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Equity Research Analyst Bias in Stock Recommendations

The bias of equity research – are analysts incentivized towards skewing stock recommendations due to the relationship with the companies they cover?

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Abstract

We acknowledge the lack of empirical studies of equity research analysts' ability to generate abnormal returns on the Swedish stock market and the global absence of studies measuring performance throughout complete recommendation periods. A unique sample of 705 equity research analyst recommendations from 2004 to 2013 from leading Swedish investment banks ABG Sundal Collier, Carnegie, Nordea and SEB on the OMXS30 constituent stocks are studied in order to investigate whether analysts have better long-run predictive abilities in their sell relative to their buy recommendations. Analyst issuance of sell recommendations on stocks can incur risks of deteriorating analyst – company relationship and reduced management access. Hence analysts should be significantly more certain in their sell recommendations.

Contrary to our hypothesis we find that analyst buy recommendations have positive abnormal returns and sell recommendations generate negative abnormal returns with significant 30-day, 180-day and Recommendation Period Return returns of 1.5%, 3.6%, and 20.9% respectively on buy recommendations adjusted with CAPM and Fama-French factors. Hence, an investor could enjoy positive abnormal returns following buy recommendations from Swedish investment banks given access to such research is available.

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Table of contents

1. Introduction	3
2. Hypothesis	5
2. Previous literature	7
3. Data	10
4. Methodology	11
4.1 Event date selection	11
4.2 Type of analyst recommendation	12
4.3 Measurement period length	12
4.4 Selection of return measurement method	12
4.4.1 Cumulative Abnormal Return (CAR)	13
4.4.2 Buy-and-Hold Abnormal Return (BHAR)	13
4.5. Models for estimation of Expected and Abnormal Returns	14
4.5.1 The CAPM asset pricing model	15
4.5.2 The multi-factor asset pricing models	17
4.5.3 The Fama-French (1992) ME and BE / ME ratio multi-factor model	17
4.5.4 The Industry Peer Adjusted Expected Return model	19
4.5.5 Long term event studies and implications for Expected Return models	20
4.6 Cross-sectional regressions of analyst recommendation returns	21
5. Results	22
5.1 Descriptive statistics	22
5.2 The Fama-French (1992) ME and BE / ME ratio multi-factor model regressions	
5.3 Cross-sectional regressions of analyst recommendation returns	26
5.4 Robustness tests	29
6. Discussion	30
6.1 Problematisation	31
6.2 Suggested future topics for research	32
7. Conclusion	
References	34
Appendix	

1. Introduction

Traditional theory on financial markets and portfolio analysis is largely based on the assumption of a market where information is efficient and symmetric, i.e. returns are over time consistent with that of the market on a risk-adjusted basis. This is most commonly expressed in terms of the efficient-market hypothesis (EMH) as stipulated by Fama¹, under which there is little room to systematically generate returns exceeding that of the market.

In the world of financial analysis, there is a strong sentiment that equity research analysts that cover stocks provide the most sophisticated analysis and opinion available on stocks and future stock prices, despite that under the EMH their recommendations should not generate any abnormal returns. However, analysts typically possess unique access to corporate management, research tools and investor network, implying that there would be room to generate positive abnormal returns under the non-strong forms of EMH. Previous research including Cowles (1933) and others² demonstrate that recommendations of most analysts do in fact not produce any abnormal returns. There is however much debate on the topic and several other studies show that analysts can indeed deliver positive abnormal returns³. Most prominent in the support that analyst recommendations can outperform market include Womack (1996) as well as other papers. The most common explanatory theory normally brought forward to explain these observations is that of Grossman and Stiglitz (1980), who argue that since arbitrageurs, including equity research analysts, incur expenses for their efforts they must be compensated in the form of excess return, which would be inconsistent with the EMH.

Another dimension to study is whether research analyst recommendations can have an explanatory effect on stock prices, and substantial testing of both long-term and short-term effects of stock recommendations has been implemented in the past^{2,3}. According to the semi-strong EMH, which allows only private information to generate excess returns, and with the additional assumption that analysts indeed convey new public information, stock prices should

¹ Fama (1970)

² Studies of securities analysts, see Bidwell (1977), Diefenbach (1972), Logue and Tuttle (1973). Studies of investment managers see Jensen (1968), Fama (1991).

³ Bjerring, Lakonishok, and Vermaelen (1983) find superior performance by a Canadian brokerage house. Dimson and Marsh (1984) find precise forecasting of U.K. stock returns, and Groth, Lewellen, Schlarbaum, and Lease (1979) find outstanding performance by a single U.S. investment firm in the-60s. Furthermore Elton, Gruber, and Grossman (1986) document excess returns for the calendar month of and the first month after brokerage recommendation changes.

adjust immediately to analyst reports and stock recommendations. Long-term studies made by Womack also demonstrate significant post-event drift, which is inconsistent with the EMH. Furthermore, analysts frequently set target prices above and below stocks' current trading price, without necessarily having a recommendation opinion on the stock, hence testing analysts' ability to predict future stock returns through actual stock recommendations could be a more relevant method than simply studying target prices and revisions of these.

There is also a complex underlying relationship between analysts and the companies they cover. Companies are generally incentivised to present themselves favorable to the analyst community in order attract and retain equity investors, and from the fact that management compensation is often partially based on stock performance. Since many investor events are jointly hosted by companies and analysts, a given company would rather associate itself with an analyst with a positive outlook than the opposite. While the analyst's main driving force is to make accurate recommendation and estimates, there is a downside risk with sell recommendations other than them being incorrect, in that is puts the relationship with the company under coverage at risk.

In this paper we analyse these dynamics in greater detail by studying sell and buy recommendations from the four leading Swedish investment banks in the Swedish market and whether these generate abnormal returns employing different event windows and expected return models. Since we believe a given sell recommendation is coupled with some relationship risk, the analyst would need greater conviction to compensate for that risk than for a buy recommendation.

Our paper provide a contribution to prior research made on Swedish equity markets, as we apply the novel database Factset and a substantial dataset of recommendations. Compared to prior work on the Swedish market by Lidén (2006, 2007) our recommendation data is sourced directly from research providers and not printed media. We further employ a novel method for measuring returns, being Recommendation Period Return (RPR) which measure stock performance from the start of the recommendation date until the recommendation is eventually changed. To the best of our knowledge this methodology has not been tested in prior studies and should prove to be of significance due to the equal relevance of analyst's initiating recommendations – as well as analyst's drawing back the recommendation.

705 analyst recommendations sourced from the ten year period 2004-2013 issued on the OMXS30 constituent stocks by the leading Swedish investment banks ABG Sundal Collier,

Carnegie, Nordea and SEB is used. Returns are measured over 30 and 180 days post-event as well as through the RPR method. Measured returns are adjusted through the method applied by Fama-French (1992), as well as controlling for industry peer group returns. The returns obtained through regressing all recommendations using OLS are all significant at the 1% percent level and amount to a positive of return of 1.5%, 3.6%, and 20.9% respectively for the 30-day, 180-day and RPR periods when Fama-French's (1992) method is used to calculate expected returns. SHORT recommendations, which is the return an investor receives who shorts a stock upon issuance of a sell recommendation yield a negative return of -0.4%, -6.0% and -4.8% respectively.

Thus the findings in this paper, in contrary to our hypothesis, do not support that sell recommendations yield a statistically higher abnormal return compared to buy recommendations. In fact, our results indicate that buy recommendations yield a positive abnormal return as opposed to the negatively yielding sell recommendations. Potential explanations to this finding is that in 7 out of the 10 years in our sample the OMXS30 index had a positive annual return averaging 10.5% per annum and that our expected return models did not fully compensate for this positive market return. Furthermore, it is appropriate to disclaim that our recommendation dataset is taken from a secondary source database, which potentially gives the risk of erroneous data.

2. Hypothesis

An analyst that issues a sell recommendation on a stock takes on a relationship risk with the company he is covering. Provided this risk is real and tangible, the analyst would only issue such a recommendation when there is enough conviction to compensate for this risk. Hence, our resulting research question becomes:

Do leading Swedish equity research analysts' sell recommendations outperform buy recommendations throughout the lifetime of the recommendation?

To give a meaningful answer to our research question the following three-stage hypothesis needs to be adopted were each of the following null-hypothesises needs to be rejected:

(i) The EMH hold in its weak form such that positive abnormal returns cannot be generated through fundamental analysis performed by equity research analysts.

If (i) is false, abnormal returns will exist after expected return adjustment.

(ii) Given the null-hypothesis in (i) is rejected and analyst recommendations do indeed contain information content, no post-event drift exist that will result in abnormal returns in our long-run event windows.

If (ii) is true, the stock price should reach the analyst's consensus target price immediately. This would in turn lead to analyst's resetting recommendations to HOLD as the stock price would reach the target price immediately. This does obviously not occur and consensus target prices frequently deviate from market prices, thus implying that there is a post-event drift towards target prices in the longer term in turn implying that (ii) is false and information content is not immediately reflected in the stock price according to weak form EMH and post-event drift exists.

Given that (ii) is false and confirming the existence of post-event drift measuring returns through RPR must be the most accurate measurement of recommendation performance, not taking into consideration the empirical measurement problems of long-run event studies. A fixed time span measurement window such as a 1-month or a 6-month window will reflect the impact of possible information content in the analyst's recommendation during the initial part of the recommendation, but not throughout the complete period. Employing fixed time span measurement windows are based on the assumption that stock recommendations impact the stock price only within these timeframes, irrespective of the actual length of the recommendation.

(iii) Given the null-hypothesis in (ii) is rejected, there are no observable differences in abnormal returns generated from buy recommendations when compared with sell recommendations.

We eventually compare performance on the studied buy and sell recommendation and whether the overarching hypothesis holds. If abnormal returns from sell recommendations exceed that of buy recommendations, we can reject the null hypothesis that sell recommendations do not generate returns in excess of that of buy recommendations.

2. Previous literature

Previous studies have mainly employed US capital markets as source for empirical data, with a wealth of methodologies practiced. To note is that relevant previous research applies a broad fauna of up to 5 different methods for the modeling of expected returns, which potentially could present materially different results. This also likely explains the substantial difference in results in the studies cited below.

Womack, "Do Brokerage Analysts' Recommendations Have Investment Value?" (1996)

Womack (1996) reaches two conclusions: There are significant discrepancies between prerecommendation prices and prices after publishing analyst recommendations, and significant post-event drifts in the direction of the analyst recommendation up to 180 days after recommendation issuance. For buy recommendations, the mean post-event drift is modest (+2.4%) and short-lived, but for sell recommendations, the drift is larger (-9.1%) and extends for six months. Analysts appear to have market timing and stock picking abilities, according to the study, thus sell recommendations are more predictive than buy recommendations and yields higher return.

Womack employs a very extensive methodology, where he uses the database *First Call*, and analyses only a subset of the star analysts, out of all available analysts. Womack pursues two distinct lines of enquiry in his paper, where the first is an ex-post and ex-ante recommendation event study in order to study price and volume reactions due to recommendation publication. The second study is that of the documented post-recommendation excess return. Womack measures this through comparing raw returns after the actual recommendation with returns after random "event" dates or randomly shuffled "event" dates. Womack's results in this study suggest that analyst's predictive ability is mainly explained by market timing and stock picking.

Womack's study covers three years of recommendation data (1989-1991) with 1573 observations. Womack employs only the strongest change in recommendations i.e. added to buy or sell, and measures long term post-event return on a one-month and six-month basis. It should be noted that Womack does not adjust for a change in recommendation, which could lead to an incorrect measurement if the specific analyst alter their recommendation during the one-month or six-month measurement period. This is a potential error source which is mitigated in our study.

Bing Liang, Price Pressure: Evidence from the "Dartboard" Column (1999)

In this study Liang investigates the Price Pressure phenomenon and whether the information in the Wall Street Journal's so called "Dartboard" column where stock market pundits publishes their best stock recommendations have an impact on stock prices and whether this impact is temporary or long-lived. The "Dartboard" column has inspired several academic studies to investigate the degree of market efficiency and investor behavior surrounding the public announcement of experts' recommendations. Several studies have documented the existence of so called "publicity effects " or "announcement effects" following the experts' recommendations in the 'Dartboard" column.

Liang uses 5 years of data that includes 208 buy recommendations and 8 sell recommendations with returns calculated using CAR methodology. In order to benchmark returns, Liang uses the market model $R_{it} = \alpha_i + \beta_i * R_{m,t}$ where R_{it} is the rate of return for the common stock of stock i on day t, $R_{m,t}$ is the rate of return for the CRSP value-weighted market index.

Desai, "Do All-Stars Shine? Evaluation of Analyst Recommendations" (2000)

Using Buy-and-Hold Abnormal Returns (BHAR) returns with holdings periods ranging from 10 to 500 days, Desai measures the performance of the Wall Street Journal's star analyst's recommendations, in order to investigate if recommendations outperform benchmarks. Desai document that stocks recommended by the all-star analysts outperform when benchmarked to peer companies of similar market capitalisation and industry. Stocks recommended by analysts who focus on a single industry outperform those recommended by analysts covering multiple industries. Desai also documented a herding behavior among analysts in an industry. Desai follows the methodology of Barber and Lyon (1997), where a matching control company is used to compute abnormal returns. For each sample company, the study identified matching peer companies that were in the same four-digit SIC code and were closest in market value to the sample company.

Lidén, "Stock Recommendations in Swedish Printed Media: Leading or Misleading?" (2006)

In Swedish markets few previous studies have examined the performance of expert's buy and sell recommendations, Lidén has however contributed to this topic. In Lidéns first study made in 2006 a Cumulative Abnormal Return (CAR) methodology is employed during a 20 day window in order to study the post-publication performance of new buy and sell recommendations published in Swedish newspapers and business magazines during the period 1996–2000. Lidén trialed whether there is a difference in returns generated by either journalists or equity research analysts. Lidéns results indicate that sell recommendations resulted in positive abnormal returns compared to buy recommendations. There was no material difference in the performance between journalists and equity research analysts.

To note is that Lidén's hypothesis explaining the positive abnormal returns for the sell recommendations is:

"Buy recommendations were misleading investors, whereas sell recommendations were leading them correctly, overall yielding returns in line with the market. This asymmetry is due to positive information from the management of the company being more intricate to interpret than negative"

Thus Lidén's hypothesis deviates from ours, where our explanatory hypothesis for the positive abnormal returns after sell recommendations is based on that analysts are reluctant to issue sell recommendations, rather than that the analyst interprets negative company information in an efficient manner. Another difference between Lidéns paper and ours is the sourcing of equity research analyst recommendations, were the equity research recommendations employed by Lidéns are taken from second hand sources such as citations and telegrams in printed media, which Lidén also rightly points out.

Lidén, "Swedish Stock Recommendations: Information Content or Price Pressure?" (2007)

In his second study, Lidén examines recommendations from six Swedish finance magazines. Secondary sources for equity research analyst recommendations is employed also in this paper. Lidén uses a sample of 541 independent recommendations in his study with a BHAR approach measuring returns during 6, 12, 18 and 24 months after recommendation publication. The main point of difference between Lidén's study and the one presented in this paper is the employment of the Factset database, enabling a no-delay follow up of analyst recommendations and the use of dynamic period returns by applying the RPR method.

Johansson, "Sell-side analysts' creation of value - key roles and relational capital" (2007)

Johansson discusses the role of relational capital between stock analysts and the firms they cover, using an interview based case study on equity research analysts at a larger Swedish investment bank. Johansson find that analysts typically have access to information and sources that are otherwise excluded from the market, such as direct contact with C-level management. The analysts' dependency, however, can make analysts' recommendations ambiguous or even biased. Johansson comments:

"The analysts do not want to irritate the company representatives [...], so as not to harm the relation and to ascertain the value-added information. They tended to disclose negative information in front of clients through verbal sources, rather than through written sources, and they often checked their own conclusions with company management before the disclosure." What is implied is that negative information could irritate the company, thus threatening the important and frail access to first-hand information.

3. Data

The data used in this study can be divided into two groups, financial data for the stocks examined and analyst recommendations for the same stocks. Both types of data are retrieved through the database Factset. In general, price data for equity securities is abundant, with several available sources such as Datastream, Yahoo Finance etc.

Analyst estimates and recommendations are provided by fewer database providers, being mainly Factset, Thomson Reuters and Bloomberg. Within the financial industry, Factset is the database considered to be the most reliant in providing estimates and company-specific financial data, and is today to a large extent considered the industry norm. Alternative sources such as the Thomson One Excel add-in or Bloomberg's Excel add-in could also have been employed in this study, however these databases are deemed to be of lower quality when referring to specifically analyst estimates and recommendations. Previous research on the subject of analyst recommendations on the Swedish market (Lidén, 2006) use secondary sources such as newspaper telegrams in order to determine occurrence of analyst recommendations.

The Factset database is used to construct a cross-sectional dataset containing 705 number of unique analyst stock recommendations, collected from the Swedish top ranked tier one brokerage houses according to TNS Sifo Prospera's survey "2013 Top 5 Domestic Equities institutions", with rankings appended in Table 12. The methodology of selecting top-ranked analysts and brokerage has also been employed in other studies⁴, as testing with only the highest quality recommendations increase the power of the test.

4. Methodology

Tracking analyst recommendation activity on the OMXS30 stocks throughout 2004-2013 generate a sample of 705 independent recommendations with an average span of 264 days. The recommendation performance of sell and buy recommendations is then regressed after adjusting for expected returns in order investigate whether significant abnormal returns can be observed.

4.1 Event date selection

We assume recommendations are published on the morning of the date of the published recommendation. The report could be published during any time of the day, however most common is that equity recommendation changes are clearly communicated after the daily early-morning conference call between the equity research, sales and trading teams at the investment bank. A reasonable assumption is thus that all recommendations are published in the morning, before the stock exchange opens for trading.

Common practice is to use the closing prices at the event day studied, however given that the recommendation is published in the morning of the event day studied, it is more appropriate to use the open price of the stock under study. If we use the closing price of the event day, there might become additional information available that can distort the price of the security during the trading day, lowering analysis quality. Further, employing the closing price of the day prior to the event important information such as financial reports, press releases and the potential value of the analyst report itself will not be incorporated in the stock price.

⁴ Womack (1996), Desai (2000) & Bing Liang (1999)

4.2 Type of analyst recommendation

Equity analysts usually recommend stocks on a 5- level scale, that are normally translated into "BUY", "OVERWEIGHT", "HOLD", "UNDERWEIGHT" and "SELL". Two methods can be employed in the interpretation of recommendation change. Firstly, returns can be measured when HOLD recommendations are either upgraded or downgraded to any other recommendation. However OVERWEIGHT and UNDERWEIGHT recommendations are frequently issued, and does not represent the equity analyst's most confident view that a stock is mispriced. Thus a more common and robust approach is to only measure returns when stocks are up- or downgraded to the most extreme categories, i.e. BUY and SELL ratings only (Womack 1996, Desai 2000). We control for both methods in our paper.

4.3 Measurement period length

We employ three measurement period lengths; 30-day, 180-day and Recommendation Period Return (RPR). The RPR period starts on the day a recommendation changes from HOLD to OVERWEIGHT, BUY, UNDERWEIGHT or SELL and stops on the day a recommendation is revised back to HOLD. The logic behind the RPR period is that the analyst actively follows the stock covered throughout the recommendation period and will change the recommendation only once the analyst's view on the stock materially change.

We employ calendar year calculation, i.e. the inclusion of weekends when calculating 30day, 180-day and RPR returns. As economic value for companies often is produced during weekends and interest accrues during weekends, it is also reasonable to include these when calculating returns.

We also exclude the measurement of returns on recommendations initiated prior to our monitored period in order to eliminate incorrect return observations. We also eliminate RPR return observations that have not been downgraded to HOLD by 2013-12-31 for the same reason.

4.4 Selection of return measurement method

Convention in event studies that analyses abnormal returns is to sum either daily or monthly returns over time. The two common methods used to calculate these returns are the Cumulative Abnormal Return (CAR) method and the Buy-and-Hold Abnormal Return (BHAR) method. Both are presented below.

4.4.1 Cumulative Abnormal Return (CAR)

Summing returns across t periods through addition generate the arithmetic summation CAR, expressed as

$$CAR_{i,t} = \sum_{t=1}^{T} R_{i,t} - \sum_{t=1}^{T} E(R_{i,t})$$

Where t is the market trading day after the event, $R_{i,t}$ is the realised return on security i day t, and $E(R_{i,t})$ is the expected return for the same period and stock given by a specific asset pricing model.

The arithmetic CAR compound the returns between each period which creates a biased estimator of long-run investor experience according to Ritter (1991), Barber and Lyons (1997) and Lyons et al. (1999) in long-run event studies. This is due to that in practice investors do not transact in the security each day and thus effectively does not compound the returns in accordance with the CAR return measurement method.

4.4.2 Buy-and-Hold Abnormal Return (BHAR)

Summing returns across t periods through multiplication yields the geometric summation BHAR, expressed as

$$BHAR_{i,t} = \prod_{t=1}^{T} (1+R_{i,t}) - \prod_{t=1}^{T} (1+E[R_{i,t}])$$

Where t is the market trading day after the event. $R_{i,t}$ is the realised return on security i day t, and $E(R_{i,t})$ is the expected return for the same period and security given by a specific asset pricing model.

Beginning with Ritter (1991) the most popular estimator of long-run abnormal return is the BHAR measure. This is a preferred alternative in long-run studies as the BHAR methodology generate a more realistic return when compared to the realised return security investors obtain. This is due to that the geometric compounding effect of BHAR gives a mathematically more correct approximation of the return an actual investor would enjoy over longer timeframes compared to the arithmetic summation method used in the CAR approach. It should be noted that Womack (1996) as well as Lidén (2007) employ BHAR in their studies to measure returns following analyst recommendations. Barber and Lyon (1997) argue that the BHAR is the appropriate estimator because "it precisely measures investor experience".

Drawbacks include what Barber & Lyon (1997) and Ikenberry, Lakonishok, and Vermaelen (1995) highlight as problems with the BHAR methodology being new listing, rebalancing, and skewness biases, where all but the skewness biases are easily corrected. In essence measuring long-term abnormal performance can be considered treacherous according to these papers. The BHAR method has also been criticised for amplifying the problem of misspecified asset pricing models for expected returns, in particular during longer time periods and that the CAR method is a better option in order to measure abnormal returns⁵.

4.5. Models for estimation of Expected and Abnormal Returns

In event studies, abnormal return is a security's ex post return during an event window minus the normal return of the security over the event window.⁶ The abnormal return can be defined as

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_{t})$$

where $AR_{i,t}$, $R_{i,t}$, and $E(R_{i,t}|X_{t})$ are the abnormal, actual, and normal returns respectively for each time period t for a security i. X_t is the conditioning information for the normal return model and can take two forms: the simple Constant Mean Return Model where X_t is a constant and the Market Model where X_t is the market return. In this thesis, we employ two methods of the Market Model form to calculate expected returns being an expanded multifactor version and a peer portfolio version.

Although included in Womack's (1996) paper, we do not employ the third method of comparing raw returns after the actual recommendation with returns after pseudo "event" dates or randomly shuffled "event" dates, in order to estimate expected returns. Although this analysis would most likely prove interesting, it is beyond the scope of this thesis.

⁵ Criticism raised by Brav and Gompers (1997), Fama (1998), Barber et al. (1999) and Mitchell & Stafford (2000)

⁶ MacKinlay (1997)

4.5.1 The CAPM asset pricing model

We employ a developed form of the market model consisting of the Capital Asset Pricing Model (CAPM) of William Sharpe (1964) and John Lintner (1965) with two additional factors described further below. The CAPM for equity securities is specified as follows:

$$E\left(R_{s,t}\right) = r_{f,t} + \beta_{s}(r_{m,t} - r_{f,t})$$

where

- (i) $E(R_{s,t})$ is the expected return for the stock s at time t
- (ii) $r_{f,t}$ is the risk-free rate at time t
- (iii) β_s , or stock beta, measure the stock's exposure to systematic risk
- (iv) $r_{m,t}$ is the expected market return at time t

Hence CAPM only employ stock beta as the sole explanatory variable for stock-specific risk and the stock's resultant expected returns, implying that only the asset's exposure to market risk is priced. Estimating the CAPM the following regression model is used

$$R_{s,t} - r_{f,t} = \alpha_s + \beta_s (r_{m,t} - r_{f,t}) + \varepsilon_s$$

where Jensen's alpha α_s and stock beta β_s are unknown parameters estimated by ordinary least squares (OLS) regression. A β_s coefficient value >1 indicate that the stock is exposed to more systematic risk than the market portfolio, with a coefficient of <1 being the opposite. The regression intercept α_s called Jensen's alpha measure the above or underperformance of the stock relative to the market portfolio. ε_s is the regression's error term that represents the return variation not explained by the variables in the regression model.

4.5.1.1 Estimation of the Equity Risk Premium and the Risk Free Rate in the CAPM

Due to the so-called equity premium puzzle there is today no single generally accepted method to estimate the equity risk premium, despite the burgeoning literature in the field⁷. As observed by Fama & French (2003) the average return on a broad portfolio of stocks is typically used to estimate the ex-post expected market return. As reference, the ex-post equity premium in US market for the period 1872-2000 amounted to 5.6% according to this typical methodology.

⁷ Mehra, Prescott (1985), Damodaran (2012)

In this study we will estimate the equity risk premium by employing the typical ex-post approach, which is measuring the total return via the OMXS30 Gross Index per day, which will work as a proxy for the market portfolio. The daily fixing of the overnight financing rate STIBOR Tomorrow / Next (T/N) interbank rate act as proxy for the risk-free rate $r_{f,t}$. Interbank rates are commonly used as proxies for short-term risk-free interest rates, and we employ the overnight rate in this particular study in order to match the stock returns which are observed on a daily basis. The STIBOR T/N fixing rate is quoted on an annual rate basis thus we re-calculate the annual interest rate to a daily interest rate through the formula

$$(r_{f,t}) = (1 + r_f)^{(\frac{1}{365})} - 1$$

We employ the spread between the daily return of the OMXS30 Gross Index and the annual mean of the STIBOR T/N rate as an estimator for the equity risk premium. The OMXS30GI price data is taken from NASDAQ OMX. The STIBOR T/N rate data is taken from the Swedish central bank Riksbanken. Thus the equity risk premium is specified as the daily return

$$(r_{m,t} - r_{f,t}) = OMXS30GI - \overline{\text{STIBOR T/N}}$$

4.5.1.2 Estimation of the CAPM stock beta

Stock betas are estimated for each individual stock using an OLS regression on daily returns of the relevant stock and the OMXS30 market proxy index throughout the 2004-2013 time period, with data provided by the Factset database. This long estimation period is suitable as it eliminates the considerable variation in each stock's beta which is otherwise observed when using shorter estimation periods. Furthermore, the stock beta estimation period of 2004-2013 coincides with the period used to observe stock recommendation returns. It should be noted however that Fama-French (1992) form portfolios of stocks based on factors such as size to estimate beta for groups of stocks, a method not employed in this thesis. These betas are then assigned to each corresponding stock together with each individual stock's ME and BE/ME factors as discussed below. The reason for deviating from this recognised methodology is due to our limited estimation sample of the OMXS30 stocks, of which all are large capitalisation stocks in which size grouping is less meaningful.

4.5.2 The multi-factor asset pricing models

Despite the CAPMs intuition, longevity and wide-spread academial and commercial adoption the theory has been severely questioned in recent decades. A well-renowned critique of the CAPM is that of Banz (1981) who show that small to medium sized firms had higher average returns than medium and large size firm's post CAPM return adjustment. Rosenberg et al. (1985) show that the CAPM is unable explain the positive relationship between stock returns and the stock's valuation through the Book Equity / Market Equity (BE/ME) ratio. Thus these findings demonstrate the fact that models with single explanatory factors using an asset's beta can be further improved by controlling returns for additional risk factors.

4.5.3 The Fama-French (1992) ME and BE / ME ratio multi-factor model

To develop the CAPM asset pricing model we apply a multi-factor model according to that used by Fama-French (1992) which in addition to the traditional CAPM also control for company size through the company's market capitalization, the Market Equity (ME) factor, and the stock's valuation through the Book Equity / Market Equity (BE/ME) ratio. Hence the Fama-French (1992) model is specified as

$$E(R_{s,t}) = r_{f,t} + \beta_{s,m}(r_{m,t} - r_{f,t}) + \beta_{s,ME} \ln(ME_{s,t}) + \beta_{s,BE/ME} \ln(BE/ME_{s,t})$$

where

- (i) $E(R_{s,t})$ is the expected return for stock s at time t
- (ii) $r_{f,t}$ is the risk-free rate at time t
- (iii) $\beta_{s,m}$ or stock beta, measure the stock's exposure to systematic risk
- (iv) $r_{m,t}$ is the expected market return at time t
- (v) $\beta_{s,ME}$ coefficient in percent explain how much of stock's return is due to the company's size
- (vi) $\ln(ME_{s,t})$ is the natural logarithm of the ME value for stock s at time t
- (vii) $\beta_{s,BE/ME}$ coefficient in percent explain how much of the stock's return is due to the BE / ME ratio for stock *s* at time *t*
- (viii) $\ln(BE/ME_{s,t})$ is the natural logarithm of the BE / ME ratio for stock s at time t

It should be noted however that it is more common to use the Fama-French (1993) Small Minus Big (SMB) and High Minus Low (HML) multifactor model which is also employed by Womack (1996) and as discussed below is the most recognised model when calculating expected returns. The reason we do not employ Fama-French's SMB & HML methodology is due to the lack of SMB & HML factor data for the Swedish market. Griffin (2002) investigates whether domestic, international or world SMB and HML factors best capture average returns when applied in the Fama-French three factor model framework. According to Griffin, none of the three factor types adequately explain the observed returns, but he finds that country specific (or domestic) SMB and HML factors prove substantially more useful than world or international factors in explaining the observed returns. Hence, Fama-French SMB and HML factors originating from the Swedish market portfolio should optimally be used in our study. Unfortunately no readily available source for such factors are available at the time of writing of this thesis, which is why we resort to Fama-French's (1992) size factor and BE/ME ratio methodology.

4.5.3.1 Estimation of the Company Size, ME, and the BE / ME factors

Estimating company size is straightforward and easy to implement through using the market capitalisation dollar value of each stock using each trading day's close price and applying the natural logarithm functional form ln(ME).

Book Equity is used in on a per share basis where the the latest book value of equity per share per the latest filed quarterly report is employed. The natural logarithm functional form of the factor is taken, ln(BE/ME). Book equity values are accounted for in the respective quarterly period as defined per the dates in the quarterly financial statement. However, book value accounting data is released to the market after the actual quarterly period, implying that we have a measurement error in the BE / ME factor as incorrect Book Equity values are applied under the period between the end of a quarter until the quarterly report is filed. Quarterly reports are normally issued 30-60 days after the end of a quarter. Given that a quarter on average is 90 days long, there is a degree of error in the BE/ME factor and the corresponding regression coefficient.

4.5.3.2 Regression of the cross-section of returns controlling for the CAPM, company size and BE/ME Ratio in the Fama-French multifactor model

We perform a time-series regression on each of the constituent OMXS30 stocks throughout the complete measurement period 2004 - 2013 based on each trading day's return, using this as our estimation period with the OMXS30 value-weighted index as a proxy for the market portfolio throughout the period. Our regression for estimating the Fama-French multifactor model expected return is specified as

$$r_{s,t} - r_{f,t} = \alpha_s + \beta_{s,m} (r_{m,t} - r_{f,t}) + \beta_{s,ME} \ln(ME_{s,t}) + \beta_{s,BE/ME} \ln(BE/ME_{s,t}) + \varepsilon_s$$

where α_s is Jensen's alpha and ε_s is the error term. Exogenous variables market return $r_{m,t}$ and risk free rate $r_{f,t}$ are measured for each trading day t. Market Equity $ME_{s,t}$ and Book Equity / Market Equity BE/ME_{s,t} are measured for each trading day t and each individual OMXS30 stock s.

4.5.4 The Industry Peer Adjusted Expected Return model

We also employ a second industry peer adjusted model as used by Womack (1996) and Lidén (2007). Womack applies the US Standard Industrial Classification (SIC) classification system to find peer companies listed in the US. Lidén employs the Global Industry Classification System (GICS), however the geographical scope of Lidéns peer group is not disclosed in his paper. In this study, STOXX European 600 NC industry sector indices are matched to the corresponding stock. These indices are maintained by STOXX, a global index provider, on a regular basis and provide the most reliable industry peer price data available. The STOXX European 600 NC indices consist of the largest European companies in each of the 19 supersectors as defined by the Industry Classification Benchmark (ICB). The constituent companies are taken from Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. The indices are non-capped (NC), thus the total market capitalisation for all companies are included in the index-weighting. The corresponding sector index for each stock used in this study can be found in table 11. As each of the OMXS30 stocks constitute a small fraction of each STOXX Sector index, we avoid a potential simultaneity bias which otherwise would occur if Swedish or Nordic sector indices were employed. If Nordic indexes were to be employed, simultaneity bias would have been

particularly present for stocks such as Hennes & Mauritz and Ericsson who constitute a significant part of their respective industry indexes.

4.5.5 Long term event studies and implications for Expected Return models

The average tenure of the RPR event period in our sample averages 264 days and our long-run fixed period event window amount to 180 trading days, making our event study fit the category of long-run event studies. It is therefore important to consider the implications of long-run event studies on our estimated expected returns and the resulting impact on measurement of abnormal returns. The most basic issues to consider include risk-adjustment, expected/abnormal return modeling, the aggregation of security specific abnormal returns and the calibration of the statistical significance of abnormal returns.⁸ Unfortunately the question of which model of expected returns that is the most appropriate remains unresolved. Results of using different long-term event studies have not been completely conclusive, but the most frequently employed methods today are the Fama and French (1993) three-factor model additionally modified by Carhart (1997) to take account for the momentum factor.⁸ Fortunately, this drawback in the estimation of expected returns for our event study will not completely cripple our empirical study. As our measured abnormal returns will likely be incorrectly estimated due to the lack of an efficient method to estimate expected returns over the long run, the incremental impact of the recommendation event should still, if significant impact the return performance when recommendations are compared to each other.

⁸ Eckbo (2007)

4.6 Cross-sectional regressions of analyst recommendation returns

In order to control for different factors and examine their relevance in explaining the abnormal returns we perform the following fixed effects regression on the cross-sectional dataset described above containing each BHAR return for its respective observed recommendation. A total of thirty-six regressions are performed on three different return datasets entailing raw unadjusted returns, returns adjusted for industry peers and returns adjusted using the Fama-French (1992) method. Due to that we regress on the 30-day, 180-day and RPR measurement periods separately the resultant amount of regressions amount to 3 x 3 x 4 = 36 as we perform each regression with four different mixes of exogenous variables. The complete regression with all exogenous factors specified is

$BHAR_{i} = \beta_{0} + \beta_{1}SHORT_{i} + \beta_{2}(LONG_{i} \times STRONG_{i}) + \beta_{3}(SHORT_{i} \times STRONG_{i}) + \varepsilon_{s}$

Where the endogenous variable $BHAR_i$ entail return for each stock recommendation *i*. The right hand side contain the following exogenous dummy variables with corresponding coefficients:

- (i) β_0 : Intercept indicating return on all LONG recommendations. As all recommendations contained in our sample are either LONG or SHORT, the intercept indicates the return of LONG recommendations
- (ii) β_1 , SHORT_i: Dummy variable indicating the return on SELL and UNDERWEIGHT recommendations through value "1", "0" otherwise
- (iii) $\beta_2(LONG_i \times STRONG_i)$: Interaction term between two dummy variables dependent on broker recommendation strength and recommendation direction. Takes the value 1 when the strong recommendation BUY is issued
- (iv) $\beta_3(SHORT_i \times STRONG_i)$: Interaction term between two dummy variables dependent on broker recommendation strength and recommendation direction. Takes the value 1 when the strong recommendation SELL is issued

We choose to employ a time fixed effects regression on an annual basis in order to control for time-varying returns due to potentially volatile bull- and bear market years that skew the adjusted returns. Our fixed effects regression result in higher significance of exogenous variable coefficients. Evidently this methodology of controlling for annual fixed effects would not be necessary if the asset pricing model used for estimating expected returns had been perfect.

5. Results

5.1 Descriptive statistics

Table 1, 2 and 3 below contain descriptive statistics of the 705 BUY, SELL, OVERWEIGHT and UNDERWEIGHT recommendations for (i) unadjusted returns (i) industry adjusted returns and (iii) Fama-French (1992) adjusted returns. These are named according to the trading direction each recommendation entail. Descriptive statistics for all trades are also included under ALLRECOMMENDATIONS. Although raw returns that are not adjusted through an expected return model are somewhat irrelevant, these returns are disclosed and analysed as they are a relevant benchmark for assessing our expected return models.

The descriptive statistics exhibit a number of interesting results: Most interestingly, LONG recommendations yield a significant positive return throughout all recommendation periods for both raw, industry adjusted and Fama-French (1992) adjusted returns, with SHORT recommendation returns being negative across all time periods for both raw and adjusted return models. These results are in direct contradiction with our hypothesis.

Examining the 30-day, 180-day and RPR return periods, we see that mean unadjusted returns deviate further from zero in the 180-day and RPR event windows, compared to the 30-day window which only is plausible due to the longer time period. Industry adjusted returns exhibit similar characteristics with more positive and negative returns under the 180-day and RPR period. Interestingly, Fama-French (1992) returns over the 180-day and RPR period which are SHORT exhibit a drastically lower standard deviation when compared to industry adjusted returns.

The STRONG BUY and SELL recommendations through the majority of time periods and adjustment methods result in a higher return compared to OVERWEIGHT and UNDERWEIGHT recommendations which are labelled as WEAK recommendations in table 1-3. Thus analysts' conviction in their opinion do result in a higher return, in-line with our hypothesis.

In theory, standard deviation of returns adjusted with expected return models should exhibit a lower standard deviation compared to unadjusted returns, as abnormal returns, if observed, invariably should be significantly lower than unadjusted returns under the assumption that the asset-pricing model used for calculating expected returns are correct. In our sample however, standard deviations across unadjusted and adjusted returns are largely the same.

Table 1: Summary statistics for unadjusted analyst stock recommendation returns

The dataset consist of a cross-sectional dataset with stock recommendations on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over 30 day, 180 day and RPR time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the the Buy-and-Hold Abnormal Return (BHAR) return methodology. The Recommendation Period Return (RPR) measurement period is the daily BHAR return for buy and sell recommendations throughout the whole length of the recommendation. The return is measured until reset by a rerating.

Variable	Obs.	Mean	Std. Dev	Min	Max
30-day return					
ALL_RECOMMENDATIONS	705	1.6%	11.4%	-51.7%	51.9%
LONG	526	2.6%	10.5%	-40.9%	51.9%
LONG_STRONG	288	3.6%	10.4%	-27.5%	51.9%
SHORT	177	-1.3%	13.5%	-51.7%	37.9%
SHORT_STRONG	107	-2.1%	13.4%	-51.7%	37.4%
STRONG	395	2.1%	11.6%	-51.7%	51.9%
WEAK	308	0.9%	11.2%	-42.4%	37.9%
180-day return					
ALL_RECOMMENDATIONS	705	3.3%	34.1%	-188.8%	212,9%
LONG	510	9.6%	29.5%	-60.4%	212,9%
LONG_STRONG	277	11.2%	31.3%	-52.7%	212,9%
SHORT	169	-15.5%	39.8%	-188.8%	77,1%
SHORT_STRONG	101	-13.6%	43.3%	-188.8%	75,3%
STRONG	378	4.6%	36.5%	-188.8%	212,9%
WEAK	301	1.8%	30.8%	-121.7%	150,3%
RPR					
ALL_RECOMMENDATIONS	705	7.5%	37.4%	-164.5%	330.8%
LONG	510	13.0%	38.2%	-69.8%	330.8%
LONG_STRONG	277	15.8%	38.5%	-69.8%	276.9%
SHORT	169	-9.0%	29.6%	-164.5%	85.7%
SHORT_STRONG	101	-7.3%	28.5%	-99.6%	85.7%
STRONG	378	9.6%	37.5%	-99.6%	276.9%
WEAK	301	4.8%	37.2%	-164.5%	330.8%

Table 2: Summary statistics for industry adjusted analyst stock recommendation

returns

The dataset consist of a cross-sectional dataset with stock recommendations on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over 30 day, 180 day and RPR time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the Buy-and-Hold Abnormal Return (BHAR) return methodology. The Recommendation Period Return (RPR) measurement period is the daily BHAR return for buy and sell recommendations throughout the whole length of the recommendation. The return is measured until reset by a rerating.

Variable	Obs.	Mean	Std. Dev	Min	Max
30-day return					
ALL_RECOMMENDATIONS	705	1.4%	8.3%	-48.7%	32.6%
LONG	528	1.9%	7.6%	-26.6%	32.6%
LONG_STRONG	290	2.4%	7.7%	-23.0%	32.6%
SHORT	177	-0.1%	9.9%	-48.7%	31.2%
SHORT_STRONG	107	-0.4%	9.9%	-48.7%	16.4%
STRONG	397	1.6%	8.4%	-48.7%	32.6%
WEAK	308	1.1%	8.1%	-26.6%	31.2%
180-day return					
ALL_RECOMMENDATIONS	705	1.9%	23.3%	-161.4%	170.4%
LONG	528	4.9%	21.3%	-53.7%	170.4%
LONG_STRONG	290	5.2%	22.3%	-53.7%	170.4%
SHORT	177	-7.2%	26.6%	-161.4%	58.5%
SHORT_STRONG	107	-6.0%	26.9%	-161.4%	58.5%
STRONG	397	2.2%	24.1%	-161.4%	170.4%
WEAK	308	1.5%	22.3%	-89.9%	132.2%
RPR					
ALL_RECOMMENDATIONS	705	3,3%	34.1%	-188.8%	212.9%
LONG	510	9,6%	29.5%	-60.4%	212.9%
LONG_STRONG	277	11,2%	31.3%	-52.7%	212.9%
SHORT	169	-15,5%	39.8%	-188.8%	77.1%
SHORT_STRONG	101	-13,6%	43.3%	-188.8%	75.3%
STRONG	378	4,6%	36.5%	-188.8%	212.9%
WEAK	301	1,8%	30.8%	-121.7%	150.3%

Table 3: Summary statistics for analyst stock recommendation return variablesadjusted according to the Fama French (1992) model

The dataset consist of a cross-sectional dataset with stock recommendations on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over 30 day, 180 day and RPR time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the Buy-and-Hold Abnormal Return (BHAR) return methodology. The Recommendation Period Return (RPR) measurement period is the daily BHAR return for buy and sell recommendations throughout the whole length of the recommendation. The return is measured until reset by a rerating.

Variable	Obs.	Mean	Std. Dev	Min	Max
30-day return					
ALL_RECOMMENDATIONS	705	1.0%	8.5%	-38.0%	38.1%
LONG	528	1.1%	6.9%	-38.0%	35.1%
LONG_STRONG	290	1.0%	5.1%	-22.5%	35.1%
SHORT	177	-0.1%	5.0%	-33.8%	38.1%
SHORT_STRONG	107	-0.2%	4.0%	-33.8%	38.1%
STRONG	397	0.8%	6.5%	-33.8%	38.1%
WEAK	308	0.2%	5.6%	-38.0%	28.0%
180-day return					
ALL_RECOMMENDATIONS	705	1.3%	23.3%	-184.4%	147.4%
LONG	528	2.8%	18.4%	-66.7%	147.4%
LONG_STRONG	290	2.0%	14.1%	-42.7%	147.4%
SHORT	177	-1.5%	14.0%	-184.4%	51.0%
SHORT_STRONG	107	-0.9%	11.8%	-184.4%	51.0%
STRONG	397	1.1%	18.5%	-184.4%	147.4%
WEAK	308	0.2%	14.2%	-83,3%	100.6%
RPR					
ALL_RECOMMENDATIONS	705	14.6%	49.0%	-131.3%	414.0%
LONG	510	14.9%	48.1%	-131.3%	414.0%
LONG_STRONG	277	10.1%	38.7%	-131.3%	306.2%
SHORT	169	-0.4%	9.1%	-107.1%	39.3%
SHORT_STRONG	101	-0.2%	5.9%	-74.5%	39.3%
STRONG	378	9.9%	39.2%	-131.3%	306.2%
WEAK	301	4.7%	31.0%	-107.1%	414.0%

5.2 The Fama-French (1992) ME and BE / ME ratio multi-factor model regressions

Table 5 contain results of the Fama-French (1992) time-series regression on daily returns of the OMXS30 stock constituents. 9 of the 30 stocks exhibit significant $\alpha_s s$, with all $\alpha_s s$ being negative between 1,9% to 5.8%. All $\beta_{s,m} s$ are significant on the 1% level, with very low or non-existent coefficient standard errors. The certainty in estimation of the $\beta_{s,m}$ coefficient is due to the large estimation sample of daily returns over ten years, with the number of observations amounting to 2,608. The $\beta_{s,ME}$ Market Equity coefficient is insignificant for most stocks which is likely explained by our regression methodology which do not sort stocks in portfolios based on size. The $\beta_{s,BE/ME}$ Book Equity / Market Equity coefficient is significant on the 1% level for all stocks, but due to high standard errors the direction of the $\beta_{s,BE/ME}$ coefficient is not significant for any stock. Finally overall adjusted R² indicate a high goodnessof-fit of the Fama-French (1992) regression for almost all stocks.

5.3 Cross-sectional regressions of analyst recommendation returns

Table 6, 7 and 8 contain the results of the cross sectional fixed effects OLS regression of analyst stock recommendations employing unadjusted and expected return adjustments through the industry peer and Fama French (1992) models. Table 4 exhibit returns of LONG and SHORT recommendations, which are the most interesting results in this study.

The most interesting find of the recommendation regressions is the consistent significant positive return of LONG and the negative return of SHORT recommendations across both 30-day, 180-day and RPR event windows for both unadjusted and adjusted returns. RPR and 180-day period returns exhibiting the highest significance. 30-day periods also exhibit significance when few exogenous variables are tested for.

RPR period returns exhibit significance beyond the 1% level when employing both industry-adjusted and Fama-French (1992) expected returns. In line with descriptive statistics means the coefficient of RPR LONG recommendations amount to a rather high 21% and SHORT recommendation returns of -5% when only regressing on LONG and SHORT recommendations. Equivalent returns using industry adjusted returns amount to 7% and -4% respectively. Thus SHORT returns exhibit roughly the same level of returns using both expected return models. There is significant variation in the magnitude of LONG returns however, making it viable to conclude that LONG recommendations are indeed on average positive, but the order of magnitude is somewhat inconclusive.

Examining the 180-day fixed period regressions we also see coefficient significance for both Fama-French (1992) and industry adjusted returns when controlling for LONG and SHORT recommendations. Both of our expected return models generate similar returns across LONG and SHORT recommendations ranging between a positive return of 3.6% to 5.0% for LONG returns and negative returns of -6.0 to -7.5% for SHORT recommendations.

Generally, LONG_STRONG and SHORT_STRONG recommendations do not exhibit significance across both expected return models, however LONG_STRONG recommendations under the Fama-French (1992) methodology exhibit an additional return on top of LONG recommendations of 2% and 8% in the 30-day and RPR periods respectively at 5% significance.

A potential cause of concern in our regressions is the low adjusted R^2 of the regressions. Although it is implausible that stock recommendations as sole explanatory variables would generate a high explanation of stock price movements, we would expect that industry adjusted and Fama-French (1992) expected returns would increase R^2 of our recommendation regressions when comparing to unadjusted returns. In our regressions the Fama-French RPR return indeed exhibit a higher R^2 of 0,17 compared to unadjusted returns R^2 however. We further note that the observed abnormal returns are significantly lower than unadjusted returns, evidencing that our estimated asset pricing models indeed control for some of the expected returns.

Standard errors for all coefficients are shown in tables 3,4 and 5. Standard errors are of such a minor magnitude so that none would reverse any of the significant LONG recommendations into negative return or any of the SHORT recommendations into positive returns.

Table 4: Recommendation return on SHORT and LONG recommendations across measurement periods and return adjustment methodologies

The table below summarize regressions results performed on the complete sample of 705 observations. Only regressions controlling for SHORT and LONG recommendations are presented. Complete regressions and disclosure of regression methodology can be found in tables 6,7 and 8. SHORT returns is the difference between the regression constant, which indicate return on LONG recommendations, and the regression coefficient of the SHORT exogenous dummy variable indicating returns on SHORT recommendations. Adjusted R_2 for each regression are given in the parenthesis below each return metric. The stars *, ** and *** denote statistical significance at the 10%, 5% and 1% two-tailed significance levels, respectively.

Measurement	Actual Returns	Industry Adjusted	Fama-French (1992)							
period		Returns	Adjusted							
LONG recommendations										
30-day	2.6% ***	1.9% ***	1.5% ***							
	(0.02)	(0.01)	0.01							
180-day	9.9% ***	5.0% ***	3.6% ***							
	(0.12)	(0.05)	(0.02)							
RPR	13.4% ***	7.2% ***	20.9% ***							
	(0.10)	(0.03)	(0.16)							
	SHOR	T recommendations								
30-day	-1.5% ***	-0.2% ***	-0.4% **							
	(0.02)	(0.01)	0.01							
180-day	-16.4% ***	-7.5% ***	-6.0% ***							
	(0.12)	(0.05)	(0.02)							
RPR	-10.3% ***	-3.9% ***	-4.8% ***							
	(0.10)	(0.03)	(0.16)							

5.4 Robustness tests⁹

A number of robustness tests are trialed. Firstly, we try a set of different exogenous variables in both our Fama-French (1992) expected return model as well as in our industry adjusted model. In our industry adjusted model we also tested with OMXS30 sector indexes as peer industries. In the Fama-French (1992) model, we tried two different risk-free rates, however yielding similar results. Furthermore the main recommendation return regression was run with a few variations in interpretations of recommendation changes, and as the difference between STRONG and WEAK recommendations proved material this setup was used.

We controlled for the documented size effect according to Elroy Marsh (1984) where smaller firms exhibit higher stock price movements after announcements in the recommendation return regressions, however no significance was attained in the size factor so this was dropped from the regression.

Secondly, we consider the regression methodology employed in our main regression of recommendation returns. By design, our employed OLS regression provide an unbiased estimator only when errors are homoscedastic, i.e. that the variance of the error term is constant and serially uncorrelated. When testing regressions for heteroscedasticity through the Breusch-Pagan test, heteroscedasticity is confirmed and therefore standard errors are corrected for heteroscedasticity using the the procedure in White (1980). Applying heteroskedasticity-consistent standard errors do not change the main results.

By employing two different asset pricing models being Fama-French (1992) and industry adjusted returns, the risk of incorrect calculation of expected returns is to some extent mitigated. When assessing which model results in the most accurate measurement of abnormal returns we favor the methodology by Fama-French (1992) compared to industry adjusted returns due to the relative low comparability between the EUROSTOXX indexes and the sample of OMXS30 stocks. Opposed to studies performed on larger stock markets such as those on US exchanges where an abundance of industry and company peer exists, comparability in our benchmarking against European peers is lower. Hence we conclude that most likely Fama French (1992) adjusted returns are of more analytical value in this study.

⁹ For convenience, not all robustness test results are displayed in this paper. All the results described in this section are however, available from the authors.

6. Discussion

Observed returns are significant across all time periods and expected return models. However - the direction of abnormal returns is reverse to that of our hypothesis as well as the consensus of previous research that indicate abnormal positive returns primarily on sell recommendations.¹⁰

Under the assumption that our results are unbiased, potential explanations to the negative return on SHORT recommendations can be derived from the conclusions of Johansson (2007), who conclude that some SELL stock recommendations are given to clients verbally rather than in writing, in order not to harm the analyst's relation with the covered company. Assuming this hypothesis is correct, our dataset suffers from a missing data bias of likely very powerful SELL recommendations, which in turn can explain the poor performance of written SELL recommendations.

Our finding of positive abnormal LONG returns and the magnitude of these returns are higher than previously observed in other studies.² The higher observed returns on LONG recommendations in our study when comparing to Liden's (2006, 2007) can potentially be explained by the direct sourcing of equity research analyst's recommendation in our study, as opposed to the secondary sources employed by Lidén were any potential recommendation information content will already be exploited by market participants that have primary access to equity research reports.

Thus according to this study, investors with primary access to equity research from the leading Swedish investment banks do have an opportunity to realize positive abnormal returns by following research analyst's buy recommendations – in particular throughout the whole recommendation period when analysing Fama-French (1992) adjusted returns. As the observed abnormal returns are recorded using each stock's opening price after the publication of each recommendation prior to market open in the morning, investor would also have been able to transact on the prices employed in calculating the abnormal returns. Further the length of our measured trades are rather long spanning between 30 days up to 282 days which is the average length of LONG recommendations, thus transaction costs will not severely impact the observed positive abnormal returns.

¹⁰ Bjerring, Lakonishok, and Vermaelen (1983) find superior performance by a Canadian brokerage house. Dimson and Marsh (1984) find precise forecasting of U.K. stock returns, and Groth, Lewellen, Schlarbaum, and Lease (1979) find outstanding performance by a single U.S. investment firm in the-60s. Furthermore Elton, Gruber, and Grossman (1986) document excess returns for the calendar month of and the first month after brokerage recommendation changes.

6.1 Problematisation

Studying analyst recommendations and returns associated with such recommendations, specifically when using a long-run event study methodology, bring up several implications with corresponding risks for bias and errors.

Incorrect estimations of Expected Returns Although we have made a wide employment of strategies through the use of the at this time appropriate Fama-French and industry adjusting models. This means that our employed models could possibly missspecify the risk of the actual stock, thus over- or undercompensating for true expected returns.

Inability to control for recommendation correctness While Factset is generally perceived as the industry benchmark in terms of aggregating analyst and company data, the database is still prone to containing errors from our own experiences. The price data is transparent and we have cross-checked with multiple sources that dividends, share splits et cetera has been properly adjusted for. On stock recommendations however we only been able to make select sample checks that the data is accurate. Since this information is proprietary for each analyst house, it is not particularly transparent.

Problem with Book Equity (BE) factor due to Factset data limitations Factset employs the process of backwards adjusting estimates when actual information is published. This entails issues with our analysis of book equity data since it is only released to the market and analysts a number of weeks post-closing of relevant trading period. We are hence looking at a short window in connection to each published report where book equity value is wrong by some degree.

Survivorship bias There may be significant risk for survivorship bias in the selection of stocks studied i.e. on the OMXS30 index. Since we have used the OMXS30 constituents as per end of 2013, this may be a biased selection as stocks that have exhibited weak price performance and over time been removed from the index due to less trading volumes in the stock. Such a bias would mean that weaker performing stocks had been excluded over time, there would be a too high return on the stocks currently constituting the index and hence our selected stocks have been outperformers.

Analyst herd behavior In studies such as Womack (2006) and Desai (2000), empirical results support the price pressure phenomena, which in turn will distort returns if analysts do indeed exhibit herd behavior and change recommendations in close proximity to each other. Thus stock prices might potentially be double or triple counted. This bias would not affect the realised excess returns per sé, but could instead overstate the true price movements in the current stock.

6.2 Suggested future topics for research

Further work can be placed into controlling the recommendation dataset by using primary sources for recommendations rather than an aggregated database. While this is coupled with difficulties in accessing data, it could improve the overall quality of the analysis.

Replicating the RPR methodology on other markets, where similar studies have been performed using fixed term event windows, can be of particular interest.

The Fama-French (1992) expected return model employed in this paper was in direct response to the lack of existing SMB and HML factors on the Swedish market. Creating SML and HML factors, similar to the availability for factors on the US and European market, would be of great interest.

Finally, the qualitative dynamic of the conflicting interests and incentives that drives the analyst community and its delicate and complex relationship with companies under coverage and investors is a topic where more research could be devoted.

7. Conclusion

Analysts' and their ability to generate positive abnormal returns through stock recommendations has been a topic of significant study during the modern era of financial economics. Previous academia has both accepted and rejected the existence of abnormal returns in relation to stock recommendations.

In this paper we test the hypothesis of whether leading Swedish equity research analysts' sell recommendations outperform buy recommendations on the back of greater conviction from sell recommendations due to greater risks associated with such recommendations. The findings in this paper do not support the hypothesis that sell recommendations generate statistically significant abnormal returns compared to buy recommendations. In fact our results indicate that buy recommendations generate a positive abnormal return as opposed to the negatively abnormal return generated by sell recommendations.

However analysts do indeed produce significant positive abnormal returns on LONG recommendations, a conclusion noteworthy in itself. Comparing our results with Lidén (2006, 2007) who investigated returns using journalist stock recommendations and secondary sources of equity research analysts' stock recommendations through printed media, our findings are somewhat different as Lidén find positive abnormal returns only in SHORT recommendations. Our findings encounter positive abnormal returns for LONG recommendations but negative abnormal returns for SHORT recommendations. Analysts' therefore appear to possess market timing and stock picking abilities when recommending stocks to buy, but not when recommending stocks to sell.

It is appropriate to disclaim however that these findings potentially are due to a bias in our expected return models, as our sample is derived from the 2004-2013 years out of which most years were bull markets - for which our expected return models potentially did not fully compensate. However it is noteworthy that also LONG recommendations in the 30-day event window exhibits significant returns across both expected return models, supporting the conclusion that analyst's do have a capability to generate abnormal returns.

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Appendix

Table 5: Fama-French (1992) expected return regression coefficients

We perform an OLS time-series regression on each of the constituent OMXS30 stocks throughout the measurement period 2004 - 2013 based on each trading day's return for each stock and with the OMXS30 value-weighted index as a proxy for the market portfolio. Exogenous variables market return $r_{m,t}$ and risk free rate $r_{f,t}$ are measured for each trading day t. The risk free rate $r_{f,t}$ is quoted as annual interest rate for each trading day and is converted to a daily compounded interest rate. Market Equity $ME_{s,t}$ and Book Equity / Market Equity $BE/ME_{s,t}$ are measured for each trading day t and each individual OMXS30 stock s. The stars *, ** and *** denote statistical significance at the 10%, 5% and 1% two-tailed significance levels, respectively.

$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Stock s	α _s	<i>r_{m,t}</i> –	r _{f,t}	$\ln(ME_{s,t})$	ln(BE /ME _s ,		No. of obs.	Adj. R ²
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	ABB	-0.008	1.108	***	0.000	-0.003	***	2,608	0.539
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	11DD	(0.007)	(0.020)		(0.001)	(0.001)	***		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Alfa Laval	0.005	1.113	***	-0.001	-0.004	***	2,608	0.533
Assa Abloy (0.207) (0.00) (0.208) (0.712) *** AstraZeneca (0.039) * (0.455) *** (0.00) (0.08) (0.07) (0.958) *** Atlas Copeo (0.00) (1.279) *** (-0.01) *** $2,608$ 0.675 Boliden (0.00) (0.362) (0.232) *** (-0.01) *** $2,608$ 0.453 Boliden (0.00) (0.453) (0.300) (0.453) (0.300) (0.453) Electrolux $(0.003$ 1.104 *** 0.000 -0.001 *** $2,608$ 0.442 Ericsson 0.045 1.025 *** -0.004 -0.003 *** $2,608$ 0.424 Getinge -0.019 ** 0.649 *** 0.000 -0.003 *** $2,608$ 0.289 Investor (0.650) (0.000) (0.632) (0.012) *** -0.002		(0.450)	(0.000)		(0.195)	(0.003)	***		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Assa Ablov	-0.011	0.995	***	0.001	0.001	***	2,608	0.533
AstraZeneca (0.081) (0.000) (0.085) (0.958) *** Adlas Copco (0.009) 1.279 *** -0.001 *** 2,608 0.675 Boliden (0.009) 1.451 *** -0.001 -0.002 *** 2,608 0.453 Boliden (0.441) (0.000) (0.453) (0.000) *** 2,608 0.460 Electrolux (0.810) (0.000) (0.791) (0.244) *** Ericsson 0.045 1.025 *** -0.004 -0.003 *** 2,608 0.442 Getinge (0.164) (0.000) (0.158) (0.084) *** -	1155a 11010 y	(0.207)	(0.000)		(0.208)	(0.712)	***		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	AstroZeneco	-0.039 *	0.455	***	0.004 *	0.000	***	2,608	0.209
Attas Copco (0.383) (0.000) (0.362) (0.232) *** Boliden 0.009 1.451 *** -0.001 -0.002 *** 2,608 0.453 Boliden (0.441) (0.000) (0.453) (0.309) *** Electrolux $(0.003$ 1.104 *** 0.000 -0.001 *** 2,608 0.460 Ericsson (0.164) (0.000) (0.71) (0.244) *** Getinge -0.019 ** 0.045 1.025 *** -0.004 -0.003 *** $2,608$ 0.442 Getinge -0.019 ** 0.649 *** 0.002 * -0.003 *** $2,608$ 0.289 H&M 0.000 (0.000) (0.082) $(0.012$ *** $2,608$ 0.493 Investor -0.015 0.997 *** 0.001 -0.002 *** $2,608$ 0.298 Petroleum	Instrazeneca	(0.081)	(0.000)		(0.085)	(0.958)	***		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Atlas Copco	0.009	1.279	***	-0.001	-0.001	***	2,608	0.675
Boliden 0.003 1.101 0.001 0.002 $***$ 0.002 $***$ Electrolux 0.003 1.104 $***$ 0.000 0.001 $***$ $2,608$ 0.460 Ericsson 0.045 1.025 $***$ -0.004 -0.003 $***$ $***$ Getinge 0.045 1.025 $***$ -0.004 -0.003 $***$ $2,608$ 0.442 M& 0.000 (0.58) (0.000) (0.58) $(0.003$ $***$ $2,608$ 0.289 H&M 0.000 (0.000) (0.082) (0.012) $***$ $***$ H&M 0.000 0.0452 (0.012) $***$ $2,608$ 0.289 Investor -0.015 0.997 $***$ 0.001 $*0.002$ $***$ $2,608$ 0.752 Lundin 0.003 1.091 $***$ 0.001 $*0.001$ $***$ $2,608$ 0.409 <t< td=""><td>Muas Copeo</td><td>(0.383)</td><td>(0.000)</td><td></td><td>(0.362)</td><td>(0.232)</td><td>***</td><td></td><td></td></t<>	Muas Copeo	(0.383)	(0.000)		(0.362)	(0.232)	***		
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Rolidon	0.009	1.451	***	-0.001	-0.002	***	2,608	0.453
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Donden	(0.441)	(0.000)		(0.453)	(0.309)	***		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Floctrolux	0.003	1.104	***	0.000	-0.001	***	2,608	0.460
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Election	(0.810)	(0.000)		(0.791)	(0.244)	***		
Getinge (0.164) (0.000) (0.158) (0.084) *** Getinge -0.019 ** 0.649 *** 0.002 -0.003 *** $2,608$ 0.289 H&M 0.000 (0.000) (0.082) (0.012) *** H&M 0.000 0.766 *** 0.000 -0.002 *** $2,608$ 0.493 H&M (0.958) (0.000) (0.632) (0.159) *** Investor -0.015 * 0.997 *** 0.001 * -0.002 *** $2,608$ 0.752 Lundin 0.003 1.091 *** 0.001 * -0.002 *** $2,608$ 0.298 Petroleum (0.804) (0.000) (0.73) (0.023) **** $2,608$ 0.493 MTG -0.008 1.057 *** 0.001 0.000 **** $2,608$ 0.676 (0.288) (0.000) (0.557) (0.73) $(***)$ MTG -0.014	Friencen	0.045	1.025	***	-0.004	-0.003	***	2,608	0.442
Gettinge (0.050) (0.000) (0.082) (0.012) *** H&M 0.000 0.766 *** 0.000 -0.002 *** 2,608 0.493 (0.958) (0.000) (0.632) (0.159) *** 1 Investor -0.015 * 0.997 *** 0.001 * -0.002 *** 2,608 0.752 Lundin 0.003 (0.000) (0.073) (0.023) *** 1 <td>Elicsson</td> <td>(0.164)</td> <td>(0.000)</td> <td></td> <td>(0.158)</td> <td>(0.084)</td> <td>***</td> <td></td> <td></td>	Elicsson	(0.164)	(0.000)		(0.158)	(0.084)	***		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Catingo	-0.019 **	0.649	***	0.002 *	-0.003	***	2,608	0.289
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Gettilge	(0.050)	(0.000)		(0.082)	(0.012)	***		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	119-14	0.000	0.766	***	0.000	-0.002	***	2,608	0.493
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	пам	(0.958)	(0.000)		(0.632)	(0.159)	***		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	T	-0.015 *	0.997	***	0.001 *		***	2,608	0.752
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Investor	(0.085)	(0.000)		(0.073)	(0.023)	***		
MTG -0.008 1.057 *** 0.001 0.000 *** 2,608 0.409 MTG (0.508) (0.000) (0.557) (0.703) *** - <td< td=""><td>Lundin</td><td>0.003</td><td>1.091</td><td>***</td><td>0.000</td><td></td><td>***</td><td>2,608</td><td>0.298</td></td<>	Lundin	0.003	1.091	***	0.000		***	2,608	0.298
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Petroleum	(0.804)	(0.000)		(0.741)	(0.112)	***		
(0.508) (0.000) (0.557) (0.703) *** Nordea -0.014 1.202 *** 0.001 -0.001 *** $2,608$ 0.676 (0.288) (0.000) (0.303) (0.176) *** $2,608$ 0.659 Sandvik 0.000 1.265 *** 0.000 -0.003 *** $2,608$ 0.659	MTC	-0.008	1.057	***	0.001	0.000	***	2,608	0.409
Nordea -0.014 1.202 *** 0.001 -0.001 *** 2,608 0.676 (0.288) (0.000) (0.303) (0.176) *** - <td>MIG</td> <td>(0.508)</td> <td>(0.000)</td> <td></td> <td>(0.557)</td> <td>(0.703)</td> <td>***</td> <td></td> <td></td>	MIG	(0.508)	(0.000)		(0.557)	(0.703)	***		
(0.288) (0.000) (0.303) (0.176) *** Sandvik 0.000 1.265 *** 0.000 -0.003 *** 2,608 0.659	NT 1	-0.014		***			***	2,608	0.676
Sandvik 0.000 1.265 *** 0.000 -0.003 *** 2,608 0.659	Nordea	(0.288)	(0.000)		(0.303)	(0.176)	***		
Sandvik	Sandvik			***	, ,		***	2,608	0.659
(0.988) (0.000) (0.877) (0.120)		(0.988)	(0.000)		(0.877)	(0.120)	***	-	
-0.058 * 0.752 *** 0.005 * 0.003 *** 2.608 0.427				***			***	2,608	0.427
SCA (0.089) (0.000) (0.090) (0.323) ***	SCA						***	,	

Scania	0.017		1.118	***	-0.002		-0.005	***	2,608	0.532
ocumu	(0.283)		(0.000)		(0.197)		(0.010)	***		
SEB	-0.043	***	1.446	***	0.004	***	0.001	***	2,608	0.623
SED	(0.007)		(0.000)		(0.008)		(0.275)	***		
Securitas	-0.022	**	0.764	***	0.002	*	-0.003	***	2,608	0.384
Securitas	(0.041)		(0.000)		(0.065)		(0.042)	***		
Skanska	0.018		1.022	***	-0.002		-0.003	***	2,608	0.594
SKallSKa	(0.433)		(0.000)		(0.422)		(0.333)	***		
SKF	0.027		1.173	***	-0.003		-0.003	***	2,608	0.625
SKF	(0.314)		(0.000)		(0.303)		(0.199)	***		
CCAD	0.004		1.311	***	0.000		-0.002	***	2,608	0.511
SSAB	(0.700)		(0.000)		(0.672)		(0.007)	***		
CLID	-0.017		1.035	***	0.001		0.000	***	2,608	0.613
SHB	(0.275)		(0.000)		(0.286)		(0.896)	***	-	
0 11 1	-0.029	**	1.316	***	0.003	**	0.001	***	2,608	0.530
Swedbank	(0.039)		(0.000)		(0.040)		(0.503)	***	2	
	-0.048	**	0.398	***	0.005	**	-0.001	***	2,608	0.146
Swedish Match	(0.022)		(0.000)		(0.021)		(0.054)	***	2	
TI 1 0	-0.047	**	0.814	***	0.004	**	0.001	***	2,608	0.366
Tele2	(0.017)		(0.000)		(0.017)		(0.490)	***	,	
Т 1 с	-0.043		0.728	***	0.003		-0.001	***	2,608	0.424
TeliaSonera	(0.222)		(0.000)		(0.242)		(0.559)	***	·)	
Valar Carros	-0.010		1.261	***	0.001		-0.001	***	2,608	0.644
Volvo Group	(0.768)		(0.000)		(0.792)		(0.771)	***	-	

Table 6: Cross-sectional regression output for analyst stock recommendation returns using raw returns over different time periods

The table below show regression coeffecients for an annual fixed-effects regression performed on a cross-sectional dataset where Buy-and-Hold Abnormal Returns (BHAR) from the 30 OMXS30 constituent stocks measured during 2004-2013 over three different event window time periods. BHAR returns serve as the endogenous variable with exogenous variables LONG, SHORT, LONG_STRONG, and SHORT_STRONG, over return metrics with on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over three different time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the the Buy-and-Hold Abnormal Return (BHAR) return methodology. Stock returns are measured during periods of 30 and 180 trading days following a buy or sell recommendation. We also employ the Recommendation. The return is measured through the whole recommendation period until reset by a rerating. The stars *, ** and *** denote statistical significance at the 10%, 5% and 1% two-tailed significance levels, respectively.

Measurement						Adjusted
period	${m eta}_0$, long	SHORT	LONG_STRONG	SHORT_STRONG	No. of obs.	\mathbf{R}_2
30-day	0.03 ***	-0.04 ***			703	
50-day	(0.00)	(0.01)			703	0,02
30-day	0.01 *	-0.03 **	0.02 **		703	0,04
J0-day	(0.01)	(0.01)	(0.01)		703	0,04
20 day	0.01 *	-0.02	0.02 **	-0.02	703	0.03
30-day	(0.01)	(0.02)	(0.01)	(0.02)	/03	0,03
180-day	0.10 ***	-0.26 ***			679	0,12
160-uay	0.00	(0.03)			0/9	0,12
180-day	0.08 ***	-0.25 ***	0.03		679	0,12
160-uay	(0.02)	(0.03)	(0.03)		0/9	0,12
100 1	0.08 ***	-0.28 ***	0.03	0.06	679	0.12
180-day	(0.02)	(0.04)	(0.03)	(0.05)	0/9	0,12
RPR	0.13 ***	-0.24 ***			705	0,10
NPN	(0.02)	(0.03)			/05	0,10
מתת	0.11 ***	-0.21 ***	0.05 *		705	0.10
RPR	(0.02)	(0.04)	(0.03)		/05	0,10
מתת	0.11 ***	-0.24 ***	0.05	0.06		
RPR	(0.02)	(0.05)	(0.03)	(0.05)	705	0,10

Table 7: Cross-sectional regression output for analyst stock recommendation returns using industry adjusted returns over different time periods

The table below show regression coefficients for a fixed-effects regression performed on a cross-sectional dataset where Buy-and-Hold Abnormal Returns (BHAR) from the 30 OMXS30 constituent stocks measured during 2004-2013 over three different event window time periods. BHAR returns serve as the endogenous variable LONG, SHORT, LONG_STRONG, and SHORT_STRONG, over return metrics with on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over three different time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the the Buy-and-Hold Abnormal Return (BHAR) return methodology. Stock returns are measured during periods of 30 and 180 trading days following a buy or sell recommendation. We also employ the Recommendation. The return is measured through the whole lifetime of the recommendation. The return is measured through the whole recommendation period until reset by a rerating. The stars *, ** and *** denote statistical significance at the 10%, 5% and 1% two-tailed significance levels, respectively.

Measurement						Adjusted
period	${m eta}_0,$ long	SHORT	LONG_STRONG	SHORT_STRONG	No. of obs.	\mathbf{R}_2
30-day	0.02 ***	-0.02 ***			705	
50-day	(0.00)	(0.01)			/05	0.01
20 1	0.01 **	-0.02 *	0.01		705	0.02
30-day	(0.01)	(0.01)	(0.01)		705	0.03
20 1	0.01 **	-0.01	0.01	-0.01	705	0.01
30-day	(0.01)	(0.01)	(0.01)	(0.01)	705	0.01
100 -	0.05 ***	-0.12 ***			705	0.05
180-day	0.00	(0.02)			/03	0.05
100 1	0.04 ***	-0.12 ***	0.01		705	0.05
180-day	(0.01)	(0.02)	(0.02)			0.05
0.0	0.04 ***	-0.14 ***	0.01	0.03	705	0.04
180-day	(0.01)	(0.03)	(0.02)	(0.04)	705	0.04
מתת	0.07 ***	-0.11 ***			705	0.02
RPR	(0.01) (0.02)			705	0.03	
RPR	0.07 ***	-0.11 ***	0.01		705	0.02
	(0.02)	(0.03)	(0.02)		705	0.03
חחח	0.07 ***	-0.11 ***	0.01	0.01		
RPR	(0.02)	(0.04)	(0.02)	(0.04)	705	0.02

Table 8: Cross-sectional regression output for analyst stock recommendation returns using the Fama French (1992) model over

different time periods

The table below show regression coefficients for a fixed-effects regression performed on a cross-sectional dataset where Buy-and-Hold Abnormal Returns (BHAR) from the 30 OMXS30 constituent stocks measured during 2004-2013 over three different event window time periods. BHAR returns serve as the endogenous variable with exogenous variables LONG, SHORT, LONG_STRONG, and SHORT_STRONG, over return metrics with on the OMXS30 constituent stocks between the years 2004-2013 with a total of 705 individual stock recommendations observations measured over three different time periods. Stock price and recommendation data are obtained through Factset. Returns are measured through the the Buy-and-Hold Abnormal Return (BHAR) return methodology. Stock returns are measured during periods of 30 and 180 trading days following a buy or sell recommendation. We also employ the Recommendation. The return is measured through the whole recommendation period until reset by a rerating. The stars *, ** and *** denote statistical significance at the 10%, 5% and 1% two-tailed significance levels, respectively.

Measurement	9 LONG		LONG STRONG	OLIODE CEDONO	No of the	Adjusted
period	β_0 , LONG	SHORT	LONG_STRONG	SHORT_STRONG	No. of obs.	R ²
30-day	0.01 ***	-0.02 **			678	
50 day	(0.00)	(0.01)			070	0.01
20.1	0.00	-0.01	0.02 **		(70	0.02
30-day	(0.01)	(0.01)	(0.01) 0	678	0.03	
20.1	0.00	0.00	0.02 **	-0.02		0.04
30-day	(0.01)	(0.01)	(0.01)	(0.01)	678	0.01
	0.04 ***	-0.10 ***		~ /		
180-day	0.00	(0.02)			655	0.02
	0.02	-0.08 ***	0.03		655	
180-day	(0.02)	(0.02)	(0.02)			0.02
	0.02	-0.08 **	0.03	0.00		
180-day		0.00			655	0.02
•	(0.02)	(0.03)	(0.02)	(0.04)		
RPR	0.21 ***	-0.26 ***			680	0.16
	(0.02)	(0.04)				5.10
RPR	0.16 ***	-0.21 ***	0.08 **		680	0.17
KPK	(0.03)	(0.05)	(0.04)		000	0.17
חחח	0.16 ***	-0.23 ***	0.08 **	0.03		
RPR	(0.03)	(0.06)	(0.04)	(0.07)	680	0.17

Table 9: RPR length per recommendation type

Overview of RPR and respective recommendation lengths in days. Statistics including both trading days and weekends.

Recommendation type	No. of Obs.	Mean	Median	Std. Dev.	Min	Max
ALL	705	264	168	281	1	2,271
LONG	510	281	179	300	1	2,271
LONG_STRONG	277	323	208	338	2	2,271
SHORT	169	212	139	208	2	954
SHORT_STRONG	101	225	134	227	2	954
STRONG	378	296	181	315	2	2,271
WEAK	301	222	154	225	1	1,583

Author	Region	Period	Sample size (No. of recommen dations)	Holding Period	Expected Return model	Recommendation Source	Number of brokerages examined	Return measure ment
Womack (1996)	USA	1989-1991	1,573	1 ,3 & 6 months after event	Matching industry peers Fama-French Monte-Carlo Randomization	<i>First Call</i> equity research database	14	CAR BHAR
Desai (2000)	USA	1993-1996	1,242	10 to 500 days	Matching control company	Wall Street Journal Dartboard	132	BHAR
Bing Liang (1999)	USA	1990-1994	216	15 periods between 0- 125 days	Market model (CAPM)	Wall Street Journal Dartboard	n.a.	CAR
Lidén(2006)	Sweden	1995-2000	2,282	20 days	Market model (CAPM)	Swedish printed media	6	CAR
Liden (2007)	Sweden	1995-2000	1,775	6,12,18 & 24 months	Matching industry peer index	Swedish printed media	6	BHAR

Table 10: Previous research on analyst recommendation performance

Table 11: Sector Indices used for calculation of industry peers expected returns

Constituent OMXS30 stocks are the constituent stocks per 2013-12-31 taken from NASDAQ OMX. STOXX Sector indexes are taken EUROSTOXX. OMXS30 constituents have been matched to the respective STOXX index where the OMXS30 constituent is present.

OMXS30 Component	Sector Index
ABB	STOXX Europe 600 NC Industrial Goods & Services
Alfa Laval	STOXX Europe 600 NC Industrial Goods & Services
Assa Abloy	STOXX Europe 600 NC Construction & Materials Index
AstraZeneca	STOXX Europe 600 NC Health Care
Atlas Copco	STOXX Europe 600 NC Industrial Goods & Services
Boliden	STOXX Europe 600 NC Basic Resources Index
Electrolux	STOXX Europe 600 NC Personal & Household Goods Index
Ericsson	STOXX Europe 600 NC Technology Index
Getinge	STOXX Europe 600 NC Health Care
H&M	STOXX Europe 600 NC Retail Index
Investor	STOXX Europe 600 NC Financial Services Index
Lundin Petroleum	STOXX Europe 600 NC Oil & Gas Index
MTG	STOXX Europe 600 NC Media Index
Nordea	STOXX Europe 600 NC Banks Index
Sandvik	STOXX Europe 600 NC Industrial Goods & Services Index
SCA	STOXX Europe 600 NC Personal & Household Goods Index
Scania	STOXX Europe 600 NC Industrial Goods & Services
SEB	STOXX Europe 600 NC Banks Index
Securitas	STOXX Europe 600 NC Industrial Goods & Services
Skanska	STOXX Europe 600 NC Construction & Materials Index
SKF	STOXX Europe 600 NC Industrial Goods & Services
SSAB	STOXX Europe 600 NC Basic Resources Index
SHB	STOXX Europe 600 NC Banks Index
Swedbank	STOXX Europe 600 NC Banks Index
Swedish Match	STOXX Europe 600 NC Personal & Household Goods Index
Tele2	STOXX Europe 600 NC Telecommunications Index
TeliaSonera	STOXX Europe 600 NC Telecommunications Index
Volvo Group	STOXX Europe 600 NC Industrial Goods & Services

Table 12: TNS Sifo Prospera's Domestic Equity 2013 Sweden

TNS Sifo Prospera is a global market information and insight group that conduct an annual ranking of investment banks and equity research houses participating in the Swedish equity capital markets. The survey is based on rankings from 69 institutional investors. The table below is taken from the Tier 1 subset of 26 institutional investors which which generate a minimum of 5 million SEK worth of commissions trading domestic Swedish equity. 19 equity houses were covered in the survey.

Ranking	Investment bank	
1	SEB	
2	Carnegie	
3	Nordea Markets	
4	ABG Sundal Collier	

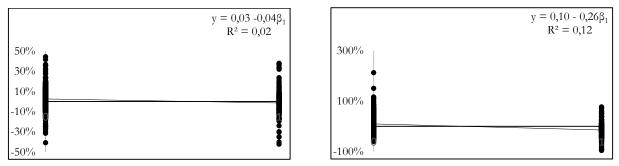
Table 13: OMXS30 price returns

Index price returns per annum during 2004 – 2013.

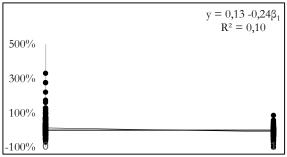
Year	Return	
2004	16.6%	
2005	29.4%	
2006	19.5%	
2007	-5.7%	
2008	-38.8%	
2009	43.7%	
2010	21.4%	
2011	-14.5%	
2012	11.8%	
2013	20.7%	

Figure 1: Plots of recommendation return regressions controlled for LONG and SHORT variables

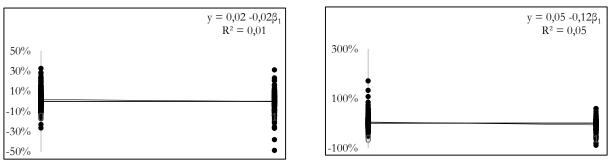
The figures below exhibit the plotted regressions for unadjusted, industry adjusted and Fama-French (1992) regressions with SHORT dummy variables.



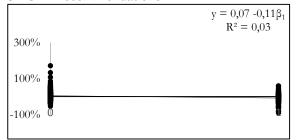
Panel A: Unadjusted returns over 30-day period regression with 1 as dummy for SHORT recommendations and unadjusted returns over 180-day period regression with 1 as dummy for SHORT recommendations.



Panel B: Unadjusted returns over RPR period regression with 1 as dummy for SHORT recommendations.



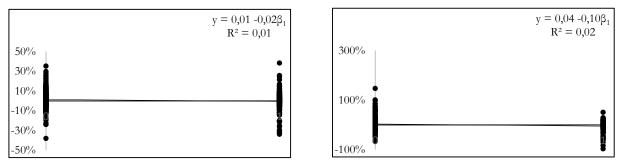
Panel C: Industry adjusted returns over 30-day period regression with 1 as dummy for SHORT recommendations and Industry adjusted returns over 180-day period regression with 1 as dummy for SHORT recommendations.



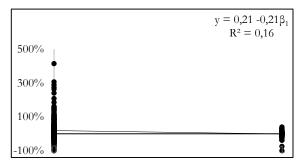
Panel D: Industry adjusted returns over RPR period regression with 1 as dummy for SHORT recommendations.

Figure 2: Plots of recommendation return regressions controlled for LONG and SHORT variables

The figures below exhibit the plotted regressions for Fama-French (1992) regressions with SHORT dummy variables.

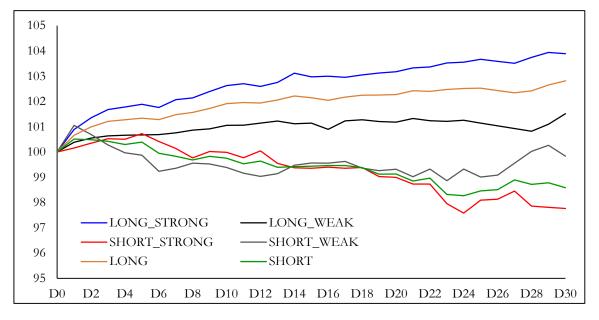


Panel A: Fama French (1992) adjusted returns over 30-day period regression with 1 as dummy for SHORT recommendations and Fama French (1992) adjusted returns over 180-day period regression with 1 as dummy for SHORT recommendations.



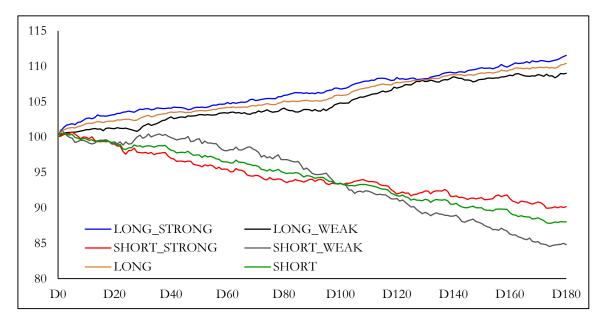
Panel B: Fama French (1992) adjusted returns over RPR period regression with 1 as dummy for SHORT recommendations.

Figure 3: Unadjusted aggregate stock recommendation performance over 30-day and 180-day windows post recommendation



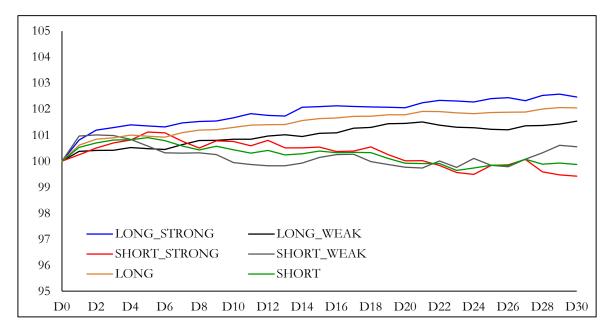
The graphs below exhibit the average return development per recommendation category per trading day.

Panel A: 30-day event window.



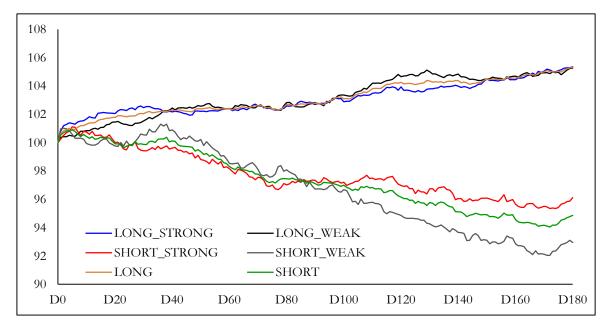
Panel B: 180-day event window.

Figure 4: Industry adjusted aggregate stock recommendation performance over 30day and 180-day windows post recommendation



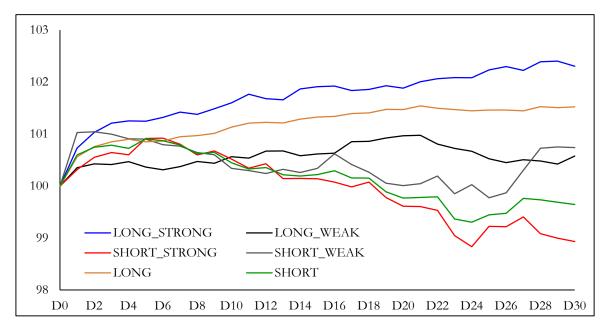
The graphs below exhibit the average return development per recommendation category per trading day.

Panel A: 30-day event window.



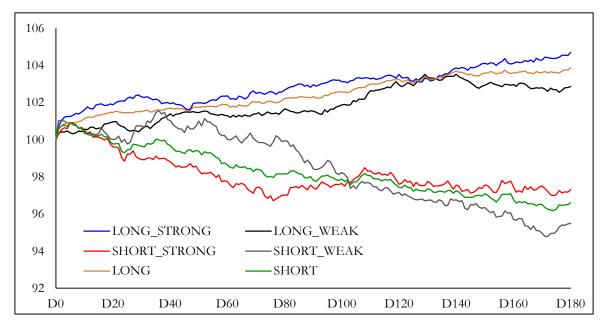
Panel B: 180-day event window.

Figure 5: Fama French (1992) adjusted aggregate stock recommendation performance over 30-day and 180-day windows post recommendation



The graphs below exhibit the average return development per recommendation category per trading day.

Panel A: 30-day event window.



Panel B: 180-day event window.