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Analyst Recommendations: Price Impact and Stock Market Predictability

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Abstract:

This paper examines the abnormal returns around analyst recommendation changes and the predictability of future returns when utilizing the mean opinion of "sell-side" brokers, i.e. the analyst market sentiment. In essence, the nature of analyst recommendations is being studied, relating both to the academic debate of market efficiency as well as to potential trading strategies. The existence and magnitude of abnormal returns are assessed on a three day cumulative basis in an event study, using both parametric and non-parametric methods. Non-standard OLS regressions, taking consideration of heteroskedasticity and autocorrelation, are executed when evaluating the predictive power of the analyst sentiment on returns. Our results show evidence of absolute abnormal returns greater than 1 percent both for recommendation changes defined as upgrades and downgrades, endorsing that recommendations have a significant short term impact. Furthermore, the analyst market sentiment is concluded to be a lagging rather than leading indicator of returns.

Key Words: Market Efficiency, Analyst Recommendations Changes, Analyst Sentiment, Abnormal returns, Event study

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I. Introduction

The general idea and meaning of the efficient market hypothesis, from here on abbreviated EMH, is that share prices always incorporate all the relevant information. Thus, investors should not be able to consistently generate abnormal returns in excess of a relevant index or normal market return model.

This thesis implicitly investigates the above assumption by examining the impact of Swedish and foreign brokers' recommendation changes on the short term return on Swedish large cap stocks. Three day cumulative abnormal returns around recommendation changes are evaluated in order to assess the price reaction. Following that examination is an in-depth study of how investors may or may not be able to predict market fluctuations and trends based on the overall analyst market sentiment.

The performed studies assess the nature of analyst recommendations from two different vantage points; impact and predictability. In essence two operational questions are being studied relating to the overall research question concerning efficient markets: (1) Are abnormal returns present around recommendation changes? (2) What is the relation between the analyst market sentiment and returns, i.e. can returns be predicted with the overall analyst market view? The studies are interesting both from an academic point of view relating to market efficiency, as well as from an investor-oriented point of view gauging a potential trading strategy. Throughout this thesis, the above examinations are continuously reported on a parallel basis so as to make a clear distinction for the reader between the two studies. Despite this distinction, it is important to note the common denominator between the studies, being the nature of analyst recommendations and their relation to stock prices.

What distinguishes this study from prior similar work is the time period and geographical scope of the collected recommendation changes associated with the first study. Not only are recommendation changes gathered on a ten year basis, but they are also subject to focusing only on Swedish large cap stocks. In addition to the examination of traditional recommendation categories such as upgrade, downgrade, added to sell etc, a mean difference test examining the potential difference in impact between Swedish and foreign broker recommendations is executed.

The second study, regarding predictability, is by our knowledge unique in the sense that no previous literature has taken an investor-oriented perspective when assessing how one could potentially exploit the analyst market sentiment in order to profit. Although Ryan and Taffler (2006) examines other trading strategies such as a daily portfolio rebalancing strategy employing timely responses to consensus recommendations, our particular methodology is clearly distinguished from such a method. We create an adjusted analyst sentiment index for 11 years and regress it predicatively against actual stock market prices forward in time, in order to see whether the analyst market sentiment can be used to trade predicatively on the index. In contrast to the portfolio performance strategy, executed by previous authors, such a strategy - if proved feasible - avoids both direct and non-direct transaction costs associated with the rebalancing of portfolios.

In accordance with previous literature, documented in passage II, our main findings in our first study shows significant evidence of abnormal returns over a three-day event window. Results also show weak evidence of a stronger price impact for Swedish brokers added to buy category recommendation changes than for foreign brokers.

Our findings in the second study show that the overall analyst market sentiment should be viewed as a lagging rather than leading economic indicator, i.e. analysts tend to adjust their recommendations partially due to historical returns. The sentiment index level has an inverse relationship with historical returns, meaning that positive (negative) historic returns is associated with near future analyst pessimism (optimism).

Furthermore, the predictive power of the analyst sentiment index level on future returns surprisingly show evidence of a counterintuitive relationship, in the sense that a pessimistic (optimistic) sentiment index level is followed by future positive (negative) returns. These results suggest, when examined on a more detailed level, that from an investor-oriented point of view, trading indices based on the overall analyst sentiment is not profitable although it indeed avoids the majority of transaction costs.

II. Previous literature

Much has been debated as to whether investment professionals such as security analysts or investment managers truly are able to add value in excess of a relevant benchmark. While this discussion relates to the debate of market efficiency, it implicitly also sheds light on the employment of event driven trading strategies. Jensen (1968) finds that mutual funds, over the period from 1955-1964, on average where not able to predict security prices and profit from those predictions better than a traditional buy-and-hold strategy. Even when the returns are measured gross of managing fees the latter strategy is favorable. Thus, during that period, investors would have been better of investing in an appropriate index fund. Although more recent studies such as Henriksson (1984) and Ippolito (1989) have contradicted the former findings of Jensen (1968), showing that mutual funds net of management fees are able to produce a small but existent abnormal return, no considerable excess return over the passive benchmark are found when load fees are included. Ackermann et al. (1999) examines the performance of hedge funds which are subject to more flexible investment strategies in contrast to mutual funds. Even though data on hedge fund performance is limited due to marketing restrictions and limited transparency, Ackermann et al. (1999) use the available reported monthly returns over the period of 1988-1995 to assess the average returns over time. Their findings suggest that hedge funds consistently outperform mutual funds but that they are still not able to beat the market on average, using absolute or total risk-adjusted return. An important note to consider in this context is the characteristics of the fee structure of funds. While mutual funds charge their clients an administrative fee, hedge funds also incorporate an incentive fee or high watermark in addition. Ackermann et al. (1999) find that these fees on average are equal to the superior gross returns, implying that the profits from exploiting market inefficiencies equals the cost of search, i.e. management's compensation and operating costs.

Market efficiency

In conjunction with the above findings is the debate of market efficiency and potentially superior trading strategies. Grossman and Stiglitz (1980) argues that markets are not efficient if the definition of efficient markets is that they are always in equilibrium and that arbitrage profits thereby are eliminated. Instead there are in fact arbitrary opportunities so that the few with skill who search and assess information will receive compensation. Thus, information efficient markets are in that sense not a reality and there must be returns to information search costs.

Womack (1996) points out an important difference between post earnings announcement drift and post "sell-side" analyst recommendation drift. The former is a new public fact while the latter can be viewed as an information signal often independent of new information. However, assuming that analysts are a type of informed investor, a recommendation will provide, if not fact based information, opinion based information founded on the extensive information that the analyst have processed and interpreted. Thus, according to the proposed model of Grossman and Stiglitz (1980), the recommendations will make the price system, i.e. the market, more informative since the number of informed individuals is increasing. In other words, their reasoning refers to the process of incorporating information into security prices. In this context it is interesting to see whether this process can be exploited to generate superior returns and if possible, what investment horizon would produce maximum returns.

Event studies and average price-reaction

Womack (1996) performs a study assessing stock price reactions to analyst recommendations. Using the Thomson *First Call* real-time database Womack (1996) draws a sample of a little above 1500 stock ratings during the period of 1989-1991. Adjusted for reiterations and coinciding earnings releases that may cause an endogeneity problem, he takes special interest in extreme recommendation changes such as added/removed to the buy or sell category - the reason behind the choice being that such changes presumably are the most prominent ones. He then conducts an event study choosing an event period of three days. Womack's (1996) results shows a mean-adjusted actual return of +3.3 percent for added to buy recommendations, -4.3 percent for added to sell recommendations, -1.62 percent for removed from buy list and +0.71 percent for removed from sell list. Furthermore, he also examines the excess return in comparison with three different return generating models – size adjusted, industry adjusted and returns in excess of the Fama-French (1993) 3-factor model based on a low-frequency monthly calculated returns. After adjusting for size, excess returns for added to buy recommendations are +3.0 percent, added to sell -4.7 percent and removed from buy list -1.9 percent. All of the results are significantly different from zero at $\alpha=0.01$. Removed from sell list excess returns are excluded because no significant results were found.

Stickel (1995) performs a similar study using a slightly longer event window of 11 days (5 days before, 5 days after) and an equally weighted market index of stocks in the same firm-size deciles as the appropriate benchmark. Using a larger sample and a longer time period of 1988-1991 he finds a CAR[1] of +1.16 percent for added to buy recommendations and a -1.28 percent for sell recommendations. In contrast to Womack (1996), Stickel (1995) defines buy and sell recommendations in a different way. Applied recommendations are not only the ones added to and from extremes (Strong Buy/Strong sell), but also the ones added to the second most extreme recommendations (Buy/Sell), coming from a less/more favorable recommendation. Stickels (1995) dataset also differs in the sense that event times are less precise.

As stated by Stickel (1995) himself, his above findings are somewhat misleading due to the determinants of stock price performance and factors that influence the price reactions. Earnings announcements is one coinciding factor of recommendations, as is the permanent firm size-effect related to differences in a firm's information environment, which is not adjusted for in the sample. Stickel (1995) also examines other determinants like analyst reputation, recommendations that skip a rank, size of brokerage houses etc. The significance-levels of his results are varying. If recommendations are skipping a rank, issued by a well-reputed analyst, issued by a large brokerage house, issued on a smaller company, coinciding with a same-sign earnings forecast revision the magnitudes of the abnormal return will according to Stickel (1995) be greater. Interestingly he finds that recommendations possessing all of the above criteria at ones are followed by an average CAR of +4.61 percent (about three times +1.61 percent) during an 11 day event window. Thus, it seems as if the nature of the recommendations is closely dependent to its informative level. Stickel's (1995) findings are partially reinforced by Ryan and Taffler (2006) who report larger abnormal returns for recommendations that: goes from sell to buy (i.e. skip a rank), are reported on small stocks or are coinciding with a negative earnings

[1] Cumulative Abnormal Return.

announcement. Interestingly the latter authors finds no significant values of how a positive earnings forecast accompanied by a buy recommendation produces more extreme returns. Neither do they find that investment banking relationships, which is an added variable in addition to the ones investigated by Stickel (1995), are of any relevance to the determination of stock prices. The study serves as a useful comparison since it in contrast to Stickel (1995) is based on data collected from the UK and not the US.

Post-recommendation drift

In addition to the initial price reactions shown by both Womack (1996) and Stickel (1995), the former author also shows evidence of post-recommendation price drift. He finds that post-event returns are large and significant in the direction predicted by the analyst. However the findings are asymmetrical in the sense that the post-event drift of buy recommendations only are significant on a one month post return basis, whereas sell recommendations are, on the other hand, significant and largest during a six month post event return period. Womack (1996) finds that the average one month post - event size-adjusted return, beginning two days after the buy recommendation, is +2.4 percent. In the case of sell recommendations the equivalent number for the sixth month period is -9.1 percent. This implies that the initial reactions are incomplete, which puts further doubt on the EMH. Performing the same type of test on the UK market, Ryan and Taffler (2006) uncovers results consistent with the above findings.

Performance studies and transaction costs

Barber et al. (2001) takes a different approach in trying to determine if abnormal returns could be achieved by trading on analyst recommendations. In contrast to both Womack (1996) and Stickel's (1995) studies, where the primary goal is to measure the average price reaction to individual recommendations, Barber et al. (2001) takes an investor-oriented perspective. Instead of performing an event-study, measuring returns gross of transaction costs, they focus on the profitability of a few selected trading strategies taking both explicit and implicit costs into account. Creating portfolios based on consensus analyst recommendations, the authors examine what the return would be, should a particular strategy be employed.

As documented by Keim and Madhavan (1998) trading costs can be categorized into, the above mentioned, explicit and implicit costs. Whereas explicit costs are the direct cost of trading, such as brokerage fees and taxes, implicit costs are the indirect costs. Examples of the latter costs are price impact, bid-ask spreads and opportunity costs associated with bad timing. While explicit costs are easy to measure, the implicit costs are harder to properly distinguish. Keim and Madhavan (1998) estimates the round-trip costs, defined as all the costs associated with a transaction, by trade-size quartile using actual data of order quantity and trade components. They find that the average round-trip cost associated with the largest trades on NASDAQ stocks to be +4.43 percent (2001). Using the authors round-trip costs coupled with small, medium and large stocks Barber et al. (2001) estimates the round-trip costs for their created portfolios to be +1.31 percent. This number is then used to assess the actual annual transaction costs for each of the portfolios computed, depending on the number of times, and how frequently, the portfolio needs to be rebalanced.

Before taking transactions costs into account, Barber et al. (2001), in accordance with previous authors, find significant proof that over the 1986 - 1996 period, gross abnormal returns can be generated by buying (shorting) stocks with the most (least) favorable consensus recommendations. However they also find that substantial trading costs are required to employ the preferred strategies resulting in abnormal net returns not reliably greater than zero.

The calendar-time constructed portfolios are created by pooling stocks into separate groups based on their ratings graded from 1 to 5. Stocks with similar average ratings from different analysts are put together. After value-weighted returns have been calculated on a daily basis, market-adjusted returns are calculated. Three measures of abnormal performance are calculated using the CAPM,[2] the Fama-French (1993) three factor model as well as a four factor model taking momentum into consideration. After subtracting the returns from the chosen market-return models, as well as annual transaction costs that are dependent of the annual portfolio turnover (i.e. the number of re-ratings in a given year), no abnormal returns are found.

Ratio of buy to sell recommendations

Finally, an important remark to make about the dataset of all of the discussed authors is the fact that there are generally more buy recommendations than sell recommendations in the market. Womack (1996) notes a seven to one ratio while Stickel's (1995) sample consists of 55 percent buy, 12 percent sell and the rest hold. Ryan and Taffler (2006) report a different number of a ratio of about 2.3 to 1, concluding that the ratio is higher in the UK market than in the US. A plausible explanation for this phenomenon is the possible conflicts of interest and costs attributed to the issue of sell recommendations.

Predictive regressions

Predictive models for common stock returns have been around for a long time. Fama (1970) relates such studies to the EMH, assessing the dependence of day-to-day price changes and returns on common stocks. Goetzmann and Jorion (1993) choose another predictive variable in dividend yields, assessing long horizon stock-returns. As mentioned by Ferson et al. (2003) a wealth of potentially predictive variables can be found, most often relating to the prediction of future stock- or bond returns. Interests, yield spreads and price-to-earnings ratios are some predictive factors thoroughly investigated, just to mention a few. The standard format for predictive regressions is as follows:

$$y_t = \alpha + \beta X_{t,t-k} + \varepsilon_t$$

where y_t usually represent future returns and $X_{t,t-k}$ is the predictive variable lagged up to k periods.

[2] Capital Asset Pricing Model.

III. Data

Event Study

The dataset consists of 5455 recommendation changes on 36 different stocks comprising the OMXS30 index during the period of year 2001 - 2011. During the period more than 36 stocks have comprised the OMXS30 index, but due to data availability reasons only recommendations on these 36 stocks have been studied. When a stock has been withdrawn from the index the recommendations that followed have thus been dropped.

The first observed recommendation was recorded on 11th January 2001 and the last one on 20th January 2011. All of the recommendations have been collected using the Institutional Brokers Estimates System (I/B/E/S), which provides consensus and detail forecasts from security analysts regarding EPS,[3] revenues, cash flow and most importantly stock recommendations. For the event study the RECDET dataset list have been used. The list includes analyst-by-analyst individual recommendations for a particular security. Since brokerage houses have different denominations of their recommendations in addition to traditional ratings of sell, hold and buy, each recommendation received from the brokerage houses is mapped to one of the Thomson Reuters standard ratings.[4] The standard maintained by Thomson Reuters is a five point scale consisting of: 1. Strong Buy, 2. Buy, 3. Hold, 4. Underperform and 5. Sell. Defining buy recommendations as strong buy (1) or buy (2), and sell recommendation as a underperform (4) or sell (5) the dataset consists of 42 percent buy recommendations, 26 percent sell recommendations and 32 percent hold recommendations. As shown in Table I[5], changes are categorized into pools based on the old and new rating. A recommendation change is defined as an alteration of the previous recommendation last recorded, within the same brokerage house.

Associated with each recommendation are 19 variables conveying information about date/time, analyst - and broker name, numeric value of recommendation, company name and an 8-digit company identifier called CUSIP. Other less relevant variables have been excluded from the panel dataset. Since stocks are trading on multiple exchanges the primary listings of each stock have been used when downloading the dataset. Of the 36 examined companies only Nokia, Astra Zeneca and ABB have primary listings on a foreign exchange. The primary listings have been used in order to collect as many recommendations as possible.

I/B/E/S records three date variables; activation date, revision date and announcement date. Activation date is the date when the recommendation was recorded by Thomson Reuters, the announcement date when it was reported and finally the review date when the recommendation was confirmed by I/B/E/S with the contributor. Thus, the relevant date is the announcement date since that is when the recommendation was being made public.

The value-weighted OMXS30 price index, used as a market proxy, has been downloaded from Thomson Reuters Datastream (2011). The return on Swedish treasury bills with one month maturity is used as the risk free rate and has been downloaded from Sveriges Riksbank (2011).

[3] Earnings Per Share.
[4] Examples of additional denominations are: Add, reduce, market outperform, neutral, accumulate, attractive.
[5] Page 18.

Analyst Sentiment Study

The data used for this method consists of 3,936 monthly mean consensus recommendations with an underlying 77,141 individual recommendations on the 46 constituents for the OMXS30 index during the time period of January 2000- January 2011. These consensus recommendations have been downloaded using the Institutional Brokers Estimates System (I/B/E/S),[6] as documented above. This data is similar in characteristics to the data used in our above event study in terms of the Thomson Reuters standard rating scale, the main difference being that the data consists of consensus recommendations rather than individual analyst recommendations.

Return data for OMXS30 have been downloaded using Thomson Reuters Datastream (2011) and constituent weight data for OMXS30 have been received from NASDAQ OMX Nordic (2011).[7]

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[6] The I/B/E/S database for consensus recommendations does not include all available recommendations as some brokers only publish their recommendations to their paying customers. However, the database is extensive and serves it purpose for this study.

[7] In addition to the web-link provided in this reference, data has also been received directly via email from Michael Olsson, Head of Index Operations – Global Index Group at NASDAQ OMX.

IV. Methodology

Event study

In order to evaluate whether abnormal returns are generated when recommendations are made public, an event window of three days has been chosen to assess the short-term price fluctuations. Theoretically, the event window could have been made shorter, looking only at intraday abnormal returns. However, although the major part of our recommendations have both a date- and an hour stamp, a significant number of observations cannot be assigned a specific time of publication, making it impossible to know exactly when the recommendation was made public. Thus, in order to make the event window as short as possible, still being sure of capturing the abnormal returns, the three-day event window was chosen. This makes our results more comparable with previous literature. The three day cumulative return is thus:

$$R_{it} = \prod_{t=-1}^{+1} (1 + r_t^i)$$

where t=0 is the recommendation day and r_t^i is the return of stock i on day t. The prior-post recommendation window is justified by the fact that there might be a leak of information prior to the announcement of the recommendation.

To appraise the events impact a measure of abnormal returns is required, and a model for normal returns is necessary. Rather than employing a constant-mean return model, normal returns are calculated on the basis of a market model. Cumulative abnormal returns are defined as:

$$CAR_{it} = R_{it} - R_t^f - \beta_t^i (R_t^{omxs30} - R_t^f)$$

where R_{it}, R_t^f, and R_t^{omxs30} are the cumulative three day- actual returns, risk-free returns and market returns for security i at time t, where t is a three day period. The β_t^i is defined as the correlated relative volatility between security i and the market portfolio, proxied by the OMXS30 Index.

$$\beta_t^i = \frac{Cov(r_{24m}^i, r_{24m}^{Omxs30})}{Var(r_{24m}^{Omxs30})}$$

Instead of using fixed betas for every single security, betas are calculated on a 24-month rolling basis using daily returns. Thus, security betas will fluctuate on a daily basis. This way, normal returns will incorporate the dynamic and sometimes changing relationship between a stocks return and market returns over time. Since the ultimate goal is to acquire a model for normal returns, not affected by the abnormal returns around the actual event period, the 24 month long estimation window is lagged one week. This way, normal returns will not incorporate the potential noise and information leakage associated with the particular recommendation change. However it should be pointed out that this is just a refinement of the model, which will have a negligible effect on the overall results. Alternatively, a multifactor model could have been used when approximating the normal returns. The gains from adding more factors is nevertheless small given that the purpose of the test is to approximate potential abnormal returns, rather than establishing the exact ones.

In similarity to both Stickel (1995) and Womack (1996), t-tests are carried out in order to establish the potential existence of abnormal returns. One-sample t-tests are executed as follows:

$$\mathrm{t} = \frac{\mathrm{ACAR_X} - \mu_0}{\frac{\mathrm{S}}{\sqrt{\mathrm{n}}}}$$

where ACAR is the average cumulative abnormal three day return of sample X, where X is the recommendation change type, i.e. downgrade, added to buy, underperform-buy etc. S is the sample standard deviation and n is the number of observations. The independent one-sample t-tests are testing the null hypothesis that the population mean is equal to zero as follows:

$$H_0\text{: } \mathrm{ACAR_X} = 0$$

As reported in Table II[8], 24 one-sample t-tests are performed. In addition to the one-sample tests, four two-sample t-tests are executed in order to assess the potential difference in impact between Swedish brokers and foreign brokers. The rationale behind the test is that the Swedish market potentially is more influenced by recommendation changes issued by Swedish brokers than foreign brokers. The tests are performed over the four categories Upgrades, Downgrades, Added to buy, Added to sell, which are from here on denominated as the aggregated recommendation pools or alternatively recommendation categories. The motivation behind the creation of the aggregated pools was to assess the recommendation changes, which would presumably result in the most abnormal returns. The two-sample t-test is executed as follows:

$$t = \frac{ACAR_X^{SWE} - ACAR_X^{FRGN}}{S_{ACAR_X^{SWE} - ACAR_X^{FRGN}}}$$

where $S_{ACAR_X^{SWE} - ACAR_X^{FRGN}}$ is the combined standard deviation of the two group samples and the null hypothesis is as follows:

$$H_0\text{: } ACAR_X^{SWE} = ACAR_X^{FRGN}$$

In order to assess the robustness of our results, non-parametric tests are conducted since the underlying assumptions of the t-tests may be violated in our subgroups and samples. Two different tests are performed. In addition to the 24 one-sampled t-tests described above, Wilcoxon signed ranked tests are conducted for the respective recommendation change type. The test allows us to rest the normality assumption assumed in the t-test. For the remaining four two-sample populations categorized by the origin of the broker, the Mann Whitney U test is used. The test allows us to relax both the normality assumption and the homogeneity in variance assumption. Finally the results of the t-tests are compared to the non-parametric results.

[8] Page 19.

Analyst Sentiment Study

In order to test whether the overall analyst market sentiment can predict future market returns and if historic returns prepossess the current analyst sentiment, we have created a monthly index-variable called S, representing the current analyst sentiment for the OMXS30 Index. This index is created by weighing the mean monthly consensus recommendations for each constituent in the OMXS30 Index with its corresponding weight in the OMXS30 Index. The variable can be interpreted as a measure of the overall analyst view on the market. When the value takes on a high number it means that analysts have a pessimistic view of the market. Correspondingly, when S is low, the overall analyst market view is positive. A high (low) S is equivalent to a high (low) analyst sentiment index and a pessimistic (positive) analyst market view. These expressions will be used simultaneously. Before calculating the index, we have cleared our dataset from missing observations. These missing observations arise from either (1) unavailable or nonexistent mean consensus recommendations or (2) return data for a constituent in a given month. If a constituent is affected by either (1) or (2) it is simply given the weight of zero for that month when creating the sentiment index. To adjust the weights so that the sum of all constituent weights equal 1 the following adjustment is made to the unadjusted weights:

$$\mathrm{w_i^{adj.}} = \frac{\mathrm{w_i^{unadj.}}}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{w_i^{unadj.}}}$$

Henceforth, the analyst sentiment variable, S, is calculated as:

$$S_t = \sum_{i=1}^{n} (\mathrm{w_i^{adj.}} * r_{it})$$

where:

i is a constituent of the OMXS30 Index and *n* is the number of constituents at time *t*

w_i^{adj} is the adjusted weight of the constituent *i* in the OMXS30 Index

r_{it} is the mean consensus recommendation of the constituent stock *i* for month *t*

and:

S_t is the monthly analyst sentiment index for OMXS30

As the consensus recommendations, r_{it}, follow the Thomson Reuters Standard rating scale from 1-5, where 1 represents Strong Buy, 2 represents Buy, 3 represents Hold, 4 represents Underperform and 5 represents Sell, the index-variable S is restricted by $1 \leq S \leq 5$.

Furthermore, taking into consideration the missing observations mentioned above, we have also adjusted our return benchmark, the OMXS30, as follows:

$$R_t^{OMXS30} = \sum_{i=1}^{n} (\mathrm{w}_\mathrm{i}^{\mathrm{adj.}} * R_{i)}$$

where:

R_i is the monthly return of the constituent stock i calculated as:

$$R_i = \frac{\mathrm{P_{it}}}{\mathrm{P_{it-1}}} - 1$$

P_{it} is the closing stock price of constituent i on the announcement day of the consensus recommendations

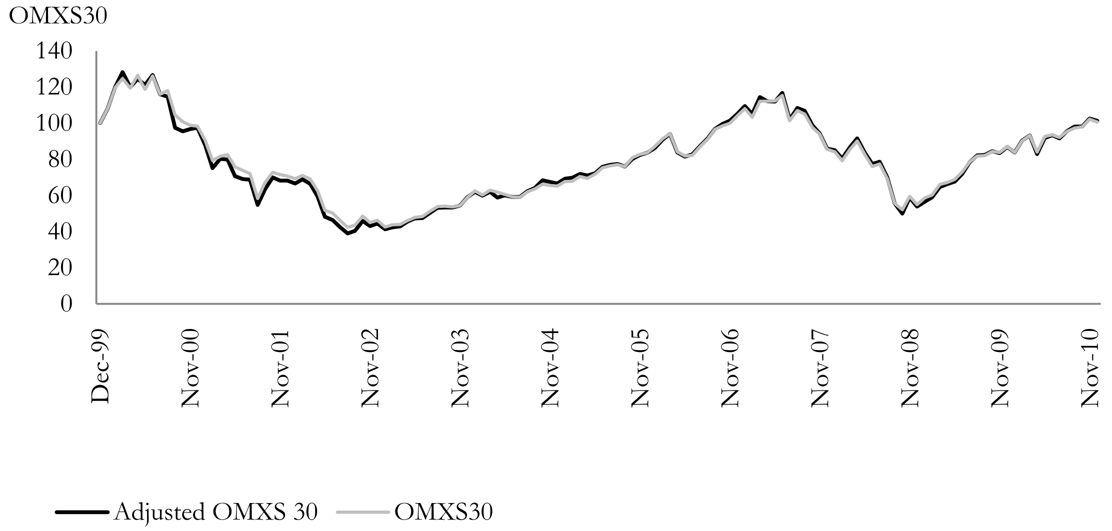
P_{it-1} is the closing stock price of constituent i on the announcement day of the consensus recommendations the month prior to t.

and:

R_t^{OMXS30} is the monthly return of the adjusted OMXS30 Index for month t

Chart I below shows the almost perfect correlation between our adjusted OMXS30 Index and the real OMXS30 Index.

Chart I. Adjusted OMXS30 Index and OMXS30 Index (rebased to 100)



We then run the following regressions using the autocorrelation-heteroskedasticity-consistent (HAC) standard errors from Newey and West (1987). This is due to overlapping time series and that the standard OLS regression produces biased estimates of the standard errors.

Predicting Sentiment Index with Historic returns:

$$(1)\ S_t = \alpha + \beta * R_{t,t-k} + \varepsilon, \text{where } 1 \leq k \leq 5 \text{ and k is on a monthly basis}$$

Predicting future returns with Sentiment index:

$$(2)\ R_{t,t+k} = \alpha + \beta * S_t + \varepsilon, \text{where } 1 \leq k \leq 5 \text{ and k is on a monthly basis}$$

Predicting future returns with Sentiment index and historic returns:

$$(3)\ R_{t,t+k} = \alpha + \beta_1 * S_t + \beta_2 * R_{t,t-1} + \varepsilon, \text{where } k = 1 \text{ and k is on a monthly basis}$$

Predicting future returns with historic returns:

$$(4)\ R_{t,t+k} = \alpha + \beta * R_{t,t-k} + \varepsilon, \text{where } 1 \leq k \leq 5 \text{ and k is on a monthly basis}$$

Predicting future returns with historic percentage change in Sentiment index:

$$(5)\ R_{t,t+k} = \alpha + \beta * \Delta S_{t,t-k} + \varepsilon, \text{where } 1 \leq k \leq 5 \text{ and k is on a monthly basis}$$

Predicting future percentage change in sentiment index with historic returns:

$$(6)\ \Delta S_{t,t+k} = \alpha + \beta * R_{t,t-k} + \varepsilon, \text{where } 1 \leq k \leq 5 \text{ and k is on a monthly basis}$$

In regression (1), (2), (3) the absolute number of S_t is being applied either as the regressor or the regressand. In regression (5) and (6) the percentage change in S_t, denominated $\Delta S_{t,t+k}$, is being applied. It is important to point out a relevant difference in interpretation between the former and latter regressions. The former regressions express the relationship between the level of the sentiment index (S) in a given month (t), and cumulative returns going forward and backward in time. The latter regressions takes the analysis one step further, assessing what implications historic returns have on the near term change of analyst opinion or on the contrary how a change in analyst opinion affect future returns.

In detail, regression types (1) and (2) are run to understand if a high or a low level of the analyst sentiment index is associated with positive or negative future returns, or alternatively if positive or negative historic returns are associated with a high or a low level of the analyst sentiment index. Regression (3) is run to check if including historic returns into our predictive regression can increase the coefficient of determination, R^2, and is only run for one month. Regression type (4) is run to facilitate the economic interpretation of regression type (1) by comparing the Beta-coefficients in the two regressions. That is, if historic positive returns lead to future positive returns this might be the economic explanation for why analysts are positive if historic returns are positive (if that is the case). Regression types (5) and (6) are run to understand if a change in the analyst sentiment index should be viewed as a leading or lagging, alternatively independent, indicator of market returns.

The six different types of regressions with differing lag structures originate a massive amount of sub-regressions. In our analysis we have therefore limited ourselves to evaluating only the paired lags (for example: two months back in time with two months forward in time) since the benefit of analyzing all of the sub-regressions hardly make up for the costs – being a less clear-cut and messy analysis. However, for the interested reader the results from all of the sub-regressions can be found in the Appendix.

V. Results

Event study

Out of the 5455 recommendation changes recorded over the most recent decade about 42 percent belongs to the positive category of Strong Buy or Buy as reported in Table I.[9] Comparing this with the negative category of Underperform and Sell it is obvious that more buy-recommendations than sell-recommendations are issued. This is consistent with previous findings reported by Stickel (1995), which provides the same definition of buys and sells as reported below. Evaluating a narrower period but including considerably more recommendation changes he finds the corresponding numbers to be 55 percent belonging to the positive category and 12 percent belonging to the negative category. Thus, the patterns are similar with the exception of the Underperform category which forms a greater bulk in our dataset. Interestingly a large number of ratings seem to be downgraded to the neutral rating of Hold, rather than tipped over into one of the negative pools. In fact, the single most common recommendation change is the downgrade from a Buy to a Hold. In contrast, the single rarest recommendation is the stronger form of downgrade, going from a Buy - to a Sell recommendation. These findings are consistent with Stickel (1995) as well. In contrast to previous authors, one should bear in mind that our study is limited to a subset of large cap stocks, during a period about two-three times longer than previously evaluated.

As reported in Table II[10], 13 out of the 20 individual recommendation changes are associated with abnormal returns at the 1 percent significance level. One individual recommendation change is significant at the 5 percent level and one at the 10 percent level. No significant abnormal returns can be attributed to the five remaining individual recommendation changes. It is noteworthy that 4 out of 5 of those recommendations are coming from an old rating of Sell. In addition, they also contain relatively few observations making it hard to establish significant results. The most extreme abnormal return associated with an individual recommendation change, occurs when going from a Strong Buy to an Underperform. Comparing the negative 2.22 percent with the most extreme positive abnormal return of 1.85 percent, it seems as if "Sell-recommendations" changes tend to have a more profound effect on stock prices. Although our aggregated pools of Upgrades and Downgrades supports that argument, the abnormal returns of the Added-to-buy category are actually greater than the absolute abnormal returns of the Added-to-sell category. Interesting is also, that recommendations going from the positive or negative category to the neutral category in most cases provides both greater and more significant returns, compared to when going from one extreme to the other. As reported in Table I[11] the neutral category is also the biggest category with respect to number of observations, implying that analysts are rather restricted to issuing recommendations that skip a rank.

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[10] Page 19.
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Table I. Matrix of Recommendation Changes - Descriptives

	New Rating						
Old rating	**1 Strong Buy**	**2 Buy**	**3 Hold**	**4 Underperform**	**5 Sell**	Total	Percent
1 Strong Buy		**366**	**270**	**66**	**41**	**743**	**14%**
2 Buy	**341**		**792**	**391**	**18**	**1542**	**28%**
3 Hold	**285**	**730**		**550**	**179**	**1744**	**32%**
4 Underperform	**73**	**414**	**517**		**91**	**1095**	**20%**
5 Sell	**43**	**37**	**179**	**72**		**331**	**6%**
Total	**742**	**1547**	**1758**	**1079**	**329**	**5455**	
Percent	**14%**	**28%**	**32%**	**20%**	**6%**		
	Upgrades	**Downgrades**	**Added to buy**	**Added to sell**	**Ratio‡**		
	1263	**1578**	**1582**	**1245**	**29%**		

Table I represents 5455 recommendation changes over the period from jan 11th 2001 to jan 20th 2011, associated with the event study. The table is supposed to be read from left to right enabling 20 different types of recommendation changes, excluding re-iterations marked in gray. In addition to the 20 different types of recommendation changes, four categories (aggregated pools) have been defined where each is incorporating 6 types of recommendation changes demarcated either by a pattern or a border. The categories have been chosen and defined on the basis of extremity, meaning that the recommendation changes that are believed to have the greatest impact on prices have been consolidated. ‡ indicates the ratio of Swedish-to-total recommendation changes (1588/5455).

Table II. Matrix of Recommendation Changes - Results

Old rating	New Rating: 1 Strong Buy	2 Buy	3 Hold	4 Underperform	5 Sell
1 Strong Buy		**-0,77%**	**-1,35%**	**-2,22%**	**-1,40%**
t-stat		**-3.42*****	**-4.38*****	**-3.36*****	**-2.80*****
St.dev		**0,043**	**0,051**	**0,054**	**0,032**
2 Buy	**0,98%**		**-1,78%**	**-0,66%**	**1,02%**
t-stat	**4.46*****		**-9.77*****	**-2.73*****	**0.72**
St.dev	**0,041**		**0,051**	**0,048**	**0,060**
3 Hold	**1,31%**	**1,23%**		**-1,19%**	**-1,01%**
t-stat	**4.85*****	**6.56*****		**-4.33*****	**-3.27*****
St.dev	**0,046**	**0,051**		**0,064**	**0,041**
4 Underperform	**1,44%**	**1,07%**	**1,85%**		**-1,51%**
t-stat	**2.21****	**5.18*****	**5.80*****		**-1.79***
St.dev	**0,056**	**0,042**	**0,072**		**0,081**
5 Sell	**0,68%**	**0,26%**	**0,64%**	**-0,11%**	
t-stat	**1,13**	**0,27**	**1,49**	**-0,189**	
St.dev	**0,039**	**0,058**	**0,057**	**0,050**	
Other tests	**Upgrades**	**Downgrades**	**Added to buy**	**Added to sell**	
AR	**1,31%**	**-1,41%**	**1,17%**	**-1,03%**	
t-stat	**7.83*****	**-11.09*****	**9.78*****	**-6.57*****	
St.dev	**0,059**	**0,050**	**0,048**	**0,055**	
Mean difference Foreign VS Swedish	**-0,67%**	**-0,06%**	**-0,47%**	**0,69%**	
t-stat	**-1.60**	**-0.24**	**-1.69***	**1.86***	
St.dev	**0,059**	**0,050**	**0,048**	**0,055**	
Foreign/Swedish - #Observations	**930/333**	**1120/458**	**1103/479**	**931/314**	

Table II is a superstructure of table I, reporting the main results associated with the number of observations and different types of recommendation changes reported in table I. In addition to the diferent types of recommendation changes and categories (aggregated pools) explained in table I, the results and descriptives from the difference in mean test between foreign and Swedish brokers are reported. All of the results above the crosshatched line roots from one sample t-test, whereas the results below the same line roots from two sample t-tests. The null-hypothesis for the results reported above the crosshatched line is H0: ACARx=0, whereas the null hypothesis for the results reported below the line is H0: ACARfrgn=ACARswe. * indicates that the estimate is significant at the 10 percent level. ** indicates that the estimate is significant at the 5 percent level. *** indicates that the estimate is significant at the 1 percent level.

While our results shows that downgrades provides the most extreme abnormal returns, which is somewhat consistent with Womack's (1996) results, the magnitude of the respective aggregated pool, such as Upgrades, Downgrades etc, is smaller in our sample. A more coinciding picture is given by Stickel (1995) who finds mean abnormal returns of 1.16 percent and -1.28 percent associated with buy- and sell recommendations. However those returns are calculated using a longer event window of 11 days. Other authors such as Ho and Harris (1998) and Ryan and Taffler (2006) reports varying results using short, but differing event windows.

The final test employed over the four aggregated recommendation pools regards the potential difference between the market impact and price pressure effects of Swedish brokers' recommendation changes to foreign brokers' recommendation changes. This is a test, by our knowledge, not examined in any previous literature. As can be seen in Table I[12] the recommendations issued by Swedish brokers' accounts for about 29 percent of the collected recommendation changes. Correspondingly, this is thus the approximate ratio of Swedish-to-Total number of observations within each of the aggregated pools. Thus, the foreign recommendation sample size is about 2-3 times greater than the Swedish recommendation sample size. Although results are neither significant at the 1 percent - level nor the 5 percent-level, weak evidence at the 10 percent - level are found rejecting the null-hypothesis that the different means are equal within the two samples, for the added-to-buy and added-to-sell category.

Resuming the previous discussion about the differing magnitude of the abnormal returns, several affecting factors can be pointed out. For instance, the choice of normal market return model may be affecting the outcome. Time and sample characteristics concerning the timeframe, size of sample and choice of brokers and stocks are other relevant factors. An alternative and more speculative explanation concerns the EMH previously discussed. Given the smaller magnitude of abnormal returns found in our study, a possible explanation could be that markets have in fact become more efficient, reducing the returns to information search costs since previous literature was published. Other variables that have an effect on the short-term price reactions around recommendation changes have been documented by both Stickel (1995) and Ryan and Taffler (2006), as stated above. An important variable to take into consideration when evaluating the abnormal returns is the same-sign earnings revision forecast. Since recommendations are sometimes triggered by earnings releases containing actual information rather than just a signal, our sample may be biased making the abnormal returns not fully representative for the isolated recommendation change price reaction. However, Womack (1996) notes that only a small percentage of recommendations happen to coincide with quarterly earnings announcement. Thus, dropping recommendations that coincide with earnings announcement would most likely not change our results and conclusions.

Potential problems associated with our tests concerns the underlying assumptions of the one- and two sampled t-tests. In order to check the robustness of our results we relaxed the normality

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assumption of the one-sampled t-tests and performed a one sample median test using the non-parametric Wilcoxon signed rank test. Results are shown in Table III.[13]

As reported in the table, the null-hypothesis which states that average cumulative abnormal returns over the three-day event window is equal to zero, is rejected at the 5 percent - level 17 out of 24 times. These results are consistent with the results in Table II.[14] Thus, our results are robust after the relaxation of the normality distribution assumption.

Regarding the two-sample t-tests that concern the disparity between Swedish- and foreign brokers' recommendation impacts, another non-parametric test, the Mann Whitney U test, was used to confirm and reexamine the weak but indicative results shown in Table II.[15] Results are shown in Table IV.[16]

Interestingly, the test confirms a significant difference in mean within the added to buy category. While this is consistent with results in Table II,[17] a significant difference in mean within the added to sell category is not established. Further contradicting the parametric test is the rejection of the null hypothesis within the upgrade category. A combined interpretation of the results in Table II[18] and Table IV[19] is thus that there is no significant difference in mean for the downgrade category, a potential difference in the upgrade and added-to-sell category, and a prevailing difference in the added-to-buy category.

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[14] Page 19.
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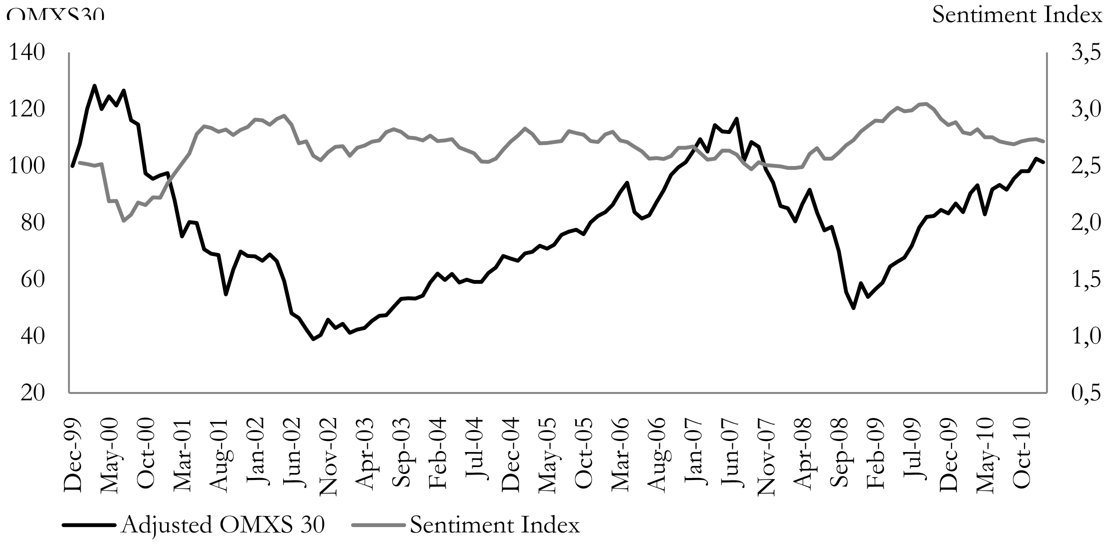
Analyst Sentiment Study

The main data used in the sentiment study is shown in Chart II below to give a better understanding of the findings we present hereon.

Chart II. Adjusted OMXS30 and Sentiment Index January 2000 - January 2011



Moreover, descriptive statistics for the data used in the analyst sentiment study is presented below in Table V.

Table V. Descriptive Statistics: Data used for Analyst Sentiment Study

						of which		
	Consensus	**Individual**	**Mean**	**Median**	**St. Dev**	**Buy**	**Hold**	**Sell**
Recommendations	3,936	77,141	2.68	2.70	0.48	33,700	16,839	26,601
As percent						43.7%	21.8%	34.5%
	Observations	**Max**	**Mean**	**Median**	**St. Dev**	**Min**		
Adjusted OMXS30(1)	134	128.23	78.52	78.34	21.84	39.00		
S_t	133	3.05	2.67	2.71	0.19	2.02		

(1) Rebased to 100 with start-date December 1999

Furthermore, a compilation of the results discussed below is presented in Table X.[20] As described in the methodology, six different regression types are run incorporating a number of sub-regressions with differing lag structures. Both the absolute value of the sentiment index, as well as the sentiment index change is being studied in order to determine the relationship between returns and the analyst sentiment index.

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Table VI. Overall results, Interpretations and Research Questions

Regression	Formula	Research question	Result	Overall Significance of Result	Relationship	One-way Interpretations	Detailed Tables
(1)	$S_t = \alpha + \beta * R_{t,t-k} + \varepsilon$	Can historic returns predict the analyst market view?	Yes	Weak	Positive	Historic positive returns is associated with pessimistic analysts	Table VII
(2)	$R_{t,t+k} = \alpha + \beta * S_t + \varepsilon$	Can the analyst market view predict future returns?	Yes	Strong	Positive	Positive analysts are associated with future negative returns	Table VIII
(3)	$R_{t,t+k} = \alpha + \beta_1 * S_t + \beta_2 * R_{t,t-1} + \varepsilon$	Can adding one-month historic returns refine the results in regression (2)?	Not Considerably	Weak	Positive	Combination of (1) and (4)	Table IX
(4)	$R_{t,t+k} = \alpha + \beta * R_{t,t-1} + \varepsilon$	Can historic returns predict future returns?	Yes	Weak	Positive	High historic returns imply high future returns	Table X
(5)	$R_{t,t+k} = \alpha + \beta * \Delta S_{t,t-1} + \varepsilon$	Can a change in the analyst market view predict future returns?	No	Insignificant	-	-	Table XII
(6)	$\Delta S_{t,t+k} = \alpha + \beta * R_{t,t-1} + \varepsilon$	Can historic returns predict a future change in the analyst market view?	Yes	Strong	Negative	High historic returns lead to less pessimistic analysts	Table XIII

Table VI summarizes our findings and interprets the results. Associated with each regression type are a number of sub-regressions that can be found in Table VII - XIII pp. 32-35

Our results from regression type (1) show significant results for four out of five sub-regressions at the 5-10 percent level, implying that the analyst sentiment index level will be positively related to historic returns going backwards *t-k* months in time. In other words positive (negative) historic returns will result in a future high (low) analyst sentiment index level interpreted as a pessimistic (positive) analyst market view. The results are shown in Table VII.[21] An important remark to make is that a pessimistic (positive) market view is defined as a value on S above (below) a certain threshold being the mean market analyst sentiment represented by the constant in the sub-regressions displayed in Table VII.[22]

Regarding the predictive power of the analyst sentiment index on future market returns examined in regression type (2), we find that negative (positive) analysts are associated with positive (negative) future returns. In this regression shown in Table VIII,[23] results are significant from two months cumulative return going forward in time and we notice a trend in that both the coefficient of determinant, R^2, and the t-stat is increasing over time. The interpretation of this result is that future returns tend to be negative (positive) when analysts adapt a positive (negative) market view. Given that our index-variable S is restricted by $1 \leq S \leq 5$, where 1 is Strong buy and 5 is a Sell, it is important to note that a negative (positive) analyst market view is associated with a high (low) number. The implications of this reverse relation is thus that regression coefficients will be positive, denoting that a higher (lower) value of the sentiment variable is interpreted as a more pessimistic (positive) view of the market.

When trying to predict one month future returns with both historic returns and the sentiment index, in regression type (3) we see a slight increase in the coefficient of determinant compared to regression (2). However, all of the results are insignificant. The results from regression (3) are shown in Table IX.[24]

In regression type (4), when predicting future cumulative returns with historic cumulative returns, we find the coefficient for historic returns to be positive in all cases, meaning that an increase (decrease) in historic returns is associated with an increase (decrease) in future returns using our simple predictive model. Intuitively one can understand that this is not always the case, which is also explained by our relatively low R^2 - values, suggesting that many other factors explain future returns. Thus, the results simply show the relationship between the dependent and independent variables. In regression (4), two out of five values are significant on the 10 percent - level. The results from regression (4) are shown in Table X.[25]

In regression type (5) we test if a percentage change in the sentiment index can predict future cumulative returns. As seen in Table XI[26] all of the results are insignificant showing no evidence of predictability.

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Finally, in regression type (6) we predict future percentage change in the sentiment index with historic returns. As shown in Table XII[27] coefficients are increasingly significant over time from the 10 percent to the 1 percent – level for three months or more with a total of 3 out of 5 significant regressions. Although our results entail a negative relationship between the two variables, implying that analysts do in fact adjust their market view based on historic returns and that the sentiment index variable should be considered as a lagging rather than leading indicator, the results are not as straightforward as one might first think. Depending on the size of the constant, positive historic returns could in fact result in an increase in the sentiment index interpreted as more pessimistic analysts. However all of the constants are not significantly different from zero which gives further credibility to our results implying that the sentiment index variable can be considered to be a lagging rather than leading indicator of returns.

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VI. Implications and conclusions

Event Study

Our results show clear evidence that abnormal returns around recommendation changes do prevail. This is consistent with the majority of the previous literature studied. In addition to previous literature that collects material from a rather short period, our study confirms the findings over a longer period of about ten years. Only focusing on large cap stocks in Sweden, our results show that the Swedish market reacts to recommendation changes in a similar way to other markets documented in the previous literature.

All of the aggregated recommendation pools demonstrate a magnitude of 3-day average cumulative abnormal returns within the 1- to 1.5 percent absolute number range. The economically small difference and relatively asymmetric returns between positive and negative recommendations seem consistent with the, compared to previous literature, less extreme ratio of positive to negative recommendations. In other words, should the ratio be greater, the cost of issuing sell recommendations would be greater, thus requiring greater returns. Putting our results in relation to what has previously been studied, it appears as if the ratio of positive to negative recommendations outstanding in a given market is related to the disparity in size of the abnormal returns associated with positive and negative recommendations. However such a relationship is not statistically established in this thesis and is left for future research to establish.

Stickel (1995) draws the conclusion that changes that skip a rank have a larger price effect than recommendations moving just one step, meaning that a downgrade (upgrade) to a strong sell (strong buy) have a greater impact than downgrades (upgrades) going to a underperform or hold recommendation (buy or hold recommendation). Our results prove contradictious on this matter. On one hand both the Strong Buy to underperform and Strong Buy to Sell proves to be more extreme than Strong Buy to Hold. On the other hand, Buy to Hold generates more abnormal returns than both Buy to Underperform and Buy to Sell. The opposite case when going from an Underperform to Hold also provides more extreme returns than recommendation changes that skip a rank or two. Although Stickel's (1995) results are intuitively reasonable, our results show that recommendations skipping a rank are not necessarily coupled with stronger price reactions.

Taking into consideration both the standard two-sample t-tests as well as the Mann Whitney U test, evidence of a difference in mean cumulative abnormal returns can be established for the added-to-buy category. Thus, we can conclude that there is weak evidence that Swedish brokers' added to buy recommendations have a greater short term price impact on the stocks included in our sample. Although evidence are weak and inconsistent over the four aggregated pools, the results open up for an interesting discussion as to whether the origin of the broker in relation to the origin of the stock could potentially explain some of the abnormal returns associated with recommendation changes. Future studies could approach this question in a similar way as Stickel (1995) and Ryan and Taffler (2006), by performing a cross-sectional analysis determining the factors that have a bearing on the magnitude of abnormal returns.

Future studies could also focus on a more in-depth examination of whether the ratio of buy to sell recommendations in a given market can help explain the magnitude of short-term abnormal returns. Such a study would have to gather data from several separate markets or time periods, with different sell/buy ratios of recommendations, in order to reliably establish a causal relationship.

Analyst Sentiment Study

The economic interpretation of our results from the analyst sentiment study might at first glance seem counterintuitive. Analysts appear to adapt a pessimistic (positive) market view when historic market returns have been positive (negative), although positive (negative) historic returns tend to lead to positive (negative) future returns, using a simplified predictive model. Moreover, future returns are positive (negative) when analysts adapt a negative (positive) market view.

A plausible explanation of the results in regression type (1) is that an increase (decrease) in returns will make analysts feel that stocks prices are overrated (underrated), partially also suggesting that market volatility is greater than the volatility of demand on the underlying goods and services that companies are providing. In other words, analysts will adapt a pessimistic (positive) view when prices increase (decrease) since an increase (decrease) in market prices might not always reflect a fundamental increase (decrease) in company performance, implying that stock markets fluctuate between an over- and undervalued state. Touching on this subject is Womack (1996), who concludes that the median I/B/E/S forecast of price-to earnings ratios of stocks that are added to the buy category are slightly lower than the ratios of those removed from the same category. Similarly the price-to-earnings ratios that are added to the sell list are higher than those removed from the category. An extended reasoning of these findings would thus be that when price-to-earnings ratios are comparatively low there are more bargains in the market and thus perhaps also relatively more buy recommendations supporting the results in our first regression type.

As for the predicting power of the sentiment index on future returns we find a negative relationship, meaning that the current analyst market view would lead to the inverse market performance in the near future. Thus, the overall analyst opinion does not seem to be a good "same sign" - indicator of how the Swedish market will perform. Instead the relationship is significantly reversed, suggesting that the overall timing of most analysts is poor. Although results are counterintuitive, sophisticated investors could potentially employ a contrarian trading strategy. Such a strategy would however assume that investors would be able to evaluate the current level of the sentiment index in relation to past levels, in order to know when to go long or short in the market. Suggestively this could be done by assessing the historical average, given that the overall analyst market sentiment tends to fluctuate around equilibrium. This seems to be supported when looking at Chart II[28] at quick glance.

The overall implication of our results in the analyst sentiment study is that although almost free from transactions costs, it is not a profitable investment idea for an investor to trade an index based solely on the current analyst sentiment for that index. As our results when trying to predict future returns with percentage change in the sentiment index turned out to be insignificant, an investor's main problem when taking advantage of our results would be timing and other influencing factors. A contrarian strategy could in theory be used, but due to in some cases large

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standard errors timing would be difficult, making the strategy as whole unfavorable. Interestingly, our findings instead suggest that the historic return going back from 3-5 month is able to predict the direction, level and cumulative change in the sentiment index, implying that the change in analyst expectations to some extent can be predicted by historic market movements.

As our dataset consists of data from January 2000 – January 2011 it is important to discuss from an economic and psychological perspective the possible influence to our results of the two major financial crises that occurred during these years. It is beyond the scope of this thesis to statistically investigate in this matter, but we are open-minded for that this might have affected our results. During these crises, prices move rapidly and unpredictably and as analysts change their recommendations more seldom than prices adjust, this may cause psychological difficulties in setting correct prices.

Combined studies

Although the sample, operational questions and time window differs considerably when comparing our two studies, the common denominator being analyst recommendation characteristics, makes it necessary and exciting to compare the two studies with each other. As concluded in the event study, average recommendation changes have an existent and profound price impact on markets. Depending on the recommendation change characteristic, the magnitude of the impact will differ. These results are to some extent contradictious to a common definition of the EMH, discussed in the introduction. Relating our second study to the EMH it appears as if overall market sentiment has no predictive power of future returns. Instead historic returns help to explain both the absolute level of the sentiment index as well as the future near term cumulative change in it. Thus, EMH can be considered to hold in this sense. Connecting these results to the price drift associated with recommendation changes documented in the previous literature, our results bring forth new questions and further topics of investigation. As documented by Womack (1996), price drift occur in the predicted direction of analyst expectations. That result is contradictious to ours. An explanation for the discrepancy could be that Womack (1996) only analyzes the recommendation changes of the 14 highest ranked U.S. brokerage firms at the time of his study. This originates the question of whether our results would have been different if consensus recommendations were calculated on the basis of top ranked brokerage firms rather than on all of the firms contributing to the I/B/E/S consensus estimates. Future studies could also focus on finding additional variables that affect the analyst market sentiment, further demystifying the characteristics of analyst recommendations and its relation to stock returns.

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Appendix

Event Study

Table III. Robustness Test - Wilcoxon Signed Ranked Test

	New Rating				
Old rating	**1 Strong Buy**	**2 Buy**	**3 Hold**	**4 Underperform**	**5 Sell**
1 Strong Buy		**Rejected**	**Rejected**	**Rejected**	**Rejected**
Positive/Negative Signs		162/204	112/158	22/44	14/27
Z		-3,165	-3,829	-3,242	-2,780
Prob > |Z|		0,002	0,000	0,001	0,005
2 Buy	**Rejected**		**Rejected**	**Rejected**	**Not Rejected**
Positive/Negative Signs	205/136		267/525	173/218	8/10
Z	4,555		-9,721	-3,481	-0,283
Prob > |Z|	0,000		0,000	0,001	0,777
3 Hold	**Rejected**	**Rejected**		**Rejected**	**Rejected**
Positive/Negative Signs	175/110	459/271		210/340	72/107
Z	5,247	7,706		-6,392	-3,113
Prob > |Z|	0,000	0,000		0,000	0,002
4 Underperform	**Not Rejected**	**Rejected**	**Rejected**		**Not Rejected**
Positive/Negative Signs	43/30	250/164	316/201		39/52
Z	1,652	5,032	6,950		-2,102
Prob > |Z|	0,099	0,000	0,000		0,036
5 Sell	**Not Rejected**	**Not Rejected**	**Not Rejected**	**Not Rejected**	
Positive/Negative Signs	23/20	19/18	101/78	31/41	
Z	0,845	-0,023	1,870	-0,645	
Prob > |Z|	0,398	0,982	0,062	0,519	
Other tests	**Upgrades**	**Downgrades**	**Added to buy**	**Added to sell**	
H_0: $ACAR_x=0$	**Rejected**	**Rejected**	**Rejected**	**Rejected**	
Positive/Negative Signs	**752/511**	**596/982**	**969/613**	**499/746**	
Z	**8,643**	**-11,421**	**10,562**	**-8,715**	
Prob > |Z|	**0,000**	**0,000**	**0,000**	**0,000**	

Table III shows the results from the Wilcoxon Signed Ranked non-parametric robustness tests, where the null hypothesis is H0: ACARx=0. As seen in the table, 13 out of 20 of the different types of recommendation changes and 4 out of 4 of the categories (aggregated pools) reports a rejection of the null hypothesis at the 1 percent significance level. *Positive/Netagive Signs* indicates how many of the observations that is associated with an abnormal return.

Table IV. Robustness Test - Mann Whitney U Test

	Upgrades	**Downgrades**	**Added to buy**	**Added to sell**
Mean difference Foreign VS Swedish	**Rejected**	**Not Rejected**	**Rejected**	**Not Rejected**
Foreign - Ranksum/Expected	575663/587760	890222/884240	852982/873025	587587/580013
Swedish - Ranksum/Expected	222553/210456	355609/361591	399171/379129	188048/195622
Z	-2,118	0,728	-2,401	1,375
Prob > |Z|	0,0342	0,4665	0,0164	0,1692

Table IV. Shows the results from the Mann Whitney U non-parametric robustness test, where the null hypothesis is H0: ACARfrgn=ACARswe. As can be seen in the table, 2 out of 4 of the categories (aggregated pools) indicates a rejection of the null hypothesis at the 5 percent significance level. *Ranksum/Expected* compare the actual sum of ranks of the abnormal returns with the expected sum of ranks. The more far away the actual ranksum is from its expected value the more likely is it that the null hypothesis van be rejected.

Analyst Sentiment Study - Regression Output

Table VII. Regression - Predicting Sentiment Index with Historic Returns

	(1) S_t	(2) S_t	(3) S_t	(4) S_t	(5) S_t
$R_{t,t-1}$	0,392				
t-stat	1,47				
$R_{t,t-2}$		0,466			
t-stat		1,9*			
$R_{t,t-3}$			0,475		
t-stat			2,02**		
$R_{t,t-4}$				0,421	
t-stat				1,96**	
$R_{t,t-5}$					0,341
t-stat					1,79*
Constant	2,673	2,673	2,674	2,675	2,676
t-stat	116,96***	98,27***	87,31***	79,85***	74,39***
Observations	133	132	131	130	129
R-squared	0,020	0,058	0,091	0,102	0,090

Note: Independent Variable: Rt,t-k.

Table VIII. Regression - Predicting Future Returns with Sentiment Index

	(1) $R_{t,t+1}$	(2) $R_{t,t+2}$	(3) $R_{t,t+3}$	(4) $R_{t,t+4}$	(5) $R_{t,t+5}$
S_t	0,047	0,116	0,190	0,252	0,335
t-stat	1,58	2,11**	2,46**	2,47**	2,74***
Constant	-0,124	-0,306	-0,504	-0,668	-0,886
t-stat	-1,56	-2,12**	-2,5**	-2,51**	-2,8***
Observations	132	131	130	129	128
R-squared	0,018	0,052	0,094	0,114	0,150

Note: Independent Variable: St

Table IX. Regression - Predicting future Returns with Sentiment Index and Historic Returns

	(1) $R_{t,t+1}$
S_t	0,044
t-stat	1,43
$R_{t,t-1}$	0,061
t-stat	0,51
Constant	-0,116
t-stat	-1,42
Observations	132
R-squared	0,021

Note: Independent Variables: St and Rt,t-1

* Indicates that the estimate is significant at the 10 percent level.
** Indicates that the estimate is significant at the 5 percent level.
*** Indicates that the estimate is significant at the 1 percent level

Table X. Regression - Predicting Future Returns with Historic Returns

	(1) $R_{t,t+1}$	(2) $R_{t,t+1}$	(3) $R_{t,t+1}$	(4) $R_{t,t+1}$	(5) $R_{t,t+1}$
$R_{t,t-1}$	0,078				
t-stat	0,69				
$R_{t,t-2}$		0,040			
t-stat		0,53			
$R_{t,t-3}$			0,071		
t-stat			1,40		
$R_{t,t-4}$				0,079	
t-stat				1,88*	
$R_{t,t-5}$					0,059
t-stat					1,66*
Constant	0,002	0,001	0,001	0,000	0,002
t-stat	0,28	0,14	0,02	0,08	0,03
Observations	132	131	130	129	128
R-squared	0,006	0,004	0,017	0,029	0,022

	(6) $R_{t,t+2}$	(7) $R_{t,t+2}$	(8) $R_{t,t+2}$	(9) $R_{t,t+2}$	(10) $R_{t,t+2}$
$R_{t,t-1}$	0,099				
t-stat	0,64				
$R_{t,t-2}$		0,123			
t-stat		1,14			
$R_{t,t-3}$			0,165		
t-stat			2,00**		
$R_{t,t-4}$				0,145	
t-stat				2,03**	
$R_{t,t-5}$					0,107
t-stat					1,83*
Constant	0,003	0,001	0,001	0,001	0,001
t-stat	0,28	0,12	0,09	0,11	0,1
Observations	131	130	129	128	127
R-squared	0,005	0,016	0,043	0,047	0,034

	(11) $R_{t,t+3}$	(12) $R_{t,t+3}$	(13) $R_{t,t+3}$	(14) $R_{t,t+3}$	(15) $R_{t,t+3}$
$R_{t,t-1}$	0,263				
t-stat	1,49				
$R_{t,t-2}$		0,251			
t-stat		1,89*			
$R_{t,t-3}$			0,249		
t-stat			(2,29)**		
$R_{t,t-4}$				0,204	
t-stat				2,14**	
$R_{t,t-5}$					0,151
t-stat					1,78*
Constant	0,003	0,002	0,002	0,002	0,001
t-stat	0,2	0,13	0,10	0,12	0,1
Observations	130	129	128	127	126
R-squared	0,023	0,044	0,065	0,061	0,045

	(16) $R_{t,t+4}$	(17) $R_{t,t+4}$	(18) $R_{t,t+4}$	(19) $R_{t,t+4}$	(20) $R_{t,t+4}$
$R_{t,t-1}$	0,359				
t-stat	1,76*				
$R_{t,t-2}$		0,299			
t-stat		1,99*			
$R_{t,t-3}$			0,279		
t-stat			2,21**		
$R_{t,t-4}$				0,225	
t-stat				1,90*	
$R_{t,t-5}$					0,176
t-stat					1,69*
Constant	0,005	0,004	0,003	0,004	0,004
t-stat	0,23	0,17	0,16	0,16	0,17
Observations	129	128	127	126	125
R-squared	0,029	0,043	0,056	0,051	0,042

	(21) $R_{t,t+5}$	(22) $R_{t,t+5}$	(23) $R_{t,t+5}$	(24) $R_{t,t+5}$	(25) $R_{t,t+5}$
$R_{t,t-1}$	0,366				
t-stat	1,81*				
$R_{t,t-2}$		0,297			
t-stat		1,77*			
$R_{t,t-3}$			0,278		
t-stat			1,83*		
$R_{t,t-4}$				0,238	
t-stat				1,69	
$R_{t,t-5}$					0,187
t-stat					1,47
Constant	0,007	0,006	0,005	0,006	0,007
t-stat	0,25	0,21	0,19	0,22	0,23
Observations	128	127	126	125	124
R-squared	0,003	0,032	0,042	0,043	0,035

Note: Independent Variables: Rt,t-k. Analyzed and discussed regressions are marked in gray.

* Indicates that the estimate is significant at the 10 percent level.

** Indicates that the estimate is significant at the 5 percent level.

*** Indicates that the estimate is significant at the 1 percent level

Table XI. Regression - Predicting Future Returns with Percentange Change in Sentiment Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
	$R_{t,t+1}$	$R_{t,t+1}$	$R_{t,t+1}$	$R_{t,t+1}$	$R_{t,t+1}$	$R_{t,t+2}$	$R_{t,t+2}$	$R_{t,t+2}$	$R_{t,t+2}$	$R_{t,t+2}$	$R_{t,t+3}$	$R_{t,t+3}$	$R_{t,t+3}$	$R_{t,t+3}$	$R_{t,t+3}$	$R_{t,t+4}$	$R_{t,t+4}$	$R_{t,t+4}$	$R_{t,t+4}$	$R_{t,t+4}$	$R_{t,t+5}$	$R_{t,t+5}$	$R_{t,t+5}$	$R_{t,t+5}$	$R_{t,t+5}$
$S_{t,t-1}$	-0,418					-0,538					-0,249					-0,740					-0,551				
t-stat	-1,46					-1,50					-0,48					-1,01					-0,58				
$S_{t,t-2}$		-0,235					-0,158					-0,258					-0,393					-0,252			
t-stat		-1,58					-0,66					-0,65					-0,69					-0,36			
$S_{t,t-3}$			-0,059					-0,144					-0,180					-0,227					-0,109		
t-stat			-0,53					-0,65					-0,50					-0,47					-0,18		
$S_{t,t-4}$				-0,126					-0,168					-0,170					-0,180					-0,079	
t-stat				-1,19					-0,77					-0,51					-0,43					-0,16	
$S_{t,t-5}$					-0,092					-0,095					-0,100					-0,095					-0,038
t-stat					-0,88					-0,45					-0,32					-0,25					-0,09
Constant	0,001	0,001	0,001	0,001	0,002	0,002	0,002	0,003	0,003	0,003	0,003	0,003	0,004	0,004	0,004	0,005	0,005	0,006	0,006	0,006	0,007	0,007	0,008	0,008	0,010
t-stat	0,24	0,16	0,19	0,18	0,22	0,21	0,19	0,21	0,21	0,19	0,19	0,19	0,21	0,19	0,21	0,22	0,22	0,23	0,24	0,25	0,24	0,23	0,25	0,26	0,32
Observations	131	130	129	128	127	130	129	128	127	126	129	128	127	126	125	128	127	126	125	124	127	126	125	124	123
R-squared	0,002	0,018	0,002	0,013	0,013	0,019	0,004	0,006	0,011	0,005	0,003	0,007	0,006	0,007	0,003	0,016	0,001	0,006	0,006	0,002	0,007	0,003	0,001	0,001	0,000

Note: Independent Variables: St,t-k. Analyzed and discussed regressions are marked in gray.

* Indicates that the estimate is significant at the 10 percent level.
** Indicates that the estimate is significant at the 5 percent level.
*** Indicates that the estimate is significant at the 1 percent level

Table XII. Regression - Predicting Percentange Change in Sentiment Index with Historic Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
	$S_{t,t+1}$	$S_{t,t+1}$	$S_{t,t+1}$	$S_{t,t+1}$	$S_{t,t+1}$	$S_{t,t+2}$	$S_{t,t+2}$	$S_{t,t+2}$	$S_{t,t+2}$	$S_{t,t+2}$	$S_{t,t+3}$	$S_{t,t+3}$	$S_{t,t+3}$	$S_{t,t+3}$	$S_{t,t+3}$	$S_{t,t+4}$	$S_{t,t+4}$	$S_{t,t+4}$	$S_{t,t+4}$	$S_{t,t+4}$	$S_{t,t+5}$	$S_{t,t+5}$	$S_{t,t+5}$	$S_{t,t+5}$	$S_{t,t+5}$
$R_{t,t-1}$	0,608					0,028					-0,056					-0,122					-0,184				
t-stat	1,61					0,47					-0,62					-1,11					-1,46				
$R_{t,t-2}$		0,012					-0,041					-0,114					-0,167					-0,222			
t-stat		0,49					-0,81					-1,49					-1,83*					-2,13**			
$R_{t,t-3}$			-0,016					-0,075					-0,128					-0,181					-0,232		
t-stat			-0,62					-1,46					-1,92*					-2,27**					-2,57**		
$R_{t,t-4}$				-0,028					-0,070					-0,119					-0,165					-0,208	
t-stat				-1,19					-1,69*					-2,17**					-2,58**					-2,74***	
$R_{t,t-5}$					-0,024					-0,064					-0,108					-0,145					-0,183
t-stat					-1,3					-1,93*					-2,38**					-2,67***					-2,91***
Constant	0,001	0,008	0,001	0,001	0,002	0,002	0,002	0,002	0,003	0,005	0,003	0,004	0,005	0,006	0,008	0,005	0,006	0,007	0,009	0,010	0,007	0,008	0,010	0,011	0,013
t-stat	0,30	0,32	0,39	0,42	0,91	0,47	0,46	0,49	0,74	1,02	0,45	0,52	0,73	0,91	1,19	0,47	0,66	0,85	1,10	1,26	0,58	0,76	0,98	1,15	1,29
Observations	132	131	130	129	128	131	130	129	128	127	130	129	128	127	126	129	128	127	126	125	128	127	126	125	124
R-squared	0,028	0,003	0,006	0,027	0,034	0,003	0,001	0,057	0,008	0,010	0,006	0,051	0,102	0,132	0,132	0,019	0,079	0,144	0,185	0,210	0,034	0,107	0,190	0,226	0,245

Note: Independent Variables: Rt,t-k. Analyzed and discussed regressions are marked in gray.

* Indicates that the estimate is significant at the 10 percent level.

** Indicates that the estimate is significant at the 5 percent level.

*** Indicates that the estimate is significant at the 1 percent level