading based on analyst recommendations can be observed as sentimental trading. It is interesting to study within the behavioral value anomaly where analyst recommendations add the most value. The value anomaly states that high book-to-market stocks outperform low book-to-market stocks. This anomaly could be explained by the findings of Lakonishok et al. (1993), who find that value investing is successful, because investors overreact to historically bad earnings and they naively extrapolate these earnings to the future (representative bias). This in turn leads to overpricing of growth stocks and underpricing of value stocks, which results in higher returns for value stocks, on average. I suppose that changes in analyst recommendations have the most impact on stocks with extreme book-to-market ratios (high growth stocks and distressed stocks), since these stocks are more driven by sentiment instead of fundamentals, compared to other stocks in the less extreme portfolios of a value strategy. My findings indicate that, though the significant alphas are all situated in the extreme portfolios, these results are not robust, so these results do not strongly support the prediction.

I expect my thesis to be of interest to both practitioners and financial academics. By examining strategies concerning analyst recommendations in a reasonably investable universe, these strategies should be replicable in the future for practitioners. The performance of the different trading strategies explored in this thesis can give an indication of the extent to which investors can earn excess returns by relying on the input of analyst recommendations for their investment allocation decisions. Although the existence of a profitable trading strategy in a reasonably investable universe shall remain an unresolved question, I hope this thesis can provide valuable insights by exploring different trading strategies. This in turn could lead practitioners to the consideration of a more diverse range of insights. Next to the practical side, this thesis can provide financial academics with additional insights on the determinants of value in financial markets, when they are able to understand the possible added value of financial analysts better in a broader perspective.

The remainder of the thesis is organized as follows. Section 2 provides the related literature; section 3 spells out the testable implications, gives a description of the dataset, and explains the methodology. Empirical results are reported in Section 4. Finally, section 5 concludes.

2. Literature review

This section provides an overview of related literature. This thesis is mainly related to two strands of research: studies that investigate the relation between analyst recommendations and (excess) stock returns and studies that identify factors that drive investor (noise trader) sentiment.

2.1.1. Studies that investigate the relation between analyst recommendations and stock returns

In 1933, Cowles was one of the first researchers to study whether recommendations of analysts produce abnormal returns in his article 'Can Stock Market Forecasters Forecast?'. His results suggest that the recommendations of most analysts do not produce abnormal returns. While the existing literature is still at odds about the possibility of excess returns using trading strategies based on analyst recommendations, most studies find that analyst' recommendations provide valuable information if investors consider for example the holding period, dispersion among analyst recommendations, consensus recommendation levels or recommendation revisions. However, when considering the daily rebalancing of portfolios that is often needed to generate positive alphas and the accompanied transaction costs, these costs often become so high that possible profits will be eaten away (Barber et al. 2001).

According to my insights, studies concerning this topic can mainly be divided in three categories: column studies, event studies, and studies that investigate calendar-based trading strategies[2]. Stickel (1995) performs an event study by investigating the stock price reaction of newly issued analyst recommendations and finds that buy recommendations are associated with an average increase of the share price of 1.16%, during 11 business days centered on the recommendation date, while sell recommendations lead to an average decrease of the share price of 1.28%. Another example of an event study about this topic is the paper of Womack (1996), who performs an event study in order to assess stock price reactions to analyst recommendations and finds that analysts appear to have market timing- and stock picking abilities. He reports that the stock price increases 2.4% after newly issued buy recommendations and that this post-event drift is short-lived, but that the drift for sell recommendations is larger with 9.1%, which extends for six months. The main conclusion of both these event studies is that the stock price increase is most evident in the one or two days around the recommendation change.

Because this thesis mainly relates to the calendar-based trading strategy studies, I review the main findings of these studies more explicitly. Barber et al. (2001) study the relation between

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[2] In this literature review, I do not elaborate on the findings of column studies, which investigate the value of analyst recommendations that are published in a newspaper column (for example the 'Dart Board' column in the Wall Street Journal). However, interesting column studies are, among others, Liu et al. (1990), Barber and Loeffler (1993), and Albert and Smaby (1997).

consensus analyst recommendation levels and stock returns for the US in the period from 1985 - 1996 and find that the abnormal returns of their analyst recommendation based strategy are significantly positive under the four-factor characteristics model (Carhart, 1997). More specifically, they find that the most favorable recommended stocks earn excess returns of more than 4% per year, while the least favorable recommended stocks suffer a loss of around 5% per year. However, the authors state that accounting for the high amount of transaction costs resulting from the need of daily rebalancing shows that in practice it is not possible to earn significant profits, regardless of the rebalancing frequency.

Jegadeesh et al. (2004) find that glamour stocks and growth stocks are the most recommended types of stocks by sell-side analysts. This is linked to the possibility of potential higher incentives for analysts, since growth firms are attractive as future clients for an investment bank, because they can generate many future profits (possible IPOs, and M&A deals for instance). They find that a trading strategy based on analyst recommendation levels adds value only for stocks with favorable characteristics that are acknowledged to produce excess returns by itself. In particular, for high value and high momentum stocks, analyst recommendations can add value. Stocks without favorable characteristics do earn worse subsequent returns after higher consensus recommendations. Moreover, the authors find that upgraded stocks outperform downgraded stocks. They compare the predictive ability of consensus recommendation level and recommendation changes and point out that changes in analyst recommendations have more predictive ability than the consensus recommendation level. They state that analysts do not change their recommendations for long periods, so the informative value of the consensus recommendation levels diminishes over time after a recommendation change.

Following the methodology of Jegadeesh et al. (2004), Jegadeesh and Kim (2006) evaluate trading strategies based on recommendation revisions in a more international perspective, by studying this topic for the G7 countries for the period 1993 - 2002. Next to studying the calendar-time method, they also perform an event study to investigate the stock price reaction after recommendation changes. They find that trading strategies based on recommendation revisions are the most profitable in the US and that stock prices react significantly in all countries of their sample, except Italy. Though they find that equally-weighted trading strategies are profitable for every G7 country except Italy, value-weighted trading strategies are profitable only for a holding period of one month and no delay after the release of the recommendations, excluding transaction costs. In addition, all explored strategies are more profitable for small firms than for large firms. In the end, their evidence indicates that the amount of economic value added by analysts is only modest, so they suggest that the market is fairly efficient, though analysts could possibly add value with their recommendations when these would be combined with other investment signals.

Green (2006) investigates the value of client access to analyst recommendations for Nasdaq listed stocks for the period 1999 - 2002 and finds that making transactions quickly following recommendation changes earns annualized excess returns of more than 30%. An important aspect of this study is the specific focus on short-term profitability and the availability of early access to recommendation changes, which is generally not the case for noise traders. The results of the paper suggest that the short-term profit opportunities are mostly existent for roughly two hours after the pre-market release of an analyst recommendation change (Green, 2006).

Overall, the majority of previous studies, which mainly have a focus on the US, find that analyst recommendations can lead to abnormal returns, but most studies find that the abnormal returns diminish when investors would account for transaction costs, extend the holding period, or delay investment decisions. Prior studies are still at odds whether analyst recommendations do add economic value to the cross-section of stocks returns. Moreover, if analysts appear to have skills to determine overvalued and undervalued shares, these skills are useful mostly for a short investment horizon.

In this thesis, I mainly combine the methodology of Barber et al. (2001), Jegadeesh et al. (2004), and Jegadeesh and Kim (2006) by studying trading strategies based on both consensus analyst recommendation levels and analyst recommendation revisions in a broad international sample. Specifically, I explore several trading strategies that are replicable for practitioners using a recent time-period which has not been explored much previously, in order to give a more comprehensive picture of the possible added value of analyst recommendations.

2.1.2. Optimism bias

Another important finding of the literature concerning analyst recommendations is the optimism bias that seems to be present in these recommendations. De Bondt and Forbes (1999) state that analysts tend to be too optimistic and too extreme in their forecasts, because of conflicts of interests. Furthermore, they find that financial analysts show herding behavior in their forecasts. They state that if analysts show herding behavior in their forecasts, this may influence market prices when it leads to herding in the behavior of investors. This in turn could motivate noise trading. Herding in analyst recommendations is also shown in the findings of Welch (2000), among others, who finds that the buy or sell recommendations of security analysts significantly influence the recommendations of the next two analysts that cover the same company.

In an earlier study, De Bondt and Thaler (1985) find that overreaction is a common theme in the stock market. Because of too optimistic and too extreme forecasts, investors could overreact in their investment decisions because they over rely on analysts as being experts. Upon observing a signal from analysts, noise traders may overreact. This would lead to overpricing following buy recommendations and underpricing following sell recommendations, which will be corrected in the longer term[3].

Michaely and Womack (2005) suggest that the optimism bias is the outcome of the working environment and the pay structure of analysts. They find that the optimism bias could possibly be a result of the compensation scheme of analysts. Since credibility and reputation have a significant impact on the compensation of analysts, it could be possible that they give optimistic recommendations about the companies they cover for the wrong reason: not because they really think that those companies are better than other companies, but that this could benefit their position in the investment bank, which in turn could lead to an increase of their compensation. On the contrary, Michaely and Womack mention a nonstrategic motive as another explanation for the optimism bias, which suggests that the optimism bias could also exist because of heuristics and cognitive biases. They point out that it is also possible that analysts really believe that the companies they cover are better than other companies.

In a more recent article, Brown et al. (2015) survey 365 sell-side analysts and conduct several follow-up interviews. The responses on their surveys suggest that especially retail investors should not listen to sell-side analysts while allocating their investments. When analysts must rate several components that could be important for their compensation, the least important components are 'the profitability of the stock recommendations for investors' and 'the accuracy and timeliness of the earnings forecasts' (Brown et al. 2015). The analysts respond in the survey that hedge funds and mutual funds are the clients that are analysts paid to cater to; retail investors are the least important. Moreover, maintaining good relationships with management of the companies they cover is crucial, so therefore they state that it is not surprising that the optimism bias is still present.

The optimism bias has been studied a lot in previous research by assessing the ratio of buy to sell recommendations. In general, sell-side analysts release more buy than sell recommendations. For instance, Barber et al. (2001) find that sell recommendations make up only 6.5 percent of the total number of recommendations; the results of Boni and Womack (2003) suggest that buy recommendations greatly outnumber sell recommendations, which make up only 3 percent of the total; in the sample of Stickel (1995), only 12 percent are sell recommendations, and Jegadeesh et al. (2004) point out that sell or strong sell recommendations make up less than 5 percent of all issued recommendations.

[3] I thank Mr. Montone for this insight

In this thesis, I investigate whether the optimism bias, that earlier research has shown to be present in the U.S., is also present in European markets and Japan. Moreover, I study whether the optimism bias has changed for the US in this more recent time period that I study. This could be the case, since analysts have been put under pressure during the IT-bubble and the financial crisis. Moreover, as Barber et al. (2005) mention in their study, the environment of analysts has changed because of the implementation of new legislation in May 2002 (NASD Rule 2711). The goal of these research analyst rules is to enhance the objectivity and transparency in research reports. For example, NASD Rule 2711 prohibits research analysts to adjust their analyst recommendations to the favor of their investment bank's clients. The rule does not allow analysts to participate in other investment banking tasks besides the writing of their research reports (Financial Industry Regulatory Authority (FINRA)).

2.2. Studies that identify factors that drive investor (noise trader) sentiment

The second strand of research this thesis adds to is the emerging literature concerning the identification of factors that drive investor (noise trader) sentiment. Baker and Wurgler (2006) define investor sentiment as the propensity to speculate. Stocks that are vulnerable to speculation are stocks which have subjective fundamental values and which are difficult to arbitrage. When retail investors do not have sufficient information about the earnings history of a firm and when the respective firm has infinite growth opportunities, then these investors could defend a wide range of possible valuations of this firm, depending on their level of sentiment about the firm (Baker and Wurgler, 2006). Baker and Wurgler (2006) construct a sentiment proxy index, which is highly correlated with the anecdotal evidence of past bubbles they investigated. Black (1986) defines noise trading as 'trading on noise as if it were information'. Following the intuition of Jegadeesh et al. (2004), trading based on the level of sell-side analyst recommendations is an example of such noise trading. Investors who make transactions based on the type of information in analyst recommendations actually do not know whether this information is true, but they just simply trust the information and act according to it, because they believe that analysts are experts in their field and they know the truth.

Schmeling (2007) finds that investor sentiment can be divided in institutional sentiment and individual sentiment. He finds that institutional sentiment is likely to represent fundamental risk ('smart money'), while individual sentiment likely identifies a proxy for noise trader risk ('dumb money'). Moreover, Schmeling finds that the level of individual sentiment does affect institutional sentiment, but that this is not true the other way around: when individual sentiment is high, institutional investors consider this and lower their sentiment. However, individual sentiment is not altered according to the level of institutional sentiment. Noise traders are assumed to be less able to separate the information content from analyst recommendations from poor incentives of analysts. Because of their overreliance on experts, small investors might not seek information about analyst distortions, even if the costs of obtaining such information are low (Schmeling, 2007). Boni and Womack (2003) mention that whereas noise traders may be influenced to purchase by the average (consensus) level of a recommendation, institutional investors are more likely to follow the direction of revisions in recommendations, if they are influenced by analyst recommendations at all. Related to this finding is the paper of Kacperczyk and Seru (2007), who find that the skills of a manager are negatively related to the use of public information such as sell-side analyst recommendations: highly skilled managers are less sensitive to changes in analyst recommendations and other public information. Malmendier and Shankthikumar (2007) find a result in the same line of thinking, namely that large traders account for the distortions of security analysts, while small brokers follow recommendations literally.

Following these findings, literally following consensus analyst recommendations can be detected as a determinant of noise trader sentiment. As a second analysis in this thesis, I look deeper into the possible impact of analyst recommendations as a determinant of noise trader sentiment, by investigating the effects of analyst recommendations on different investment styles: I suppose that analyst recommendation revisions have more impact on the extreme categories (growth and value stocks) when sorting according to a value strategy, since these types of stocks are harder to value based on their fundamentals.

3. Testable implications, data, and methodology

3.1. Testable implications

As a first analysis, I investigate whether analyst consensus recommendation levels add value to stock returns by performing time-series regressions, which include several control factors. Barber et al. (2001) state that the consensus level is a good indicator of future performance that is easily accessible by a large group of investors, because it appears on many internet sources and financial newspapers. The measure combines a great number of opinions by calculating the average opinion about a stock of all analysts covering the stock.

I conduct the first analysis by testing several asset pricing models that include different specifications of total systematic risk in the market. I start with the Capital Asset Pricing Model (hereafter CAPM) (Sharpe, 1964). Thereafter, I use the Fama & French three-factor model (Fama and French, 1993), the Carhart four-factor model (Carhart, 1997), and as a fourth model I add the Pástor and Stambaugh liquidity factor to the Carhart four-factor model (Pástor and Stambaugh, 2003).

After studying trading strategies based on consensus recommendation levels, I follow the intuition of Jegadeesh et al. (2004), who use consensus recommendation revisions (upgrades versus downgrades) instead of consensus recommendation levels as a measure, since they note that the explanatory power of the quarterly change in the consensus analyst recommendation is more robust than that of the level of the mean consensus analyst recommendation. An explanation for this can be found in the intuition of Boni and Womack (2003), among others, who state that there is a difference between the information processing of analyst recommendations of smart money and noise trader investors. Smart money investors put more weight on the information from recommendation changes compared to recommendation levels. They know that the stock picking abilities of analysts will be better measured by upgrade and downgrade activity instead of mean consensus levels; changes show more explanatory power than levels. This could be due to the fact that the consensus level can remain the same for a long time. The predictive value could be decreasing after some time when the information in the recommendation is already incorporated into the stock price and the effect of trading on it just before the consensus level is changed has less explanatory power than trading just after a change in recommendation has been released.

As a second analysis, I investigate whether analyst recommendations have possibly more impact on the extreme portfolios of a value strategy compared to the stable middle portfolios of this strategy. Growth and distress firms both lie at the opposing extremes, while more stable firms are situated in the middle portfolios (Baker and Wurgler, 2006). It is interesting to consider extreme book-to-market portfolios in the analyst recommendation context, since these extreme portfolios consist of stocks which are most hard to value and are more difficult to arbitrage, so these portfolios could be more vulnerable to analyst recommendations (as a determinant of noise trader sentiment). As Baker and Wurgler (2006) state: 'a broad wave of sentiment will disproportionally affect stocks whose valuations are highly subjective and are difficult to arbitrage'. When investors have little information about a stock, they are more prone to heuristics – simplified ways of thinking – because it is simply harder for them to value these stocks. When individual investors consider analysts as experts, then I suppose it could be possible that they rely more heavily on their recommendations when they have little information about the fundamental value of stocks.

Summarized, the testable hypotheses of this thesis are:

H_{1A}: *Stocks with high consensus analyst recommendation levels outperform stocks with low consensus analyst recommendation levels*

H_{1B}: *Upgraded stocks outperform downgraded stocks*

H_2: *Shifts in analyst recommendations have most impact on extreme portfolios of a value strategy*

The null hypothesis of hypothesis 1a is that stock market returns are unaffected by analyst recommendations. This hypothesis embeds the view that investors are rational, that markets are efficient, and that the economic benefits resulting from analyst recommendations are too small to conclude that analysts are able to detect underpriced and overpriced shares. Under the null hypothesis, the coefficient on the alpha should be indifferent from zero.

The null hypothesis of the hypothesis 1b is that stock market returns are unaffected by analyst' recommendation upgrades or downgrades. By the time a new recommendation is issued, the information from this publication should already be incorporated into the price and hence, the alpha should be indifferent from zero.

The null hypothesis of hypothesis 2 is that analyst recommendations have no explanatory power in the cross-section of stock returns, either on extreme book-to-market portfolios or on book-to-market portfolios in the middle portfolios. Analyst recommendations as a determinant of investor sentiment should have no impact, since stock prices should already incorporate any publicly available information and investor sentiment should not play a role, since investors are assumed to be rational. Although irrational investors can exist according to the EMH, this will not lead to mispricing, because rational investors are assumed to arbitrage this away immediately.

3.2. Data

The data on analyst recommendations are retrieved from the Bloomberg database with a professional subscription. In this way, I have access to the recommendations of several large brokers, which are only available for paying clients. While constructing the sample, my goal is to ensure that the different trading strategies are replicable in the future for other investors, so I decide to include only firms and countries in a reasonably investable universe. I decide to focus on all firms (excluding financial institutions) from developed markets from Kenneth French's database. Only firms with a market capitalization bigger than 3 billion, which have at least five analyst recommendations in the Bloomberg database, for the period 2000 – 2015, are included, again to ensure the replicability of the trading strategies. The restriction of investigating only developed markets results in a sample that includes the United States, 16 countries in Europe, and Japan.

Because of data limitations on the availability of analyst recommendation data in Bloomberg, I cannot start the analyses earlier than the year 2000. The recent time period from 2000 - 2015 is interesting to study, since the availability of data has improved and it has become easier for all types of traders to receive analyst recommendation information than before the 1980s, because of the internet and the increased level of information sharing. This period contains both bull and bear markets, as well as analyst conflicts of interest and a positive recommendation bias. The period includes the burst of the IT bubble (March 2000, Griffin et al. (2011)) and the financial crisis, which can have had a significant impact on the recommendations of analysts. As stated in the literature review, many retail investors rely on the opinion of sell-side analysts, so difficult financial periods could have had an impact on the trading behavior of those noise traders. Barber et al. (2001) find that in bull markets, noise traders are likely to overreact to good news and neglect negative news. In bear markets, this is the exact opposite. Moreover, it could be possible that the recent controversy around sell-side analyst, which was largely motivated by complaints of retail investors that sell-side analysts had not anticipated on the burst of the tech bubble, has changed the value of analyst recommendations (Boni and Womack, 2003). Just before the IT bubble began to burst investor sentiment was high, as measured by the six proxies of Baker and Wurgler (Baker and Wurgler, 2006). By studying several historical bubbles, Baker and Wurgler find evidence that there seems to be a pattern in the effect of sentiment on the cross-section of stock returns. They mention that in all bubbles they have investigated, an increase in sentiment will increase the relative price of stocks with a subjective fundamental value. Because noise trader demand is larger in periods of sentiment (other things being equal) and the relative price increases, subsequent stock returns for these stocks will be lower. Examples of stocks with a subjective fundamental value are young stocks, small stocks, extreme-growth, and distressed stocks. In my opinion, studying the recent time period from 2000 - 2015 while considering an international sample can give a more complete picture of the extent to which analyst recommendations can add value for investors.

Monthly holding period return data are retrieved from Bloomberg. The data comprises the total return including reinvested dividends and are computed using the following equation:

$$Ri,t = \frac{\mathrm{Pi,t}}{\mathrm{Pi,t-1}} - 1$$

where R denotes the return of company i at time t, and P denotes the closing price of company i at time t.

Accounting information such as the market capitalization and book-to-market value of firms is retrieved from the Bloomberg database. Because of the data availability of Bloomberg, I retrieve the Price-to-Book ratio from Bloomberg, which is the inverse of the Book-to-Market ratio.

The market factor, risk-free rate, size factor, book-to-market factor, and momentum factor (Jegadeesh and Titman, 1993) data can be retrieved from the online data library of Kenneth French[4], which are available from 1990. Kenneth French calculates these factors on a monthly basis. I use the global factors, which include only developed markets, since this is the closest benchmark for my sample.

The data for the traded liquidity factor is available on the website of Pástor[5]. The regressions including this factor will have a lower number of observations, since the liquidity factor is only available until December 2014.

3.3. Methodology

In order to conduct this study, I mainly follow the methodology of Barber et al. (2001), Jegadeesh et al. (2004), and Jegadeesh and Kim (2006), although I use a broader sample and test the implications for a more recent time period, using several robustness checks. Analyst recommendations are rated on a 5 point-scale; normally a 1 represents a strong buy recommendation, a 3 a hold recommendation and a 5 represents a strong sell recommendation. However, Bloomberg provides consensus analyst recommendation levels with an inverse rating scale: a 1 represents a strong sell recommendations and a 5 represents a strong buy recommendation.

The consensus recommendation level and change are calculated quarterly, applying the methodology of Jegadeesh et al. (2004, p. 1083), who find that "the quarterly change in the consensus recommendation is a robust return predictor that appears to contain information that is orthogonal to a large range of other predictive variables". For comparability reasons, I use the same rebalancing period for the level of consensus recommendations.

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[4] Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5] Pástor's website: http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2014.txt

To ensure that other investors can replicate the trading strategies investigated in this thesis, I think that quarterly rebalancing is more realistic than monthly or daily rebalancing. According to Stickel (1989), sell-side analysts time their recommendations in respond to interim earnings announcements, which are published quarterly. They find that analysts avoid to change their recommendation two weeks before a calendar quarter as well as early in the fiscal year. Also Womack (1996) finds that new analyst recommendations are often published around quarterly earnings announcements. For this reason, rebalancing monthly or daily would not result in considerably more new consensus recommendation levels, since the analyst recommendations are not evenly distributed over time but they seem to be concentrated around quarter ends and major news events. Furthermore, previous research, such as the paper of Barber et al. (2001), shows that daily or monthly rebalancing results in high transaction costs, which diminishes the effect of realized excess returns from a trading strategy based on analyst recommendations.

The consensus recommendation level is measured as the mean of all outstanding analyst recommendations for a given firm one day prior to the calendar quarter end. The consensus recommendation change is measured as the increase or decrease in the consensus recommendation level, from the end of the prior calendar quarter to the end of the current calendar quarter (Jegadeesh et al., 2004). An overview of the performed trading strategies is as follows:

Table 1: Trading strategies

Table 1 provides the main trading strategies performed in this thesis. Firstly, consensus analyst recommendation levels are used as a measure. I construct portfolios based on several portfolio partitions. Secondly, I specifically follow Barber et al. (2001) by using their portfolio breakpoints. After that, upward and downward recommendation changes are used, following Jegadeesh et al. (2004).

Strategy	Long	Short
Consensus recommendation level	Stocks with a high consensus recommendation level	Stocks with a low consensus recommendation level
Consensus recommendation level (Barber et al. 2001)	Stocks with a mean recommendation level >4.5[6]	Stocks with a mean recommendation level <3
Recommendation change	Upgraded stocks	Downgraded stocks

3.3.1. Regression analyses using the CAPM, three- and four-factor model, including a liquidity factor

The first regression analyses test the consensus analyst recommendation level and recommendation change in the CAPM by applying a strategy that goes long in stocks that have a high consensus recommendation or an upward revision and goes short in stocks that have a low consensus recommendation or a downward revision. I create different portfolios based on several breakpoints

[6] These values follow the methodology of Barber et al. (2001). They perform a strategy that goes long in stocks with a mean consensus recommendation level <1.5 (strong buy recommendation) and short in stocks with a mean consensus recommendation level >3 (hold/sell/strong sell recommendation). I reverse these values because I work with the inverse Bloomberg scaling

and go long in the highest portfolio concerning stocks with the highest recommendations and short in the lowest portfolio concerning stocks with the lowest recommendations. For example, firms in portfolio 5 are in the top 20% of classifying in terms of their consensus recommendation level in the first quarter of the year 2000. The stocks in portfolio 4 fall in the next 20%, while those in portfolio 1 are the stocks in the bottom 20%. The reason for construction alternative portfolio formations is to examine whether the results of the asset pricing models are sensitive to the partition of the sample portfolios[7]. Furthermore, I use the specific breakpoints from Barber et al. (2001), who classify all stocks with a hold/sell/strong sell recommendation in the low portfolio and all stocks with a strong buy recommendation in the high portfolio.

The CAPM is an asset-pricing model that compensates investors for the time value of money and the risk investors bear. I construct value-weighted, as well as equally-weighted portfolios. With value-weighted portfolios, larger firms are more heavily represented in the return than smaller firms are. Barber et al. (2001) state that this can bias against finding results, since larger firms are known to be more efficient. However, value-weighted portfolios are better in capturing the economic significance of the results, since they are able to implement in practice as a buy-and-hold strategy (Barber et al., 2001). As a robustness check, I construct equally-weighted portfolios, since this allows me to prevent a tilt to larger firms in the aggregate return. However, this strategy is more difficult to implement, since you have to rebalance daily to keep the same proportions of every stock relatively to the total size of the portfolios for each quarter. Using monthly return data, the first time-series regression equation is as follows:

$$R_p - R_f = \alpha + \beta^{MKT} * (R_m - R_f) + \varepsilon,$$

where Rp is the return of the portfolio and Rf is the risk-free rate. Subtracting the risk-free rate from the return of the portfolio gives excess returns. α denotes the excess return per dollar long or short per month (intercept), β^{MKT} measures the risk arising from exposure to market movements, Rm corresponds to the market's expected rate of return and ε is the error factor.

After performing the CAPM regression, more control factors are included. Fama and French (1993) argue that the CAPM seems to oversimplify the market by using only one risk factor (the market risk factor) to explain excess returns of a portfolio, so they note that it is useful to add other risk factors. They find that, next to the market risk factor of the CAPM, a size factor and a book-to-market value factor also explain cross-sectional variation in average stock returns. Firstly, I add the

[7] For this thesis, I constructed portfolios based on quintiles, quartiles, median, deciles, and vigintiles. In the results section, I only report results based on quintile portfolio partition. The results based on other partitions of the sample are qualitatively similar.

size (SMB) and book-to-market (HML) factors (Fama & French three-factor model, 1993), then the momentum factor (MOM) (Carhart four-factor model, 1997), and finally a liquidity factor (LIQ) (Pástor & Stambaugh, 2003).
As a result, the complete regression equation becomes the following:

$$R_p - R_f = \alpha + \beta^{MKT}(Rm - Rf) + \beta^{S}\,SMB + \beta^{H}\,HML + \beta^{M}\,MOM + \beta^{L}\,LIQ + \varepsilon$$

where $R_p - R_f$, α, $\beta^{MKT,}$ and Rm-Rf, and ε are defined as in the CAPM. The size factor, SMB, is the monthly return of a portfolio that is long on small stocks and short on large stocks. Historically, small cap stocks have outperformed large cap stocks. The book-to-market factor, HML, measures the monthly return that is long on high book-to-market value stocks and short on low book-to-market value stocks. Historically, high book-to-market stocks (value stocks) have outperformed low book-to-market stocks (growth stocks). The momentum factor, MOM, is the monthly return of a portfolio that is long on past one-year return winners and short on past-year return losers. LIQ is the liquidity factor, consistent with liquidity risk being priced. I use the traded liquidity factor from Pástor and Stambaugh (2003), which is "the value-weighted return on the long-short portfolio from a sort on historical liquidity betas" (Pástor and Stambaugh, 2003). Finally, the betas measure the risk arising from exposure to the separate risk factors. For example, if βs is higher than zero and significant, the portfolio would be most exposed to a small cap portfolio. If these five factors explain all excess returns, the intercept (α) of this model should be zero.

Using the four different factor models described above allows me to assess whether any excess returns that are found, expressed in the intercept, are due to stock picking skills of sell-side analysts or to the fact that analysts just choose stocks which happen to to have characteristics that are known drivers of stock returns (style-driven effects and momentum and liquidity effects). When the intercept is indistinguishable from zero, this means that the portfolio returns are explained away by the risk factors in the asset pricing models, which in turn means that analyst recommendations have no predictive power. Since there seems no agreement about the best reality representing risk-return model in the current literature, I follow previous related studies on the analyst recommendation literature and add different risk factors every step.

3.3.2. Second analysis, using a double sorting method

Considering the second analysis, I construct portfolios using a double sorting method, in order to investigate the effects of analyst recommendations on different investment styles. First, I sort stocks into portfolios based on their book-to-market value (high to low). After that, I sort each portfolio into two portfolios based on a shift in consensus analyst recommendation, which can be upward or downward. As an alternative check, I first sort stocks into portfolios based on their book-to-market value again (high to low) and afterwards on their analyst consensus recommendation level (based on Barber et al. (2001) partitions. Comparable to previous analyses, I construct alternative portfolio formations, to examine whether the results of the asset pricing models are sensitive to the partition of the sample portfolios.

3.4. Descriptive statistics of the sample

This section reports the descriptive statistics of the sample and assesses the ratio of buy versus sell recommendations. Table 2 presents the descriptive statistics. To assess the ratio of buy versus sell recommendations in the sample, I divide all recommendations for each year in three categories: strong buy/buy, hold, and strong sell/sell.

The optimism bias decreases sharply between 2000 and 2002. In 2000, there are more than 20 buy recommendations to 1 sell recommendation. The buy/sell ratio is 10.2 buy recommendations to 1 sell recommendation in 2001, and 5.4 buy recommendations to 1 sell recommendation in 2002. This sharp decrease is also found by Barber et al. (2006, p.87), who document that "the percentage of buys decreased steadily in mid-2000, likely due, at least partly, to the implementation of NASD Rule 2711, requiring the public dissemination of ratings distributions". After the bubble burst, sell-side analysts were criticized by a broad range of people, including regulators, politicians, and investors. New rules were implemented by the FINRA because of the major concern about the integrity of financial markets and their 'experts', in the hope to improve this in the future.

After 2002, the buy/sell ratio slightly increases and decreases to 7.6 in 2011, and afterwards the ratio slightly decreases again. Jegadeesh and Kim (2006) find that the level of optimism among analysts does depend on past market performance. They state that more buy recommendations are issued during bull markets, and more sell recommendations are issued during bear markets. The results of my sample do not show this. The sharp decrease of the buy/sell ratio is visible after the IT bubble burst, but afterwards the ratio remains stable. This could possibly be explained by the findings of Brown et al. (2015), who find that the incentive for analysts to publish recommendations which contribute positively to their compensation is still much present.

To look into the buy/sell ratio more deeply for the different countries in the sample, table 3 provides the distribution of recommendation levels and the buy/sell ratio for each country separately. For all countries, the number of sell recommendations is considerably lower than the number of buy or hold recommendations. Confirming prior research, the frequency of sell recommendations is the lowest in the U.S. Overall, the frequency of sell recommendations is 9.3%

throughout the sample period, while excluding the US leads to a percentage of 12.7%, which is considerably higher. Sell recommendations are about 1.5 to 4.7 times as frequent in other countries as in the U.S. Jegadeesh et al. (2004) also find this result. While Balboa et al. (2009) find that the buy/sell ratio is most optimistically biased in countries with a high investor participation level (such as the U.S., the U.K., and Sweden), I find that indeed the U.S. has a skewed buy/sell distribution, but the U.K. and Sweden have a similar buy/sell distribution as countries with a low investor participation level (such as Germany and France), so this particular finding is not applicable to my sample.

In total, there are 2,939 unique firms in the sample. The number of recommendations increases throughout the sample period. The average consensus recommendation level throughout the sample period lies is within the range of 3.41 and 4.10. Table 1 in the appendix reports the number of consensus recommendations and the average recommendation level per country separately.

Table 2: Descriptive statistics analyst recommendations for the period 2000 – 2015

Table 2 presents the descriptive statistics for the sample. The sample is restricted to stocks (excluding financial institutions) in developed markets, that have a market capitalization of more than 3 billion, and have at least five analysts that cover them. For each year, the table provides the number of firms, number of recommendations, number of new firm recommendations (the same firm can get a new recommendation in another quarter of the same year), the overall average recommendation level, and the recommendation frequency for that year. Moreover, the last column provides the buy/sell ratio for each year for the full sample. The sample period is from January 2000 to December 2015.

					Recommendation Frequency						
					Strong Buy/Buy (4 & 5)		Hold (3)		Sell/Strong Sell (1 & 2)		Buy/Sell ratio
Year	No. of firms	No. of recommendations	No. of new firm recommendations	Average recommendation level	N	Percent of total	N	Percent of total	N	Percent of total	Rounded to one decimal
2000	757	18,923	2,062	4.20	12,994	68.7	5,281	27.9	648	3.4	20.1
2001	1,098	47,020	3,622	3.97	27,310	58.1	17,028	36.2	2,682	5.7	10.2
2002	1,182	63,947	4,044	3.77	32,770	51.2	25,058	39.2	6,119	9.6	5.4
2003	1,100	63,548	3,879	3.62	28,248	44.5	27,101	42.6	8,199	12.9	3.4
2004	1,234	68,597	4,444	3.68	31,739	46.3	29,167	42.5	7,691	11.2	4.1
2005	1,305	69,813	4,610	3.66	31,711	45.4	30,676	43.9	7,426	10.6	4.3
2006	1,411	74,469	4,914	3.71	35,845	48.1	31,114	41.8	7,510	10.1	5.8
2007	1,586	82,525	5,579	3.72	39,948	48.4	34,234	41.5	8,343	10.1	5.8
2008	1,500	78,586	5,183	3.79	40,590	51.7	30,582	38.9	7,414	9.4	5.5
2009	1,277	72,860	4,395	3.61	34,113	46.8	28,306	38.8	10,541	14.4	3.2
2010	1,405	89,687	5,050	3.82	46,888	52.3	33,835	37.7	8,964	10.0	5.2
2011	1,531	99,985	5,494	3.88	53,578	53.6	38,290	38.3	8,117	8.1	7.6
2012	1,502	99,230	5,495	3.85	51,724	52.1	39,412	39.7	8,094	8.2	6.4
2013	1,627	106,340	5,816	3.77	52,405	49.3	43,786	41.2	10,149	9.5	5.2
2014	1,785	118,142	6,564	3.77	57,258	48.5	49,635	42.0	11,249	9.5	5.1
2015	1,825	118,039	6,600	3.80	57,851	49.0	49,297	41.8	10,891	9.2	5.3

Table 3: Distribution of recommendation levels per country: 2000m1 - 2015m12

Table 3 provides for each year the percentage buy, hold, and sell recommendations, as well as the overall average of the sample period for each country. Consensus recommendation levels are measured at day t-1 of the beginning of a new quarter. The sample starts in January 2000 and ends December 2015.

Country		2000-2015	'00	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	'13	'14	'15
Austria	Buy	43.0	0.0	0.0	-	61.7	43.9	40.1	57.9	50.2	59.2	37.3	29.6	39.6	46.1	37.8	33.9	38.6
	Hold	39.4	100	88.9	-	23.4	33.3	43.7	29.4	39.8	32.1	42.8	46.1	43.0	36.1	37.8	41.3	38.0
	Sell	17.6	0.0	11.1	-	14.9	22.8	15.5	12.7	10.0	8.8	19.9	24.3	17.4	17.8	24.4	24.9	23.4
Belgium	Buy	40.1	52.1	44.8	50.6	40.3	53.4	46.2	46.6	42.4	39.7	32.0	37.4	40.3	34.2	29.0	35.2	33.9
	Hold	40.9	42.4	45.9	37.2	43.5	34.4	40.0	37.1	37.4	38.5	38.5	43.9	40.5	43.1	47.3	41.3	44.8
	Sell	19.0	5.5	9.3	12.2	16.3	12.3	13.9	16.3	20.2	21.8	29.5	18.7	19.2	22.7	23.7	23.6	21.3
Denmark	Buy	48.5	71.4	67.8	63.0	46.7	44.4	42.7	42.6	44.8	51.3	47.0	47.8	54.2	47.9	45.0	46.2	48.8
	Hold	29.5	28.6	26.4	24.8	26.5	25.7	29.1	30.3	29.2	28.4	27.2	28.6	27.8	32.5	32.7	33.6	33.8
	Sell	22.0	0.0	5.8	12.2	26.8	30.0	28.2	27.1	25.9	20.2	25.9	23.6	17.9	19.5	22.3	20.1	17.4
Finland	Buy	48.1	86.2	65.1	62.2	58.9	51.8	41.5	54.9	55.7	57.4	48.7	45.0	49.7	44.8	38.8	28.6	32.6
	Hold	29.2	13.8	25.1	26.4	24.8	31.9	34.8	26.9	25.0	25.4	28.3	31.0	28.6	31.6	30.3	34.0	35.8
	Sell	22.7	0.0	9.8	11.5	16.3	16.3	23.7	18.2	19.3	17.2	23.0	24.0	21.6	23.5	30.8	37.5	31.6
France	Buy	53.2	68.9	58.8	54.0	50.7	52.5	51.5	52.7	54.0	57.0	49.5	52.8	56.7	51.5	50.8	48.6	50.3
	Hold	32.8	25.1	30.2	30.8	34.4	34.6	34.2	33.3	31.7	29.1	28.1	29.5	30.9	34.6	34.8	38.3	38.3
	Sell	14.0	6.0	11.0	15.2	15.0	12.9	14.3	13.9	14.4	13.8	22.4	17.7	12.4	13.9	14.4	13.2	11.4
Germany	Buy	49.6	52.5	45.3	46.1	46.9	48.8	50.0	51.0	54.6	61.6	46.1	51.5	56.4	51.0	44.9	44.1	44.6
	Hold	34.7	39.3	41.3	35.8	35.0	34.1	34.6	35.3	31.5	25.1	27.8	28.9	30.1	35.7	37.7	38.9	41.0
	Sell	15.7	8.2	13.4	18.0	18.1	17.1	15.3	13.8	13.9	13.3	26.1	19.6	13.5	13.3	17.4	17.0	14.4
Greece	Buy	56.4	75.0	75.5	77.5	68.8	58.0	56.8	51.4	51.0	45.6	55.6	48.0	49.1	35.1	25.0	48.4	73.3
	Hold	34.9	25.0	23.4	22.1	25.7	32.9	36.7	37.3	34.8	44.3	34.9	40.6	41.7	45.9	64.6	41.4	26.7
	Sell	8.7	0.0	1.1	0.4	5.4	9.0	6.5	11.4	14.2	10.2	9.5	11.4	9.3	18.9	10.4	10.2	0.0
Ireland	Buy	61.1	81.8	71.0	61.9	57.9	57.2	61.8	65.9	65.3	58.2	61.9	65.1	64.4	59.8	55.1	56.2	60.4
	Hold	31.4	18.2	26.6	31.1	33.5	33.0	34.0	29.1	30.4	34.9	27.4	26.9	27.7	32.2	33.8	34.1	33.5
	Sell	7.5	0.0	2.4	7.0	8.6	9.7	4.2	5.0	4.3	6.9	10.6	8.0	7.9	7.9	11.1	9.7	60.4
Italy	Buy	47.1	51.9	47.8	44.6	42.8	50.1	41.3	48.8	49.8	55.0	49.8	52.9	48.3	53.5	44.3	39.8	39.2
	Hold	36.1	38.9	36.7	37.4	33.5	36.1	39.4	36.0	34.7	30.3	27.3	30.2	35.9	33.0	38.8	40.9	44.7
	Sell	16.8	9.3	15.5	18.0	23.7	13.8	19.3	15.2	15.5	14.8	22.8	16.9	15.8	13.5	16.9	19.3	16.1
Japan	Buy	40.6	46.9	40.5	36.1	38.7	40.6	37.4	36.5	38.5	40.8	34.1	44.9	45.0	44.0	41.9	43.5	44.1
	Hold	49.9	46.8	53.2	53.8	50.6	50.7	53.8	53.8	52.5	49.4	50.0	46.4	47.4	47.8	47.9	47.1	46.4
	Sell	9.5	6.3	6.3	10.1	10.8	8.7	8.8	9.8	9.0	9.8	15.9	8.7	7.5	8.2	10.2	9.4	9.5
Netherlands	Buy	51.2	69.1	54.5	48.8	47.4	43.6	47.8	50.8	53.5	57.1	49.7	57.5	58.1	49.3	46.4	44.3	44.7
	Hold	35.6	27.3	35.0	37.9	36.2	36.0	34.1	33.4	33.8	30.2	29.5	29.8	31.2	39.1	41.0	42.9	43.1
	Sell	13.3	3.5	10.5	13.3	16.3	20.4	18.0	15.7	12.8	12.7	20.9	12.8	10.7	11.7	12.6	12.8	12.2
Norway	Buy	60.2	50.0	57.8	58.0	57.0	61.7	57.6	68.7	57.1	60.6	57.7	66.5	66.6	67.2	61.3	53.2	47.0
	Hold	26.5	36.4	29.1	28.8	25.2	20.2	31.3	19.4	27.1	26.4	25.7	23.9	24.1	24.5	28.9	30.7	30.5
	Sell	13.3	13.6	13.2	13.3	17.8	18.1	11.1	11.8	15.8	13.0	16.6	9.6	9.3	8.2	9.9	16.1	22.5
Portugal	Buy	52.2	83.3	65.9	67.0	64.4	57.9	45.7	38.5	38.9	52.0	52.3	54.3	50.1	49.9	57.4	56.3	42.4
	Hold	31.2	16.7	25.4	26.2	22.3	29.3	39.0	44.4	35.6	26.2	25.8	31.1	32.2	36.6	29.0	24.3	40.9
	Sell	16.6	0.0	8.7	6.8	13.3	13.0	15.2	17.1	25.6	21.8	21.9	14.6	16.8	13.5	13.6	19.3	16.8
Spain	Buy	47.9	71.6	51.9	47.3	42.8	41.9	39.0	43.6	44.8	57.9	53.8	56.3	59.9	54.0	46.4	39.6	42.6
	Hold	32.1	23.9	36.4	35.4	38.9	39.1	36.1	32.4	28.7	22.0	22.5	25.8	27.0	31.0	34.6	37.7	38.4
	Sell	20.0	4.5	11.7	17.3	18.4	19.0	24.8	24.0	26.5	20.1	23.8	17.8	13.1	14.9	18.9	22.7	19.0
Sweden	Buy	43.7	53.8	41.1	37.6	44.0	45.1	39.9	46.7	45.3	50.8	37.6	45.2	48.1	47.8	42.3	39.7	39.9
	Hold	33.3	29.8	34.4	34.2	29.1	31.6	33.4	28.9	34.3	31.5	31.0	31.8	32.9	33.3	33.5	38.3	38.3
	Sell	22.9	16.3	24.5	28.3	26.9	23.3	27.4	24.4	20.4	17.7	31.4	23.0	19.0	18.9	24.1	22.0	21.7
Switzerland	Buy	51.7	74.8	57.5	51.0	45.1	47.1	50.8	55.5	59.4	57.6	51.9	54.8	50.9	51.4	49.1	42.7	40.9
	Hold	36.8	20.8	34.9	36.4	39.5	40.1	37.5	34.3	31.5	31.0	32.4	33.3	37.9	38.7	40.7	44.6	44.8
	Sell	11.5	4.4	7.6	12.5	15.5	12.8	11.7	10.1	9.1	11.4	15.7	12.0	11.2	9.9	10.3	12.7	14.4
UK	Buy	48.1	61.5	53.6	49.1	48.8	45.8	43.2	45.7	46.5	49.1	48.2	52.2	55.1	51.7	45.4	43.5	42.6
	Hold	36.2	29.2	35.4	35.8	34.9	36.0	38.9	36.8	36.0	34.0	32.1	32.7	32.1	34.8	38.6	40.2	40.8
	Sell	15.8	9.3	11.0	15.1	16.3	18.1	17.9	17.5	17.5	16.9	19.7	15.1	12.9	13.6	16.0	16.3	16.7
US	Buy	54.4	79.3	70.2	61.5	44.6	47.8	47.8	51.3	50.4	53.7	52.2	55.4	56.1	55.8	53.3	52.8	53.8
	Hold	40.7	20.1	28.7	35.1	45.2	44.2	45.3	42.8	44.0	42.0	42.0	40.2	40.0	40.3	42.2	42.5	41.8
	Sell	4.9	0.6	1.1	3.4	10.2	8.1	6.9	5.9	5.7	4.3	5.7	4.5	3.8	3.9	4.5	4.6	4.4

4. Results

In this section, I present my main empirical findings. Firstly, I discuss the results of the regression analyses based on consensus recommendation levels and consensus recommendation changes. Secondly, I report the findings regarding the double-sorting analyses and finally several robustness checks. As Jegadeesh et al. (2004) note, analyst recommendations tend to be stable across quarters, so the regression coefficients tend to be serially correlated. Therefore, I follow their intuition and report standard errors that are adjusted for autocorrelation and heteroskedasticity (Newey-West) in all tables.

4.1.1. Results regression analyses based on consensus recommendation levels

Table 4 provides the results of several regression analyses using the CAPM, the Fama French three-factor model and the Carhart four-factor model, including the Pástor and Stambaugh liquidity factor. As explained in the methodology section, all portfolios are value-weighted. The results of using equally-weighted quintile portfolios are qualitatively similar and are provided in table 2 in the appendix. Following Barber et al. (2001), table 4 reports the results of a trading strategy that goes long in the 20% stocks that have the highest consensus recommendation level and goes short in the 20% stocks that have the lowest consensus recommendation level (showed in the rows with R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly. Monthly return data are used in the time-series regressions. For all specifications, except the four-factor model including the Pástor and Stambaugh liquidity factor, this results in 192 monthly observations. Because the data on the Pástor and Stambaugh liquidity factor are only available until December 2014, the specifications including this factor have 180 monthly observations.

The coefficient on the market factor is significant and less than 1. This coefficient is used to describe the relationship between movements of a portfolio versus the entire market. A coefficient less than 1 indicates that the stocks in the sample have a below average market risk and that they are less sensitive to shocks in the market portfolio. Similar to the results found by Barber et al. (2001), the coefficient on the market factor is consistently higher for stocks with a high consensus recommendation level than for stocks with a low consensus recommendation level. This indicates that favorable analyst ratings are associated with stocks of higher market risk.

The coefficient on the size factor is significantly negative. This means that the portfolios consist predominantly of large-cap stocks. For analysts, large caps could be more attractive to cover, since these companies are more liquid, on average. This in turn is related to the compensation of most analysts, since they often get rewarded based on the turnover that is generated upon their recommendations.

The coefficient on the book-to-market factor is significantly negative. This suggests that the portfolios constructed using consensus recommendation levels predominantly consist of growth stocks. Jegadeesh et al. (2004) find that recommendations are more favorable for growth stocks than for value stocks. This can be explained by the fact that growth stocks are attractive as customers for investment banks, since these businesses have a possibility of many future business activities (a possible IPO in the future, etc.). Barber et al. (2003) find that, on average, analyst tend to give sell recommendations to growth stocks and buy recommendations to value stocks. In my case, both sell and buy recommendations are mainly given to growth stocks. This could also partly explain in a later stage why the results that I find are different compared to results from existing literature.

The coefficient on the momentum factor is significantly positive for portfolios with high consensus recommendation level stocks and significantly negative for portfolios with low consensus recommendation level stocks. This means that analysts seem to favorably recommend stocks which have had, on average, a positive momentum (which have been winners over the past 11 months) and unfavorably recommend stocks which have had, on average, a negative momentum (and performed badly over the past 11 months). This finding shows that analysts tend to be trend-following while issuing their recommendations. This result is also found by Jegadeesh et al. (2004) who state that the level of analysts' consensus recommendations shows a preference for positive momentum stocks.

Most alphas are outside the rejection region using the CAPM, three-factor, and four-factor model, including the liquidity factor. This is not in line with hypothesis 1a, which predicts that stocks with high consensus recommendation levels outperform stocks with low consensus recommendation levels. An insignificant alpha in the regression models means that investors are not able to yield positive risk-adjusted returns on a long-short strategy based on analyst recommendations.

When using the CAPM as the asset pricing model, the alpha coefficient on the long-short portfolio is significantly negative. This suggests that investors should use the consensus recommendation level as a contrary indicator: investors would earn a positive risk-adjusted return when going long in stocks with low recommendation levels, and short in stocks with high recommendation levels. However, this result does not remain robust when using the three-factor or four-factor model, including the liquidity factor of Pástor and Stambaugh. Although the result seems contrary to conventional wisdom, this result is found earlier. Barber et al. (2003) mention in their study that particularly 'the years 2000 and 2001 were disasters'. They find that in these years, highly recommended stocks performed extremely bad, while stocks with a low consensus recommendation level performed extremely well. They state that the poor results in these years were driven by the tendency to recommend small-cap growth stocks. The negative alpha, which is not in line with most results found in previous research, could be a result of the sample period of this thesis, which starts in the year 2000. Most previous studies are focused on the the years before 2002 while using US data. Since the period 2000 – 2015 comprises the internet trading era, the IT bubble, and the financial crisis, this could possibly have increased the level of noise trading. When noise trader demand is larger, the relative price increases and this in turn leads to lower subsequent stock returns upon buy recommendations. Noise traders could possibly overreact to a signal they receive from analysts (in the form of a recommendation) and this in turn could lead to overpricing of stocks with a buy recommendation and underpricing of stocks with a sell recommendation, which can explain the negative alpha on the long-short portfolio when rebalancing quarterly.

One possible explanation for the significant positive alpha for the low portfolio (when using the Carhart four-factor model, also including the Pástor and Stambaugh liquidity factor) could also be the overreaction story. Overreaction of noise traders could lead to underpricing of stocks with a low consensus recommendation level, which in turn leads to higher returns. Investors are likely to capture these positive returns when rebalancing quarterly. Section 4.4 describes other possible explanations for the results.

Table 4: Coefficient estimates of a trading strategy based on consensus recommendation levels: 2000m1 - 2015m12

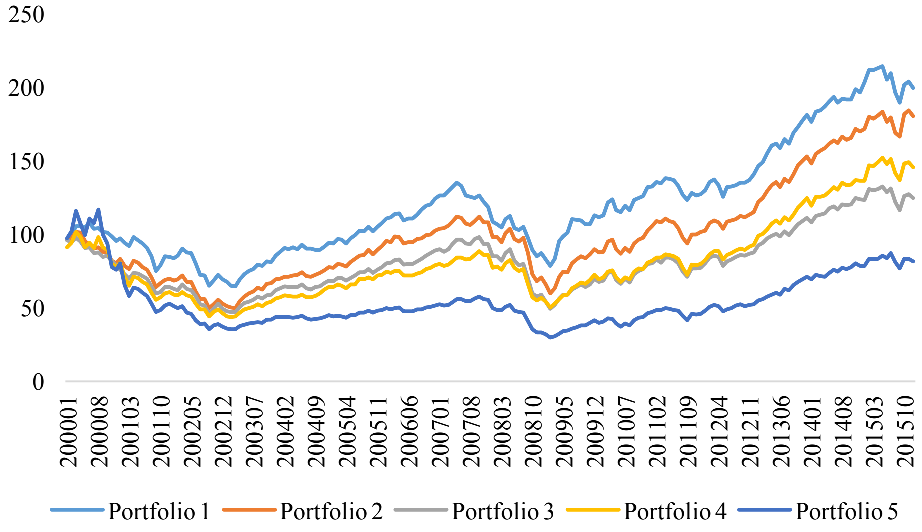
Table 4 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as dependent variable, using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.2616 (-1.15)	0.9496*** (7.95)					0.78
R^{LOW}	0.2218 (1.53)	0.7042*** (14.82)					0.75
$R^{HIGH} - R^{LOW}$	-0.4834** (-2.06)	0.2454** (2.33)					0.13
R^{HIGH}	0.1198 (0.79)	0.9235*** (17.05)	-0.3325*** (-4.84)	-0.6318*** (-7.81)			0.87
R^{LOW}	0.2287 (1.54)	0.7062*** (13.96)	-0.0736 (-1.10)	0.0093 (0.16)			0.75
$R^{HIGH} - R^{LOW}$	-0.1089 (-0.64)	0.2173*** (3.75)	-0.2589** (-2.13)	-0.6411*** (-5.62)			0.37
R^{HIGH}	0.0804 (0.51)	0.9468*** (20.31)	-0.3741*** (-4.94)	-0.6134*** (-6.91)	0.0687** (2.07)		0.87
R^{LOW}	0.3044** (3.07)	0.6615*** (15.44)	0.0064 (0.08)	-0.0261 (-0.54)	-0.1320*** (-3.16)		0.76
$R^{HIGH} - R^{LOW}$	-0.2240 (-1.58)	0.2853*** (4.83)	-0.3806*** (-3.27)	-0.5873*** (-5.11)	0.2006*** (4.08)		0.43
R^{HIGH}	0.0924 (0.56)	0.9399*** (20.04)	-0.3837*** (-4.48)	-0.6190*** (-6.63)	0.0695** (2.10)	0.0164 (0.72)	0.87
R^{LOW}	0.3066** (2.71)	0.6540*** (15.44)	0.0475 (0.82)	-0.0072 (-0.18)	-0.1449*** (-3.49)	-0.0196 (-0.49)	0.77
$R^{HIGH} - R^{LOW}$	-0.2142 (-1.35)	0.2859*** (4.80)	-0.4312*** (-3.92)	-0.6117*** (-5.29)	0.2144*** (4.62)	0.0359 (0.85)	0.45

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Graph 1 shows what an investor would have earned when he/she would have invested $100 in the year 2000 in each of the five portfolios. The graph shows that stocks in portfolio 5 (stocks with high consensus recommendation levels) experienced a sharp decrease during the period from 2000 to 2003, while stocks in portfolio 1 (stocks with low consensus recommendation levels) performed relatively well. Overall, the graph suggests that investors would be better off investing in stocks with low recommendation levels, which is contrary to most results from prior literature.

Graph 1



Note: \$100 is invested January 1st 2000 in each of the portfolios

To explore whether the years 2000 - 2003 possibly wipe out results for other years of the sample, I exclude these years, which comprise the burst of the IT bubble and its aftermath, and run the regressions again. The results are reported in table 3 in the appendix. The alphas on the portfolio concerning stocks with high consensus recommendation levels are outside the rejection region, while the alphas on the portfolio concerning stocks with low consensus recommendations levels are positive and robust to most specifications. The alphas on the long-short strategy are negative and more significant compared to table 4, which implies that again the low portfolio performed better than the high portfolio when excluding these years. This means that it is not the case that the years 2000 - 2003 wipe out the results for other years of the sample, since the conclusion is qualitatively similar. The signs of the coefficients on the market, size, book-to-market, momentum, and liquidity factor are similar to previous results, though the magnitude differs somewhat.

Barber et al. (2003) suggest that the poor results in 2000 and 20001 could be driven by the inability of analysts to adapt to changing market conditions. In these years, analyst kept the tendency to recommend small-cap growth stocks and give sell recommendations for value stocks, which is in line with the optimism bias. This in turn could explain the bad results, since especially growth stocks performed much worse than value stocks back then (Jegadeesh and Kim, 2006). Hence, it could also be the fact that the years 2000 and 2001 have set a trend for the years thereafter. Therefore, I divide the sample period in two periods: The first half (2000 - 2008) and the second half (2009 - 2015). Table 4 and 5 in the appendix tabulate these results.

The results for the first period (2000 - 2008) show mostly insignificant alphas. However, using the CAPM as asset pricing model leads to a significant negative alpha for the portfolio with high consensus recommendation levels and a more negative alpha on the long-short strategy, compared with the results using the full sample period. This means that especially in the early years of the sample, the portfolio consisting of stocks with high consensus recommendation levels performed poorly compared to the portfolio consisting of stocks with low consensus recommendation levels. The signs of the coefficients on on the market, size, book-to-market, momentum, and liquidity factor are qualitatively similar.

The outcomes for the second period (2009 - 2015) exhibit more positive alphas for the portfolios consisting of stocks with high recommendation levels compared to the results using the full sample period. The coefficients on momentum are more positive for the high level portfolio and more negative for the low level portfolio, compared to earlier results. Moreover, the liquidity sign on the long-short portfolio is significantly positive. It could be possible that analysts in the period 2009 - 2015 indeed showed a higher level of stock-picking abilities, but it could also be the case that the trend following of analysts (give buy recommendations to stocks with a positive momentum and sell recommendations to stocks with a negative momentum) explains this result. These results suggest that in the latter period, stocks with a buy recommendation have yielded higher risk-adjusted returns, though the low level portfolio still earned somewhat higher alphas. However, the difference between the high and low portfolio is not significantly different.

Because of the mixed outcomes, the results are inconclusive and not in line with the prediction in hypothesis 1a.

4.1.2. Second trading strategy based on consensus recommendation levels

The second trading strategy based on consensus recommendation levels follows the portfolio partition method of Barber et al. (2001). In this specific case, all stocks with a strong buy recommendation (consensus recommendation level >4.5) are allocated to the long portfolio, and all stocks with a hold, sell, or strong sell recommendation (consensus recommendation level <3) are allocated to the short portfolio. Table 5 provides the results. The insignificant difference between the high and the low portfolio suggests again that it is not possible to earn positive risk-adjusted returns based on this trading strategy. This is contrary to the findings of Barber et al. (2001). While studying the period 1986 - 1996 and using daily rebalancing, they find a long-short portfolio yields positive risk-adjusted returns, excluding transaction costs. The differences could be explained by the use of more frequent rebalancing, or, as stated before, by the more recent sample period of this thesis. Equally-weighted results are reported in table 6 in the appendix. When using equally-weighted returns, the alpha on R^{LOW} increases, which results in significant negative alphas on the long-short portfolio. A reason for this difference between the value-weighted and equally-weighted results could be that especially the relatively small firms in the low portfolio performed well during the sample period. Compared to the results in table 4, the alpha on the high level portfolio is higher, which suggests that a portfolio consisting of stocks with a strong buy recommendation performs better than a portfolio consisting of the 20% with the highest consensus recommendation level. Using the partition method of Barber et al. (2001) the coefficients on the market factor are no longer consistently higher for R^{HIGH} than for R^{LOW}. This indicates that favorable analyst ratings are no longer associated with stocks of higher market risk. This finding can be due to the fact that using this partition method, the R^{LOW} portfolio consists of more stocks compared to the R^{LOW} portfolio with the 20% stocks with the lowest recommendation level, since the portfolio now consists of all stocks with a hold/sell/strong sell recommendation. This result is not similar when using equally-weighted returns, since these results again show consistently higher coefficient of Rm for R^{HIGH} than for $R^{LOW.}$ The coefficients on the size and book-to-market factor are qualitatively similar to the results in table 4.

Overall, the results suggest that it is not possible to profit from a no-cost trading strategy based on consensus recommendation levels, since most alphas are outside the rejection region.

Table 5: Value-weighted coefficient estimates of a trading strategy based on Barber et al. (2001) portfolio partitions: 2000m1 - 2015m12

Table 5 reports the results of the OLS regression models with portfolios based on consensus recommendation levels as dependent variable, using value-weighted returns. The dependent variable R refers to excess returns on portfolios with consensus recommendation levels higher than 4.5 (strong buy recommendations) (R^{HIGH}), consensus recommendation levels lower than 3 (hold, sell, or strong sell recommendations) (R^{LOW}), or the difference in the returns on portfolios with strong buy and hold/sell/strong sell recommendations (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.0365 (0.31)	0.8384*** (21.14)					0.91
R^{LOW}	0.0003 (0.00)	0.8561*** (19.57)					0.91
$R^{HIGH} – R^{LOW}$	0.0362 (1.07)	-0.0177** (-2.01)					0.03
R^{HIGH}	0.1543* (1.65)	0.8331*** (32.23)	-0.1796*** (-5.98)	-0.1715*** (-5.73)			0.92
R^{LOW}	0.1472* (1.79)	0.8488*** (38.18)	-0.2031*** (-4.55)	-0.2202*** (-7.85)			0.93
$R^{HIGH} – R^{LOW}$	0.0072 (0.28)	-0.0156* (-1.67)	0.0235 (0.85)	0.0486* (1.85)			0.10
R^{HIGH}	0.1536* (1.72)	0.8335*** (37.94)	-0.1804*** (-4.33)	-0.1712*** (-4.49)	0.0012 (0.04)		0.92
R^{LOW}	0.1491* (1.93)	0.8476*** (47.21)	-0.2010*** (-4.55)	-0.2211*** (-7.17)	-0.0034 (-0.14)		0.93
$R^{HIGH} – R^{LOW}$	0.0045 (0.18)	-0.0141 (-1.62)	0.0207 (0.71)	0.0499*** (2.09)	0.0046 (0.34)		0.10
R^{HIGH}	0.1377 (1.33)	0.8246*** (44.34)	-0.1733*** (-5.59)	-0.1638*** (-5.43)	-0.0036 (-0.10)	0.0149 (0.74)	0.92
R^{LOW}	0.1388 (1.66)	0.8398*** (51.83)	-0.1906*** (-4.12)	-0.2156*** (-6.88)	-0.0075 (-0.31)	0.0035 (0.18)	0.93
$R^{HIGH} – R^{LOW}$	-0.0011 (-0.04)	-0.0152* (-1.86)	0.0173 (0.66)	0.0518** (2.41)	0.0039 (0.32)	0.0114 (1.39)	0.10

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

4.2. Results regression analyses based on recommendation changes

Table 6 provides the results of several regressions using consensus recommendation changes instead of consensus recommendation levels as dependent variable. The returns are value-weighted and most alphas are outside the rejection region. The results of using equally-weighted portfolios are qualitatively similar and are provided in table 7 in the appendix. Although the result is not robust to using different model specifications, the significant negative alpha that is found in the four-factor model including the liquidity factor suggests that portfolios with downward recommendation changes outperformed portfolios with upward recommendation changes during the sample period. This is not in line with hypothesis 1b, which predicts that upgraded stocks outperform downgraded stocks, but it could be explained with the overreaction explanation that is already mentioned in section 4.1.

The coefficients on the market, size, book-to-market, and the momentum factor are qualitatively similar to the results of the trading strategy based on consensus recommendation levels.

The results suggest that a long-short trading strategy based on analyst recommendation revisions is not profitable considering the 18 developed countries in my sample for the period between January 2000 and December 2015. Jegadeesh et al. (2004) find that long-short portfolio excess returns are sensitive to a delay in buying/shorting upon a new recommendation revision. When investors buy or sell a stock based on a recommendation revision with a five-day delay instead of no delay, the excess return declined from 5.79% to 1.38% in the U.S. in their sample (equally-weighted returns). They find a similar pattern in the other countries of the G7 they investigate. Moreover, when they exclude any delays from the strategies, but they increase the holding period from a one month to six months, the excess return declined as well from 5.79% to 1.10% (equally-weighted returns). When the authors consider value-weighted returns, which do not require to rebalance daily as stated in the methodology section, the trading strategy is not profitable in the G7 countries, except in a few cases.

This shows that although it could be possible to profit from trading strategies based on analyst recommendation revisions when considering the optimal reaction time to new revisions, daily rebalancing, and a short holding period, it certainly is not an easy to replicate strategy and investors should thus not blindly follow analyst recommendations or recommendation revisions.

Table 6: Coefficient estimates of a trading strategy based on recommendation changes: 2000m1 - 2015m12

Table 6 reports the results of the OLS regression models with portfolios based on recommendation changes as dependent variable, using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either upward recommendation changes (R^{HIGH}), downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with upward and downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.0455 (0.30)	0.8448*** (21.53)					0.83
R^{LOW}	0.0757 (0.72)	0.8461*** (13.19)					0.80
$R^{HIGH} – R^{LOW}$	-0.0301 (-0.22)	-0.0014 (-0.03)					-0.01
R^{HIGH}	0.1481 (0.92)	0.8376*** (25.74)	-0.0850 (-1.61)	-0.1712*** (-3.20)			0.84
R^{LOW}	0.2297** (2.29)	0.8399*** (20.42)	-0.2497*** (-3.50)	-0.2196*** (-3.62)			0.83
$R^{HIGH} – R^{LOW}$	-0.0816 (-0.54)	-0.0023 (-0.07)	0.1647** (2.15)	0.0484 (0.55)			0.01
R^{HIGH}	0.1097 (0.75)	0.8602*** (21.44)	-0.1255** (-2.05)	-0.1533*** (-3.51)	0.0668 (1.31)		0.84
R^{LOW}	0.3172*** (2.84)	0.7882*** (21.42)	-0.1572*** (-2.65)	-0.2605*** (-5.34)	-0.1526*** (-3.07)		0.84
$R^{HIGH} – R^{LOW}$	-0.2075 (-1.41)	0.0721*** (2.94)	0.0317 (0.51)	0.1072* (1.93)	0.2194*** (10.22)		0.20
R^{HIGH}	0.0295 (0.22)	0.8467*** (22.67)	-0.0937* (-1.80)	-0.1237** (-3.22)	0.0541 (1.19)	0.0263 (0.99)	0.84
R^{LOW}	0.3330*** (3.31)	0.7768*** (24.34)	-0.1698*** (-2.95)	-0.2646*** (-5.57)	-0.1538*** (-2.68)	0.0367 (1.53)	0.84
$R^{HIGH} – R^{LOW}$	-0.3035** (-2.39)	0.0700** (3.06)	0.0762 (1.46)	0.1409** (3.58)	0.2079*** (11.66)	-0.0104 (-0.42)	0.20

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

4.3. Region-level analysis: Regression results when testing the United States, Japan, and Europe separately

To explore whether the results differ when distinguishing between several regions in the sample, I perform the regression analyses for each region (United States, Japan, and Europe) separately. Griffin (2002) finds in his paper that the explanatory power to explain time-series variation in returns is higher for domestic factor models than for world models. I decide to aggregate the data for all European countries, since not every European country has enough stocks in the sample to provide reliable results. In the regression analyses, I use Kenneth French's North American/Japanese/European factors, because these are a better benchmark when testing the regions separately. In order to perform this analysis, I construct portfolios for each region, where stocks are ranked according to their consensus recommendation level or upward/downward recommendation change. The results are provided in table 7, 8, and 9. Again I use quintile partition for constructing the portfolios. I report value-weighted results for both a strategy based on consensus recommendation levels as recommendation changes. I only report the results for the most comprehensive model (The Carhart four-factor model, including the liquidity factor of Pástor and Stambaugh). The results using other asset pricing models are qualitatively similar.

Table 7, 8, and 9 show that distinguishing between regions does not result in different outcomes of the regressions. Most alphas are insignificantly different from zero, which means that the value-weighted strategy does not earn abnormal profit. Jegadeesh et al. (2004) and Jegadeesh and Kim (2006) also find this result, when they use less frequent rebalancing or some delay in their response time on new analyst recommendations. The coefficients on the size, book-to-market, and the momentum factor are similar to section 4.1. and 4.2. Table 9 shows that the coefficient on the market risk premium are lower for Europe than for the United States and Japan. This means that the European stocks that are covered by more than five analysts are, on average, less exposed to shocks in the market portfolio than US or Japanese stocks are. In most cases, the coefficients on the market factor are higher for R^{HIGH} than for R^{LOW}. This is in line with the results found in section 4.1.

Table 7: Coefficient estimates United States: 2000m1 - 2015m12

Table 7 reports the coefficient estimates for the United States, for the period between January 2000 and December 2015. Firstly, I report the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are reported, again using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-0.1875 (-1.18)	1.0876*** (14.83)	-0.2564*** (-3.00)	-0.4214*** (-4.60)	0.1107** (2.10)	0.0089 (0.20)	0.86
R^{LOW}	0.1902 (1.47)	0.8595*** (15.95)	-0.0602 (-1.07)	0.2877*** (5.56)	-0.1832*** (-5.44)	-0.0431 (-1.05)	0.86
$R^{HIGH} - R^{LOW}$	-0.3777* (-1.68)	0.2281*** (2.86)	-0.1962 (-1.37)	-0.7091*** (-6.24)	0.2939*** (5.25)	0.0520 (0.75)	0.53
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.0455 (0.54)	0.9624*** (22.59)	-0.0780* (-1.81)	0.0181 (0.46)	0.0415 (0.93)	0.0789*** (3.97)	0.90
R^{LOW}	0.3398*** (2.89)	0.9646*** (18.89)	-0.0651 (-1.07)	-0.2047*** (-3.13)	-0.1153*** (-2.68)	0.0068 (0.13)	0.86
$R^{HIGH} - R^{LOW}$	-0.2943* (-1.89)	-0.0022 (-0.05)	-0.0129 (-0.28)	0.2228** (2.37)	0.1568*** (5.24)	0.0721 (1.21)	0.17

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 8: Coefficient estimates Japan: 2000m1 - 2015m12

Table 8 reports the coefficient estimates for Japan, for the period between January 2000 and December 2015. Firstly, I report the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are reported, using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.0918 (0.30)	0.8346*** (11.52)	-0.3931*** (-3.45)	-0.2793** (-2.24)	0.0370 (0.44)	0.0582 (0.85)	0.62
R^{LOW}	0.2613 (0.89)	0.8383*** (15.62)	-0.1374 (-1.30)	0.2632** (2.35)	-0.1460** (-2.01)	0.0236 (0.38)	0.57
$R^{HIGH} - R^{LOW}$	-0.1695 (-0.53)	-0.0037 (-0.06)	-0.2557* (-1.74)	-0.5425*** (-3.68)	0.1830 (1.48)	0.0347 (0.45)	0.17
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.2373 (0.71)	0.8485*** (10.49)	-0.3913*** (-3.70)	0.0116 (0.06)	0.0872 (1.14)	0.0895 (1.19)	0.53
R^{LOW}	0.4504 (1.43)	0.7682*** (10.73)	-0.3401*** (-3.07)	-0.0456 (-0.32)	-0.2493*** (-3.42)	0.1027 (1.49)	0.59
$R^{HIGH} - R^{LOW}$	-0.2130 (-0.95)	0.0803 (1.29)	-0.051 (-0.37)	0.0572 (0.51)	0.3364*** (4.73)	-0.0132 (-0.14)	0.10

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 9: Coefficient estimates Europe: 2000m1 - 2015m12

Table 9 reports the coefficient estimates for the 16 countries in Europe that I study, for the period between January 2000 and December 2015. Firstly, I report the OLS results of the regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are reported, again using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.1903 (0.90)	0.6505*** (19.58)	-0.3062** (-2.62)	-0.4558*** (-6.16)	-0.1059*** (-2.74)	0.0384 (0.90)	0.69
R^{LOW}	0.4003 (1.63)	0.5294*** (8.82)	-0.2530 (-1.40)	-0.1454 (-1.36)	-0.0536 (-0.44)	0.0298 (0.49)	0.53
$R^{HIGH} - R^{LOW}$	-0.2099 (-0.73)	0.1211* (1.74)	-0.0532 (-0.26)	-0.3104*** (-2.69)	-0.0524 (-0.52)	0.0086 (0.12)	0.07
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.2514 (0.94)	0.7203*** (20.72)	-0.0961 (-1.25)	-0.4189*** (-3.65)	-0.0371 (-0.91)	0.0507 (1.03)	0.69
R^{LOW}	0.2186 (0.97)	0.6443*** (11.60)	-0.1676* (-1.84)	-0.2405** (-2.26)	-0.0277 (-0.29)	0.0181 (0.45)	0.63
$R^{HIGH} - R^{LOW}$	0.0328 (0.11)	0.0759 (1.08)	0.0715 (0.53)	-0.1784 (-1.01)	-0.0094 (-0.09)	0.0327 (0.49)	0.01

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

4.4 Possible explanations

There are multiple possible explanations for the results in section 4.1. - 4.3.

Stock price drift explanation and overreaction in the stock market

Stickel (1995) and Womack (1996) find that both portfolios consisting of stocks with high consensus recommendation levels/upward revisions and portfolios consisting of stocks with low consensus recommendation levels/downward revisions experience a significant price drift after a revision. This suggests that stock prices do not immediately incorporate all information from analyst recommendations. As stated in the literature review in section 2, overreaction is a common theme in the stock market. Noise traders could overreact in their investment decisions because they over rely on analysts as being experts. Noise traders will try to extract information from agents that have more information (sell-side analysts in this case). Upon observing a signal, noise traders may overreact. This would lead to overpricing following buy recommendations and underpricing following sell recommendations. This mispricing is a product of noise traders' overreaction. When investors decide not to rebalance daily, they are less likely to capture possible profits resulting from the overreaction, but are more likely to capture the adversely price reaction and therefore this can explain the negative alpha of the long-short strategy that is visible using some specifications.

Considering quarterly rebalancing rather than monthly or daily probably makes it more likely to capture the impact of overreaction. Compared to prior research, which mostly shows either insignificant or positive alphas on the long-short portfolios, the negative alphas in some specifications in section 4.1. - 4.3. are different. As stated in the introduction, most prior research is focused on US data in the period up to 2002. Since the period 2000 - 2015 comprises the internet trading era, the IT bubble, and the financial crisis, this could have increased the relative level of noise trading, which could possible explain the different results.

Sample specific results

The results could be sample specific. This means that changing the universe, time period, or region could have led to different results. For instance, as shown in section 4.1 - 4.3., changing the time period of the sample can lead to different results.

Barber et al. (2001) show that daily portfolio rebalancing, which is a transaction intensive strategy, yields the largest abnormal returns. This could be another potential explanation why the alphas that I find are negative or insignificant instead of the positive, mostly significant alphas that Barber et al. (2001) find. However, the goal of thesis thesis is to investigate replicable trading strategies. Although I recognize that strategies with a shorter holding period make use of more recent information, these strategies entail more transactions. In the end, the costs of trading should outweigh the benefits of using fresh information, so that is why I decide to explore a trading strategy using quarterly rebalancing. Barber et al. (2001, p.531) state 'that high trading levels are required to capture the excess returns generated by the strategies analyzed, entailing substantial transaction costs and leading to abnormal net returns for these strategies that are not reliably greater than zero.' Since daily rebalancing requires an investor to react at recommendations timely, I think this is not a feasible strategy for the average investor to replicate.

Moreover, it could be the case that the results reflect some error in the data or a possible omitted correlated variable. I tried to minimize this possibility by retrieving data from Bloomberg, which is a widely recognized data provider, and using existing research methods to analyze the data.

The use of wrong asset pricing models

As Fama (1970) states, a test of market efficiency is always a joint-hypothesis problem. When testing my hypothesis, I assume that the asset pricing models that I use are right, but that does not have to be true. It could be that the results that I find are not related to market efficiency, but that these results are just a product of using a specific asset-pricing model. I tried to minimize this possible explanation by employing the asset-pricing models that are used many in previous papers concerning this research topic.

Favorable/Unfavorable quantitative characteristics

It could be possible that during the sample period of this thesis, stocks in the portfolio with low recommendation levels were mainly stocks with favorable characteristics that are known to produce excess returns by itself, and that stocks in the portfolio with high recommendation levels did mainly have unfavorable characteristics. This explanation is related to the findings of Barber et al. (2002).

As Jegadeesh et al. (2004) show, higher consensus recommendation levels are associated with worse subsequent returns when stocks have unfavorable characteristics. They state that when investors have to select firms that have unfavorable quantitative signals, it is better to invest against analyst recommendations than to invest accordingly. The authors find that the direction of the preference of an analyst is often the opposite of the normative direction for predicting future stock returns. For example, analysts seem to highly recommend stocks with high recent turnover, low book-to-market value, and stocks with a high CAPEX, which are empirically predicted to have low future stock returns. This is related to the optimism bias, which can be explained by the incentives analysts face. Firms with a low book-to-market value, growth firms, are attractive to cover for analysts, since these firms have many potential mandates for the future for the investment bank they work for. As Brown et al. (2015) find in their recent article, the optimism bias is still much present.

Moreover, as Glezakos and Merika (2011) find, analysts tend to follow stocks that are already popular to institutional investors, who are their major clients. As a result, they tend to recommend stocks that already have high enough market prices. In that case, a high recommendation level has little investment value to investors. Related to this is the finding that analysts tend to be trend-following: they often give buy recommendations to stocks with a positive momentum and sell recommendations to stocks with a negative momentum, which could possible turn out in an unprofitable strategy in years with a volatile stock market and when a reversal strategy based on the momentum of stocks would be more profitable.

While the 'real' explanation for the results shall remain an unresolved question and some results in this thesis are contrary to conventional wisdom, the fact that an active trading strategy using analyst recommendations seems not to have outperformed a passive benchmark between 2000 - 2015 seems confirmed by the the fact that index funds and ETFs have experienced an increase in net inflows in these years, while actively managed mutual funds experienced outflows (as noted by Savita Subramaniam from Bank of America Merrill Lynch and Eric Balchunas from Bloomberg[8], amongst others).

As Franck and Kerl (2013) find, mutual funds significantly increase their investments in stocks with an increase in their consensus forecast and vice versa. They state that, just like other types of investors, mutual fund managers experience time constraints to make their investment allocation decisions. The net outflow from mutual funds, which are major clients of sell-side analysts, is likely to be related to their underperformance compared to passive benchmarks, while they were using analyst recommendations as part of their input.

As an active investor does mainly concern about allocating their investments into a portfolio that produces the highest returns, their goal is to earn returns at least above a passive investment strategy. As a result, when an active investment strategy underperforms a passive investment strategy, some investors will decide to switch to a passive strategy as an index funds or an ETF, which in turn implies that sell-side analyst recommendations as partial input for allocation decisions has not led to abnormal returns.

[8] http://www.bloomberg.com/news/articles/2015-12-01/vanguard-s-gain-is-wall-street-s-pain-as-billions-leave-the-financial-industry
http://www.bloomberg.com/news/articles/2015-12-30/these-charts-show-the-astounding-rise-in-passive-management

4.5. Results double-sorting analysis: Do analyst recommendations have more impact on stocks which are harder to value, when sorting according to a value strategy?

In order to conduct the second analysis, I create double-sorted portfolios based on the book-to-market value of stocks (quintiles) and the recommendation change compared to the beginning of the previous quarter (upward/downward). As a result, portfolio 9 and 10 consist of stocks with high book-to-market values and a downward/upward recommendation change. Alternatively, portfolio 1 and 2 consist of stocks with low book-to-market values and a downward/upward recommendation change. Portfolio 3 - 8 consist of stocks with medium book-to-market values and upward/downward recommendation changes. Similar to the previous analyses, the portfolios are rebalanced quarterly and the value-weighted returns are measured on a monthly basis. Table 10 reports the results, using the Carhart four-factor model, including the Pástor and Stambaugh liquidity factor. The results using other asset pricing models are qualitatively similar.

Most alphas are outside the rejection region, but the two most significant alphas are situated in the extreme portfolios (portfolio 2 and 9). This suggests that investors would have earned positive alphas over the period 2000 - 2015 when they would have combined quarterly rebalancing on either the highest book-to-market stocks with a recent downward recommendation change or the lowest book-to-market stocks with a recent upward recommendation change. However, since most alphas are outside the rejection region, the findings in table 10 do not strongly support hypothesis 2, which predicts that shifts in analyst recommendations have most impact on extreme portfolios of a value strategy.

The coefficients on the market, size, and book-to-market factor are in line with earlier analyses. The coefficients on the momentum factor show that the stocks in the high book-to-market bucket have most exposure to negative momentum stocks and that the low book-to-market bucket has more exposure to positive momentum stocks. The coefficients on the liquidity factor are positive and significant for the high and medium book-to-market portfolios, but they turn negative for the low book-to-market portfolio. This seems intuitively right, since low book-to market stocks (growth stocks) are often argued in the literature to have relatively few outstanding shares that are less frequently traded, which in turn makes the stocks more illiquid.

To test whether the results of the double-sorting analysis are sensitive to using different portfolio partitions, I also tested the asset pricing models using tercile and above/below median portfolios. These unreported results are qualitatively similar. Next to this, I performed the region-specific analyses (US, Europe, Japan) to look deeper into the effects of this analyses for the different regions. These results, which are also unreported, are qualitatively similar.

Table 10: Results of combining a value strategy and recommendation changes

Table 10 provides the OLS results of double-sorted portfolios based on a value strategy and recommendation changes. Portfolio 9/10 consist of stocks with a high book-to-market value and a downward/upward recommendation change and portfolio 1/2 of stocks with a low book-to-market value and a downward/upward recommendation change. The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

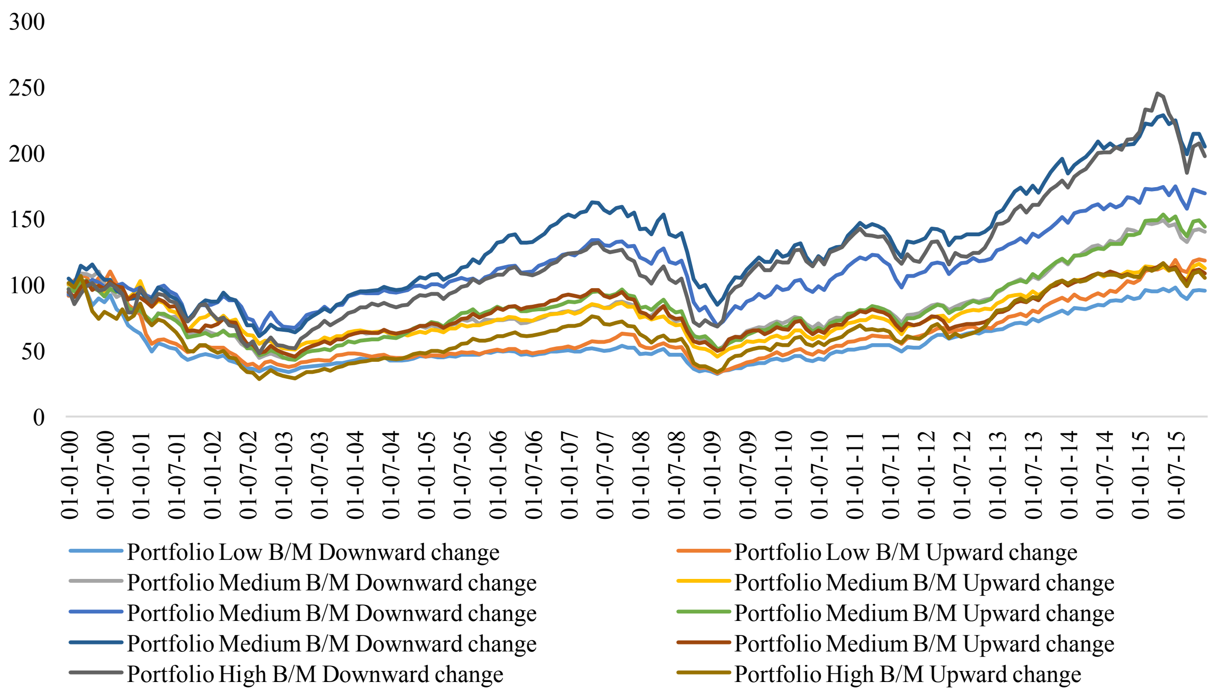
Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
Portfolio 10	-0.0662	0.9236***	-0.1564	-0.0475	-0.2844***	0.1167**	0.72
	(-0.26)	(23.24)	(-1.39)	(-0.50)	(-5.33)	(1.28)	
Portfolio 9	0.5120***	0.8274***	-0.2281	-0.1420	-0.4829***	0.1438***	0.76
	(2.87)	(17.72)	(-1.48)	(-1.24)	(-9.54)	(2.54)	
Portfolio 8	-0.2472	0.8656***	-0.2263**	0.1592**	-0.0182	0.0717	0.74
	(-1.25)	(15.99)	(-3.63)	(2.65)	(-0.32)	(1.70)	
Portfolio 7	0.1329	0.8443***	-0.0788	0.1163**	-0.1486**	0.1035***	0.81
	(1.15)	(22.89)	(-1.15)	(2.51)	(-2.46)	(2.57)	
Portfolio 6	-0.0713	0.8571***	-0.3317***	0.0305	0.1142**	0.0547**	0.80
	(-0.39)	(24.34)	(-2.85)	(0.50)	(2.29)	(2.07)	
Portfolio 5	0.1439	0.8326***	-0.2164**	0.0159	-0.1594**	0.0915**	0.84
	(1.14)	(25.67)	(-2.43)	(0.34)	(-2.07)	(2.22)	
Portfolio 4	0.1445	0.7419***	-0.1354	-0.2834***	-0.0808	0.0438	0.74
	(0.82)	(21.14)	(-1.13)	(-4.34)	(-0.80)	(1.61)	
Portfolio 3	0.2845*	0.7784***	-0.3982***	-0.2898***	-0.0512	-0.0364	0.80
	(1.72)	(20.94)	(-4.54)	(-4.82)	(-1.40)	(-0.89)	
Portfolio 2	0.3220**	0.8787***	-0.4633***	-0.6683***	0.2040***	-0.0555	0.85
	(2.19)	(30.88)	(-5.52)	(-11.48)	(6.90)	(-1.41)	
Portfolio 1	0.1151	0.8123***	-0.3831***	-0.5717***	0.1262***	-0.0726**	0.85
	(0.99)	(18.54)	(-3.70)	(-13.98)	(3.54)	(-2.58)	

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

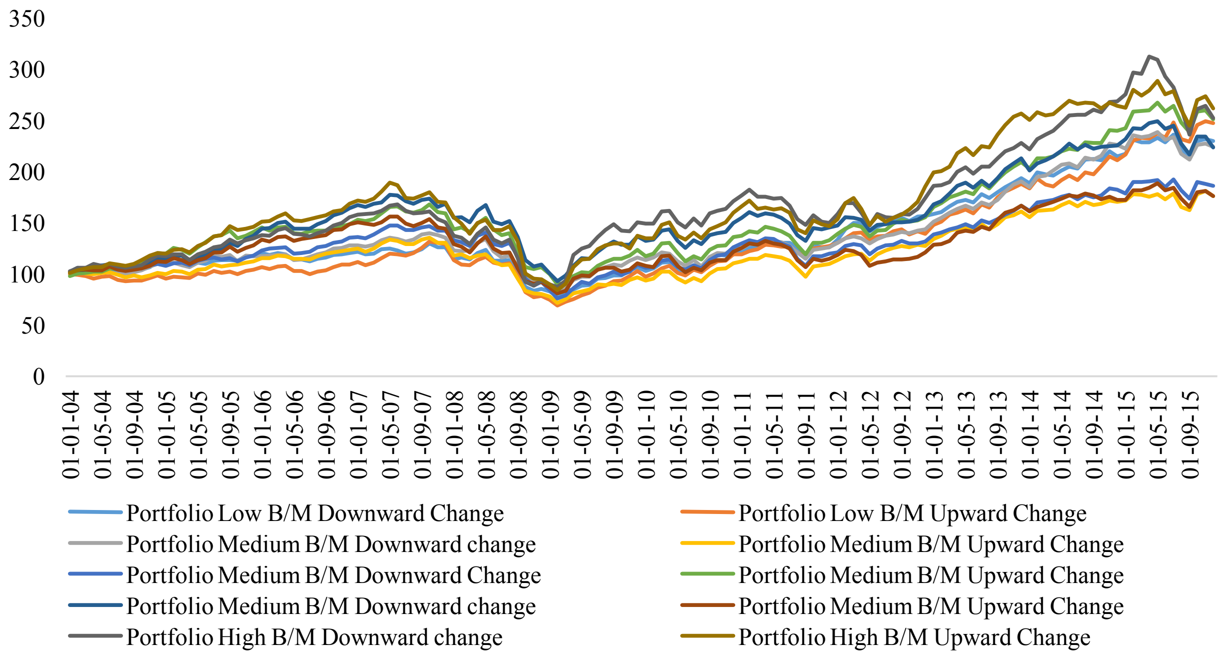
Graph 2 shows what an investor would have earned when he/she would have invested $100 in the year 2000 in a trading strategy that combines a value strategy with upward/downward recommendation changes. There is no pattern of a monotonic increase or decrease visible in the graph when considering the full sample period from 2000 - 2015. The graph suggests that investors would have earned the highest buy-and-hold returns using quarterly rebalancing when they would have taken a long position in stocks with a high book-to-market value that experienced a recent downward recommendation change and a short position in stocks with a low book-to-market value that experienced a recent downward recommendation change. It seems counterintuitive that the portfolio consisting of high book-to-market stocks with an upward recommendation change, which are empirically predicted to have favorable quantitative characteristics to earn high returns, ends in the bottom three portfolios with the lowest returns. Similar to graph 1 in section 4.1.1., a sharp decline is visible between the years 2000-2003, so I exclude these years to see whether these years wipe out the results for other years in the sample (graph 3). Graph 3 shows that the low book-to-market and the high book-to-market portfolios end up with the highest returns. The middle book-to-market portfolios do not differ much from each other. This suggests that taking into account the book-to-market value of a stock while combining this with recommendation revisions could provide abnormal returns to investors.

Although both portfolios consisting of high book-to-market stocks combined with recommendation changes earn the highest returns over the years 2004-2015, the findings show that the outcomes of the trading strategies are not robust to changing the sample period. The abnormal returns of this strategy are sensitive to the chosen universe, region, and time-period, so a trading strategy that is providing investors with excess returns remains an unresolved question.

Graph 2



Graph 3



Next to combining a value strategy with recommendation revisions, I test whether combining a value strategy while taking into account consensus recommendation levels (using the Barber et al. (2001) portfolio partition method) leads to potential abnormal profits. I construct 25 double-sorted portfolios; the sample is divided in five portfolios based on the book-to-market value of stocks and five portfolios based on the consensus recommendation level. Table 11 reports the value-weighted results over the period 2000 - 2015 using the Carhart four-factor model.

Although most alphas are outside the rejection region, the four significant alphas are all situated in the extreme book-to-market portfolios. Because many alphas are insignificant and there is no clear monotonic pattern in the size of the alphas, these findings again only weakly support hypothesis 2, which states that analyst recommendations possibly have more impact on extreme portfolios when sorting according to a value strategy. Because the stocks situated in these portfolios are harder to value, investors could be more prone to heuristics and the value of analyst recommendations is possibly larger. The coefficients on the market, size, and the book-to-market factor are qualitatively similar to previous tables. The momentum factor is significantly negative for the high book-to-market ratio stocks, which is similar to table 10.

Table 11: Results of combining a value strateg and consensus recommendation levels

Table 11 provides the OLS results of 25 double-sorted portfolios based on a value strategy and consensus recommendation levels. The portfolio partitions of the consensus recommendation levels are based on the methodology of Barber et al. (2001). This means that the lowest five portfolios (1-5) consist of low book-to-market stocks, portfolio 6-20 consist of medium book-to-market stocks, and the highest five portfolios (20-25) consist of high book-to-market stocks. More precisely: portfolio 25 consists of high book-to-market stocks with a strong buy recommendation (consensus level > 4.5), while portfolio 21 consists of high book-to-market stocks with a hold/sell/strong sell recommendation (consensus level < 3). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	Adjusted R^2
Portfolio 25	0.2867 (1.13)	1.1278*** (19.17)	-0.1884 (-0.77)	-0.4564*** (-4.84)	-0.3840*** (-4.49)	0.60
Portfolio 24	0.3339 (1.64)	0.8657*** (13.63)	-0.1802 (-1.35)	-0.0474 (-0.48)	-0.2926*** (-3.24)	0.70
Portfolio 23	0.5478** (2.57)	0.7967*** (9.98)	-0.1151 (-0.69)	0.1173 (0.98)	-0.4325*** (-5.55)	0.70
Portfolio 22	0.3203* (1.82)	0.7638*** (8.61)	0.0991 (0.71)	0.4602*** (2.66)	-0.3953*** (-4.85)	0.64
Portfolio 21	0.7724*** (3.31)	0.7704*** (9.01)	0.1557 (1.10)	0.1556 (1.58)	-0.5544*** (-10.45)	0.61
Portfolio 20	0.0590 (0.26)	0.9331*** (11.03)	-0.1893 (-1.61)	-0.0965 (-0.75)	-0.0087 (-0.13)	0.54
Portfolio 19	-0.1377 (-0.96)	0.8450*** (15.76)	-0.3433** (-2.53)	0.1307 (1.52)	-0.0255 (-0.35)	0.74
Portfolio 18	0.1592 (0.79)	0.8682*** (19.68)	-0.2639* (-1.94)	0.1020 (0.98)	-0.0682 (-0.88)	0.70
Portfolio 17	0.1057 (0.54)	0.7374*** (11.15)	0.1860* (1.54)	0.3231*** (5.92)	-0.2170*** (-3.43)	0.64
Portfolio 16	0.0794 (0.32)	0.7792*** (8.12)	0.1664 (0.91)	0.2493* (1.78)	-0.3232** (-2.36)	0.59
Portfolio 15	-0.0058 (-0.02)	0.8566*** (21.28)	-0.2932** (-2.21)	-0.1981** (-3.41)	-0.0104 (-0.19)	0.68
Portfolio 14	0.2095 (1.44)	0.8620*** (20.87)	-0.3537*** (-2.77)	0.0060 (0.06)	-0.0349 (-0.34)	0.79
Portfolio 13	0.1672 (1.08)	0.8765*** (23.05)	-0.3510*** (-3.01)	0.1871** (2.35)	-0.0514 (-0.67)	0.78
Portfolio 12	-0.0405 (-0.23)	0.7700*** (10.53)	-0.5507*** (-3.20)	0.3564*** (4.76)	-0.1026* (-1.25)	0.65
Portfolio 11	0.2785 (0.87)	0.6471*** (3.71)	0.4989 (1.27)	0.1280 (0.72)	-0.2960*** (-2.13)	0.35
Portfolio 10	-0.0071 (-0.04)	0.8312*** (13.22)	-0.2876** (-2.07)	-0.2789* (-1.90)	0.0509 (0.55)	0.64
Portfolio 9	-0.0625 (-0.31)	0.8098*** (22.12)	-0.3867*** (-4.68)	-0.1371** (-1.21)	-0.0141 (-0.28)	0.74
Portfolio 8	0.1688 (0.97)	0.7448*** (16.13)	-0.2437 (-1.54)	0.0285 (0.22)	-0.0630 (-0.86)	0.66
Portfolio 7	0.3553 (1.71)	0.7622*** (12.31)	-0.3030** (-2.48)	0.1336 (0.92)	-0.1466 (-1.57)	0.60
Portfolio 6	0.1803 (0.70)	0.5248*** (3.84)	-0.8765** (-2.39)	-0.7112 (-1.41)	-0.1807 (-1.01)	0.22
Portfolio 5	0.3607* (2.48)	1.0228*** (17.68)	-0.5225*** (-3.53)	-0.9226*** (-14.27)	0.2521*** (7.48)	0.77
Portfolio 4	0.2591 (1.81)	0.7417*** (15.46)	-0.2947** (-2.22)	-0.2139 (-1.17)	0.0957** (2.54)	0.70
Portfolio 3	0.0288 (0.16)	0.7616*** (11.86)	-0.2518** (-2.16)	-0.1707 (-1.18)	0.1961*** (3.23)	0.60
Portfolio 2	0.2521 (1.59)	0.5443*** (13.86)	-0.3002** (-2.44)	0.0428 (0.41)	-0.0449 (-0.81)	0.49
Portfolio 1	0.7344** (2.17)	0.5988*** (5.33)	-0.1265 (-0.94)	-0.4964*** (-3.18)	-0.1614* (-1.04)	0.37

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

4.6. Robustness checks

To check whether the results found in section 4.1 - 4.5. are robust to other model specifications or additional risk factors, I perform several robustness checks.

4.6.1. Possible differences for the results between the relative smallest and largest companies

As a first robustness check, I use a double-sorting technique that sorts stocks into ten portfolios based on their size[9], as measured by market capitalization, and by an upward or downward recommendation revision, in order to assess whether the relative smallest companies of the sample possibly outperform the relative largest companies of the sample. As the studies of Womack (1996) and Barber et al. (2001) show, the results from trading strategies based on analyst recommendations are most pronounced for small firms. They state that on average, there is less publicly information available about smaller firms, so it could be possible that the consensus analyst recommendation level has more value for these firms. Following Barber et al. (2001), large firms are situated in the highest three portfolios, medium sized firms in the middle four portfolios, and small firms in the lowest three portfolios. Portfolio 1 - 6 consist of relative small stocks with upward/downward recommendation changes. Medium stocks are situated in portfolio 7 - 14, while large stocks are situated in portfolio 15 - 20. The results are reported in table 8 in the appendix.

Most alphas are outside the rejection region. Due to my sample selection, I already exclude 'really small' firms by only considering stocks which are covered by more than five analysts and that have a market capitalization larger than 3 billion. This could explain why I do not find more pronounced results for the relative smallest firms in my sample. The coefficient on the market factor is qualitatively similar to previous tables. The coefficients on the size and book-to-market factor are negative for the portfolios consisting of large stocks and positive for the portfolios consisting of small stocks. In most cases, the coefficient on the momentum factor are positive for portfolios consisting of upward revised stocks and negative for portfolios consisting of downward revised stocks, which again confirms the trend-following behavior of analysts.

4.6.2. Fama-MacBeth

As a second robustness check, I use the Fama-MacBeth procedure and run regressions for each month separately. In this way, all observations from the panel are used. After that, I report the time-series averages of the slope coefficients to determine the expected premium for a unit exposure to each risk factor over time. Table 9 in the appendix provides the results of the regressions using the Fama-MacBeth procedure.

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[9] I also performed this robustness check while using other portfolio partitions. These results are qualitatively similar.

The results of the long-short portfolio of Panel A using Fama-MacBeth show qualitatively similar coefficients on the market, size, book-to-market, momentum, and the liquidity factor. The alpha is positive using recommendation levels as a measure, but not significant, so the conclusion is qualitatively similar to using OLS regressions. The alpha on the long-short portfolio using recommendation changes is significantly negative, which is consistent with previous results.

Panel B - F in table 9 in the appendix provide the results of several subsets of stocks using the Fama-MacBeth procedure. The results of panel B report alphas outside the rejection region. The coefficients on the market, size, book-to-market, momentum, and liquidity factor are qualitatively similar to the results of the double-sorting on size robustness check (table 8 in the appendix).

Panel C shows a significant negative alpha on the long-short portfolio concerning value portfolios. Interestingly, the alpha on the long-short portfolio of growth stocks is positive, which means that going long in growth stocks with upward recommendations and going short in growth stocks with downward recommendations would yield positive excess returns. The coefficients on the market, size, book-to-market, momentum, and the liquidity factor are qualitatively similar to the results reported in table 11 in the main text. Using the Fama-Macbeth method instead of time-series OLS regressions has no impact on the results for the subset of US, Japanese, or European stocks (Panel D - F) compared to table 7, 8, and 9 in the main text.

4.6.3. Investor sentiment as an additional risk factor

To examine the role of investor sentiment in the cross-section of stock returns, I include sentiment as a risk factor in the regressions. Investor sentiment reflects the general attitude of investors towards the current state and the expectations of the market (Baker and Wurgler, 2006). Since sentiment is not always based on fundamental information and can thus move prices away from their fundamental values, it can be considered as a risk factor in multi-factor asset pricing models. This might influence the alpha I find in the model, since part of the value of analyst recommendations can also stem from investor sentiment in the market. As DeLong, Schleifer, Summers, and Waldman (1990) explain, investors can require additional compensation for fluctuations in 'noise-trader' sentiment, because this can be an additional source of systematic risk when holding investments. I include the sentiment proxy of Baker and Wurgler (2006), which is orthogonal to macroeconomic situations. Baker and Wurgler (2006) construct six different proxies, which they orthogonalize from several macroeconomic components and which they then combine into one proxy for sentiment. After their 2006 article, they updated this proxy and nowadays it is only based on five instead of six proxies, since they excluded 'Turnover' as one of the proxies. Baker and Wurgler state that: "turnover does not mean what it once did, given the explosion of institutional high-frequency trading and the migration of trading to a variety of venues". When adding the investor sentiment factor, I include the value of this factor of the previous month. Including sentiment leads to the following regression equation:

$$R_p - R_f = \alpha + \beta^{MKT} (Rm - Rf) + \beta^{S} SMB + \beta^{H} HML + \beta^{M} MOM + \beta^{L} LIQ + \beta^{S} SENTIMENT_{t-1} + \varepsilon$$

Table 10 in the appendix reports the results including investor sentiment as a risk factor. The results are robust to adding the sentiment factor, since this factor is not significant for both of the model specifications. The coefficients on the market, size, book-to-market, and momentum factor are qualitatively similar to previously reported tables.

4.6.4. Using logarithmic returns instead of simple returns

Additionally, monthly regressions of a trading strategy based on consensus recommendation levels using logarithmic returns instead of simple returns are included in table 11 in the appendix. Logarithmic returns are continuously compounded, rather than discrete. Because of the difference between the calculations of simple and logarithmic returns, the results show that the magnitude of the results is lower, but the significance is not much affected. Using the CAPM as asset pricing model, the long-short portfolio yields -51 basispoints per month (t-stat -2.18). However, this result is not robust while using more comprehensive asset pricing models, so the results are qualitatively similar to using models with simple returns. The difference of the results between using logarithmic returns instead of simple returns is qualitatively similar when implementing a trading strategy based on recommendation changes.

4.6.5. Using quarterly returns instead of monthly returns

Furthermore, I include the regression results using quarterly instead of monthly returns for the stocks and the Kenneth French factors in the appendix in table 12. Again, these returns are converted into logarithms, because of mathematical convenience, since the Kenneth French factor also had to be converted to quarterly returns. The coefficients on the market, size, book-to-market, momentum, and liquidity factor are qualitatively similar, but the magnitude differs. The alpha of the long-short portfolio in the CAPM model is weakly significant and reports that this strategy yields -3.14% per quarter (t-stat -1.96). Again, this result is not robust to using more comprehensive asset pricing models. The conclusion is qualitatively similar to previous regression analyses.

4.6.6. Excluding widely covered stocks (>15 analysts)

Table 13 in the appendix reports the results for the trading strategy based on consensus recommendation levels when excluding widely covered stocks[10], which are defined as stocks that are covered by more than 15 analysts (Boni and Womack, 2006). Boni and Womack (2006) state that analyst recommendations do probably add less value for widely covered stocks, since the share prices for these stocks more rapidly incorporate information than prices of less widely followed stocks. Following this intuition, I predict that the alphas excluding widely covered stocks show a higher magnitude.

The findings weakly support this prediction. Most alphas are outside the rejection region, but the significant alphas show a higher positive magnitude, especially for the high level portfolios. This suggests that focusing on analyst recommendations of less widely followed stocks provides possibly more value for investors compared to a focus on all analyst recommendations. Using this subsample, the coefficients on the market factor are consistently higher for the high level portfolio and lower for the low level portfolio (which is in line with previous results), regardless of the asset pricing model used. The coefficient on the size factor is significantly positive for portfolios consisting of low level stocks, whereas this coefficient was outside the rejection region for these portfolios in previous tables. This means that stocks in the low level portfolios (excluding widely covered stocks) are mostly weighted towards small stocks. The coefficients on the book-to-market and the momentum factor are qualitatively similar to previous tables. The coefficient on the liquidity factor is significant: high level portfolios have a positive coefficient on the liquidity factor and low level portfolios have a negative coefficient on this factor. This means that stocks with a high consensus recommendation level predominantly are relatively liquid stocks and stocks with a low consensus recommendation level predominantly are relatively illiquid stocks.

4.6.7. Two measures of crisis dummies

To look whether the state of the economy in a country or periods of a banking crisis possibly influence the alphas that I find in section 4, I include two measures of crisis dummy variable to control for these two possible effects.

First, I use real Gross Domestic Product growth data from the Organization of Economic Co-Operation and Development (OECD) to define the turning points of recessions or boom periods. For every country in the sample, the OECD database provides annual real GDP growth data. According to the OECD, the 'GDP is the standard measure of the value of final goods and services produced by a country during a period minus the value of imports. The dummy variable Crisis has a value of 1 in case of a recession (negative real GDP growth) and a value of 0 in case of a booming economy (positive real GDP growth). The regression equation becomes:

[10] The results are qualitatively similar when performing the trading strategy based on recommendation revisions

$$R_p - R_f = \alpha + \beta^{MKT} (Rm - Rf) + \beta^{S} SMB + \beta^{H} HML + \beta^{M} MOM + \beta^{L} LIQ + \beta^{C} dCrisis + \varepsilon$$

The results using the Carhart four-factor model, including the Pástor and Stambaugh liquidity factor, are reported in table 14 in the appendix. The results are qualitatively similar to previous analyses. The coefficients on the crisis dummy are outside the rejection region and the coefficients on the other risk factors are qualitatively similar. This means that the state of an economy of a country does not seem to influence the value of analyst recommendations in the cross-section of stock returns. This result is also found by Barber et al. (2001), who distinguish between a bull or a bear market using the CRSP value-weighted market index return. When the value-weighted market index is larger then 1, the authors define the period as a boom, and when the value weighted index is smaller than 1, they define the period as a recession. Although they use another measure, they find that the state of the economy leads to indifferent results compared to other analyses.

Secondly, I use World Bank data to include a country-level banking crisis dummy for each year. I use the IMF systematic banking crises database from Laeven and Valencia (2012), which is updated until the year 2011. For the countries that have a systematic banking crisis which has not ended in 2011, I assume the years 2012 – 2015 to have a systematic banking crisis as well[11]. The dummy variable Bankcrisis has a value of 1 in case of a systematic banking crisis and a value of 0 in case of no systematic banking crisis. The regression equation becomes:

$$R_p - R_f = \alpha + \beta^{MKT} (Rm - Rf) + \beta^{S} SMB + \beta^{H} HML + \beta^{M} MOM + \beta^{L} LIQ + \beta^{B} dBankcrisis + \varepsilon$$

The results are reported in table 15 in the appendix. The results suggest a systematic banking crisis does have a significant impact on portfolios consisting of stocks with downward analyst recommendation changes and the long-short portfolio. A systematic banking crisis increases the positive alpha on the low portfolio and decreases the negative alpha on the long-short portfolio. This means that especially in the years of systematic banking crises (particularly the years 2007/2008 until 2015), the low portfolio yields positive risk-adjusted returns which in turn leads to a significant negative alpha on the long-short portfolio, suggesting that using analyst recommendations in periods of a systematic banking crises would yield positive risk-adjusted returns when this signal would be used in a contrarian manner: i.e. long in stocks with a downward revision, and short in stocks with an upward revision. This seems counterintuitive, but it could explain the differences between the alphas that I find and most alphas from earlier research, since

[11] I also performed the regressions without this assumption, which leads to qualitatively similar results

this thesis comprises another time period that includes relatively many years of systematic banking crises and financial volatile periods compared to sample periods of other researchers.

4.6.8. Distinguish between high, medium, and low investor participation countries

Barniv et al. (2010) compare sell-side analyst recommendations and analysts' earnings forecasts and notice that these two types of analysts' output differ in their usefulness. They find that while analysts' earnings forecasts add more value for high investor participation countries compared to low investor participation countries, the opposite is true for sell-side analyst recommendations. Balboa et al. (2009) explain this by distinguishing between the difficulty of interpreting the two pieces of information: sell-side recommendations are just one simple 'word' in the end, which is easy to interpret for noise traders, while earnings forecasts need to be studied more deeply to interpret them. Following this reasoning, they find that sell-side analysts in low investor participation countries are less likely to gain from issuing positively biased recommendations (because there are less noise traders in these countries). As a result, Barniv et al. (2010) state that analyst recommendations add probably more value in countries with a low individual investor participation rate, since there will be possibly less positively biased recommendations there.

In this final robustness check, I will test whether the alphas that I find in previous analyses change when I distinguish between high, medium, and low individual investor participation countries. Like Barniv et al. (2010), I use the investor participation rates that are provided by Giannetti and Koskinen (2010). Giannetti and Koskinen calculate the country-level investor participation rates by assessing the fraction of households that privately hold shares in the stock market of their country. By definition, institutional investors represent a relatively larger proportion of the total stock demand in low individual investor participation countries compared to high individual investor participation countries. When less noise traders (individual traders) are active, it is possible that the level of mispricing in the stock market is lower, because institutional investors are less likely to make mistakes in their evaluations and therefore I suppose that - at least - the negative alpha that is found in some specifications in previous analyses is less negative for low investor participation countries than for high investor participation countries.

I run separate Carhart four-factor model regressions for high, medium, and low investor participation countries. All stocks from Spain are excluded in this analysis, since there is no data available for this country regarding the level of investor participation. The results are reported in table 16 in the appendix.

The results show a monotonic increase in the alpha on the long-short portfolio. The alpha on the long-short portfolio when following a trading strategy based on analyst consensus recommendation levels is consistently negative, which is qualitatively similar to some specifications in section 4. The fact that this negative alpha is less negative for low investor participation countries compared to high investor participation countries is interesting. The monotonic pattern could be explained as follows: countries with lower individual investor participation rates have less noise traders, so there should be less overreaction stemming from this type of investors. This in turn should lead to less mispricing in the market, which results in relatively less negative alphas on the long-short portfolio.

Although the alpha on a portfolio consisting of stocks with an upward revision is only significant for low investor participation countries, this also suggests that recommendation changes add more value in these countries.

Both these findings support the prediction of Barniv et al. (2010) and Balboa et al. (2009). The coefficients on the market-, size-, book-to-market, and momentum factor are qualitatively similar to previous analyses.

5. Conclusion and discussion

Prior research concerning sell-side analyst recommendations shows that analysts are affected by an optimism bias, and this in turn could affect how investors, mainly noise traders, allocate their investments. In this thesis, I investigate whether it is possible to yield positive risk-adjusted returns while following trading strategies based on analyst recommendations. While investigating firms with a market cap larger than 3 billion that are covered by more than five analysts for a recent time period, I do not find significant robust differences between the returns of the most favorably recommended stocks and the least favorably recommended stocks.

Using some model specifications, the results of the long-short portfolio (going long in stocks with a high consensus recommendation level/upward revision and short in stocks with a low analyst recommendation level/downward revision) are the opposite of what I empirically predicted the results to be in the testable hypotheses. The results of negative alphas on the long-short portfolio, instead of the positive alphas that I predicted in hypotheses 1a and 1b, speak to the overreaction and price drift explanation. Previous research shows that there is some price drift after a newly issued recommendation, especially the first and the second day after the publication. When noise traders overreact to an observed signal (the recommendation of an analyst), prices become too high for stocks with buy recommendations and too low for stocks with sell recommendations, which is corrected in the longer term and can explain the negative alpha on the long-short portfolio. Most previous studies that investigate trading strategies in the research area of analyst recommendations have a focus on US data before the year 2002. Since the more recent time period in this thesis comprises the internet trading era, the IT bubble, and the financial crisis, this could explain why the results I find are different. Because trading in stocks has become easier for every type of investor, it is possible that the amount of noise traders has increased, which in turn could lead to more overreaction upon analyst recommendations.

There are a few other possible explanations for the empirical results in this thesis. Firstly, the results can be due to my sample selection or research methods. The findings can be driven by the selection of a time period and a geographical region, which leads to sample specific results which cannot be generalized to other regions or time periods. Perhaps choosing another subset of recommendations, another time period, other holding periods, or rebalancing more frequently could lead to profitable trading strategies which earn abnormal returns. The fact that I find insignificant or sometimes negative alphas does not rule out the possibility of profitable trading strategies based on analyst recommendations. It could be possible that other trading signals in combination with the trading strategies explored in this thesis would be able to generate abnormal profits.

Secondly, it could be possible that especially in the recent time period, stocks with unfavorable quantitative characteristics were positively recommended, while stocks with favorable quantitative characteristics were negatively recommended. The empirical findings of this thesis confirm the results of Jegadeesh et al. (2004), who notice that analysts tend to recommend growth stocks, which are attractive from a viewpoint of potential future profit. Moreover, I find that stocks recommended by analysts are most exposed to large capitalization stocks. This again is linked to analysts' incentives. As my findings suggest, analysts tend to be trend-following in their recommendations: they tend to give buy recommendations to stocks with a positive momentum and sell recommendations to stocks with a negative momentum. This can possibly turn out in positive abnormal returns in stable financial years, but when the stock market is more volatile, it could also be possible that a contrarian strategy based on analyst recommendations would be more profitable.

Thirdly, the results could be explained by the findings of Brown et al. (2015), who find that the incentive for analysts to publish recommendations that contribute positively to their compensation is still much present. The findings of this thesis confirm indeed that the optimism bias is still present in the recent time period. This could mean that the analyst recommendations are biased in such manner, that they would not add any value in the cross-section of stocks returns since they do not issue objective recommendations about stocks.

Next to the first analysis, I also perform a second analysis by combining a value-strategy with shifts in analyst recommendations. To see whether analyst recommendations have possibly more impact on the extreme portfolios when sorting according to a value strategy, I sort stocks quarterly into value buckets (using their book-to-market value as a measure) and I look into the impact of analyst recommendations on the different portfolios. I find that though the significant alphas are situated in the extreme portfolios, these results are not robust, so they do not strongly support hypothesis 2, which predicts that recommendation changes have more impact on extreme portfolios of a value strategy, since these stocks are harder to value and investors may be more prone to heuristics when valuing these stocks.

While this thesis looks into many aspects concerning analyst recommendations, which can be illustrated by several possible explanations, the main insight that this thesis could provide investors and financial academics with is the insight that investors should not blindly follow sell-side analyst recommendations when making their investment allocation decisions. The conclusion is that the semi-strong form of market efficiency is probably not violated by analysts' information.

Another finding is that, especially in markets with a relatively large number of noise traders, it could be possible to gain from a trading strategy based on analyst recommendations when using these recommendations as a contrary signal. This means that investors in these countries should go long in stocks with a sell recommendations and short in stocks with buy recommendations.

It is important for investors to look into the analysis behind a published recommendation and relate a recommendation to their personal situation. Moreover, it could be useful to combine other signals such as favorable quantitative characteristics (such as high value or positive momentum) with the advice of sell-side analysts (Jegadeesh et al. 2004), while at the same time considering the state of the economy (whether there is a systematic banking crisis going on), whether the individual investor participation rate in their country is high or low, and so on. This implies that trading based on analyst recommendations is certainly not a straightforward trading strategy that will work at all times and under all conditions.

A possible limitation of this study is that the Bloomberg database does not distinguish between recommendations of IPOs or 'normal' recommendations and between affiliated and non-affiliated analysts. This could lead to a biased dataset, since IPOs are generally treated as underpriced; at least in the first days after an IPO. Next to this, as Michaely and Womack (1999) find, especially analysts that work for the underwriters of new equity issues tend to issue biased recommendations (they are affiliated). Further studies could combine a different database with Bloomberg to extract the IPO recommendations from the non-IPO recommendations and distinguish between affiliated and non-affiliated sell-side analysts.

Another possible limitation of this study is that it is not possible to divide the data based on the type of analysis behind an issued analyst recommendation. Gerritsen (2014) finds that investors would be wise when they ignored recommendations that are based solely on technical analysis. On average, these recommendations, which are based on recent stock prices, do not add value. However, Gerritsen (2014) states that recommendations based on fundamental analysis are relevant. Future research could therefore distinguish between recommendations based on technical analysis and fundamental analysis.

Besides, further research could include more control factors in the regression equations, which could possibly result in a more accurate determination of the alphas found in the results. I tried to follow existing research and included as much control factors as possible with the existing internet data.

Moreover, studying different holding periods and other rebalancing frequencies using the recent sample period of this thesis could explain the results more extensively. However, since my main goal is to find out whether analyst recommendations do add value that is replicable for investors, I decided to rebalance quarterly, also taking in mind the high transaction costs that go along with rebalancing more frequently and the fact that most analysts issue new recommendations around quarterly earnings announcements.

Finally, less restrictions concerning the sample selection could be applied to end up with a larger sample, which also includes stocks with a market capitalization less than 3 billion and stocks which are covered by less than 5 analysts. However, for the same reason as I did not perform analyses using more frequent rebalancing and other holding periods, I chose to include only the most liquid stocks which can be easily invested in to ensure a feasible replicable trading strategy, which is why I leave this to further research.

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Appendix

Table 1: Number of consensus recommendations and average recommendation level per country: 2000m1 - 2015m12

Country	Number of consensus recommendations 2000-2015	Average recommendation level 2000-2015
Austria	219	3.55
Belgium	449	3.41
Denmark	1,101	3.60
Finland	482	3.48
France	3,206	3.76
Germany	2,310	3.66
Greece	219	3.88
Ireland	647	4.10
Italy	956	3.61
Japan	22,060	3.60
Netherlands	1,229	3.76
Norway	1,388	4.01
Portugal	233	3.72
Spain	1,161	3.48
Sweden	2,228	3.50
Switzerland	2,017	3.74
UK	3,853	3.65
US	33,957	3.95

Table 2: Coefficient estimates of a trading strategy based on consensus recommendation levels: 2000m1 - 2015m12

Table 2 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using monthly equally-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.0641 (-0.35)	1.0219*** (11.01)					0.82
R^{LOW}	0.3490* (1.83)	0.7826*** (13.81)					0.68
$R^{HIGH} – R^{LOW}$	-0.4131* (-1.65)	0.2394** (1.99)					0.10
R^{HIGH}	0.1387 (0.80)	0.9968*** (19.48)	0.1308 (1.13)	-0.4307*** (-6.17)			0.86
R^{LOW}	0.1593 (0.82)	0.7929*** (16.74)	0.2361* (1.84)	0.2924*** (3.22)			0.70
$R^{HIGH} – R^{LOW}$	-0.0206 (-0.10)	0.2038*** (3.08)	-0.1053 (-1.43)	-0.7230*** (-9.34)			0.37
R^{HIGH}	0.1090 (0.58)	1.0143*** (24.94)	0.0994 (0.86)	-0.4168*** (-6.39)	0.0518 (1.18)		0.87
R^{LOW}	0.2741 (1.59)	0.7251*** (17.27)	0.3575*** (3.27)	0.2387*** (3.29)	-0.2002*** (-4.59)		0.73
$R^{HIGH} – R^{LOW}$	-0.1651 (-0.85)	0.2892*** (5.16)	-0.2581** (-2.31)	-0.6555*** (-7.87)	0.2520*** (5.53)		0.46
R^{HIGH}	0.1025 (0.48)	1.0077*** (23.27)	0.0703 (0.60)	-0.4166*** (-5.85)	0.0516 (1.27)	0.0559 (1.57)	0.87
R^{LOW}	0.2436 (1.47)	0.7149*** (16.44)	0.4189*** (4.55)	0.2658*** (3.89)	-0.2152*** (-5.09)	-0.0482 (-1.09)	0.74
$R^{HIGH} – R^{LOW}$	-0.1411 (-0.75)	0.2928*** (5.30)	-0.3486*** (-4.48)	-0.6824*** (-8.28)	0.2668*** (6.66)	0.1040*** (3.88)	0.50

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 3: Coefficient estimates of a trading strategy based on consensus recommendation levels, excluding the years 2000 - 2003

Table 3 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using monthly value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2004 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.0542 (0.39)	0.8132*** (15.90)					0.87
R^{LOW}	0.2781** (2.27)	0.6519*** (19.98)					0.74
$R^{HIGH} – R^{LOW}$	-0.2239 (-1.34)	0.1612*** (2.66)					0.11
R^{HIGH}	0.0647 (0.60)	0.8630*** (21.32)	-0.2509*** (-5.52)	-0.4181*** (-5.99)			0.90
R^{LOW}	0.2822** (2.20)	0.6457*** (15.03)	-0.0667 (-0.61)	0.0801 (0.65)			0.74
$R^{HIGH} – R^{LOW}$	-0.2175 (-1.47)	0.2173*** (4.33)	-0.1842** (-2.31)	-0.4982*** (-4.68)			0.23
R^{HIGH}	-0.0132 (-0.15)	0.8859*** (30.82)	-0.2675*** (-5.06)	-0.3425*** (-4.60)	0.1250*** (3.31)		0.91
R^{LOW}	0.3179** (2.52)	0.6353*** (13.46)	-0.0591 (-0.54)	0.0455 (0.39)	-0.0572 (-0,96)		0.74
$R^{HIGH} – R^{LOW}$	-0.3311* (-1.88)	0.2506*** (5.78)	-0.2084** (-2.39)	-0.3879*** (-3.68)	0.1822* (1.85)		0.29
R^{HIGH}	-0.0146 (-0.13)	0.8668*** (33.59)	-0.2525*** (-4.85)	-0.3019*** (-3.32)	0.1227*** (3.43)	0.0216 (0.74)	0.91
R^{LOW}	0.3536*** (2.91)	0.6202*** (15.70)	0.0347 (0.42)	0.0670 (0.77)	-0.0590 (-1.04)	-0.0649** (-2.34)	0.75
$R^{HIGH} – R^{LOW}$	-0.3682** (-2.33)	0.2466*** (6.56)	-0.2872*** (-4.15)	-0.3689*** (-3.30)	0.1817** (2.43)	0.0865*** (2.65)	0.34

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 4: Coefficient estimates of a trading strategy based on consensus recommendation levels for the first half of the sample period (2000 - 2008)

Table 4 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using monthly value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2008. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.5771**	1.0423***					0.75
	(2.28)	(6.56)					
R^{LOW}	0.1493	0.7336***					0.75
	(0.79)	(8.29)					
$R^{HIGH} – R^{LOW}$	-0.7264**	0.3087***					0.15
	(-2.31)	(2.72)					
R^{HIGH}	0.1880	0.9266***	-0.3942***	-0.6909***			0.86
	(0.71)	(14.01)	(-3.73)	(-7.65)			
R^{LOW}	0.1292	0.7477***	-0.0774	0.0394			0.75
	(0.53)	(8.26)	(-1.01)	(0.47)			
$R^{HIGH} – R^{LOW}$	0.0588	0.1789**	-0.3169**	-0.7303***			0.42
	(0.22)	(2.13)	(-2.08)	(-5.31)			
R^{HIGH}	0.1688	0.9403***	-0.4253***	-0.6837***	0.0348		0.86
	(0.62)	(12.90)	(-3.52)	(-8.15)	(0.70)		
R^{LOW}	0.2296	0.6762***	0.0844	0.0018	-0.1814***		0.78
	(0.99)	(8.63)	(1.00)	(0.02)	(-4.00)		
$R^{HIGH} – R^{LOW}$	-0.0609	0.2641**	-0.5096***	-0.6855***	0.2162***		0.48
	(-0.21)	(2.56)	(-3.83)	(-5.53)	(3.59)		
R^{HIGH}	0.1567	0.9344***	-0.4295***	-0.6883***	0.0346	0.0168	0.86
	(0.63)	(13.33)	(-3.52)	(-6.60)	(0.62)	(0.31)	
R^{LOW}	0.2213	0.6721***	0.0814	-0.0014	-0.1816***	0.0115	0.78
	(0.85)	(8.63)	(1.01)	(-0.01)	(-3.36)	(0.20)	
$R^{HIGH} – R^{LOW}$	-0.0646	0.2622***	-0.5110***	-0.6869***	0.2162***	0.0052	0.47
	(-0.22)	(2.75)	(-3.77)	(-5.46)	(3.56)	(0.10)	

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 5: Coefficient estimates of a trading strategy based on consensus recommendation levels for the second half of the sample period (2009 - 2015)

Table 5 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using monthly value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2009 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.3251** (2.24)	0.8049*** (10.58)					0.86
R^{LOW}	0.3700*** (3.21)	0.6606*** (13.03)					0.74
$R^{HIGH} – R^{LOW}$	-0.0449 (-0.34)	0.1443 (1.27)					0.07
R^{HIGH}	0.1963 (1.60)	0.8770*** (14.70)	-0.1808*** (-2.81)	-0.4253*** (-4.44)			0.89
R^{LOW}	0.4189*** (3.46)	0.6376*** (9.64)	-0.0699 (-0.40)	0.1058 (0.59)			0.74
$R^{HIGH} – R^{LOW}$	-0.2226 (-1.38)	0.2394*** (2.77)	-0.1109 (-0.76)	-0.5311*** (-4.10)			0.18
R^{HIGH}	0.1206 (1.23)	0.9276*** (25.96)	-0.1184 (-1.48)	-0.3246*** (-3.64)	0.1924*** (7.08)		0.92
R^{LOW}	0.4416*** (3.58)	0.6225*** (9.26)	-0.0886 (-0.54)	0.0757 (0.43)	-0.0576 (-0.75)		0.74
$R^{HIGH} – R^{LOW}$	-0.3210** (-2.55)	0.3051*** (5.85)	-0.0298 (-0.28)	-0.4003*** (-3.32)	0.2500*** (2.85)		0.30
R^{HIGH}	0.2025** (1.99)	0.8910*** (34.65)	-0.0838 (-1.33)	-0.2209** (-2.18)	0.1927*** (8.51)	0.0456** (2.08)	0.93
R^{LOW}	0.5206*** (4.25)	0.5809*** (11.71)	0.0556 (0.41)	0.1425 (1.05)	-0.0626 (-0.78)	-0.0614 (-1.44)	0.75
$R^{HIGH} – R^{LOW}$	-0.3181** (-2.12)	0.3101*** (7.42)	-0.1394 (-1.35)	-0.3634*** (-3.16)	0.2553*** (3.13)	0.1070*** (3.11)	0.38

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 6: Equally-weighted coefficient estimates of a trading strategy based on Barber et al. (2001) portfolio partitions: 2000m1 - 2015m12

Table 6 reports the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using monthly equally-weighted returns. The dependent variable R refers to excess returns on portfolios with consensus recommendation levels higher than 4.5 (strong buy recommendations) (R^{HIGH}), consensus recommendation levels lower than 3 (hold, sell, or strong sell recommendations) (R^{LOW}), or the difference in the returns on portfolios with strong buy and hold/sell/strong sell recommendations (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.0234 (-0.13)	0.9769*** (11.94)					0.81
R^{LOW}	0.4953** (2.18)	0.7741*** (12.25)					0.60
$R^{HIGH} - R^{LOW}$	-0.5187* (-1.90)	0.2028* (1.88)					0.06
R^{HIGH}	0.1415 (0.77)	0.9564*** (19.01)	0.1088 (0.86)	-0.3509*** (-5.36)			0.85
R^{LOW}	0.2816 (1.32)	0.7851*** (15.22)	0.2848** (2.27)	0.3237*** (3.21)			0.63
$R^{HIGH} - R^{LOW}$	-0.1401 (-0.72)	0.1713** (2.35)	-0.1760** (-1.97)	-0.6746*** (-8.81)			0.27
R^{HIGH}	0.1171 (0.63)	0.9708*** (23.72)	0.0830 (0.67)	-0.3395*** (-4.37)	0.0426 (0.64)		0.85
R^{LOW}	0.4395** (2.38)	0.6918*** (13.42)	0.4517*** (4.42)	0.2499*** (3.19)	-0.2752*** (-5.18)		0.68
$R^{HIGH} - R^{LOW}$	-0.3224* (-1.77)	0.2790*** (5.70)	-0.3687*** (-2.66)	-0.5894*** (-8.60)	0.3178*** (6.17)		0.38
R^{HIGH}	0.0750 (0.38)	0.9603*** (24.35)	0.0493 (0.40)	-0.3287*** (-4.42)	0.0384 (0.62)	0.0916** (1.99)	0.85
R^{LOW}	0.3851** (2.13)	0.6801*** (13.61)	0.5101*** (5.09)	0.2824*** (4.58)	-0.2919*** (-4.46)	-0.0233 (-0.52)	0.68
$R^{HIGH} - R^{LOW}$	-0.3102* (-1.71)	0.2802*** (5.63)	-0.4608*** (-4.46)	-0.6110*** (-9.71)	0.3303*** (7.24)	0.1150** (2.83)	0.42

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 7: Coefficient estimates of a trading strategy based on recommendation changes: 2000m1 - 2015m12

Table 7 reports the results of the OLS regression models with portfolios based on recommendation changes as the dependent variable, using monthly equally-weighted returns. The dependent variable R refers to excess returns on portfolios with either upward recommendation changes (R^{HIGH}), downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with upward and downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.1928 (1.15)	0.8754*** (22.23)					0.81
R^{LOW}	0.2733 (1.58)	0.9066*** (20.52)					0.79
$R^{HIGH} – R^{LOW}$	-0.0805 (-0.63)	-0.0313 (-0.75)					0.00
R^{HIGH}	0.0982 (0.51)	0.8777*** (24.34)	0.1959** (2.03)	0.1217 (1.58)			0.82
R^{LOW}	0.2540 (1.41)	0.9083*** (20.29)	0.0076 (0.05)	0.0349 (0.37)			0.78
$R^{HIGH} – R^{LOW}$	-0.1558 (-0.91)	-0.0306 (-0.85)	0.1884* (1.76)	0.0868 (1.09)			0.04
R^{HIGH}	0.1024 (0.68)	0.8752*** (21.05)	0.2003** (2.31)	0.1198* (1.76)	-0.0072 (-0.16)		0.82
R^{LOW}	0.3919*** (2.75)	0.8269*** (17.36)	0.1533 (1.39)	-0.0295 (-0.46)	-0.2404*** (-4.41)		0.82
$R^{HIGH} – R^{LOW}$	-0.2895** (-2.35)	0.0484** (2.05)	0.0470 (0.74)	0.1493*** (2.82)	0.2331*** (10.23)		0.31
R^{HIGH}	0.0009 (0.01)	0.8599*** (22.70)	0.2312*** (2.92)	0.1594*** (2.83)	-0.0243 (-0.57)	0.0440 (1.21)	0.82
R^{LOW}	0.3482** (2.35)	0.8130*** (17.69)	0.1503 (1.42)	-0.0138 (-0.22)	-0.2483*** (-5.33)	0.0494 (1.27)	0.82
$R^{HIGH} – R^{LOW}$	-0.3473*** (-3.12)	0.0469** (1.97)	0.0810 (1.33)	0.1732*** (4.27)	0.2240*** (10.05)	-0.0054 (-0.25)	0.32

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 8: Results double-sorting on size and recommendation changes

Table 8 reports the results of regression analyses which include double-sorted portfolios based on size and recommendation changes. The portfolios are rebalanced quarterly and are monthly regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period is from January 2000 to December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	Adjusted R^2
Portfolio 20	0.0754 (0.60)	0.7744*** (19.48)	-0.5191*** (-9.75)	-0.3997*** (-7.68)	0.0727 (1.35)	0.87
Portfolio 19	0.0944 (1.34)	0.7889*** (30.66)	-0.5777*** (-15.72)	-0.3784*** (-6.69)	0.0338 (1.49)	0.88
Portfolio 18	0.0167 (0.13)	0.9300*** (28.47)	-0.0473 (-0.56)	-0.2892*** (-5.39)	0.1484*** (5.41)	0.84
Portfolio 17	0.2866** (2.31)	0.8487*** (19.79)	-0.0043 (-0.06)	-0.2411*** (-5.62)	-0.1438* (-1.77)	0.83
Portfolio 16	-0.0088 (-0.07)	0.8876*** (35.53)	-0.0641 (-0.79)	-0.0867* (-1.75)	0.0681** (2.04)	0.83
Portfolio 15	0.2578 (1.40)	0.8744*** (22.90)	0.0836 (1.16)	-0.1518** (-2.05)	-0.0415 (-1.11)	0.83
Portfolio 14	0.1276 (1.11)	0.9665*** (26.56)	-0.0494 (-0.34)	-0.1126* (-1.89)	0.0209 (0.49)	0.84
Portfolio 13	0.2303** (1.99)	0.8529*** (27.59)	0.2089*** (4.19)	-0.0829* (-1.78)	-0.1677*** (-4.61)	0.86
Portfolio 12	0.2717* (1.88)	0.9335*** (33.08)	0.0694 (0.73)	-0.0305 (-0.57)	-0.0808** (-2.05)	0.84
Portfolio 11	0.3214*** (2.63)	0.8388*** (18.66)	0.0457 (0.44)	-0.0061 (-0.09)	-0.1421*** (-2.90)	0.80
Portfolio 10	0.2253 (1.04)	0.9212*** (22.69)	0.3620*** (4.19)	0.0118 (0.14)	0.0544 (1.35)	0.77
Portfolio 9	0.3990** (2.54)	0.8568*** (18.42)	0.1554** (2.15)	0.0809 (0.86)	-0.1168*** (-2.62)	0.79
Portfolio 8	-0.0769 (-0.44)	0.9464*** (21.28)	0.4239*** (4.32)	0.0964** (1.96)	-0.0490 (-0.68)	0.80
Portfolio 7	0.2672* (1.68)	0.8988*** (16.33)	0.2185 (1.40)	0.0386 (0.42)	-0.3064*** (-3.78)	0.79
Portfolio 6	0.2673 (1.15)	0.9054*** (21.34)	0.2559** (2.04)	0.1520 (1.51)	-0.0707 (-0.67)	0.75
Portfolio 5	0.3926** (2.13)	0.8670*** (18.94)	0.1296 (0.91)	0.1273 (1.58)	-0.2449*** (-3.52)	0.79
Portfolio 4	0.1309 (0.55)	0.8646*** (14.88)	0.3857** (2.27)	0.2649*** (2.78)	-0.0871 (-1.22)	0.63
Portfolio 3	0.2222 (0.91)	0.7720*** (10.95)	0.4349** (2.10)	0.1988* (1.42)	-0.2539*** (-2.25)	0.59
Portfolio 2	0.2669 (0.88)	0.7295*** (12.09)	0.4126 (1.61)	0.2944*** (2.69)	-0.0824 (-1.15)	0.48
Portfolio 1	0.2558 (0.77)	0.7532*** (9.62)	0.5595* (1.88)	0.3291*** (2.61)	-0.1611** (-2.50)	0.50

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 9: Results of Fama-MacBeth regression

Table 9 reports the results of using the Fama-MacBeth two step method. The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). R^{HIGH} defines portfolios of the 20% stocks with the highest consensus recommendation levels or upward recommendation revisions. R^{LOW} defines portfolios of the 20% stocks with the lowest consensus recommendation levels or downward recommendation revisions. Consensus recommendation levels are measured at t-1 at the beginning of each quarter. The recommendation change is defined as the difference between the consensus recommendation level of the current quarter and the quarter before (Jegadeesh et al. 2004). Panel A consists of all stocks pooled together. Panel B - F look deeper into subsets of stocks; large vs. small stocks, value vs. growth stocks, US stocks, Japanese stocks, and European stocks, respectively. t-statistics are provided in parentheses.

Panel A: All stocks: 2000m1 – 2015m12

Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-4.6368 (-1.03)	1.1066*** (4.47)	-0.0056 (-0.02)	1.1507 (0.70)	2.4377 (0.97)	-6.0301 (-0.99)	0.95
R^{LOW}	-0.0386 (-0.37)	0.5906*** (12.96)	-0.0185 (-0.31)	0.2938 (1.43)	-0.2180** (-2.34)	0.0081 (0.23)	0.87
$R^{HIGH} - R^{LOW}$	0.0176 (0.32)	0.2615*** (19.53)	-0.2570*** (-11.89)	-0.4595*** (-7.80)	0.2351*** (5.58)	0.0703*** (4.14)	0.53
Barber et al. (2001) levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-0.0335 (-0.39)	0.8262*** (67.21)	-0.1671*** (-9.02)	-0.1088 (-1.21)	-0.0463 (-1.26)	0.0256 (2.10)	0.94
R^{LOW}	-0.0344 (-0.35)	0.8226*** (68.01)	-0.1665*** (-9.09)	-0.1368 (-1.34)	-0.0579 (-1.52)	0.0263 (2.15)	0.94
$R^{HIGH} - R^{LOW}$	0.0010 (0.06)	0.0036 (1.12)	-0.0006 (-0.14)	0.0280 (2.15)	0.1167 (3.07)	-0.0007 (-0.34)	0.33
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	1.68 (1.06)	0.7830*** (8.45)	0.0480 (0.22)	-0.3354 (-0.55)	-0.7752 (-0.87)	2.2001 (1.03)	0.93
R^{LOW}	0.3722*** (5.74)	0.7377*** (26.53)	-0.0999 (-1.25)	-0.1378*** (-3.00)	-0.1397*** (-3.26)	-0.0037 (-0.14)	0.93
$R^{HIGH} - R^{LOW}$	-0.1611** (-2.60)	0.1066*** (6.37)	0.0236 (0.98)	0.1318*** (6.94)	0.1981*** (10.62)	-0.0037 (-0.37)	0.38

Panel B: Large versus Small stocks: 2000m1 – 2015m12

Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH} Large stocks	0.6087 (0.94)	0.6404*** (6.29)	-0.2857 (-1.11)	-0.2001** (-2.57)	-0.0691 (-0.32)	0.0848 (1.55)	0.92
R^{LOW} Large stocks	0.1366 (1.48)	0.7296*** (41.68)	-0.5467*** (-10.41)	-0.1619*** (-2.77)	0.0812 (1.67)	0.0447 (1.49)	0.92
$R^{HIGH} - R^{LOW}$	-0.0889 (-1.88)	-0.0020 (-0.13)	0.1059*** (7.81)	-0.0142 (-0.91)	0.0566*** (3.61)	-0.0064 (-0.64)	0.29
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH} Small stocks	1.017 (1.71)	0.8242*** (3.45)	1.5107 (1.47)	0.5652 (0.55)	0.5049 (1.23)	0.1252 (0.39)	0.81
R^{LOW} Small stocks	0.6916 (1.31)	0.6424*** (4.05)	0.8661*** (7.22)	-0.2135 (-1.03)	-0.0616 (-0.35)	-0.0458 (-0.32)	0.79
$R^{HIGH} - R^{LOW}$	-0.0889 (-1.88)	-0.0020 (-0.13)	0.1059*** (7.81)	-0.0142 (-0.91)	0.0566*** (3.61)	-0.0064 (-0.64)	0.29

Panel C: Value versus Growth stocks: 2000m1 – 2015m12

Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH} Value stocks	0.5125 (1.14)	0.7049*** (5.15)	0.5205 (1.30)	0.2580 (0.65)	-0.2914 (-1.43)	0.2320 (1.55)	0.88
R^{LOW} Value stocks	0.8474*** (3.09)	0.7069*** (6.21)	-0.1159 (-1.16)	0.2509* (1.89)	-0.3463*** (-3.52)	0.1170* (1.83)	0.89
$R^{HIGH} - R^{LOW}$	-0.2428** (-2.17)	0.1176** (2.46)	-0.0469 (-1.30)	0.3032*** (3.50)	0.0537 (1.13)	-0.0044 (-0.16)	0.29

Recommendation changes	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH} Growth stocks	0.4546	0.7253***	-0.2908**	-0.3964*	0.1870	0.0002	0.94
	(1.59)	(12.31)	(-2.40)	(-1.91)	(1.20)	(0.00)	
R^{LOW} Growth stocks	0.1829	0.8256***	-0.0569	-0.4416***	0.1112	-0.0230	0.93
	(0.88)	(9.01)	(-0.47)	(-3.08)	(1.37)	(-0.26)	
$R^{HIGH} - R^{LOW}$	0.1744**	0.0292	-0.0801***	-0.0825**	0.0533**	0.0390**	0.30
	(2.55)	(1.44)	(-2.85)	(-2.44)	(2.48)	(2.58)	
Panel D: US stocks: 2000m1 – 2015m12							
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-0.7958	1.0836***	0.1051	0.52600	0.3006	0.1416	0.95
	(-0.97)	(19.03)	(0.29)	(0.69)	(1.57)	(0.69)	
R^{LOW}	0.8494*	0.6999***	-0.0468	-0.4552	-0.5036	-0.2442	0.92
	(1.85)	(10.77)	(-0.23)	(-1.19)	(-1.53)	(1.43)	
$R^{HIGH} - R^{LOW}$	-1.4641*	0.3101***	0.1058	0.4785	0.7790***	0.2373	0.52
	(1.90)	(5.11)	(0.33)	(0.69)	(3.20)	(1.24)	
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-0.2759	1.0217***	-0.2309***	0.0361	0.3780*	0.1590*	0.96
	(-1.42)	(32.86)	(-2.85)	(0.37)	(1.84)	(1.67)	
R^{LOW}	-0.0160	0.9063***	-0.2007*	-0.0394	0.3701	0.1529	0.95
	(-0.06)	(21.46)	(-1.96)	(-0.31)	(1.42)	(1.26)	
$R^{HIGH} - R^{LOW}$	-0.8009***	0.1651*	-0.0833	0.2183***	0.1208***	0.1302***	0.40
	(-7.26)	(1.91)	(-1.12)	(2.66)	(3.62)	(4.60)	
Panel E: Japanese stocks: 2000m1 – 2015m12							
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.3236	0.8653***	-0.3597***	-0.4563***	0.1694**	0.1953***	0.81
	(1.54)	(12.99)	(-4.19)	(-3.83)	(2.09)	(3.08)	
R^{LOW}	-0.3728	0.7063***	-0.0511	0.2515	-0.1780**	-0.1233	0.79
	(-0.48)	(8.44)	(-0.53)	(1.60)	(-2.83)	(-1.07)	
$R^{HIGH} - R^{LOW}$	0.0931**	0.0508***	-0.2282***	-0.6861***	0.2652***	0.0347***	0.40
	(2.22)	(3.75)	(-11.80)	(24.02)	(15.71)	(2.84)	
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.2997	0.8919***	-0.4277***	0.0661	-0.0446	-0.0442	0.79
	(0.73)	(9.34)	(-5.40)	(0.24)	(-0.43)	(-0.38)	
R^{LOW}	-7.1154	1.1080**	-0.7918	-1.2077	2.6277	0.1187	0.79
	(-1.18)	(2.06)	(-0.99)	(-0.41)	(0.87)	(0.31)	
$R^{HIGH} - R^{LOW}$	0.0641	0.02311	0.0955	0.1164	0.3016***	-0.0275	0.34
	(0.63)	(0.78)	(1.06)	(0.96)	(12.74)	(-1.17)	
Panel F: European stocks: 2000m1 – 2015m12							
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	-0.2852	0.5381***	-0.6308*	-0.0144	-0.0844	-0.0352	0.86
	(-0.76)	(-6.26)	(-2.58)	(-0.12)	(-0.41)	(-0.09)	
R^{LOW}	0.7448	0.4127***	-0.0730	-0.0864	0.0858	0.0315	0.80
	(1.39)	(2.97)	(-0.37)	(-0.37)	(0.42)	(0.36)	
$R^{HIGH} - R^{LOW}$	-0.9778	0.1555***	-0.1180**	-0.3181***	-0.0332	0.0676***	0.37
	(-1.00)	(4.52)	(-2.47)	(-3.11)	(-0.61)	(3.07)	
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**Adjusted R^2**
R^{HIGH}	0.1576	0.7843***	-0.4311	-0.0367	-0.2023	-0.1323	0.87
	(0.90)	(5.13)	(-1.20)	(-0.23)	(-0.76)	(0.35)	
R^{LOW}	-2.5135	0.8641***	-0.0278	-1.0048	-0.1796	-0.5457	0.83
	(-0.92)	(2.89)	(-0.09)	(-0.75)	(-0.64)	(-1.01)	
$R^{HIGH} - R^{LOW}$	-0.2659	0.1013***	-0.0417	-0.0523	0.1160	0.0830**	0.33
	(-1.67)	(4.49)	(-0.41)	(-0.46)	(1.48)	(2.31)	

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 10: Coefficient estimates including investor sentiment as a risk factor

Table 10 reports the coefficient estimates including investor sentiment for the period between January 2000 and December 2015. Firstly, I report the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are shown, again using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), the liquidity factor of Pástor and Stambaugh (2003), and the investor sentiment factor from Baker and Wurgler (2003). t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**SENT**	**Adjusted R^2**
R^{HIGH}	0.0860 (0.57)	0.9412*** (19.04)	-0.3827*** (-4.50)	-0.6237*** (-6.20)	0.0685** (2.08)	0.0149 (0.71)	0.0544 (0.37)	0.87
R^{LOW}	0.3090*** (2.58)	0.6535*** (14.62)	0.0471 (0.80)	-0.0055 (-0.12)	-0.1445*** (-3.35)	-0.0190 (-0.51)	-0.0201 (-0.13)	0.77
$R^{HIGH} – R^{LOW}$	-0.2229 (-1.46)	0.2876*** (4.56)	-0.4297*** (-3.88)	-0.6182*** (-5.11)	0.2130*** (4.43)	0.0340 (0.88)	0.0745 (0.35)	0.45
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**SENT**	**Adjusted R^2**
R^{HIGH}	0.0346 (0.25)	0.8457*** (23.95)	-0.0945* (-1.74)	-0.1199** (-2.81)	0.0549 (1.26)	0.0275 (1.18)	-0.0435 (-0.22)	0.84
R^{LOW}	0.3245*** (3.38)	0.7785*** (23.89)	-0.1684*** (-2.86)	-0.2709*** (-5.32)	-0.1551*** (-2.83)	0.0348* (1.65)	0.0718 (0.44)	0.84
$R^{HIGH} – R^{LOW}$	-0.2899** (-2.28)	0.0672*** (2.67)	0.0739 (1.40)	0.1509*** (3.08)	0.2101*** (11.66)	-0.0073 (-0.33)	-0.1152 (-0.69)	0.20

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 11: Coefficient estimates of a trading strategy based on consensus recommendation levels: 2000m1 - 2015m12

Table 11 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using monthly value-weighted log returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.0062**	1.0719***					0.81
	(-2.41)	(9.96)					
R^{LOW}	-0.0011	0.7993***					0.72
	(-0.64)	(13.94)					
$R^{HIGH} – R^{LOW}$	-0.0051*	0.2726**					0.13
	(-1.75)	(2.12)					
R^{HIGH}	-0.0037**	1.0448***	0.0431	-0.5457***			0.87
	(-2.16)	(17.92)	(0.28)	(-5.84)			
R^{LOW}	-0.0027	0.8078***	0.2023*	0.2711***			0.74
	(-1.42)	(17.36)	(1.74)	(2.93)			
$R^{HIGH} – R^{LOW}$	-0.0010	0.2370***	-0.1592*	-0.8168***			0.43
	(-0.52)	(3.25)	(-1.88)	(-7.18)			
R^{HIGH}	-0.0039**	1.0627***	0.0115	-0.5305***	0.0536		0.87
	(-2.37)	(21.63)	(0.08)	(-5.36)	(1.29)		
R^{LOW}	-0.0019	0.7511***	0.3021***	0.2232***	-0.1691***		0.76
	(-1.08)	(16.73)	(3.20)	(3.03)	(-3.90)		
$R^{HIGH} – R^{LOW}$	-0.0020	0.3117***	-0.2906**	-0.7537***	0.2227***		0.50
	(-1.29)	(4.67)	(-2.25)	(-6.33)	(5.88)		
R^{HIGH}	-0.0039**	1.0576***	-0.0249	-0.5339***	0.0544	0.0560	0.87
	(-2.10)	(20.08)	(-0.16)	(-5.01)	(1.44)	(1.38)	
R^{LOW}	-0.0024	0.7429***	0.3536***	0.2546***	-0.1821***	-0.0312	0.77
	(-1.39)	(16.77)	(4.13)	(3.97)	(-4.12)	(-0.68)	
$R^{HIGH} – R^{LOW}$	-0.0015	0.3147***	-0.3785***	-0.7885***	0.2365***	0.0872***	0.54
	(-1.19)	(4.73)	(-3.70)	(-6.83)	(6.58)	(2.93)	

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 12: Coefficient estimates of a trading strategy based on consensus recommendation levels: 2000m1 - 2015m12

Table 12 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using quarterly value-weighted log returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	-0.0385** (-2.20)	2.3462*** (10.17)					0.82
R^{LOW}	-0.0071 (-1.12)	1.6966*** (20.46)					0.75
$R^{HIGH} - R^{LOW}$	-0.0314* (-1.67)	0.6495*** (2.67)					0.17
R^{HIGH}	-0.0195*** (-2.99)	2.2398*** (23.13)	0.1100 (0.56)	-1.3309*** (-6.92)			0.90
R^{LOW}	-0.0161 (-1.37)	1.6150*** (15.96)	1.1872*** (3.83)	0.3038 (1.26)			0.79
$R^{HIGH} - R^{LOW}$	-0.0034 (-0.30)	0.6247*** (3.31)	-1.0771*** (-3.11)	-1.6347*** (-4.57)			0.54
R^{HIGH}	-0.0222*** (-2.82)	2.2906*** (26.03)	0.1383 (0.65)	-1.2828*** (-5.63)	0.1645 (0.97)		0.90
R^{LOW}	-0.0085 (-0.73)	1.4767*** (22.71)	1.1103*** (4.11)	0.1730 (1.09)	-0.4474*** (-3.08)		0.82
$R^{HIGH} - R^{LOW}$	-0.0137 (-1.34)	0.8139*** (6.18)	-0.9720*** (-3.38)	-1.4558*** (-4.51)	0.6119*** (8.64)		0.64
R^{HIGH}	-0.0174 (-1.63)	2.2959*** (26.07)	0.1482 (0.77)	-1.3315*** (-6.19)	0.1897 (1.20)	-0.1135 (-0.70)	0.90
R^{LOW}	-0.0125 (-0.99)	1.4578*** (18.16)	1.1404*** (5.28)	0.2369 (1.75)	-0.4662*** (-3.31)	0.0419 (0.34)	0.83
$R^{HIGH} - R^{LOW}$	-0.0049 (-0.44)	0.8381*** (6.62)	-0.9922*** (-4.70)	-1.5684*** (-5.64)	0.6559*** (9.45)	-0.1555 (-0.96)	0.68

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 13: Coefficient estimates of a trading strategy based on consensus recommendation levels, excluding widely covered stocks: 2000m1 - 2015m12

Table 13 reports the results of the OLS regression models with portfolios constructed based on consensus recommendation levels as the dependent variable, using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels (R^{HIGH}), low consensus recommendation levels (R^{LOW}), or the difference in the returns on portfolios with high and low consensus recommendation levels (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). The sample period starts in January 2000 and ends in December 2015. t-statistics are provided in parentheses.

Panel A	Alpha	Rm-Rf	SMB	HML	MOM	LIQ	Adjusted R^2
R^{HIGH}	0.0463 (0.28)	1.0157*** (9.59)					0.79
R^{LOW}	0.2964 (1.60)	0.6734*** (14.85)					0.64
$R^{HIGH} - R^{LOW}$	-0.2502 (-1.23)	0.3423*** (2.60)					0.20
R^{HIGH}	0.2838* (1.80)	0.9921*** (15.78)	-0.0055 (-0.04)	-0.4554*** (-6.05)			0.83
R^{LOW}	0.1684 (0.75)	0.6796*** (17.44)	0.1818 (1.51)	0.1906*** (2.43)			0.65
$R^{HIGH} - R^{LOW}$	0.1154 (0.53)	0.3125*** (4.12)	-0.1873* (-1.80)	-0.6460*** (-7.09)			0.39
R^{HIGH}	0.2399 (1.38)	1.0180*** (25.15)	-0.0519 (-0.38)	-0.4349*** (-4.94)	0.0765* (1.26)		0.84
R^{LOW}	0.2035 (0.93)	0.6588*** (16.07)	0.2189* (1.82)	0.1742** (2.34)	-0.0612 (-1.68)		0.65
$R^{HIGH} - R^{LOW}$	0.0364 (0.16)	0.3592*** (5.64)	-0.2708** (-2.04)	-0.6091*** (-6.62)	0.1377*** (2.17)		0.41
R^{HIGH}	0.2153 (1.15)	1.0052*** (22.30)	-0.0903 (-0.69)	-0.4324*** (-4.85)	0.0750* (1.35)	0.0919** (3.39)	0.84
R^{LOW}	0.1868 (1.08)	0.6527*** (15.74)	0.3031*** (3.06)	0.1983*** (3.32)	-0.0746* (-2.24)	-0.1160*** (-3.11)	0.67
$R^{HIGH} - R^{LOW}$	0.0285 (0.18)	0.3525*** (6.00)	-0.3934*** (-4.37)	-0.6307*** (-8.37)	0.1496*** (2.99)	0.2079*** (5.88)	0.50

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 14: Crisis dummy measure 1: OECD Real GDP Growth

Table 14 reports the coefficient estimates including a real GDP growth dummy to define a recession or a boom period for the period between January 2000 and December 2015. When the crisis dummy has a value of 1, the economy is in a state of recession. When the crisis dummy has a value of 0, the economy experiences a boom period. Firstly, I report the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are shown, again using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), the liquidity factor of Pástor and Stambaugh (2003), and the crisis dummy. t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**CRISIS Dum=1**	**Adjusted R^2**
R^{HIGH}	0.1153	0.9398***	-0.3837***	-0.6206***	0.0692**	0.0153	-0.0377	0.87
	(0.77)	(19.41)	(-4.44)	(-5.93)	(2.05)	(0.77)	(-0.10)	
R^{LOW}	0.2350	0.6539***	0.0488	-0.0005	-0.1435***	-0.0176	0.1210	0.77
	(-0.44)	(15.48)	(0.84)	(-0.01)	(-3.45)	(-0.44)	(0.64)	
$R^{HIGH} – R^{LOW}$	-0.1198	0.2859***	-0.4326***	-0.6201***	0.2127***	0.0329	-0.1588	0.45
	(-0.38)	(4.68)	(-3.89)	(-4.91)	(4.58)	(0.81)	(-0.46)	
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**CRISIS Dum=1**	**Adjusted R^2**
R^{HIGH}	-0.0609	0.8457***	-0.0935*	-0.1161***	0.0559	0.0293	0.1567	0.84
	(-0.31)	(22.45)	(-1.82)	(-2.94)	(1.15)	(1.15)	(0.61)	
R^{LOW}	0.3805***	0.7773***	-0.1696***	-0.2684***	-0.1547***	0.0352	-0.0815	0.84
	(2.97)	(24.66)	(-2.95)	(-5.62)	(-2.69)	(1.49)	(-0.48)	
$R^{HIGH} – R^{LOW}$	-0.4414**	0.0684***	0.0761	0.1522***	0.2105***	-0.0059	0.2382	0.20
	(-2.25)	(2.82)	(1.41)	(3.36)	(12.04)	(-0.25)	(-0.98)	

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 15: Crisis dummy measure 2: Systematic Banking Crisis

Table 15 reports the coefficient estimates including a systematic banking crisis dummy to distinguish between periods of banking crisis or 'normal' periods between January 2000 and December 2015. When the banking crisis dummy has a value of 1, the country experiences a systematic banking crisis. When the crisis dummy has a value of 0, the economy of a country is in a 'normal' state. Firstly, I report the results of the OLS regression models with portfolios based on consensus recommendation levels as the dependent variable, using value-weighted returns. After that, the results of the regression models with portfolios based on recommendation revisions as the dependent variable are shown, again using value-weighted returns. The dependent variable R refers to excess returns on portfolios with either high consensus recommendation levels/upward recommendation changes (R^{HIGH}), low consensus recommendation levels/downward recommendation changes (R^{LOW}), or the difference in the returns on portfolios with high levels/upward and low levels/downward recommendation changes (R^{HIGH} - R^{LOW}). The portfolios are rebalanced quarterly and are regressed on the market, size, and book-to-market factor from Fama and French (1993), the momentum factor from Carhart (1997), the liquidity factor of Pástor and Stambaugh (2003), and the crisis dummy. t-statistics are provided in parentheses.

Consensus recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**CRISIS Dum=1**	**Adjusted R^2**
R^{HIGH}	-0.1610 (-1.49)	0.9436*** (19.50)	-0.3742*** (-4.29)	-0.6095*** (-6.16)	0.0724** (2.15)	0.0188 (0.85)	0.3648* (1.83)	0.87
R^{LOW}	0.2448 (1.24)	0.6554*** (15.03)	0.0509 (0.90)	-0.0046 (-0.12)	-0.1442*** (-3.52)	-0.0192 (-0.48)	0.0866 (0.37)	0.77
$R^{HIGH} – R^{LOW}$	-0.4058** (-1.98)	0.2881*** (4.74)	-0.4251*** (-3.80)	-0.6050*** (-5.02)	0.2166*** (4.70)	0.0380 (0.88)	0.2783 (1.25)	0.45
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**LIQ**	**CRISIS Dum=1**	**Adjusted R^2**
R^{HIGH}	-0.1832 (-0.78)	0.8498*** (23.01)	-0.0858 (-1.47)	-0.1165*** (-2.60)	0.0565 (1.31)	0.0287 (1.16)	0.3056 (1.06)	0.84
R^{LOW}	0.5540*** (4.28)	0.7735*** (23.66)	-0.1777*** (-3.19)	-0.2721*** (-6.08)	-0.1563*** (-2.70)	0.0343 (1.37)	-0.3166* (-1.92)	0.84
$R^{HIGH} – R^{LOW}$	-0.7372*** (-3.07)	0.0763*** (3.49)	0.0918* (1.85)	0.1556*** (4.62)	0.2128*** (11.72)	-0.0055 (-0.23)	0.6222** (2.55)	0.22

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*

Table 16: Distinguishing between high, medium, and low investor participation countries: 2000 - 2015

Table 16 reports the coefficients for the Carhart four factor-model when distinguishing between high, medium, and low investor participation countries. The data regarding the level of investor participation of a country are retrieved from Giannetti and Koskinen (2010). All countries, except Spain, are included. For both trading strategies based on analyst recommendation levels as analyst recommendation revisions the coefficients are reported. The sample period is from January 2000 to December 2015. t-statistics are provided in parentheses.

High Investor Participation Countries						
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	-0.3863 (-1.19)	0.7420*** (10.32)	-0.6355*** (-3.13)	-0.2171 (-1.21)	-0.0721 (-0.83)	0.41
R^{LOW}	0.5394** (2.03)	0.4598*** (6.07)	0.0487 (0.19)	0.1010 (0.90)	-0.0954 (-1.62)	0.30
$R^{HIGH} – R^{LOW}$	-0.9257** (-2.14)	0.2822*** (3.25)	-0.6842* (-1.76)	-0.3181 (-1.28)	0.0233 (0.23)	0.08
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	0.2350 (1.03)	0.7569*** (11.63)	-0.3302* (-1.95)	-0.3755*** (-4.17)	0.1310* (1.79)	0.53
R^{LOW}	-0.0198 (-0.06)	0.7037*** (12.27)	-0.2349 (-1.29)	-0.0984 (-1.09)	-0.0637 (-1.13)	0.53
$R^{HIGH} – R^{LOW}$	0.2548 (0.65)	0.0531 (0.52)	-0.0953 (-0.31)	-0.2772* (-1.77)	0.1946*** (2.70)	0.04
Medium Investor Participation Countries						
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	-0.4421 (-1.45)	0.8317*** (9.39)	0.1743 (1.02)	-0.1342 (-0.98)	0.1368 (1.61)	0.47
R^{LOW}	0.1994 (0.64)	0.5723*** (7.98)	0.5388** (2.29)	0.2166* (1.75)	-0.0850 (-1.16)	0.32
$R^{HIGH} – R^{LOW}$	-0.6415** (-2.15)	0.2595*** (3.51)	-0.3645** (-2.01)	-0.3508** (-2.17)	0.2219* (1.72)	0.16
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	-0.1354 (-0.38)	0.8164*** (12.32)	0.4728*** (3.26)	0.0404 (0.34)	0.1281** (2.35)	0.45
R^{LOW}	0.2245 (0.82)	0.6819*** (8.12)	0.4605*** (2.92)	0.0245 (0.20)	-0.1493*** (-2.77)	0.44
$R^{HIGH} – R^{LOW}$	-0.3598 (-1.57)	0.1344** (2.02)	0.0123 (0.08)	0.0159 (0.13)	0.2774*** (4.66)	0.07
Low Investor Participation Countries						
Recommendation levels	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	0.0969 (0.66)	0.9721*** (16.22)	-0.4561*** (-4.85)	-0.6468*** (-6.89)	0.0815** (2.17)	0.85
R^{LOW}	0.3007*** (3.17)	0.7391*** (15.63)	-0.1342 (-1.46)	-0.0186 (-0.34)	-0.1848*** (-3.57)	0.80
$R^{HIGH} – R^{LOW}$	-0.2038* (-1.72)	0.2331*** (2.60)	-0.3219* (-1.90)	-0.6281*** (-5.20)	0.2663*** (4.80)	0.36
Recommendation changes	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**MOM**	**Adjusted R^2**
R^{HIGH}	0.2170* (1.94)	0.9165*** (26.28)	-0.2882*** (-4.06)	-0.1290** (-2.21)	0.0423 (0.76)	0.85
R^{LOW}	0.5269*** (3.07)	0.8645*** (21.70)	-0.2164*** (-2.73)	-0.3842*** (-5.64)	-0.1822** (-2.51)	0.83
$R^{HIGH} – R^{LOW}$	-0.3098 (-1.45)	0.0521* (1.92)	-0.0718 (-0.74)	0.2552** (2.47)	0.2245*** (5.79)	0.14

**significant at the 10%-level; **significant at the 5%-level; ***significant at the 1%-level*