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Do Analyst Recommendations Yield Profitable Trading Strategies?

- Evaluation of Analysts Covering European Stocks

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In addition to evaluating the performance of security analysts covering stocks traded on the European bourses we investigate the existence of any profitable trading strategies based on the same analysts' recommendations. The performance is analyzed by forming portfolios (rebalanced weekly) based on the consensus recommendations for each covered company during the period January 1st 2001 to December 31st 2005. The returns earned from each portfolio are further evaluated against both market returns and a constructed benchmark consisting of value weightings of the stocks within the sample. In order to measure the impact of trading, and hence the cost of following the advice given by analysts, we also record each portfolio's annual turnover. The recommendations of analysts are evaluated for robustness over time and across different market conditions. Efforts are made to prosper from the recommendations as an investor by constructing trading strategies. Additionally attempts to mitigate transaction costs are made in order to improve the net returns from the trading strategies. Our obtained results suggest that stock recommendations issued on European companies generate investment value but the costs inflicted by following the recommendations diminish the net returns. Using derivatives mitigates the costs inflicted by the high turnover which the strategies generate but fail to yield positive net returns.

Keywords: stock analyst, stock recommendation, analyst performance, trading strategy

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1. INTRODUCTION

1.1 BACKGROUND

Is there any substance in trading on stock market analysts' recommendations or are they just a means of the brokerage houses to inflict more frequent trading? In the academic world of finance the efficient market hypothesis is widely accepted. Under the semi-strong form no investor should with publicly available information be able to get returns larger than the market return unless she takes on a larger portion of risk. On the other hand brokerage houses whose business is to evoke trades among their clients spend large amounts on analyses of stocks. It is in their interest to spread the image that an investor can get abnormal returns by pursuing an active strategy. In this study we investigate if the work of analysts actually has value for an investor in European stocks. Can she by trading actively on the recommendations from the analysts get returns higher than the market portfolio? If so, will this be profitable even after paying for these recommendations in the form of commission and potential other costs?

Several studies have been done in this area starting back in 1933 with Cowle's study that was performed during the depression. He did not find any evidence that analysts have forecasting abilities. In more recent studies the results are mixed. Stickel (1995) finds that there is value in analyst recommendations and that some brokerage houses even have the ability to move the stock prices themselves thereby creating a self-fulfilling recommendation.

1.2 PURPOSE AND CONTRIBUTION

The purpose of this paper is twofold; to investigate whether the recommendations of the analyst collective focusing on stocks denoted in Euros are able to separate the high performers from the low performers. Secondly we will investigate if these recommendations can be used for constructing trading strategies that actually are profitable after all commensurate costs for trading are taken into account.

Previously the value of analyst recommendations has been researched for mostly U.S.- data but also for the G7-countries (Jegadeesh 2006) as well as for single countries (for example Cervellati 2005). The contribution of this paper is firstly to study data for the Euro zone. Secondly we take trading costs as a critical factor and explore different ways of reducing them. We determine whether the surplus value analysts are able to detect can be reaped in reality, thereby violating the semi-strong form of the efficient market hypothesis.

1.3 Results

Our findings show that analyst recommendations actually contain valuable information about which stocks to buy and which stocks to sell. The cumulative return for the most favorably recommended stocks in our sample is nearly 80 percent compared to 55 percent for the least favorably recommended stocks. To take advantage of this heavy trading is needed which brings with it heavy transaction costs. After subtracting these from the possible trading strategies no abnormal returns are to be found.

1.4 Outline

This paper is structured in the following way. In section two, we give an overview of previous research performed within the area of analysts' recommendations and their ability to add investment value. Section three describes the data used while the method of research is described in section four. Section five examines the return characteristics of the portfolios formed during differing market periods. An attempt to capture the value of analysts' recommendations is enclosed in section six where the effects of costs entailed are examined in particular. A conclusion of our findings ends the paper in section seven.

2. Theoretical Framework

2.1 Analyst Recommendations

As mentioned in the introduction there has been a fair amount of research regarding stock analysts and their recommendations. Stickel (1995) finds that when a brokerage house changes its recommendation for a stock to “buy”, the average abnormal return over the following 11 business days is 1.16 percent for stocks listed on the NYSE and Amex. The corresponding negative return for a sell recommendation is -1.28 percent. On a more detailed level the article finds that changes to “strong buy” or “strong sell” have greater price impact than other positive or negative revisions. Changes in recommendations that skip a rank also have a larger impact. Recommendations from brokerage houses that have a better reputation than others as well as recommendations from large firms are found to have a larger price impact. All these changes have a temporary price effect. The stock price reaction for smaller firms is greater than that of larger firms. If the recommendation change is accompanied by a revision of the earnings forecast in the same direction, the price effect is larger. The last two effects are found to be of a permanent nature.

Womack (1996) analyzes a sample of 1,573 analysts’ recommendation changes, issued between 1989 and 1991, with respect to 822 companies, listed on the US stock exchange. The study utilizes the information contained in the database of First Call Corporation (now Thomson Reuters), a company that records all reports issued by analysts. The empirical evidence shows that the stocks subject to a recommendation change records an abnormal return significantly different from zero: positive (+ 2.4 percent) in case of an upgrade, negative (- 9.1 percent) in case of downgrade. The asymmetry between the two values can be explained with the greater frequency with which analysts tend to issue upgrades and with the greater cost of issuing a negative report. Several cases are known both in the academic literature and in the financial press of analysts that have been excluded from informative meetings or that have not received relevant information from the management of a company on which they issued a negative recommendation. Thus, an analyst faces a trade-off between the need of issuing reports that are reliable, to defend her reputation, and the necessity to maintain good relationships with the management of the covered companies. The empirical results clearly show that stock prices and volumes are influenced by recommendation changes. The author highlights that analysts are particularly good at stock picking but also in market timing; however they mostly issue positive reports and focus on companies with higher market capitalization.

Jegadeesh et al. (2002) find that buying the stocks with the highest recommendations and selling the stocks with the lowest recommendations earns 2.3 percent over the next six months. The authors find that the analyst recommendations do not have incremental information. Consistent with Womack (1996) they find that the change of a recommendation is a more robust indicator of future returns. The level of analysts' recommendations derives its predictive power largely from a tilt towards high momentum stocks. After controlling for the return predictability of other signals, the marginal predictive ability of the level of an analyst's recommendation is not significant. They also show that analysts fail to quickly downgrade stocks rejected by the other investment signals. For stocks where the other signals predict low future returns, they find that favorably recommended stocks actually significantly underperform unfavorably recommended stocks. For this subset of stocks, favorable analyst recommendations may temporarily support prices and delay the eventual incorporation of information into stock prices. However, within the subset of stocks where other signals predict high future returns, stocks favorably recommended by analysts outperform stocks unfavorably recommended by them. Further, upgraded stocks outperform downgraded stocks. The tests show that the predictive power of changes in analysts' recommendations is more robust than the predictive power of the level of their recommendations. Specifically, the recommendation changes add value to characteristic-based investment strategies that include 12 other predictive variables. Further analysis shows that the superior performance of recommendation changes is due largely to the fact that recommendation changes are less affected by a growth bias. Prior studies comparing the earnings forecasts and stock recommendations of analysts from affiliated and unaffiliated firms (e.g., Lin and McNichols (1998) and Michaely and Womack (1999)) show that existing, and potential, investment banking relationships can affect analyst judgment. The results indicate that the economic consequences of sell-side incentives that impair analyst objectivity can also extend to the type of the stocks they choose to recommend. Specifically, the findings suggest that analysts' recommendations may be partly driven by incentives that are not entirely related to the investment performance of their recommendations

Desai and Jain (1995) examine the performance of common stocks recommended by so called "superstar money managers" who are invited to the world leading business publication Barron's "Annual Roundtable" (Desai & Jain (1995)). The authors reach the conclusion that buy recommendations earn statistically insignificant abnormal returns decreasing from 0.33 percent to -0.71 percent over holding periods of 25 days to 750 days respectively following the publication day. Overall, their findings suggest that the so-called "superstar" money managers do not manage to generate abnormal returns on average suggesting that buy recommendations lack investment value. When the authors examine the performance of sell recommendations on the other hand, they find that those earn an abnormal return of -8.12 percent on average. This is somewhat contradictory to the performance of the issued buy recommendations, suggesting that money managers only have skills in making sell recommendations. These results could partly be explained by analysts being reluctant to issue sell recommendations unless they have substantial evidence supporting their case. It should also be pointed out that only 9 percent of the recommendations given by the money managers at the “Roundtable” were sell recommendations suggesting that the evidence of their over performance is less general than perhaps as with the results from the buy recommendations. Similar results are obtained by Stickel (1995) and Womack (1996).

In contrast to Desai & Jain (1995) Barber et al. (2001) examine whether investors can profit from the publicly available recommendations of security analysts and arrive at the conclusion that both buy and sell recommendations generate abnormal returns. They further construct portfolios numbered 1-5 according to the average consensus recommendation for each covered stock. Portfolio 1 represents stocks with a strong buy recommendation while portfolio 5 represents those with a strong sell recommendation. They re-balance their portfolios on a daily basis in order to incorporate changes in stock recommendations. The authors confirm the fact that analysts are reluctant to issue sell recommendations as 47.1 percent of the total represent buy recommendations while only 6.3 percent are sell recommendations, which confirms the pattern observed by Desai & Jain (1995). A possible explanation for the pattern is that larger financial institutions do not want to risk losing firms as future investment banking clients as a result of an issued sell recommendation. The authors conclude that the most highly recommended stocks have an average annual abnormal return of 4.2 percent while the portfolio with the least recommended stocks earned an average annual abnormal return of -7.6 percent, after controlling for size and book-to-market effects. Thus buying the most highly rated stocks and selling short the least highly rated ones yields an abnormal return of 11.8 percent annually, gross of transaction costs. However, pursuing such a strategy requires frequent trading activity which will generate substantial costs due to the bid-ask spreads and commission to brokers. They find that the minimal annual cost of the trading conducted in portfolio 1 is 4.56 percent and similarly 4.76 percent for portfolio 5. This results in a total annual transaction cost from running the trading strategy of 9.32 percent, compared to the annual abnormal gross return of 11.8 percent. The authors trading strategy yields approximately 2.5 percent net of transaction costs.

The technique of consensus-based portfolios is also used by Boni and Womack (2003) who examine the competition between analysts. To add value to the recommendations, analysts specialize in the study of a few stocks. The period considered is 1996 to 2001. This work highlights that the returns achievable through strategies based on their reports and on changes of recommendations, record a Sharpe ratio that is five times greater than the one associated with a “price momentum” strategy. In particular, a strategy consisting of buying stocks that have been upgraded and selling stocks that have been downgraded is able to generate a monthly return of 1.4 percent, about 18 percent per year. After a month from the change of recommendation, the returns from the stocks recommended by analysts are positive for 53 firms out of 59. Analysts' competition reduces the opportunity to profit from changes of a recommendation: portfolios formed with stocks which have a large number of analyst recommendations generate lower returns.

In conclusion Todd and McKnight (2006) study stock price reactions to analyst forecast revisions on European data. They find that a portfolio consisting of the quintile of the stocks that have been the most heavily upward revised outperforms a portfolio consisting of the quintile of the stocks with the lowest revision values by more than 16 percent per year. In the study trading costs have not been taken into account which the authors believe is the reason that the possibility of creating a profitable trading strategy from their findings exists. They find the firm size effect and book-to-market effect presented by Fama and French (1992) to hold even for European data.

2.2 Transaction Costs

There is also the necessity to consider the costs associated with trading stocks. Barber et al. (2001) conclude that high trading activity is needed if the returns are not to be diminished which in turn generate substantial costs. Similarly Jegadeesh et al (2002) find that holding a position for 6 months and rebalancing thereafter reduces the return from a similar strategy to theirs substantially. In addition Dimson & Marsh (1984) find that although analysts might be able to generate excess returns gross of fees through their issued stock recommendations, they might not be able to generate excess return significantly different from zero net of fees.

Transaction costs encompass the *bid-ask spread*, *commission fees* charged by brokers and the *market impact of trading*. Barber et al. (2001) estimate the total round-trip costs for the bid-ask spread of 0.7, 1.9, and 4.1 percent for Large-, Medium- and Small Cap stocks respectively based on estimates from Keim & Madhavan (1998). This cost structure suggests that for every 100 percent increase in turnover, annual market adjusted return drops by about 1 percent.

Fleming, Ostdiek & Whaley (1996) find that the derivative markets offer investors an opportunity to trade at substantially lower costs than trading directly in the stock market, hence futures lead a comparable stock basket in market reaction. The cost of trading S&P 500 futures is merely 3 percent of the cost of trading an equivalent stock portfolio. Additionally for positions with similar risk/return characteristics, the direct trading costs in the S&P 100 option market are more than four times higher than in the S&P 500 futures market. Thus including index futures in a trading strategy would be a way of reducing transaction costs. The authors compare the total direct trading costs for the different alternatives used to establish a long position of USD 25 million in the S&P 500 index. The first alternative is buying a basket of the stocks composing the S&P 500 index which results in total roundtrip trading costs of USD 139,500 or 55.8 basis points. In contrast S&P 100 index option trading results in substantially reduced costs. An investor can create a synthetic long stock position by buying calls and selling puts with the same strike price and expiration and then buying T-bills. The total round trip costs for establishing the USD 25 million dollar position is then USD 20,700 or 8.3 basis points. Buying S&P 500 index futures reduces transaction costs to USD 4,510 or 1.8 basis points in order to establish the equal position. The comparisons only take direct trading costs in to account, but including costs of market impact would not alter the conclusions according to the authors. Index futures and options markets are highly liquid so the large direct trading costs advantages are not mitigated by market impact.

2.3 Hypothesis

Following the review of previous research within the field leads us to pose two hypotheses regarding the results we expect to find.

Hypothesis 1: Analysts' recommendations add value to an investor, i.e. separate high performing stocks from low performers.

Hypothesis 2: After adjusting for costs of trading the returns of the plausible trading strategies will diminish consistent with the efficient market hypothesis.

3. DATA DESCRIPTION

3.1 INTRODUCTION TO THE DATA

The sample consists of the stocks making up the DJ EURO STOXX Euro Zone index as of October 20th 2008. We will use data from Thomson Reuters on consensus figures covering the years 2001 to 2005 to perform our study. The consensus figures are for each stock the average of the analyst recommendations. The different types of recommendations are all assigned a number which is described in greater detail in chapter four.

3.2 REPORTING OF ANALYST RECOMMENDATIONS

The data comes from the databases Thomson Reuters Datastream and First Call. First Call is broker-sourced and provides research, earnings estimates and analyst recommendations. Thomson Datastream is more oriented towards company data. The covered period is the five years 2001 throughout the full year of 2005. All the data has been recorded on a weekly basis. All the recommendations and other data types are from the first business day of each week.

The extensive databases of Thomson Reuters cover many data types. Among these are the time series we have selected for this paper: Analyst Consensus Recommendations (RECCON), Market Values (MV) in million Euros, Price-to-Book Values (PTBV), Total Return Indexes (RI) and number of EPS estimates (F##NE).

In total more than 700 brokerage firms report recommendations to the First Call database which covers more than 21,500 companies worldwide. The Datastream database covers about 80,000 active stocks. A vast majority of the world's equity research houses provide their estimates to the databases why there is no reason to doubt the quality of the data. In this study only companies that have a wide analyst coverage are included which adds to our conformability with the data.

The analyst recommendations are converted into the scale shown in Table I before added to the database. Institutional buy-side analysts can get access to individual analyst's recommendations. The same is true for the brokerage house where the analyst is employed. All other users only have access to the average of all analysts' recommendations. In the case analysts use another scale than a 1-5 scale, for example a 1-3 scale with the steps ("Sell", "Hold", "Buy") it is converted into the 1-5 scale. The conversion is made by the brokers themselves in a way they find appropriate.

TABLE I. RECOMMENDATION AND THEIR ASSIGNED NUMBERS

The table shows the numbers that are associated with each recommendation in the Thomson Reuters database.

Recommendation	Number
Strong Buy	1
Buy	2
Hold	3
Reduce	4
Sell	5

The databases have automatic filters that alert the administrators if an estimate is posted that is very different from the previous estimates. The analyst report to Thomson Reuters and then the public databases are updated at different time intervals. I/B/E/S data is typically updated every 3rd Thursday of the month whereas more frequent data such as analyst recommendations is updated once a week. This might have a small delay effect on the returns from our portfolios. Clients at the individual brokerage houses might get the data quicker which could make our tests less powerful. A stock recommendation in these databases is valid for 180 days. If it is not changed during this period it is removed.

Many of the companies in our sample are listed on more than one stock exchange. Some are listed both on “Deutsche Börse” and on “NYSE”. For some symbols this implies multiple listings in the database with different values in the downloaded time series. In this paper we use only stocks denominated in Euros. For the euro-denominated companies we have not found any time-series that diverge from the ones used[1].

[1] Information about the databases was provided by the Thomson Reuters London helpdesk.

TABLE II. DESCRIPTIVE STATISTICS FOR THE WHOLE SAMPLE

The number of covered firms is the number that at the start of each year has at least one recommendation outstanding. The mean and median figures over analysts per covered firm are also computed at the start of the year. The last column shows the average rating of all covered firms at the start of each year.

	Number of covered firms	**Analysts per covered firm**		**Average Rating**
		Mean	Median	
2001	195	15.59	13	2.36
2002	212	10.01	13	2.48
2003	216	12.27	14	2.53
2004	221	14.89	14	2.56
2005	229	15.53	15	2.56
Mean	214.60	13.66	13.80	2.50

4 METHOD

4.1 PORTFOLIO CONSTRUCTION

The stocks will be grouped according to the average consensus numbers found in

Table I. The average consensus values, $\bar{A}$, are computed as the sum of all outstanding recommendations for each company, *i*, at time *t* divided by the number of recommendations for company *j* = 1 to n_{it}. Formally this is written as:

$$\bar{A}_{it} = \frac{1}{n_{it}} \sum_{j=1}^{n_{it}} A_{ijt} \qquad (1)$$

The group limits that will be used are found in Table III.

TABLE III. PORTFOLIO GROUPING

The portfolios will be grouped according to the consensus recommendations with the following limits. "CONSREC" refers to the consensus recommendation numbers that have been downloaded from the database.

Portfolio	Limits in consensus number		
1		CONSREC	<= 1.5
2	1.5 <	CONSREC	<= 2
3	2 <	CONSREC	<= 2.5
4	2.5 <	CONSREC	<= 3
5	3 <	CONSREC	

The stocks are grouped in this way in order to draw conclusions whether a certain consensus number has explanatory power for future returns. A consensus-number lower than 3 means that the average analyst recommendation is "buy". These stocks are grouped in 4 different portfolios in order to get a high differentiation among the degree of "buy"-recommendations. For the rest of the stocks the consensus recommendation is to "hold" or "sell". These stocks are all in the same group due to the small number of stocks that receive these unfavorable recommendations. The stocks will also be grouped into quintiles and returns will be measured from these. This will in contrast to the other grouping result in portfolios with the same number of stocks in them but with no set consensus recommendation in each portfolio.

4.2 BENCHMARKS

4.2.1 MARKET PORTFOLIO

A market capitalization weighted average of the returns of 10 European country portfolios is used as a proxy for the market portfolio in the CAPM regressions. This index is also used when comparing returns to that of the market as a whole. When weighting the portfolios, the EAFE-weights used by Morgan Stanley in constructing their benchmark indexes were employed. The country portfolios were those of Austria, Belgium, Switzerland, Germany, Spain, France, Great Britain, Ireland, Italy and the Netherlands. This data has been downloaded from Kenneth French's homepage. By using this as a proxy for the market we aim to capture a broad market risk for European stocks. The index is inclusive of dividends. For the rest of this paper, this index will be referred to as the market portfolio.

4.2.2 BENCHMARK INDEX

The stocks included in our sample are the 319 stocks that as of October 20th, 2008, made up the Dow Jones EURO STOXX Euro zone index. This index contains large- mid- and small cap-companies from 12 Euro zone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The index is a broad and liquid subset of the DJ STOXX 600 index. The constituent stocks all have many analysts following each company. This will add to the comparability between companies' consensus estimates. We construct a market value-weighted benchmark index consisting of all the stocks in our study. The return from the index, R_{xt}, is each stock's weight at the last rebalancing times the returns of the next period. Formally it is written:

$$R_{xt} = \sum_{i=1}^{319} w_{i(t-1)} R_{it} \qquad (2)$$

Where $w_{i(t-1)}$ is the weight of stock *i* at time *t-1*. It corresponds to the fraction of stock *i*'s market value to the sum of the market values of the *n* stocks in the benchmark at time *t-1*. Formally:

$$w_{it} = \frac{MV_{it}}{\sum_{i=1}^{n} MV_{it}} \qquad (3)$$

This index will for the rest of this paper be referred to as the benchmark index.

4.3 PERFORMANCE EVALUATION

Returns will be measured and compared as cumulative abnormal returns, CAR, and we will test for alphas according to CAPM.

$$CAR = \sum_{t=1}^{T}(R_{it} - E(R_{it})) \qquad (4)$$

The CAPM regression:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p\left(R_{mt} - R_{ft}\right) + \varepsilon_p \qquad (5)$$

where

$R_{ft} =$ the return of an investment at EURIBOR at week t

$\alpha_p =$ the intercept from the CAPM regression, known as Jensen's alpha

$\beta_p =$ the estimation of the market beta

$\varepsilon_p =$ the error term from the regression

If we find significant alphas for any portfolio it will indicate analysts' recommendations have value and that an investor will be able to achieve returns in excess of the market-return. The beta values show how much market risk there is for each of the portfolios. A higher value for any of the portfolios shows that the stocks with that particular recommendation covary to a larger extent with the market and vice versa.

Portfolio rebalancing will be made on a weekly basis i.e. stocks are assigned a portfolio number at the start of each week. If this portfolio number is different than the week before, the stock is moved to the portfolio that contains stocks carrying consensus ratings in the same range. By doing this on a weekly basis, trading costs will be kept at a lower level than by rebalancing daily. Thereby we aim to increase the possibility of finding a trading strategy that will be profitable taking trading costs into account. Barber et al (2001) find that a trading strategy under which the portfolios are rebalanced daily does not yield a return higher than the risk free rate due to trading costs. As trading will be active in order to keep the portfolios intact with analysts recommendations´, attempts will be made to reduce trading further. The resulting returns from the portfolio grouping will be the starting point in creating these strategies aimed to reduce transaction costs.

We will test the null hypothesis that the abnormal returns for "buy"- and "sell"-recommended stocks are different from zero. The regressions will be run on a monthly basis. Due to economic incentives analysts tend to recommend stocks that have performed well in the past and show certain characteristics (high growth-companies, stocks with a high trading volume and that are relatively expensive) (Jegadeesh et al 2002). To test this, a zero investment momentum portfolio will be formed. The return will be that of the equally-weighted 30 percent of the stocks with the lowest price momentum during the last nine weeks subtracted from the return of the equally weighted 30 percent of the highest price momentum stocks. This variable will be included in the regressions. We will also include the Fama and French risk factors, i.e. the portfolios Small minus Big (SMB) and High minus Low (HML) to a four-factor model in order to see if the analysts prefer small companies to large ones or if they tend to recommend firms with a high book-to-market value ratio. HML is computed by using data from Kenneth French' homepage on the return from European stocks sorted according to their book-to-market ratio. HML is computed by subtracting the returns of the stocks with a lower book-to-market ratio than the 30th percentile from the returns of the stocks with a higher book-to-market ratio than the 70th percentile. The SMB risk factor is obtained using data from the stocks making up the broad DJ EURO STOXX 600-index. SMB is for each week going to be computed by subtracting the returns of the stocks that are larger than the median firm size from the returns of the companies that are smaller than the median firm size for every week. Both the HML and the SML are computed using equal weights in the portfolios.

We will check if the results are robust over sub periods. The tests and regressions will be run on the first half of the period and the second half of the period individually. We will also compare returns in periods with rising prices and in periods with falling prices. Months in which the market portfolio is rising will be sorted as bull market months and months with a falling benchmark index will be sorted as bear market months.

Further, it will be investigated whether it would be possible to create profitable trading strategies taking trading costs into account. As a first step we will form long legs consisting of the stocks in groups 1-4, with consensus recommendation between 1 and 3 and stocks in group 1-2 with a consensus recommendation between 1 and 2. The reason for choosing these groupings is that we want to use the stocks that carry a "buy" recommendation on average (portfolio 1-4) as well as the stocks the most favorably recommended on their own. The latter are found in portfolio number one, but as it has a very low mean number of stocks in it we add the stocks in portfolio number 2 (Table IV).

The short leg will be formed from the stocks with consensus recommendation 3-5, i.e. from the stocks carrying an average recommendation of "hold" or lower. The value of the portfolios will after each rebalancing be the same of the long legs and the short legs which gives a zero net investment. This implies that in the first strategy the weights of each long portfolio will be 0.5. In the second strategy the weights will for each long portfolio be 0.25.

TABLE IV. TRADING STRATEGIES.

The construction of the legs in the two trading strategies.

Strategy	**Buy**	**Sell short**
1	0.25 x Portfolios (1+2+3+4)	Portfolio 5
2	0.5 x Group (1+2)	Portfolio 5

For comparisons weekly Sharpe ratios, S, for the returns will be calculated as below.

$$S = \frac{R_S}{\sigma_{R_S}} \qquad (6)$$

Where

$R_s =$ Return from strategy s, i.e. the return from the long position less the return from the short position.

$\sigma_{Rs} =$ volatility of the return of strategy s

The weekly Sharpe ratio will be annualized by multiplying the strategy return by 52 and the strategy standard deviation by the square root of 52. This will be compared to the Sharpe ratio of the market return.

4.4 TURNOVER

Rebalancing of the portfolios sorted by consensus recommendations will be made every week. The portfolios will be equally weighted. Brokerage commissions will be calculated by multiplying the portfolio turnover by a fixed percentage fee. The portfolio turnover, PT, will be calculated at each rebalancing as the sum of the absolute value of the differences between 1, the weights of each stock in a portfolio after the rebalancing at *t-1* plus the return from that stock during the time period between *t-1* and *t* and 2, its weight after rebalancing at time *t*. As the portfolios will be equally weighted the weight for stock *i* at time will be:

$$w_{it} = \frac{1}{n_{pt}} \qquad (7)$$

Where $n_{pt}$is the number of stocks in portfolio p at time t.

At each time *t* the portfolio is rebalanced and the turnover is equal to:

$$PT_{pt} = \sum_{i=1}^{n_{p,t}} |w_{it-1}(1 + R_{it}) - w_{it}| \qquad (8)$$

4.5 FURTHER ANALYSIS

Stickel (1995) and Logue (1986) discuss the price impact of resources spent on marketing of the analyst recommendations and the number of recommendations a brokerage house has for a stock outstanding, i.e. the price impact caused by trading on the recommendation itself. We will use the total number of recommendations for each stock as a proxy for how much marketing resources that are spent by brokerage houses. With these numbers we will check if returns are related to the number of estimates. The idea is that many estimates imply many analysts following a company. The more analysts following a company the more clients will be encouraged to act on a recommendation change for a stock thereby causing a larger price reaction. The following steps will be taken: 1, the average number of estimates, *e*, for the whole sample is calculated. 2, for each week a ratio, *q*, of each of the portfolios average number of estimates to this average is calculated. We will test the null hypothesis that the correlation between the weekly reading of this ratio and the weekly returns is zero.

$$\rho_{eq} = \frac{cov_{eq}}{\sigma_e \sigma_q} \qquad (9)$$

The return used is going to be the abnormal return. This implies that if we find a negative correlation for the “sell”-recommendations and/or a positive correlation for the “buy”-recommendations a relationship exists.

4.6 DESCRIPTIVE STATISTICS

In our dataset, Table V shows that the average number of firms differs across the portfolios. The first portfolio has a very low mean of 1.87 firms per week which makes the significance of the performed tests low for that group. The low number of firms reflects the fact that it is very hard for a firm to get an average number below or equal to 1.5. Barber et al find that for a firm to get into the first group it needs to be relatively small and have few analysts covering them. This study is based on a smaller sample with firms that are more similar to each other in terms of number of analysts per firm and market capitalization. We believe this is the reason for the low number of firms within this group.

Even though the companies in our study are more similar to each other in the above mentioned way we can see these tendencies in our sample as well as the first portfolio has the lowest mean number of stocks and the lowest market capitalization. For the other portfolios the average number of stocks is lower for portfolio 2 (18) and portfolio 5 (28.74) than for portfolios 3 and 4 (76.26 and 66.37). As these two groups are the largest in terms of number of firms this means that the majority of the ratings are found close to the sample mean (2.5) because this is the average consensus recommendation between the group limits of these groups. Without running any tests we see that the consensus recommendations are fairly normally distributed.

The HML and SML portfolios are factors that have shown to yield higher returns in past studies (Fama and French 2007). Table V shows that analysts for the stocks with the average recommendation “Strong buy” do not show a tilt towards any of the these factors. Nor is their return similar to that of momentum stocks. This contrasts the findings of Jegadeesh et al (2002). However, for the almost as favorably recommended stocks in portfolio 2 the regressions indicate that this portfolio contains growth stocks and the least favorably recommended stocks in portfolio 5 have returns similar to that of large companies. Consequently the latter is also the portfolio with the largest mean market value.

In our sample the stocks are homogenous in terms of market value why the analysts tilt towards small stocks, consistent with the findings in Barber et al (2001), is not found here except for portfolio 3. The returns for portfolios 2-5 all have a negative relationship to stocks having had a high return in the past. This can be seen by looking at their coefficients on our momentum portfolio which are all significant and negative. The implication is that stocks with a consensus recommendation less favorable than that corresponding to portfolio 1 have returns that are different from those of stocks that have performed the best in the last 9 weeks. Thus, stock market analysts are not shown to not have a tilt towards high momentum stocks contrary to the Jegadeesh et al findings. Rather stocks having performed poorly (which outperform the past winners) in the past dominate all portfolios except for number 1.

TABLE V. DESCRIPTIVES FOR THE PORTFOLIOS FORMED

The weekly average number of firms throughout our sample period is shown when stocks are grouped according to their consensus number. The third column shows the per week average firm market value in each group in million Euros. Column 4 shows the weekly average number of analysts per company on a group basis. Column number 5 shows the average rating within each group. Column 6 shows the coefficient on the momentum portfolio followed by the t-value from the regression in parenthesis. The coefficient is followed by *,,*** for significance on the 1%, 5%**

and 10% level respectively. Columns 8 and 9 show in the same fashion the coefficients for the SMB-, and HML-portfolios. The last column shows the adjusted R-square from the four- factor model regressions.

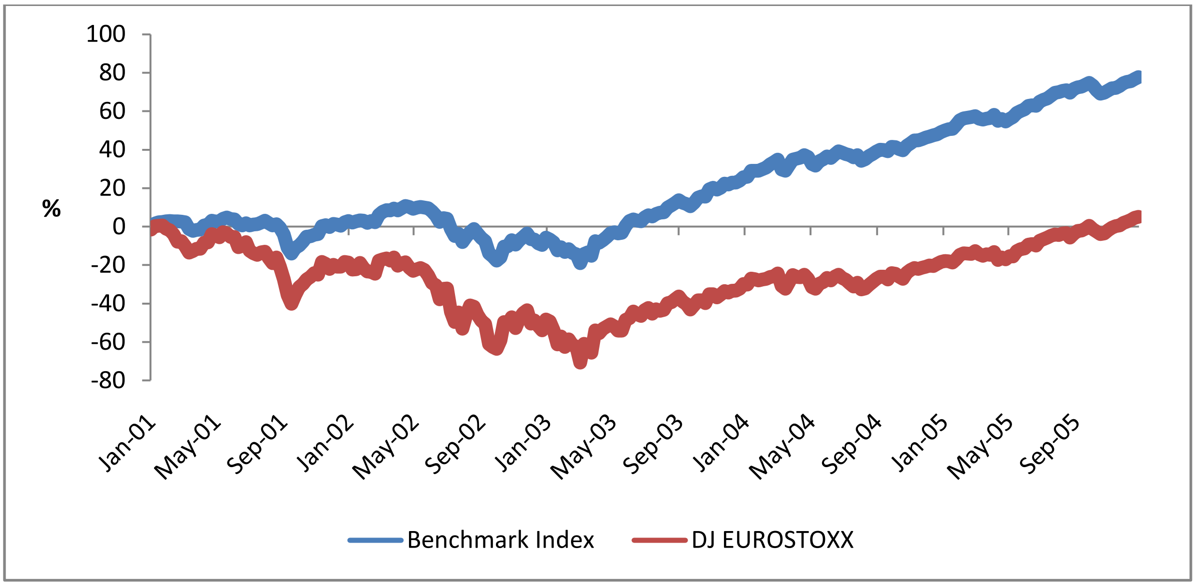
	Descriptive statistics				**Coefficients for different risk factors**				
Portfolio	*Avg Number of firms (Highest – Lowest)*	*Average Mean Market Value*	*Average number of analysts*	*Average rating*	*Rm - Rf*	*Momentum*	*SMB*	*HML*	*Adjusted R-square*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
1	1.87 (4-0)	7269.49	12.64	1.33	**0.686** (2.211)**	-0.116 (-0.219)	0.860 (0.523)	-0.041 (-0.081)	0.088
2	18.00 (32-7)	9549.96	14.38	1.83	**0.914*** (9.732)**	**-0.359 ** (-2.242)**	0.682 (1.368)	**-0.451*** (-2.905)**	0.741
3	76.26 (92-61)	9545.07	12.76	2.28	**0.946*** (10.061)**	**-0.563*** (-3.510)**	**0.874* (1.752)**	**-0.464*** (-2.982)**	0.779
4	66.37 (85-43)	8586.75	13.41	2.71	**1.017*** (10.612)**	**-0.950*** (-5.816)**	0.423 (0.832)	-0.259 (-1.632)	0.853
5	28.74 (49-7)	11707.2	13.42	3.37	**1.023*** (8.576)**	**-0.881*** (-4.334)**	**-1.185* (1.872)**	-0.071 (-0.359)	0.794

The market risk premium coefficients, known as the betas, are slightly increasing going from portfolio 1 to 4. Portfolio 5 breaks this trend with a slightly lower beta. Portfolio 1 has a very low coefficient. This is partly a result of the portfolio being empty for 9.2 percent of the weeks which reduces the market risk. Table **V** shows that this portfolio only has a mean of 1.87 firms per week.

4.4 SURVIVORSHIP BIAS

The sample used consists of the stocks that as of October 20th, 2008 made up the Dow Jones EURO STOXX index. Comparing the return from these stocks (benchmark index) during the sample period to the return of the DJ EURO STOXX index for the same period shows that they are largely different. The DJ EURO STOXX index, which is updated quarterly to consist of the stocks with the highest market capitalization, had a cumulative return over the period of 5.05 percent compared to the benchmark index return of 77.68 percent. This is the result of the index constituents of today including past winners, i.e. stocks that have performed well relative others. We expect this to have a significant impact on our empirical findings.

FIGURE 1. BENCHMARK INDEX VS DJ EURO STOXX



Benchmark Index vs DJ EURO STOXX Cumulative returns chart for our benchmark index compared to the DJ EURO STOXX over the time period 2001-2005.

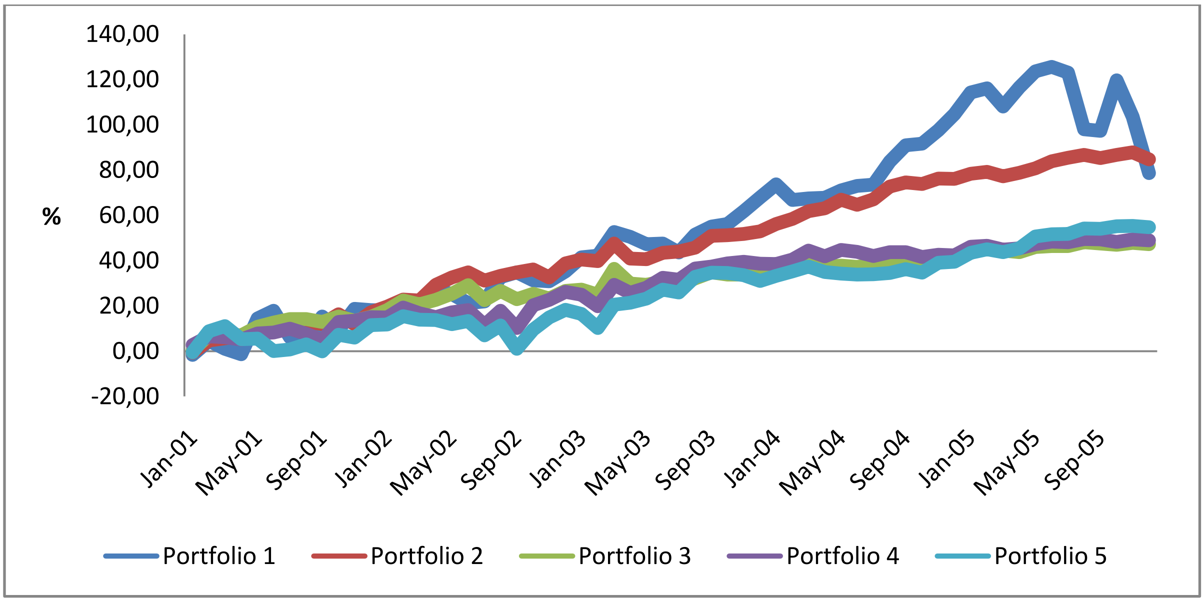
5. Portfolio Characteristics and Returns

5.1 Portfolios Grouped According to Consensus Figure

Regarding the assumption that the stocks more favorably recommended by the analysts outperform the ones less favorably recommended we see a clear trend. Portfolio 1 and 2 with the highest analyst recommendations, have a higher mean raw return, than the rest of the portfolios as can be seen in Table VI. In Figure 2 it can be seen that these two portfolios consequently outperform the rest of the portfolios from year 2002 and onwards.

All portfolios have positive alphas except for portfolio 1 whose alpha is not significant as a result of a low power of the tests of this portfolio's returns. All the portfolios also outperform the market and the abnormal returns for all the portfolios except for portfolio 1 are significantly positive. This is somewhat contradictory to what might be expected as even the portfolio with unfavorable recommendations (5) has a significantly positive alpha. This is no doubt due to the issue of non-randomness in our sample as highlighted in 3.3.

Figure 2. Abnormal returns



Cumulative abnormal returns for the five portfolios sorted to their consensus number.

Portfolios 1 and 2 outperform the rest of the stocks within our sample. They have a higher mean return than the rest of the portfolio returns. The cumulative market adjusted returns as can be seen in Figure 2 are 78.62 percent and 84.81 percent for portfolio 1 and 2 respectively compared to still positive but lower returns for the three other portfolios (47.25 percent, 48.91 percent and 54.71 percent).

Interestingly the market adjusted return of portfolio 5 is higher than that for the stocks in portfolios 3 and 4. These findings are unanticipated and contradict previous research which concludes that the most significant returns tend to stem from analysts´ sell recommendations. This is again most likely a result of the bias in our sample wherefore specific inferences cannot be made. Taken together, the aggregated market adjusted mean for the portfolios containing stocks that have been recommended “buy” or higher, is larger than for the “sell”-recommended stocks in portfolio 5.

In order to control for the previously mentioned bias relative comparisons within our sample have been made. Table XVII confirms our suspicions, highlighting a significant negative alpha for portfolio 5 when the regressions in Table VI are run using our benchmark as a proxy for the market. By comparing the two tables it is evident that the original significant positive returns for this portfolio diminish.

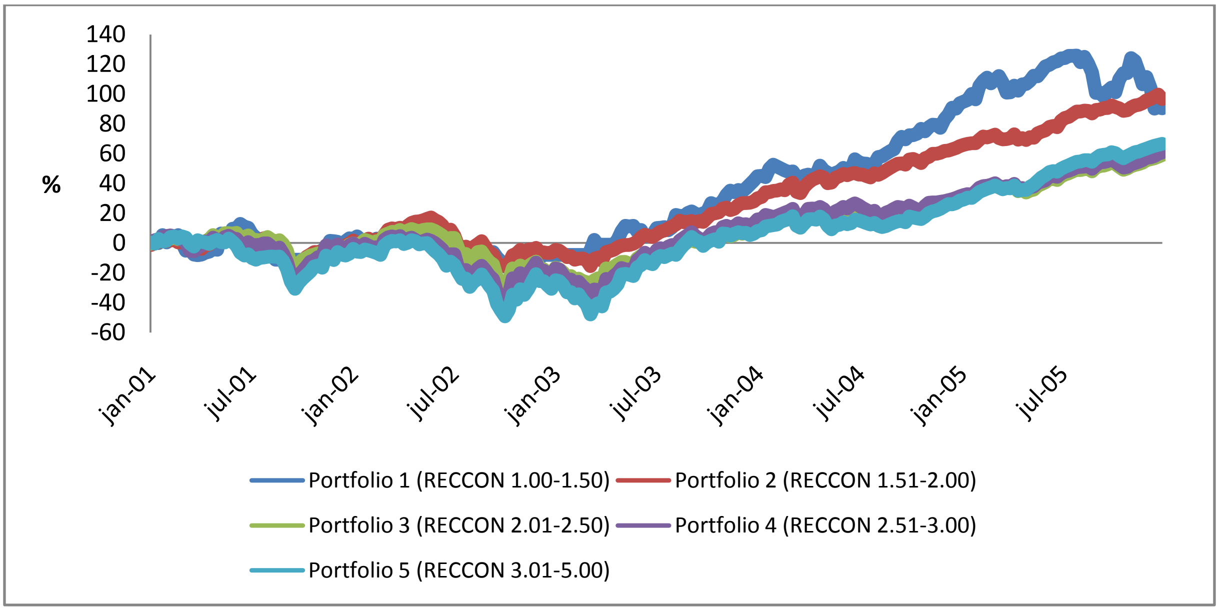
TABLE VI. PORTFOLIO RETURNS AND INTERCEPTS

The mean monthly raw return is shown for each portfolio as is the mean market adjusted return, i.e. where the return from market return has been subtracted from the portfolio return. In the fourth column the intercept from the CAPM-regression is shown, known as "Jensen's alpha" or the tracking error and in the last column the intercept when this regression is run with the market risk premium (R_m-R_f) and the risk factors HML, SML and the momentum portfolio are included. In these regressions the "Market Portfolio", described in 4.2.1, has been used as the market return.

Portfolio	Mean Raw Return	Mean Market Adjusted-Return	CAPM Intercept	Intercepts four-factor model
1	0.01506	0.01310 (1.262)	0.013 (1.262)	0.008 (0.573)
2	0.01610	**0.01414*** (4.005)**	**0.014*** (4.110)**	**0.011*** (2.690)**
3	0.00984	**0.00788** (2.180)**	**0.008** (2.171)**	0.003 (0.803)
4	0.01011	**0.00815* (1.942)**	**0.008** (2.033)**	0.004 (0.895)
5	0.01108	**0.00912* (1.868)**	**0.009* (1.945)**	0 (-0.029)
¼ (1+2+3+4)	0.01278	**0.01082*** (2.780)**	**0.011*** (2.776)**	0.007 (1.365)
S1	0.0017 (0.702)	**-**	0.002 (0.391)	0.007 (1.340)
S2	0.0031 (0.650)	**-**	0.003 (0.459)	0.009 (1.085)
Risk Free asset	0.0024	**-**	**-**	**-**

If portfolio 1 would be bought and portfolio 5 would be sold and the position would be held throughout the entire sample period an investor would earn a gross profit of 23.9 percent, or an annual average of 4.8 percent. Barber et al find it to yield 11.8 percent annually. One of the main differences from their analysis is that in this paper we rebalance weekly whereas Barber et al (2001) rebalance daily. Jegadeesh et al (2002) find frequent rebalancing to be a crucial factor in keeping returns high. Our results are thus consistent with their findings in the sense that the portfolios are rebalanced less frequently and consequently the returns are lower. Further, the sample is smaller, consists of European data, and has an analyst coverage spread more evenly among the constituent stocks. The first two should have a marginal impact whereas in our sample we have a higher average number of analysts per covered firm (13.66) compared to (4.74) in the Barber et al (1998) study. As more analysts follow a company less of any mispricing should remain to be found (Boni & Womack 2003). This explains part of the difference in returns.

FIGURE 3. RAW RETURNS



Cumulative Raw returns of the 5 portfolios sorted and grouped according to consensus figure.

5.2 PORTFOLIOS SORTED ON CONSENSUS NUMBERS AND GROUPED INTO QUINTILES

Among these portfolios the stocks in the portfolio with the highest analyst recommendations have a higher mean than the rest of the portfolios. For the rest of the portfolios the trend is unclear. Portfolio number five has the second highest mean return and alpha. As the returns of the stocks with more favorable recommendations are lower it is hard to construct a trading strategy according to analyst recommendations which is the scope of this paper. We will continue the analysis with the stocks grouped after consensus number as the returns from the two top portfolios are higher than the rest.

5.3 Sub Sample Periods

The sampled period was divided in halves and t-tests and regressions were run on these which are enclosed in Table XVIII. The returns follow mainly the same pattern as under 5.1 with smaller returns as we move down in order from portfolio 1. In the second sub period covering the period July 1st 2003 – December 31st the pattern is somewhat less clear. Portfolio 2 has positive alphas in both sub periods from the CAPM-regression showing that these stocks have higher returns than the rest which is in line with the pattern discussed in 5.1 with same considerations about the selection issue in mind. The alphas for the portfolios with on average “buy”-recommended stocks are positive.

5.4 Bear and Bull Market

During the bear market months the pattern is pretty much the same as in section 5.1 in that the returns generally decrease as we move from portfolio 1 to 5. The alpha is robust for portfolio 2 showing that the high recommendations for these stocks hold in both bull and bear markets. Further, what is similar to the findings for the whole period is that the alphas for both bull and bear markets are positive for the return on the “buy”-or-higher recommended stocks. The alpha for portfolio 1 with the most highly recommended stocks is insignificant here as well as in the other tests due to the low frequencies in this portfolio. We conclude that in this sample analysts are able to pick the winners in bear markets as well as in bull markets. Controlling for the upward bias with the benchmark index return shows that no alpha exists for the “buy” recommended stocks as a whole. The alpha for portfolio 2 exists only in bull markets. We also find a negative alpha for the worse-than-“buy” recommended stocks during bear markets which indicates that analysts more accurately find winners in periods with rising prices and losers in periods with falling pricesTable XXV. Trading strategy

TABLE VII. BULL AND BEAR MARKET RETURNS.

The sample has been sorted into bull market months (rising prices) and bear market months (declining prices) according to the sign of the market return.

Portfolio	**"Bear Market"**			**"Bull market"**		
	Mean Raw Return	*Mean Market Adjusted Return*	*CAPM Intercept*	*Raw Return*	*Market Adjusted Return*	*CAPM Intercept*
1	-0.0163	0.0233 (1.350)	0.011 (0.394)	0.0408	0.00478 (0.379)	0.033 (1.463)
2	-0.0154	**0.0242***** **(4.596)**	**0.033***** **(4.223)**	0.0419	0.00590 (1.367)	**0.024***** **(3.330)**
3	-0.0243	**0.0154**** **(2.381)**	**0.009***** **(3.276)**	0.0377	0.0017 (0.475)	**0.018***** **(3.005)**
4	-0.0368	0.0029 (0.416)	**0.023**** **(2.487)**	0.0485	**0.0125**** **(2.427)**	0.015 (1.510)
5	-0.0373	0.0023 (0.282)	**0.021*** **(1.766)**	0.0507	**0.0147**** **(2.596)**	0.015 (1.429)
¼ (1+2+3+4)	0.0141	**0.0164**** **(2.520)**	**0.024**** **(2.440)**	-0.0084	0.0062 (1.358)	**0.022***** **(2.844)**
S1	**0.0141*** **(-2.015)**	**---**	0.003 (0.298)	-0.00932 (-1,192)	**---**	0.007 (0.817)
S2	**0.0214*** **(-1.902)**	**---**	0.001 (0.042)	-0.00844 (-1.667)	**---**	0.013 (0.971)

If an equally weighted portfolio would be formed out of the portfolios 1, 2, 3 and 4 and a zero investment made by selling an equal amount of portfolio 5 this would yield a gross return of 0.014 percent per month. This cannot be seen in the bull market periods. Interestingly the same investment yields a negative return during the second sub period described above. During this period the market rose by 49 percent compared to a return of -37 percent during the first period. For the whole sample we cannot draw any conclusions about this return, but the sub samples thus indicate that the total value, i.e. the value of "buy"- and "sell"- recommendations taken together, is the highest during periods with falling prices.

Our results show that analysts have a remarkable inability to find stocks that underperform the market. This is evident from Table XVI. This is inconsistent with the Desai and Jain (1995) findings which state that analysts should more accurately be able to pick losers than winners. Once again this is likely due to the mentioned issue of a non-random sample.

5.5 Implications of Bias in Stock Selection

As is mentioned in 3.3 the sample consists of stocks that have performed well in the past which results in that all the recommendation-grouped portfolios have positive market adjusted returns. This bias has been recognized and controlled for. By further studying if the most favorably recommended stocks have a higher return than the least favorably recommended we have analyzed the returns compared to the benchmark index constructed in 4.2. This index is a value weighted average of all stocks in the sample. Comparing the relative returns within our sample highlights that portfolio 5 which contains the stocks with the least favorable recommendations underperforms the weighted average sample return. Running the CAPM-regression with this index return as a proxy for the market return yields negative alphas (Table XVII) for the portfolios 3-5. The average abnormal return of the "buy"-recommended stocks is also positive. A negative alpha for portfolio 5 and abnormal returns for portfolios 1-4 come as important findings and adds relevance for creating the trading strategies described in section 4.3.

5.6 Marketing Efforts

We find no indication that marketing efforts according to our definition should have any impact on abnormal returns. The correlation tests show that a positive correlation of 0.15 exists between the abnormal return of portfolio 5 and the mean number of estimates to total number of estimates in the sampled periods for that portfolio. This is the opposite to what we would find if the number of non-"buy" recommendations by analysts following the companies in this portfolio really would be a determinant of returns. If this would have been the case the correlation should have been negative as a larger number of analysts would imply a more negative return. No other correlations were found. Further if an increase (decrease for sell recommended stocks) in market adjusted returns because of a higher number of recommendations outstanding would exist, this would have contradicted our reflections under 5.1 that a larger number of analysts following a company would lead to smaller abnormal returns.

6. TRADING STRATEGIES

Several previous studies have concluded that it is possible to prosper from actively trading on consensus recommendations (Barber et al (2001)) among others. However when transaction costs are taken into account it becomes more difficult to achieve material market adjusted returns. Nonetheless we aim to evaluate if it is possible based on our findings in the previous chapter.

As expected, chapter 5 highlighted that portfolios 1 and 2 yielded a higher return than the other portfolios over the period. Both the stocks in portfolio 1 and 2 as well as the stocks with a non-sell recommendation as a whole (portfolios 1-4) have higher means than the portfolio 5-stocks. The findings are consistent over most sub-periods although the absolute returns are not as large as in previous research due to the characteristics of our sample. We proceed and form the zero investment strategies described in

Table **IV**.

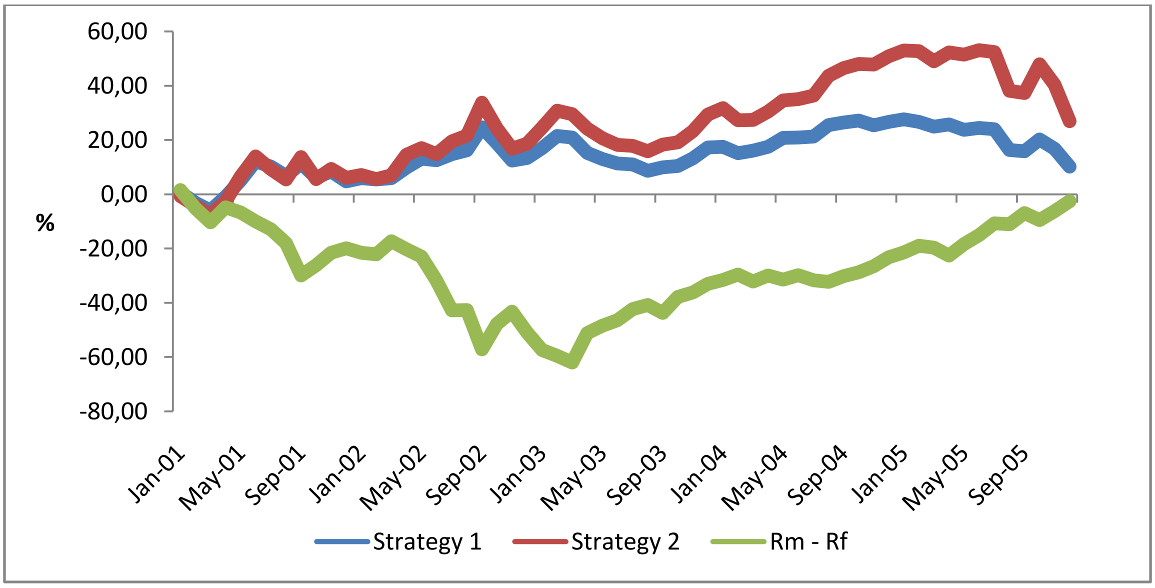
The returns from Strategy 1, where a long position is taken in the portfolios 1-4 and a short position in portfolio 5, yields a cumulative abnormal return of 10.19 percent over the five year period. Strategy 2 yields a higher return, 27.00 percent over five years, due to strong returns in the long leg. Thus consistent with previous research there are possibilities of capturing excess returns based on analyst recommendations before accounting for transactions costs. None of the existing returns are however significant at the 10 percent-level when they are measured on a monthly basis as can be seen in Table VIII.

TABLE VIII. TRADING STRATEGY GROSS RETURNS

The mean monthly return is shown for each strategy as is the intercept from the CAPM-regression, known as "Jensen's alpha".

Trading Strategy	Monthly Return	CAPM Intercept
1	0.0017	0.002
	(0.702)	(0.391)
2	0.0031	0.003
	(0.650)	(0.459)
Risk Free asset	0.0024	

FIGURE 4. TRADING STRATEGIES



The cumulative gross returns from Strategy 1 and 2.

Table IX shows the turnover rates for the different legs of Strategy 1 and 2. Consistent with Barber et al (2001) high trading activity is needed in order to pursue the strategies outlined which results in substantial turnover rates for the different portfolios. The turnover is the highest in the long leg of the second strategy, ranging from nearly 9 times the portfolio value in 2005 to a bit more than 12 times the value in 2001. Thus there are more frequent changes to the constituent list in portfolios 1 and 2 where each stock has a higher weight as the total number of stocks within the portfolios is smaller. Portfolio 5 also shows a high turnover, especially during 2001, the year in which the positions were opened.

2001 saw a markedly higher turnover for all the legs compared to the following years likely attributable to the general downturn in the stock markets.

TABLE IX. TURNOVER RATES

The turnover rates for the different legs in the trading strategies

Year	**Turnover**		
	Portfolio 1+2	Portfolio 1+2+3+4	Portfolio 5
2001	1235.23%	922.41%	924.72%
2002	716.03%	346.57%	604.17%
2003	702.18%	275.51%	520.19%
2004	735.42%	224.16%	450.33%
2005	890.39%	321.98%	560.75%
Mean	847.21%	442.16%	624.85%

6.1 TRANSACTION COSTS

So far the returns analyzed from different portfolios and strategies have been gross returns which do not take transaction costs into account. In this section we will examine the impact of trading costs to the portfolio returns. Adjusting the obtained empirical results for transaction costs properly is crucial in order to determine profitable strategies.

If we posit that an investor is a client at a brokerage firm enabling the investor to construct the trading strategies described above. For this she has to pay for the analysts’ work by paying commission on the transactions to the brokerage house. Running the first strategy would give a turnover of nearly 11 times the value of each leg.

TABLE X. COMMISSION COSTS

The costs for brokerage commissions are based on two different rates. The costs are shown as a percentage of the total market value of each leg in the strategies.

Year	**Brokerage Commission costs**			
	Strategy 1		*Strategy 2*	
Commission	*3 basis points*	*10 basis points*	*3basis points*	*10 basis points*
2001	0.55%	1.85%	0.65%	2.16%
2002	0.29%	0.95%	0.40%	1.32%
2003	0.24%	0.80%	0.37%	1.22%
2004	0.20%	0.67%	0.36%	1.19%
2005	0.21%	0.68%	0.44%	1.45%
Mean	**0.30%**	**0.99%**	**0.44%**	**1.47%**

We have used commission rates of 3 and 10 basis points as it represents a conservative yet feasible span of what an institutional investor is charged by her stock broker. After subtraction of the lower rate, the average annual market adjusted return for Strategy 1 is 1.73 percent. Using the higher rate it yields 1.05 percent. These returns are lower than investing in the risk free asset which yields 2.73 percent annually over the period.

For Strategy 2 the returns and the turnover rates are higher but the gross return from the strategy is also higher. The average annual turnover is almost 13 times the value of one leg. Using the higher commission rate gives a net annual average return of 3.93 percent and 4.96 percent using the rate of 10 and 3 basis points respectively. These returns are higher than the return for the risk free asset. After subtracting brokerage commissions the Sharpe ratios decline to annualized numbers of 0.16 and 0.095 for the Strategy 1 with the higher and the lower rate of commission respectively. For Strategy 2 the numbers are higher at 0.28 and 0.23 respectively (Table XI).

TABLE XI. SHARPE RATIOS

Sharpe ratios for Strategy 1 and 2 with different commission rates applied.

Annualized Sharpe ratio, Net returns				**Sharpe ratios, Gross Returns**		**Sharpe ratio on market portfolio**
Strategy 1		**Strategy 2**		**Strategy 1**	**Strategy 2**	
Commission rate						
3 BP	10 BP	3 BP	10 BP			
0.158	0.095	0.283	0.226	0.184	0.307	0.142

The returns adjusted for commission fees are well in excess of the risk free rate for Strategy 2 which indicate that analysts work actually has investment value. According to the Sharpe ratios the investor has to have a high tolerance for volatility in the returns as the payoff for each unit of risk is lower than one.

Keim and Madhavan (1998) provide an estimate of transactions costs incurred by institutions trading US stocks, broken down by firm size quintile. Based on those approximations Barber et al (2001) estimate a total round-trip costs for the bid-ask spread of 0.7, 1.9, and 4.1 percent for Large-, Medium- and Small Cap stocks respectively. By weighting these percentages by the fraction that each firm size classification makes up of the total market capitalization the following estimates are obtained. Large firms comprise 83.25 percent of the total, medium-sized firms 11.83 percent, and small firms 4.93 percent yielding round-trip transactions costs for our portfolios at 1.01 percent of share value traded.

This is in line with the rough estimates for the average total round-trip cost of an institutional investor for the bid-ask which is referred to in Barber et al (2001) and Carhart (1997). The mentioned cost structure would suggest that for every 100 percent increase in turnover, annual market adjusted return drops by 1.01 percent. This implies an annual cost of around 11 percent and 13 percent for Strategy 1 and 2 respectively bearing in mind the portfolios turnover rates (Table XIV). This would imply negative net returns from the strategies. Thus as previous research also has indicated when transaction costs are taken into account the abnormal returns from analysts' recommendations diminish.

6.2 STRATEGIES TO REDUCE TRANSACTION COSTS

Our findings confirm what previous studies have also indicated. Trading strategies based on analysts' consensus recommendations which generate sufficient market adjusted returns net of transaction costs are difficult to come by. Thus in order to develop and enhance the strategies further it is essential to try to limit the costs associated with trading. As noted in chapter 2.2 high trading activity is needed if the returns from the strategies are not to be diminished. Increasing the holding period of the portfolios affects the returns in a negative way.

An alternative would be to explore the use of derivatives which offer a cost effective way of trading. As the cost of trading S&P 500 futures is merely 3 percent of the cost of trading an equivalent stock portfolio, there is scope to develop a strategy utilizing index futures as a cost effective way of reducing market beta (Fleming, Ostdiek & Whaley (1996)).

The assumption that costs for trading European futures would not differ in a material way from those in the US could be deemed valid as the financial markets become ever more global and interlinked. It is therefore assumed that the trading costs encountered when trading US index futures estimated by Fleming, Ostdiek & Whaley (1996) are applicable to European index futures as well.

We continue to focus on zero investment portfolios as a way to find significant alphas which would be profitable to pursue net of trading fees. Our aim is also that of constructing strategies applicable in practice by an investor. In order to take advantage of the cost effectiveness of trading index futures, strategies will be developed where one leg of the trade is made up of a position in the Dow Jones STOXX 600 E index future in order to neutralize market beta. This is to our knowledge the broadest index future in Europe which constitutes the best practical way for an investor to neutralize market risk in a cost efficient manner. It is also highly liquid wherefore is assumed that there is no cost of market impact.

TABLE XII. TRADING STRATEGIES FOR REDUCED TRANSACTION COSTS

Description of how the legs in trading strategies 3 and 4 are constructed in order to reduce transaction costs.

Strategy	Buy	Sell short
3	0.25 x Group (1+2+3+4)	DJ STOXX 600 E Index Future
4	0.5 x Group (1+2)	DJ STOXX 600 E Index Future

Strategies 1 and 2 pursued in chapter 6 are altered by changing the short leg of the strategies to a position in the chosen index future. This in an attempt to reduce the costs inflicted from rebalancing stock holdings and instead rebalancing the position in the index future.

The cumulative gross return for Strategy 3, a long position in portfolios 1-4 and a short position in the index future is 69.7 percent (Figure 6) which is substantially higher than the comparable Strategy 1. The average annual return of the strategy is 13.9 percent. By switching the short leg from portfolio 5 to the index future the gross return rises considerably. The alpha from the strategy is significant at the 1%-level (Table XIII). Transaction costs are also reduced as the high turnover of the short position in portfolio 1 is reduced.

Strategy 4, where the short leg in Strategy 2 is altered to the index future, also shows significant profits with a cumulative return of 86.6 percent and on average 17.3 percent annually. The measured alpha is significant at the 5%-level. The same argument as before regarding the non randomness in our sample is also valid here where Table XXV highlights the meager returns with the benchmark index as a market proxy. Transaction costs are also here significantly reduced although still somewhat higher than Strategy 3 given the higher turnover in the long leg.

TABLE XIII. TRADING STRATEGY GROSS RETURNS

Mean monthly returns for each strategy together with the intercept from the CAPM-regression, known as "Jensen's alpha".

Strategy	**Mean Return**	**CAPM Intercept**
3	**0.0116**	**0.012**
	(3.779) *	**(3.749) *****
4	**0.0144**	**0.014**
	(2.592) **	**(2.590) ****
Risk Free asset	0.000548	

Average annual commission costs inflicted by the strategies drop to 0.49 percent for Strategy 3 and 1.01 percent for Strategy 4 compared to 0.99 percent and 1.47 percent for Strategy 1 and Strategy 2 respectively, assuming 10 basis points commission for the portfolio leg and 1.8 basis points for the future leg.

The round-trip transaction costs are also reduced with Strategy 3 and 4 as the total cost for the short leg in the index future is estimated at 1.8 basis points. As previously mentioned a 100 percent increase in turnover results in a drop of 1.01 percent in the annual market adjusted return. For Strategy 3 and 4 this only affects one leg of each strategy resulting in an annual total cost of 4.91 and 9.48 percent for 3 and 4 respectively. This represents a significant reduction to the annual costs incurred of 13.8 and 15.8 percent for Strategy 1 and 2 (Table XIV).

TABLE XIV. STRATEGY RETURNS

Gross annual returns for the for trading strategies followed by the annual total trading costs including commission (10 basis points) and costs for the bid/ask-spread. In the last column these are subtracted from the gross returns.

Strategy	Gross Annual Return	Annual Trading costs	Net annual returns
1	2.38%	13.77%	-11.39%
2	5.40%	15.75%	-10.35%
3	13.95%	4.91%	9.04%
4	17.32%	9.48%	7.83%
¼ (1+2+3+4)-Benchmark	-0.33%	4.91%	-5.24%
½ (1+2)-Benchmark	2.78%	9.48%	-6.70%
Benchmark-5	2.24	6.97%	-4.73%

As is evident in Table XIV, strategies based on following the analysts' "buy" recommendations in the long leg with an offsetting short position in the DJ STOXXX 600 E index future yields substantially higher returns. In addition when the short leg is composed of rebalancing an index future instead of a stock portfolio transaction costs are significantly reduced due to the lower turnover. The Sharpe ratios net of commission costs for Strategy 3 and 4 of 1.25 and 0.95 respectively are also much higher than 0.18 and 0.09 for Strategy 1 and 2. It is notable that Strategy 1 and 3 which yield lower returns than 2 and 4 have higher Sharpe ratios emphasizing the lower standard deviation of the returns incurred.

Given that the high gross returns from Strategy 3 and 4 stem from a bias in our sample the returns from Strategy 3 and 4 have also been measured as if an investor could trade an index future on our benchmark index. When switching the short positions from the Euro STOXX 600 E index future to our benchmark index the average annual gross returns drop to -0.33 and 2.78 percent from 13.95 and 17.32 percent respectively. Adding on the annual costs of trading would yield negative net annual returns of -5.24 percent and –6.70 percent for Strategy 3 and 4. Thus the high returns achieved from Strategy 3 and 4 are largely due to the outperformance of the stocks within the sample relative to the market and not owing to analyst´s performance. Table XXV also shows insignificant alphas for the mentioned alterations. Given that a tradable index future based on our benchmark index were to exist then the logical trading strategy based on the findings in Table XVII would be to go long the index future and short portfolio 5. This strategy however yields insignificant returns and the scarce gross returns turn negative after accounting for transaction costs.

In summary the quest of reducing transaction costs by using an index future, results in substantially lower gross returns making the savings irrelevant if our constructed benchmark index is used as a proxy of market risk. By using the Euro STOXX 600 e index future, which is an applicable strategy for an investor, yields high returns net of transaction costs but the determinants of the gross returns are questionable. Controlling for the sample bias reveals that the attraction of annual returns of 8-10% annually net of transaction costs vanish. Nonetheless transaction costs are significantly reduced showing the prospect to decrease the costs associated by the use of an index future.

TABLE XV. SHARPE RATIOS

Sharpe ratios for Strategy 3 and 4 with different commission rates applied.

Annualized Sharpe ratio, Net returns				**Sharpe ratios, Gross Returns**		**Sharpe ratio on market portfolio**
Strategy 3		**Strategy 4**		**Strategy 3**	**Strategy 4**	
Commission rate						
3 BP	10 BP	3 BP	10 BP			
1.279	1.253	0.954	0.921	1.297	0.977	0.142

7. CONCLUSIONS

The purpose of this paper was twofold; to investigate whether stock analysts are able to separate high performing stocks from the low performers, i.e. add value to investors and secondly to investigate if their recommendations can be used to construct trading strategies which are profitable after taking transaction costs into account. With respect to our initial hypotheses and based on our empirical results we conclude the following.

Analysts successfully pick stocks that yield future returns superior to that of the market. Forming portfolios according to the average recommendation of the stocks and measuring the average return shows that all stocks with an average “buy”-recommendation or higher outperform the market. This cannot be significantly determined for the stocks with the very highest recommendations but the authors of this paper dare say that this is due to the scarcity of stocks within this portfolio implying a low power of the tests performed. In this study, with the sample used, an investor has not been able to reap any value by following the “sell”-recommendations of analysts. These stocks have outperformed the market as well and consequently the investor would have been better off by only holding the market portfolio than selling these short.

As our sample is a non-random selection containing past winners relative the market as a whole, there is a survivorship bias inherent. The analysts’ performance has been studied controlling for this bias by testing the constructed portfolio’s relative performance to the average weighted sample return. From this it can be concluded that “hold” and “sell”-recommended stocks underperform the benchmark index. These stocks also have a negative tracking error which supports our first hypothesis.

We have been able to construct trading strategies that yield positive gross returns measured on a monthly basis. Buying the stocks with the average analyst recommendation of “buy” or “strong buy” and selling the stocks with the recommendations “hold” or lower yields an average annual gross return of 5.4 percent. This is the highest return for any zero net investment strategy constructed from the consensus based portfolios during the period. The value of analysts work is thus on average worth 5.4 percent annually. After paying her brokerage house an investor is still better off than investing in the risk free rate indicating market inefficiency. However additional costs accrue which we believe is the reason for these abnormal returns. By keeping the portfolios up to date with the recommendations the portfolio turnover gets high enough to cause costs for bid/ask-spreads which erode the profits induced from the strategies.

By employing the use of derivatives transaction costs have been reduced substantially. This results in significant abnormal returns net of costs coherent when trading the “buy”-recommended stocks. However, we deem these abnormal returns stem from the bias our sample contains. Controlling for this bias by altering the trading strategies to include a hypothesized index future on our benchmark index representing the stocks in the sample severely alter the results. The gross returns diminish and after accounting for costs the strategies yield negative returns. In accordance with our second hypothesis the efficient market hypothesis is therefore not found to be violated.

We conclude that the possibilities to construct profitable trading strategies net of transaction costs based on the analysts’ recommendations do not exist. The meager returns present are not high enough to compensate an investor for the costs inflicted by the high turnover needed to comply with the recommendations.

7.1 Suggestions for Further Research

In this study we have used the monthly returns from the portfolios and rebalanced on a weekly basis. As there seems to be a link to returns and the frequency with which the rebalancing is made this is something we suggest for future research. Both transaction costs and gross returns are affected by this. There might be possibilities to optimize this variable with respect to these properties. Further, the analyst recommendations are determined by expectations of several company specific factors. If any of these factors are more tightly linked to stock performance that would suggest analysts putting more effort in that certain factor. It also would also allow for a study like this focusing on that particular factor. We would also have liked to check if analysts add more or less value to stocks of a certain sector which is also something we suggest for future research.

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Electronic and Other Sources

Data downloaded 11/28/08 from Kenneth French's homepage, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

APPENDICES

TABLE XVI. ANNUAL RETURNS

The table shows the cumulative market adjusted returns for the different portfolios as described in the research design section and the annual averages.

Portfolio	Cumulative Raw return		Cumulative market adjusted return 2001-2005	Average Annual market adjusted Return
1	90.39%	18.08%	78,62%	15,723%
2	96.58%	19.32%	84,81%	16,963%
3	59.02%	11.80%	47,25%	9,451%
4	60.68%	12.14%	48,91%	9,782%
5	66.48%	13.30%	54,71%	10,943%
S1	10.19%	2.04%	-	-
S2	27.00%	5.40%	-	-
Risk Free asset	14.35%	2.87%	-	-
Market return	77.67%	15.53%	-	-

TABLE XVII. PORTFOLIO CHARACTERISTICS

The returns from the different portfolios have been recorded together with the alphas from the CAPM-regression when the benchmark index return was used as market return.

Portfolio	**Mean Raw Return**	**Mean Market-Adjusted Return**	**CAPM intercept**
1	0.0151	0.0020	0.005
	(1.371)	(0.201)	(0.474)
2	**0.0161**	0.0032	0.003
	(2.583)**	(1.416)	(1.346)
3	0.0098	**-0.0031***	**-0.005*****
	(1.455)	**(-1.950)**	**(-3.246)**
4	0.0101	-0.0028	**-0.007*****
	(1.198)	(-0.905)	**(-3.442)**
5	0.0111	-0.0019	**-0.006***
	(1.248)	(-0.458)	**(-1.893)**
S1	-0.0009	**0.0128***	-0.001
	(-.306)	**(1.873)**	(-0.314)
S2	0.0017	-0.0084	0.005
	(0.385)	(-0.775))	(1.353)
Risk Free asset	**0.0105****	0.0017	0.002
	(2.019)	(0.391)	(0.274)

TABLE XVIII**. SUB SAMPLE PERIODS**

The table shows the raw returns, market adjusted returns and the alphas for the sub sample periods.

Portfolio	**01 Jan 01 – 30 Jun 03**			**1 Jul 03 – 31 Dec 05**		
	Raw Return	*Market Adjusted Return*	*CAPM Intercept*	*Raw Return*	*Market Adjusted Return*	*CAPM Intercept*
1	0.00338	0.01583 (1.442)	0.012 (1.067)	0.02675	0.01038 (0.582)	0.023 (1.124)
2	0.00205	**0.01450** (2.373)**	**0.012* (1.983)**	0.03014	**0.01377*** (3.771)**	**0.019*** (4.787)**
3	- 0.00218	.01027 (1.548)	0.010 (1.382)	0.02186	**0.00548* (1.859)**	**0.008** (2.544)**
4	- 0.00164	.01081 (1.389)	0.015 (2.046)	0.02187	0.00550 (1.679)	0.006 (1.672)
5	- 0.00338	.00907 (1.008)	0.014 (1.541)	0.02554	**0.00916** (2.297)**	**0.010** (2.220)**
S1	0.00040	**0.01285** (2.261)**	**0.012** (2.060)**	0.02515	0.00878 (1.631)	**(0.014)** (2.344)**
S2	0.00378 (0.515)	0.01623 (1.016)	-0.001 (-0.199)	-0.00038 (-0.077)	**-0.01676** (-2.222)**	0.004 (0.657)
Risk Free asset	0.00609 (0.515)	0.01854 (1.001)	-0.001 (-0.165)	0.00291 (0.308	-0.01347 (-1.177)	0.011 (0.969)

TABLE XIX. QUINTILE PORTFOLIOS

The table shows measures for the five portfolios that have been grouped in quintiles with an even number of stocks in each portfolio.

Portfolio	Mean Raw Return	Mean Market Adjusted-Return	CAPM Intercept
Q1	**0.015** (2.362)**	**.0130*** (3.895)**	**0.013*** (3.3947)**
Q2	0.0096 (1.483)	**.0076* (1.995)**	**0.008** (2.020)**
Q3	0.0086 (1.058)	.0067 (1.645)	**0.007* (1.694)**
Q4	0.0117 (1.321)	**.0097** (2.079)**	**0.010** (2.189)**
Q5	**0.0135* (1.893)**	**.0115*** (3.167)**	**0.012*** (3.140)**

TABLE XX. BENCHMARK INDEX RETURNS

The table shows the annual returns for the benchmark index.

Year	Index Return
2001	2.11%
2002	-9.65%
2003	35.46%
2004	25.55%
2005	32.51%

TABLE XXI. CORRELATIONS BETWEEN NUMBER OF ESTIMATES AND RETURNS

The Pearson correlations between the portfolio abnormal returns to the weighted average return for the sample (vertical) and the ratio of the number of analyst estimates to the average number of estimates per stock for the entire sample (horizontal) are shown.

		Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**	**Portfolio 5**
P1NumDivAvg	Pearson Correlation	0.150*	0.099	0.083	0.078	0.064
	Sig. (2-tailed)	0.017	0.116	0.188	0.218	0.311
	N	252	252	252	252	252
P2NumDivAvg	Pearson Correlation	0.150*	0.099	0.083	0.078	0.064
	Sig. (2-tailed)	0.017	0.116	0.188	0.218	0.311
	N	252	252	252	252	252
P3NumDivAvg	Pearson Correlation	0.089	0.138*	0.136*	0.122*	0.154*
	Sig. (2-tailed)	0.152	0.026	0.028	0.048	0.013
	N	261	261	261	261	261
P4NumDivAvg	Pearson Correlation	0.105	0.159*	0.139*	0.127*	0.157*
	Sig. (2-tailed)	0.090	0.010	0.024	0.041	0.011
	N	261	261	261	261	261
P5NumDivAvg	Pearson Correlation	0.079	0.147*	0.134*	0.131*	0.185**
	Sig. (2-tailed)	0.205	0.018	0.030	0.035	0.003
	N	261	261	261	261	261

TABLE XXII. TRANSACTION COSTS FOR STRATEGY 3 AND 4

The costs for brokerage commission are based on two different rates. The costs are shown as a percentage of the total market value of each leg in the strategies. The commission costs for trading futures are estimated to 1.8 basis points according to Fleming, Ostdiek & Whaley (1996).

Year	**Brokerage Commission costs**			
	Strategy 3		*Strategy 4*	
Commission	*3 basis points*	*10 basis points*	*3 basis points*	*10 basis points*
2001	0.44%	1.09%	0.59%	1.46%
2002	0.17%	0.41%	0.34%	0.84%
2003	0.13%	0.33%	0.34%	0.83%
2004	0.11%	0.26%	0.35%	0.87%
2005	0.15%	0.38%	0.43%	1.05%
Mean	**0.20%**	**0.49%**	**0.41%**	**1.01%**

TABLE XXIII. AUTOCORRELATIONS WEEKLY MARKET ADJUSTED RETURNS

The autocorrelation for the weekly market adjusted returns of the long legs and the short legs in the trading strategies are shown. The number in parenthesis is the Box-Ljung Statistic, followed by the corresponding p-values.

	Market Adjusted Returns		
Autocorrelation, lag no.	**½ (1+2)**	**¼ (1+2+3+4)**	**5**
1	0.007	0.042	-0.045
	0.014	(0.467)	(0.530)
2	0.078	0.110	0.136
	1.612	(3.675)	(0.757)
3	0.091	0.098	0.042
	(3.818)	(6.231)	(5.706)
4	0.037	0.041	-0.043
	(4.183)	(6.684)	(6.175)
5	-0.049	-0.018	-0.045
	(4.835)	(6.766)	(6.682)

TABLE XXIV. AUTOCORRELATIONS MONTHLY MARKET ADJUSTED RETURNS

The autocorrelation for the monthly market adjusted returns of the long legs and the short legs in the trading strategies are shown. The number in parenthesis is the Box-Ljung Statistic, followed by the corresponding p-values.

	Market Adjusted Returns		
Autocorrelation, lag no.	**½ (1+2)**	**¼ (1+2+3+4)**	**5**
1	0.156 (1.542)	0.041 (0.107)	-0.014 (0.013)
2	-0.108 (2.291)	0.081 (0.526)	0.134 (1.159)
3	-0.068 (2.595)	-0.100 (1.184)	-0.053 (1.345)

TABLE XXV. TRADING STRATEGY WITH BENCHMARK INDEX

The mean monthly return is shown for each strategy when the market risk is offset by the benchmark index as is the intercept from the CAPM-regression.

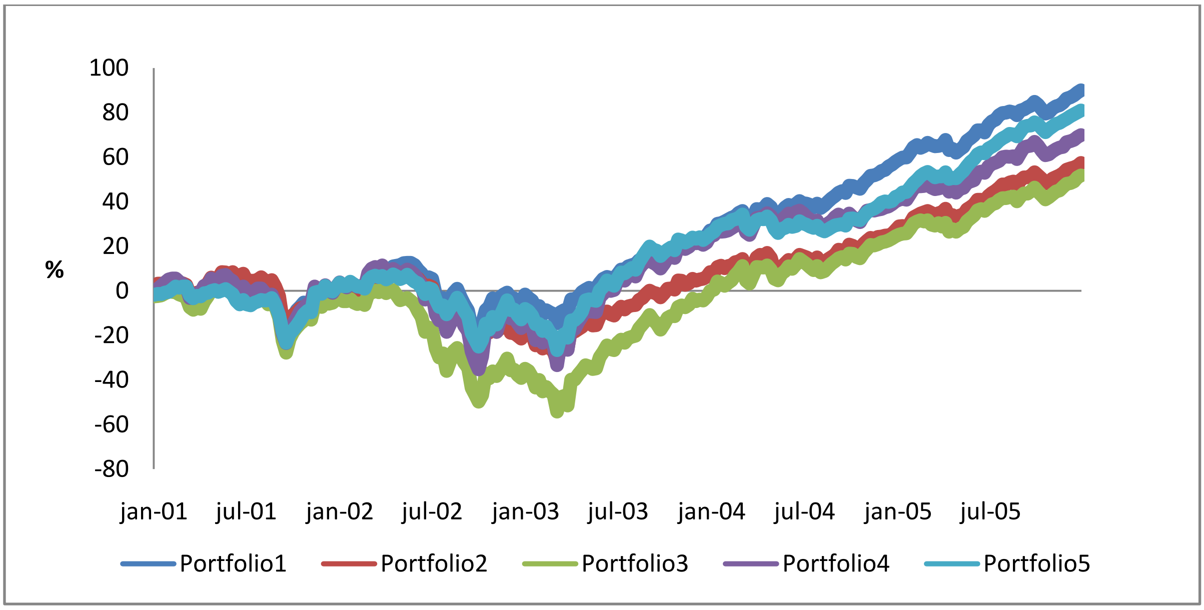
Portfolio	Mean Return	CAPM Intercept	Intercept Four-factor model
¼ (1+2+3+4)-Benchmark	-0.0002	0.000	0.001
	(-0.059)	(-0.046)	(0.213)
½ (1+2)-Benchmark	0.0026	0.003	0.004
	(0.484)	(0.477)	(0.517)
Benchmark-5	0.0019	0.002	0.006
	(0.458)	(0.520)	(1.526)

TABLE XXVI. BEAR AND BULL MARKET WEEKS

The table shows the portfolio characteristics when the returns have been sorted according to weeks with rising or declining prices in the benchmark index described in 4.2.2.

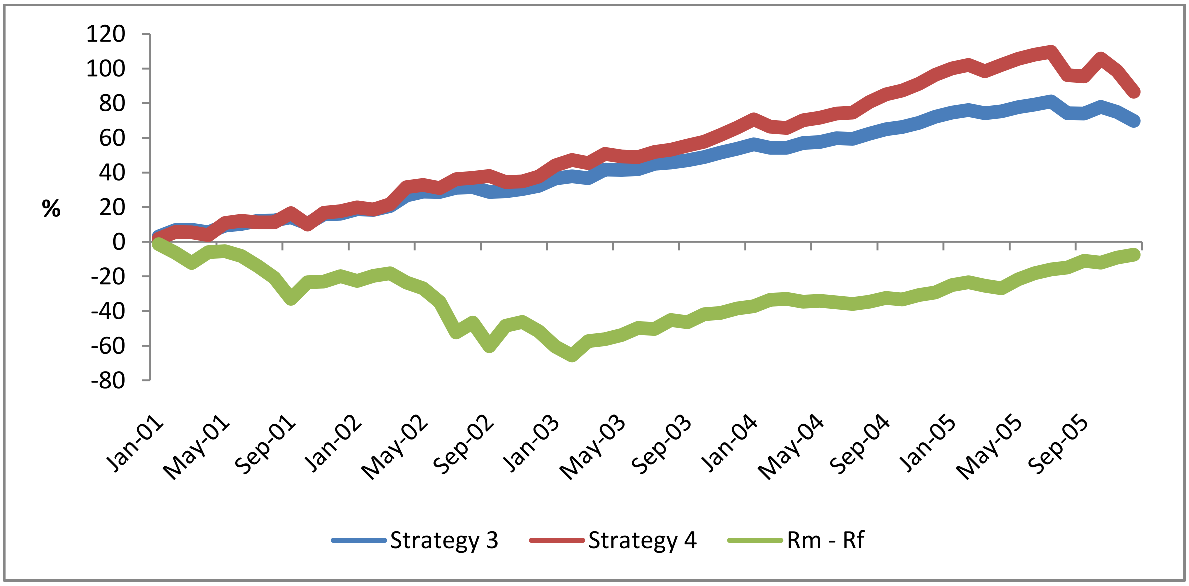
Portfolio	**"Bear Market"**			**"Bull market"**		
	Mean Raw Return	Mean Market Adjusted Return	CAPM Intercept	Raw Return	Market Adjusted Return	CAPM Intercept
1-1.5	-0.0039	**0.0083*** (2.934)**	-0.001 (-0.337)	0.0076	-0.0040 (-1.435)	0.001 (0.225)
1.5-2	-0.0146	0.0006 (0.508)	0.002 (1.102)	0.0140	0.0008 (1.092)	**0.002** (2.158)**
2-2.5	-0.0192	**-0.0040*** (-5.234)**	**0.002* (1.874)**	0.0144	0.0012 (2.297)	**-0.002*** (-2.672)**
2.5-3	-0.0245	**-0.0093*** (9.467)**	**-0.004*** (-3.193)**	0.0174	0.0042 (5.363)	**-0.003*** (-3.587)**
3-5	-0.0220	**-0.0068*** (-6.617)**	**-0.004*** (-2.627)**	0.0164	0.0032 (3.005)	-0.002 (-1.362)
1+2+3+4	-0.0623	-0.0011 (-1.218)	-0.002 (-0.380)	0.0534	0.0006 (0.761)	-0.002 (-0.406)
¼*(1+2+3+4)-5	0.0064	**0.0216*** (10.051)**	0.003 (1.546)	-0.0055	-0.0162 (-8.118)	0.001 (0.591)
½*(1+2)-5	0.0127	**0.279*** (9.606)**	0.004 (1.333)	-0.0030	-0.0188 (-9.857)	0.003 (1.172)

FIGURE 5. QUINTILE PORTFOLIOS



Cumulative raw returns for the five portfolios sorted after their consensus recommendation and grouped into quintiles.

FIGURE 6. ZERO INVESTMENT PORTFOLIOS



The cumulative gross returns from Strategy 3 and 4.