Measuring Swedish Investor Sentiment

and its effect on

Stock Market Response to Earnings News

Stockholm School of Economics

Degree Project in Accounting & Financial Management

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”Finance is the art of passing money from hand to hand until it finally disappears.”

Robert W. Sarnoff

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EXECUTIVE SUMMARY

The purpose of this thesis is to examine whether the Swedish stock market reacts differently to earnings announcements during periods of high investor sentiment than during periods of low investor sentiment. We define investor sentiment as investor beliefs about future cash flows or discount rates not supported by prevailing economic and financial fundamentals. Research in the field of behavioral finance has found that when investor sentiment is high, investors place excessively optimistic valuations on future cash flows and discount rates, whereas when investor sentiment is low, investors are excessively pessimistic. Therefore we hypothesize that the stock market should react more strongly to good news during periods of high sentiment, and more strongly to bad news during periods of low sentiment.

Using six proxy variables for investor sentiment previously employed in investor sentiment research, we construct a composite sentiment index controlled for macroeconomic indicators. We then use standard earnings response methodology, and test whether the earnings response coefficient is significantly different for positive and negative earnings announcements during periods of high and low sentiment. We also test whether firm size can explain the effect of investor sentiment on the cross-sectional returns surrounding the earnings announcement. Further, we investigate whether accounting earnings' information content co-varies with degrees of investor sentiment.

The major finding in this study is that the earnings response coefficient for good news is significantly larger during periods of high sentiment than during periods of low sentiment, and that the earnings response coefficient for bad news is significantly larger during periods of low sentiment than during periods of high sentiment. We find that the information content of earnings follow this pattern, with a larger information content inherent in good news during high sentiment and bad news during low sentiment. These findings are consistent with previous research on, and central theories of, investor sentiment. Further, we are unable to show that firm size is a relevant factor in determining the outlet of investor sentiment on the cross-sectional stock returns.

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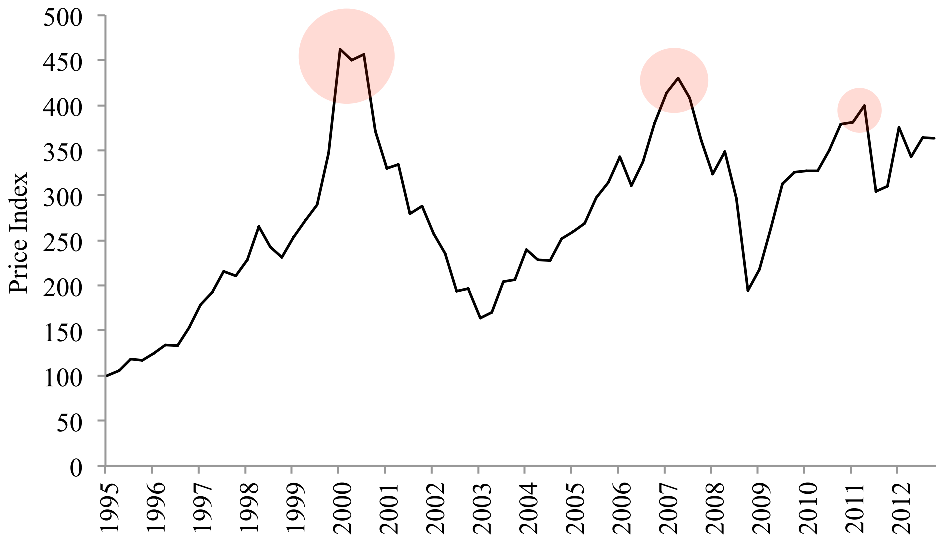
1 Introduction

During the last twenty years, the Swedish stock market has endured a number of dramatic events, both large bubbles and devastating crashes. Coming out of the Swedish financial crisis during the early 1990s, the IT bubble,[3] as the main catalyst, inflated the Swedish stock market by almost 450 percent in just five years. When the bubble burst in the early 2000s, the OMX Stockholm index lost 70 percent of its value in less than two years. No lessons learned, the stock market again began to rise drastically and lacking sustainable economic fundament, suffered another blow during the 2008 financial crisis.

Figure I

The OMXS30 1995 – 2012

The figure depicts the development of the OMXS30 index during the time period relevant in this thesis. The OMXS30 index is a value-weighted index consisting of the 30 most traded stocks on the Stockholm Stock Exchange. Note that we have changed the base period to the first quarter 1995, with base value equal to 100. Marked with red circles of corresponding size are the three stock market crashes during the time period, the IT bubble crash in the early 2000s, the global financial crisis in 2007 – 2008 and the European sovereign debt crisis in 2011.



Source: Thomson Datastream

Traditional financial theory, wherein rational investors forces the market prices of securities to accord with their expected future cash flows, has difficulties explaining these saw-tooth patterns recurring on the world’s

[3] The common English term for the IT-inflated bubble during the late 1990s and early 2000s is the Dotcom-bubble. As the same bubble was called the IT bubble (Swe ”IT-bubblan”) in Sweden, we use this term throughout this thesis.

financial markets. The evolution of behavioral financial models, however, allows investors to act irrational, thus providing the possibility and inevitability of bubbles and subsequent crashes, and also, in our opinion, involving less abstraction from reality than traditional financial models.

In this thesis, we attempt to historically capture the Swedish market's irrational beliefs about the future cash flows of securities, *investor sentiment* as it is called, and examine whether investor sentiment causes the Swedish stock market to respond differently to earnings news during periods of optimism (high sentiment) versus periods of pessimism (low sentiment).

> *"How do we know when irrational exuberance has unduly escalated asset values?"*
>
> Alan Greenspan, December 5th 1996

1.1 Purpose

This thesis is divided into two parts. The *first* part is our attempt to capture and index the prevailing level of investor sentiment on the Swedish market during the period 1995 – 2012. Our ambition is to identify periods of high and low investor sentiment on the Swedish stock market, i.e. periods during which Swedish investors on aggregate have held overly optimistic or pessimistic views on the future performance of the stock market in particular – and the Swedish economy in general.

In the *second* part, we examine whether the degree of investor sentiment affects how investors react to earnings announcements, both in terms of valuation and value relevance. This provides us with an understanding of if and why the market's response to seemingly equal earnings announcements can differ so vastly in the time series dimension.

On a more general level, our thesis shows how Swedish investors' behavioral biases can affect how accounting information is impounded into stock prices, and how the misreaction to earnings announcements can act as one outlet of the sentiment held by Swedish investors towards the market.

1.2 Question Formulations

Our thesis could be the subject of a number of question formulations. However, due to our scope as described under section 1.3, we have limited this thesis to answer the following questions:

1. *The investor sentiment problem*
   Is there a common component in our proxy variables for Swedish investor sentiment that cannot be explained by macroeconomic indicators? In other words, does investor sentiment exist on the Swedish market?
2. *The valuation problem*
   Does the Swedish market respond differently to earnings surprises during periods of high investor sentiment than during periods of low investor sentiment?
3. *The value relevance problem*
   Does earnings news' information content differ during periods of high investor sentiment than during periods of low investor sentiment?
4. *A firm size phenomena*
   Is firm size a relevant factor in solving the valuation problem and the value relevance problem?

Investor sentiment research has found that investors place overly optimistic valuations on the incremental cash flows represented by a positive earnings deviation during periods of high sentiment, and overly pessimistic valuations of negative earnings deviations during periods of low sentiment. In accordance with these findings, we hypothesize that, taking the existence of investor sentiment on the Swedish market as exogenous, the market will react stronger to good news during periods of high sentiment, and stronger to bad news during periods of low sentiment.

With regards to the value relevance problem, we want to understand whether changes in stock prices during the days surrounding an earnings announcement can be attributed to the earnings' deviation from the market expectations to a different extent, depending on the prevailing investor sentiment.

1.3 Scope

This thesis could have quite easily been divided into equal parts and formed two separate bachelor theses. Due to the limitations imposed, we have tried to be as straightforward and blunt as possible throughout the thesis.

Direct and simple language aside, we have been forced to narrow the scope of this thesis. Beyond the boundaries of this thesis are subjects such as a more in-depth discussion about our choice of asset pricing models including controlling for factors such as growth and financial distress[4], proxies for investor sentiment considered but not ultimately used, a more detailed account of the field of behavioral finance in general and noise traders in particular, post-earnings announcement stock price drift and differences in the earnings response coefficient on positive and negative earnings.

1.4 Disposition

This thesis starts of with a brief account of previous research within the field of behavioral finance and the market's response to information under *section 2*. We then move on by describing the method we apply when constructing the indices and measuring the earnings response coefficients and the value relevance in *section 3*.

> *"Investors have feelings too, and lately, some analysts fear, they may have been letting those feelings run a little to wild."*
>
> Wall Street Journal, June 18th 2001

In *section 4*, we describe the underlying theoretical logic behind our proxies for investor sentiment, as well as an account of our data collection and a presentation of the Swedish data on each proxy. The reason of this section's mix of theory and empirics is our belief that such a disposition provides the most favorable reading experience. In *section 5* we further describe how the data for the indices and the earnings response study has been collected, processed and compounded.

Our results are then presented in *section 6*, where the sentiment indices are presented and scrutinized, and in *section 7* where we present the results of our earnings response study. Finally, in *section 8*, we analyze our results and in *section 9* we conclude our study with some final discussions and comments.

[4] C.f. the Fama French Three-factor Model

2 Previous Research

Traditional research in the field of finance rests on the formal concept of rationality. More specifically, but simplified, it rests on three propositions:

1. investors (and other economic agents) are rational actors who seek to maximize a utility function;
2. financial markets are perfectly competitive, and;
3. information is publicly available.

The behavioral school of finance has developed since the 1980s, and challenges the formal concept of rationality. Instead, it allows features of irrational behavior, and incorporates it into financial models.[5]

In this section, we first account for the basic noise trader model, courtesy of the field of behavioral finance, and the development of the investor sentiment concept. We then move on with a description of the theories underlying the market's response to earnings news.

2.1 The Behavioral Model

2.1.1 Noise Traders

The notion of how irrational beliefs held by investors affected the market by way of i.e. asset pricing and expected returns was presented by DeLong et. al. in 1990. In the model developed by DeLong et. al., some investors, denominated *noise traders*, were subject to sentiment – a belief about future cash flows and risks of securities not supported by economic fundamentals of the underlying asset(s) – while other investors were rational arbitrageurs, free of sentiment. The irrational beliefs were caused by noise, interpreted by the irrational traders as information, thus the term noise traders. Even though such noise traders were recognized by proponents of an efficient market, they believed that the noise traders were exploited by rational arbitrageurs, who drove prices towards fundamental values. Therefore it was believed that these irrational investors could safely be ignored from financial theories such as asset pricing models. However, DeLong et. al. found that because these noise traders' sentiment was difficult to predict and in part due to high enough transaction costs, the rational investors were

[5] Ryan, Scapens & Theobald (2002) *"Research method and methodology in finance and accounting"*, pp. 52 ff.

unable to systematically arbitrage on the noise traders' mispricing and the noise traders' sentiment could therefore persist on the financial markets.[6]

There are a number of ways investors can act irrational – or rather – behaviorally biased. Investors' decisions can be disturbed by how investments are *framed*. For example, an investor's decision may be to reject an investment when it is offered in terms of the risk of the possible profit, but may undertake an identical investment if it is offered in terms of the risk of the possible losses. Investors may also segregate investment decisions by way of *mental accounting*. For example, an investor may take on a lot of risk in one investment account, while taking a very risk-averse position in another investment account instead of rationally viewing both accounts as part of the investor's overall portfolio. It has also been found that individuals tend to bear more regret when unconventional decisions turn out badly, than when more conventional decisions turn out badly. Such *regret avoidance* can thus be a factor causing bubbles – during which investors follow the stream instead of forming their decisions on the basis of information about economic fundamentals at hand.[7] *Overconfidence* and *herd behavior* have also been proven to be ever-recurring human traits. Traits that seem to be overly represented amongst investors.[8]

As quoted in the introduction to this paper, Alan Greenspan described the IT bubble as an example of "irrational exuberance". Many behavioralists have ascribed bubbles to, at least partially, investor irrationality. One study has even found that the announcement of firms changing their name to Internet-related dotcom names enjoyed large non-transitory price increases following the announcement, regardless of whether the firms were involved with the "new economy" or not.[9]

2.1.2 Investor Sentiment

Since 1990, a number of attempts have been made of explaining market anomalies and other phenomena by employing behavioral, investor sentiment-incorporating models. Researchers have found that investor sentiment affects market mechanisms such as mutual fund flows,[10] trading volume,[11] short interest rates,[12] the equity share in new issues,[13] closed-end

[6] DeLong, Shleifer, Summers & Waldmann (1990) *"Noise trader risk in financial markets"*
[7] Bodie, Kane & Marcus (2011) *"Investments and portfolio management"*, pp. 412 f.
[8] Shiller (2000) *"Irrational exuberance"* and Berk & DeMarzo (2011) *"Corporate finance"*, pp. 423
[9] Cooper, Dimitrov & Rau (2001) *"A rose.com by any other name"*
[10] Frazzini & Lamont (2008) *"Dumb money: Mutual fund flows and the cross-section of stock returns"*
[11] Scheinkman & Xiong (2003) *"Overconfidence and speculative bubbles"* and Baker & Stein (2004) *"Market liquidity as a sentiment indicator"*
[12] Brown & Cliff (2004) *"Investor sentiment and the near-term stock markets"*
[13] Baker & Wurgler (2000) *"The equity share in new issues and aggregate stock returns"*

fund discounts,[14] stock market volatility,[15] ratio of trading volume on put and call equity options,[16] volume of initial public offerings (IPOs)[17] and IPO first-day returns.[18] The list goes on. Research has also found that stock returns are driven by factors such as the weather[19]and international sports results.[20]

Coincidentally, the same market mechanisms explained by investor sentiment have in some studies been used as proxies for investor sentiment. Baker and Wurgler constructed a composite ”sentiment index” based on a number of proxies’ first principal component. They then used the index to explain how investor sentiment affected the cross-section of stock returns.[21] The method employed by Baker and Wurgler is our primary inspiration and reference in our endeavors to construct a similar index for the Swedish market.

For the avoidance of doubt, in the remainder of this thesis, we define investor sentiment as ”investor beliefs about future cash flows or discount rates not supported by prevailing economic and financial fundamentals”.[22]

2.2 The Market’s Response to Information

2.2.1 Market Efficiency and Asset Pricing

The study of how the market incorporates information into stock prices enjoyed an extensive amount of empirical research during the late 1950s and 1960s. In 1970, a landmark paper by Fama discussed the concept of three degrees of market efficiency – weak, semi-strong and strong. A classification still widely applied within the field of finance.[23]

[14] Lee, Shleifer & Thaler (1991) *”Investor sentiment and the closed-end fund puzzle”*, Neal & Wheatley (1998) *”Do measures of investor sentiment predict returns?”*. Qiu & Welch (2006) *”Investor sentiment measures”* however attempts to debunk the relationship between the closed-end fund discount and investor sentiment.
[15] Whaley (2000) *”The investor fear gauge: Explication of the CBOE VIX”*
[16] Brown & Cliff (2004)
[17] Lowry (2003) *”Why does IPO volume fluctuate so much?”*
[18] Ljungqvist, Nanda & Singh (2006) *”Hot markets, investor sentiment and IPO pricing”*
[19] Hirshleifer & Shumway (2003) *”Good day sunshine: Stock returns and the weather”*
[20] Edmans, Garcia & Norli (2007) *”Sports sentiment and the stock returns”*
[21] Baker & Wurgler (2006) *”Investor sentiment and the cross-section of stock returns”*, further developed in Baker & Wurgler (2007) *”Investor sentiment in the stock market”*
[22] C.f. Baker & Wurgler (2006) and Mian & Sankaraguruswamy (2012) *”Investor sentiment and the stock market response to earnings news”*
[23] Ryan, Scapens & Theobald (2002), pp. 55 f.

Table I

Versions of the Efficient Market Hypothesis

Form of EMH	*Information impounded in prices*
Weak form	All information in market trading data
Semi-strong form	All publicly available information
Strong form	All information, public and private

Parallel to the research concerning market efficiency, Sharpe, Lintner and Mossin developed the capital asset pricing model (CAPM) in the late 1960s. In the CAPM, the equilibrium prices of assets solely depend on their systematic risk, or their covariance with the (indefinable) market portfolio.[24]

Similar to the CAPM, but lacking an underlying theory of equilibrium, is the strictly empirical single-index model, originally developed by H.M. Markowitz. Under the single-index model, the variation in the rate of return of any security can be decomposed into two sources, a firm-specific source and a systematic source (i.e. a certain macroeconomic condition). The systematic factor used is commonly the rate of return of a broad index of securities such as the S&P 500, or in the Swedish case, the OMXS30, hence its name single-index model.[25]

The market efficiency concept and the CAPM were two monumental findings, which paved the way for huge amounts of research concerning, inter alia, the market's reaction to accounting information.[26] Pioneering this field of research was a seminal paper by Ball and Brown in 1968, ”An Empirical Evaluation of Accounting Income Numbers”.

2.2.2 Earnings Response

Ball and Brown's study documented the relationship between stock returns and accounting earnings. They divided firms into portfolios of good news firms (if reported earnings exceeded forecasts) and bad news firms (if reported earnings were below forecasts). They found, inter alia, that good (bad) news firms earned, on average, positive (negative) abnormal returns, and that approximately 80% to 85% of the abnormal performance arose before the reported earnings were published - findings implying that accounting information is value relevant. The focus of Ball and Brown´s study was the sign of the relationship between unexpected income changes

[24] Bodie, Kane & Marcus (2011), pp. 308 ff.
[25] Ibid., pp. 274 ff.
[26] Lev (1989) *”On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research”*

and associated stock price changes rather than the magnitude of the changes.[27]

A vast amount of research following Ball and Brown's study closer discussed the choice of the appropriate accounting variable and the event window of the variable measuring market performance. They also focused on and how to test the relationship between earnings surprises and abnormal returns, and introduced the *earnings response coefficient* (the ERC).[28]

The fundamental reason to why the market rewards firms for meeting the market's earnings expectations, is because earnings announcements contains information about the future cash flows of the firm relevant to fundamental valuation models.[29]

Table II
The Earnings Response Equation

$$CAR_{it} = \alpha + \beta * UX_{it} + \varepsilon_{it}$$

CAR_{it}	Some risk-adjusted return for firm *i* in period *t*
α	Intercept
β	Earnings response coefficient
UX_{it}	Unexpected earnings for firm *i* in period *t*
ε_{it}	Error term for firm *i* in period *t*

The ERC is the coefficient β in the regression of a firm's risk adjusted returns on the firm's unexpected earnings, and should thus, ceterus paribus, reflect the firm's price-earnings capitalization (c.f. Table II above).[30] The relationship is generally assumed to be linear, however some studies suggest that the model is nonlinear with a declining marginal response to unexpected earnings.[31]

The slope coefficient, the ERC, explains the size of the effect of the earnings announcement's deviation from the market expectations on the stock's return. The regression's coefficient of determination, the R^2, implies to what extent the variance in the stock's return can be explained by the variance in the earnings deviation. The ERC (as well as its significance level) and the R^2 are considered to be the main interest when evaluating the stock market's response to earnings announcements.[32]

[27] Ball & Brown (1968) *"An empirical evaluation of accounting income numbers"*
[28] White, Sondhi & Fried (2003) *"The analysis and use of financial statements"*, pp. 171 ff.
[29] Kasznik & McNichols (2002) *"Does meeting earnings expectations matter?"*
[30] Ibid.
[31] Freeman & Tse (1992) *"A non-linear model of security price responses to unexpected earnings"*
[32] Collins & Kothari (1989) *"An analysis of inter-temporal and cross-sectional determinants of earnings response coefficients"*

Two different methods are commonly used when estimating the ERCs – namely firm-specific coefficient methodology (FSCM) and cross-sectional regression methodology (CSRM). Applying FSCM, one estimates firm-specific ERCs for each firm in the sample, whereas applying CSRM; one ERC is estimated for the entire pooled sample of firms. It is important to distinguish between these methods and use the method coherent with one's hypothesis, since the two methods may lead to different results. Research confirms that ERCs using the average of firm-specific data systematically exceeds those from using the corresponding pooled cross-sectional data.[33] Previous research has also found that the ERC varies across firms as a result of firm-specific factors such as earnings persistence, earnings predictability and growth prospects.[34]

Value relevance, the degree to which stock price changes can be attributed to different types of accounting disclosures, has been a well-researched phenomenon since the Ball and Brown study. Instead of focusing on hypotheses concerning the size of the ERC, the value relevance framework is primarily concerned with the market's usefulness of accounting earnings.[35] In value relevance studies, the main way of operating value relevance is through the goodness-of-fit, the R^2, from the earnings response regression. The R^2 tells us how much of the variation in the stock prices can be explained by the, in our example, earnings' deviation from the market expectations. The R^2 measure has, however, received criticism as an unreliable statistic, and one should be cautious in drawing inference from the plain differences in R^2 from samples drawn from different samples in the time-series or cross-sectional dimension.[36]

2.3 Market Response and Sentiment

Two market anomalies, or inconsistencies with the efficient market hypothesis, commonly advocated by opponents to said hypothesis is the market's short-term (1 – 12 months) underreaction and long-term (3 – 5 years) overreaction to information. In 1998 Barberis, Shleifer and Vishny published a paper of a model of investor sentiment and how it affects the stock market's reaction to news such as earnings announcements. Their

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[33] Teets & Wasley (1996) *"Estimating earnings response coefficients: Pooled versus firm-specific models"*
[34] Collins & Kothari (1989), Lipe, Bryant & Widener (1998) *"Do non-linearity, firm-specific coefficients and losses represent distinct factors in the relation between stock returns and accounting earnings"* and Easton & Zmijewski (1989) *"Cross-sectional variation in the stock market response to accounting earnings announcements"*
[35] Lev (1989)
[36] Brown, Lo & Lys (1999) *"Use of the R^2 in accounting research: Measuring changes in value relevance over the last four decades"*

theoretical model, supported by statistical and empirical evidence, indicated that these anomalies could be partially explained by investor sentiment. And that, inter alia, investors overreact to news (such as earnings announcements) when the news follow their expectations, and underreact when it opposes their expectations.[37] Fama however discarded similar theories, as he found that underreaction was as common as overreaction, and ascribed the anomalies to chance rather than to inconsistencies with the market efficiency concept.[38]

In line with Barberis, Shleifer and Vishny's theoretical model, Mian and Sankaraguruswamy finds that misreactions to earnings announcements are one outlet through which investor sentiment causes stock mispricing. Using the Baker and Wurgler index and U.S. data, the authors find that the market responds stronger to good news during periods of high sentiment than during periods of low sentiment, and that the market responds stronger to bad news during periods of low sentiment than during periods of high sentiment.[39]

A 2012 paper studies investor sentiment's effect on the other side of the earnings announcement, in part using the Baker and Wurgler index. The authors find that as investor sentiment increases, managers are more prone to disclose adjusted earnings metrics exceeding U.S. GAAP earnings in their earnings announcements, as well as an increased manager propensity to emphasize the adjusted earnings number in the earnings press release.[40] This could possibly cause a compounding of the effect of investor sentiment on the market's response to earnings news.

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[37] Barberis, Shleifer & Vishny (1998) *"A model of investor sentiment"*
[38] Fama (1998) *"Market efficiency, long-term returns and behavioral finance"*
[39] Mian & Sankaraguruswamy (2012)
[40] Brown et. al. (2012) *"Investor sentiment and pro forma earnings disclosures"*

3 Method

In this section, we describe how we construct the investor sentiment index, and how we design and perform the tests of the earnings response coefficient.

3.1 The Swedish Sentiment Index

3.1.1 Time Period

As we construct the sentiment index by compounding a number of proxy variables, data availability in several dimensions imposes restrictions on the time period possible. The time period we have chosen is 1995 – 2012. Within this period, the Swedish stock market has experienced swindling bull markets as well as devastating bear markets, supposedly allowing us to clearly identify periods of high and low sentiment, respectively.

We use quarterly data, rendering an index of 72 data points (four quarters from each of the eighteen years). When data is only available in daily, weekly or monthly intervals, we calculate and use the quarterly average.

3.1.2 Proxies

Based on previous research, we have identified six proxies for investor sentiment that we use to construct our index. The proxies are described more in-depth in section 4. Of our six proxies, all but one – the consumer confidence index – are indirect market-based proxies. The consumer confidence index is instead a direct survey proxy. Market-based proxies are the most commonly used, but some behavioralists have argued that indirect market-based proxies are inferior to direct survey proxies, since market-based proxies suffer from problems with omitted variables. On the other hand, direct survey proxies are subject to respondent biases.[41]

Any one single proxy is likely to be imperfect and noisy. By averaging out the different proxies and using their common component as a measure of sentiment, the noise problem is, albeit unsolved, reduced.

[41] C.f. Zhang (2008) *"Defining, modeling, and measuring investor sentiment"*

Table III
Investor Sentiment Proxies

Proxy	Paper
Trading Volume	Baker & Stein (2004) Scheinkman & Xiong (2003)
Closed-end Fund Discount	Lee, Shleifer & Thaler (1991)
Option Implied Volatility	Whaley (2000)
IPO Volume	Baker & Wurgler (2007) Lowry (2003)
IPO First-day Return	Baker & Wurgler (2007) Ljungqvist, Nanda & Singh (2006) Lowry (2003)
Consumer Confidence Index	Qiu & Welch (2006) Zhang (2008)

There are several other variables that could have been used to proxy sentiment in our composite index. Our main constraint is, as mentioned above, the availability of Swedish data over a sufficiently long time period. Also, a number of proxies for investor sentiment are, at an initial reflection, not as applicable on the Swedish market as they are on the U.S. market, primarily due to the relatively small size of the Swedish market. One example is debt issues, which we believe is a too rare a phenomenon to adequately incorporate investor sentiment.[42]

We handle IPO volume, IPO first-day returns and trading volume more delicately than other proxies. IPO volume is the only proxy not determined directly by the market, but is instead determined by individual firm decisions. Proxies that are based directly on investor trading patterns or investor beliefs are more likely to reflect a shift in investor sentiment sooner than proxies that involve firm decisions. Therefore we lag IPO volume with one year, i.e. the IPO volume of the first quarter of 1998 reflects the investor sentiment of the first quarter of 1997. A one-year time frame is also a reasonable estimate of the time passing from deciding to go public and the actual stock listing. IPOs also follow a clear pattern of seasonal variation; more than half of the IPOs in our sample occur during the second quarter of each year. As this seasonal variation is due to factors other than investor sentiment, we control for this variation by smoothening the time series, using rolling semi-annual averages. To avoid too many drastic up and downs in IPO first-day returns, we interpolate linearly over quarters with missing data.

[42] Niemeyer (2000) *”Finanssektorns framtid”*, pp. 317 ff.

Trading volume, measured in MSEK turnover, suffers from a largely positive trend during our time period, much due to the dramatic increase in e-trading. Therefore we use the logarithm of turnover, and detrend the proxy by subtracting the rolling one-year average turnover, enabling us to distinguish quarterly deviations in trading volume more clearly.[43]

3.1.3 Statistical Method

To construct the sentiment index, we apply two different statistical methods, thereby constructing two indices. In the first index, we standardize each proxy variable and put equal weights on each standardized proxy variable, thus generating an equally weighted index with zero-mean over the time period 1995 – 2012.

Table IV
Standardization of Proxy Variables

$$\tilde{y}_{it} = \frac{y_{it} - \mu_i}{\sigma_i}$$

$\tilde{y}_{it}$	Standardized proxy
y_{it}	Raw proxy
μ_i	Sample mean
σ_i	Sample standard deviation

In the second index, we standardize each proxy variable and then apply factor analysis. Factor analysis is a statistical method that allows us to isolate part of the variability in the proxies to an unobserved factor – i.e. investor sentiment. The procedure converts our set of proxy variables into a set of principal components. Under each principal component, each proxy is ascribed a coefficient. Each principal component is uncorrelated with the preceding components, thus each principal component can be ascribed to a certain factor influencing the variability in our proxy variables. We form our sentiment index based on the proxy variables' first principal component.

3.1.4 Macroeconomic Effects

We do not want to construct a business cycle index. We want to construct an investor sentiment index. In other words – we do not want to identify when

[43] Baker & Wurgler (2006, 2007) also detrend the logarithm of MUSD turnover, but instead uses the past five-year average. Due to our shorter sample period, a rolling one-year average acts more favorable.

trading volume increases due to a rising stock market, we want to identify when trading volume increases due to an increased investor sentiment. To prevent that the common component of the proxy variables is a common business cycle component rather than an investor sentiment component, we regress each proxy variable on a set of macroeconomic indicators, namely growth in employment, growth in industrial production and growth in durable and services consumption. We then use the residuals from these regressions as our proxy variables, and form the indices as described above.[44] Think of investor sentiment as the error term in each of these regressions – the portion of variability in each proxy variable that remains unexplained (rationally) by the macroeconomic indicators. Under the assumption that we are able to control for all, or more realistically the majority of, rational macroeconomic variables affecting the variation in our proxy variables, the remaining common variation in the proxies can be ascribed to investor sentiment.

3.2 The Earnings Response Regression

3.2.1 Data and Sample Selection

After the Swedish investor sentiment index has been constructed, we identify periods of significantly high, respectively low, investor sentiment. From these periods we then sample a number of earnings announcements, and their forecasted consensus earnings.

The ERC is the relation between the accounting variable (e.g. EPS, EBITDA or EBT) and the market-based variable (e.g. abnormal return). The method can be divided into three steps[45]:

1. identifying the accounting variable;
2. identifying the market-based variable, and;
3. testing the relationship between the two variables.

3.2.2 Accounting Variable

We use earnings before tax (EBT) as our base variable when estimating our accounting variable, each firm's unexpected earnings. Our choice of accounting variable is determined by the available data on earnings expectations. EBT provides a rather immediate reflection of the bottom-line

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[44] The method of using the residuals from regressions on macroeconomic variables is also employed by Baker & Wurgler (2006, 2007) with great success. Baker & Wurgler uses growth in industrial production, growth in durable, nondurable and services consumption, growth in employment and a recession indicator.
[45] White, Sondhi & Fried (2003), pp. 170 ff., Ball & Brown (1968)

income available to shareholders and hence makes it relevant from a valuation perspective.

In some cases, we do not use each firm's *actual* EBT stated in each firm's quarterly or annual reports. Instead we use adjusted numbers, in general excluding non-recurring items. Excluding such items is justified, since these items in general are difficult to estimate and not taken into account by the market when forming expectations on future earnings. Non-recurring items are also not as value relevant for investors, since they are expected not to persist in the future, thus not affecting each firm's economic fundamentals.[46]

In order to calculate each firm's unexpected earnings we also need a proxy for the expected earnings – the market earnings expectation ex ante the earnings announcement. Ball and Brown's initial research regarding ERC used two models for identifying expected earnings – a linear *time-series forecasting model* and a *naïve model*. In the time-series forecasting model current expected earnings is a function of previous years' earnings and the stock's correlation with the market. For time-series data the naïve model states that the forecasted earnings equals the previous period's earnings.[47] An alternative method is to use *consensus-estimates* based on the average of analysts' forecasted earnings for each given period.

Previous research has shown that earnings response coefficients, using historical time-series forecasting models as a proxy for the market's earnings expectations, are underestimated by approximately 70 – 80%.[48] Further research suggests that the average of financial analysts' forecasts, or consensus estimates, mirror the market's expectations more accurately than historical time-series regressions.[49] Based on the research in favor of consensus estimates, we intend to use these as the proxy for each firm's expected earnings. This method is also applied extensively in recent research.[50]

Our chosen accounting variable is defined in Table V. We define our exogenous unexpected earnings variable as the percentage deviation of the actual EBT from the expected EBT.

[46] Livnat & Mendenhall (2006) *"Comparing the post-earnings announcement drift for surprises calculated from analyst and time-series forecasts"*, Mian & Sankaraguruswamy (2012)
[47] Ball & Brown (1968)
[48] Beaver, Lambert & Morse (1980) *"The information content of security prices"*
[49] O´Brien (1988) *"Analyst's forecasts as earnings expectations"*, Griffin et. al. (1987) *"An evaluation of alternative proxies for the market's assessment of unexpected earnings"*
[50] C. f. Freeman & Tse (1992), Kasznik & McNichols (2002)

Table V

Unexpected earnings

$$UX_{it} = \frac{EBT_{it} - E(EBT_{it})_m}{E(EBT_{it})_m}$$

UX_{it}	Unexpected earnings for firm *i* in period *t*
EBT_{it}	Earnings before tax for firm *i* in period *t*
$E(EBT_{it})_m$	Expected earnings before tax for firm *i* in period *t*

3.2.3 Market-based Variable

In our study, we use standard event study methodology to compute the abnormal returns around the announcement of earnings. We use two different normal performance models, models that give us the expected return of each security. First, we use a single-index model, using the OMXS30 index as proxy for the securities' common factor. We estimate the index model parameters over the 40 days prior to the tenth day before the earnings announcement, as it is included in one of our event windows. A longer estimation window, of up to 120 days is customary. Due to the vast amount of immediately following quarterly reports, varying delays of the earnings announcements following the quarter-end, we use a shorter estimation window; so one firm's earnings announcement's event window does not overlap with a following earnings announcement's estimation window. As an alternative normal performance model, we simply use the return of the OMXS30 index as our normal performance model. The market-based variable we employ is then the cumulative abnormal return earned by each firm's stock during the event window of choice.

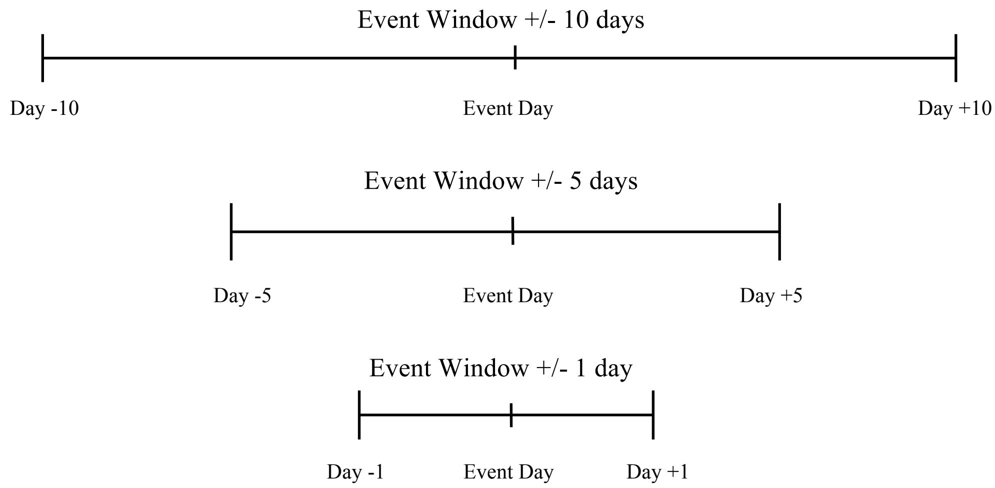
Table VI

Market Variable

Single-index Model	$E(R_{it}) = \alpha_{it} + \beta_{it}R_{OMX,t}$
Simple Model	$E(R_{it}) = R_{OMX,t}$
Abnormal Return	$AR_{it} = R_{it} - E(R_{it})$
Cumulative Abnormal Return	$\Sigma_{-t,t}AR_{it}$

Under a strongly efficient market, we would expect the information to be incorporated immediately into the stock prices, and the event window would include the one day of the announcement. We use three different lengths of event windows, twenty-one days, eleven days and three days, all centered on the day of the earnings announcement. A large event window allows us to capture any leakage of information prior to the announcement as well as post-announcement drifts, while at the same time capturing more noise – increasing the possibility that the abnormal returns reflect other information than the one published in the earnings announcement. A smaller event window, on the contrary, does not capture said leakage or drift, but is less corrupted by noise.[51] In their study similar to ours, Mian and Sankaraguruswamy employs a three-day event window centered on the earnings announcement day, as well as a post-announcement window of sixty days.[52] We focus on the three-day event window as our primary interest, but also report our results using the two longer event windows when appropriate, for completeness and reliability.

Table VII
Event Windows



3.2.4 ERC Tests

After we have established the accounting variable and the market-based variable(s), we can then perform our regressions and tests. Our intention is to use the cross-sectional regression methodology in our study (as described in section 2.2.1). Our *first* test is a basic regression of the cumulative abnormal return on the unexpected earnings deviation, wherein we perform four separate regressions – one for each combination of high or low sentiment and good or bad earnings news.

[51] MacKinlay (1997) *"Event studies in economics and finance"*
[52] Mian & Sankaraguruswamy (2012)

In our *second* test we perform a different regression, where we regress the cumulative abnormal return on the unexpected earnings deviation, a sentiment dummy variable and an interaction variable of the two. In this test we perform two separate regressions – one for good earnings news and one for bad earnings news. By employing this setup of independent variables, we can examine whether the effect of investor sentiment on the earnings response coefficient is significantly different from zero, using a two-tailed t-test, thus enabling us to reject the hypothesis that sentiment bears no effect on the earnings response coefficient. In our *third* test, we perform the same regression as above, but instead of a sentiment dummy variable, we use the FA Index, thus allowing for more subtle nuances in sentiment rather than a high-low binary setting.

In our *fourth* test, we employ a regression model developed by Mian and Sankaraguruswamy, wherein we regress the cumulative abnormal return on a more intricate setup of independent variables, including the FA Index itself. The setup includes two dummy variables, ”Good” and ”Bad”, where Good (Bad) is equal to 1 if the unexpected earnings news is positive (negative). Thereby, we can separate one earnings response coefficient for each of the four possible scenarios in the same model, good and bad news in high and low sentiment, and measure the earnings response coefficient's sensitivity to changes in the FA Index. Our four regression models are summarized in Table VIII below.

Table VIII

Regression Models

Model	*Dependent Variable*	*Independent Variables*
1st – Separated	CAR (-10;10) CAR (-5;5) CAR (-1;1)	UX_{it}
2nd – Dummy Interaction	CAR (-1;1)	UX_{it} $SentD_i$ $UX_{it}SentD_i$
3rd – Full Index Interaction	CAR (-1;1)	UX_{it} $Sent_i$ $UX_{it}Sent_i$
4th – Full Index Advanced Setup	CAR (-1;1)	Bad_{it} $Good_{it}UX_{it}$ $Bad_{it}UX_{it}$ $Good_{it}UX_{it}Sent_i$ $Bad_{it}UX_{it}Sent_i$

3.2.5 Value Relevance

When measuring the information content of the earnings announcements during different levels of investor sentiment, we use the method of simply comparing the adjusted R^2 of the different regressions described under section 3.2.4 and in Table VII above.

3.2.6 Firm Size

In our tests of whether investor sentiment has a larger effect on smaller firms, we sub-sample firms in the 25 largest and 25 smallest percentiles, by market capitalization. We then perform the different regressions described under section 3.2.4 and in Table VII above on our two sub-samples.

4 Investor Sentiment Proxies

In this section we present our six proxies for investor sentiment. This section is unfortunately a combination of theory and empirics, but we believe that it is the most favorable alternative in presenting the proxies. All data presented is raw data, unless stated otherwise.

4.1 Trading Volume

4.1.1 Economic Intuition

A vast amount of research has empirically found that trading volume, or rather liquidity, can predict cross-sectional stock returns at the firm level as well as in the time series of the aggregate stock market. Liquidity can however also be used as an indicator of investor sentiment. Baker and Stein formulated the intuition behind the concept, that under the premise (which can be empirically shown) that short-selling involves higher transaction costs than opening and closing long-positions, irrational investors (or noise traders) are more prone to take long bets on stock they believe will rise, i.e. when they are optimistic, than to take short bets on stock they believe will fall, i.e. when they are pessimistic.[53] Applying similar logic, Scheinkman and Xiong construct a model in which bubbles (i.e. periods of high sentiment) are accompanied by high levels of trading volume and stock price volatility.[54]

4.1.2 Swedish Data

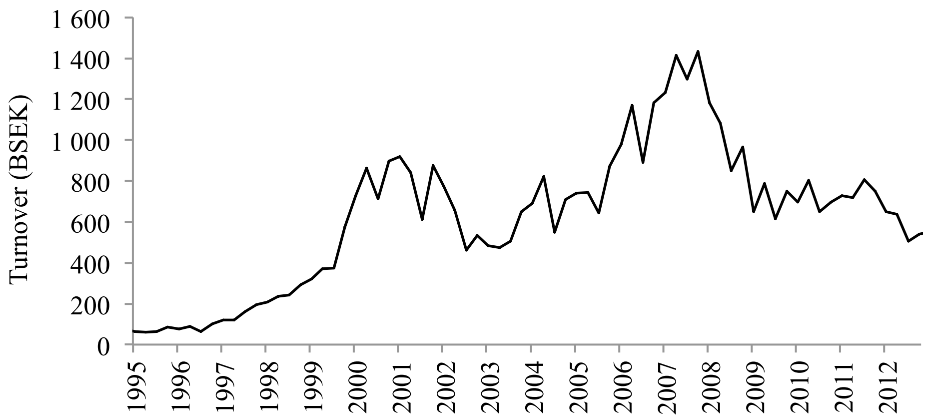
We collect data on the daily turnover of the OMXS30 from the Thomson Datastream database for our entire sample period, and then compute the quarterly turnover. In Figure II below, we present the turnover time series without the detrending measures taken on behalf of the construction of the sentiment index. Still, we can clearly identify two periods of relatively high trading volume, 2000 – 2002 and 2006 – 2008, during which the OMXS30 peaked prior to the subsequent crashes.

[53] Baker & Stein (2004)
[54] Scheinkman & Xiong (2003)

Figure II

OMXS30 Turnover 1995 – 2012

Depicted below is the quarterly turnover of the OMXS30 in billion SEK. The OMXS30 is a value-weighted index consisting of the 30 most traded stocks on the Stockholm Stock Exchange.



Source: Thomson Datastream

4.2 Closed-end Fund Discount

4.2.1 Economic Intuition

Closed-end funds are investment firms that have a fixed number of shares that are traded on stock exchanges. Investor cannot redeem their shares for the net asset value, as is the case of open-end funds, but must sell their shares to other investors. Swedish examples are Investor, Kinnevik and Industrivärden. Closed-end funds often sell for discounts from the net asset value of the funds' portfolio. The law of one price suggests that the value of the fund should be equal to the value of the shares the fund holds. The closed-end fund discount puzzle can thus be described as a violation of the law of one price. Research has found that the closed-end fund discount puzzle can be solved by taking investor sentiment into account, and the closed-end fund discount is the to-date most widely accepted proxy measure for investor sentiment. [55] There are also, however, more rational explanations of the discount, such as agency costs, asset illiquidity and tax liabilities.[56]

[55] Bodie, Kane & Marcus (2011), pp. 417 ff. and Lee, Shleifer & Thaler (1991)

[56] Zhang (2008)

Table IX

The Closed-end Fund Discount

$$CEFD_{it} = 1 - \frac{MCAP_{it}}{NAV_{it}}$$

$CEFD_{it}$	Closed-end fund discount
$MCAP_{it}$	Market capitalization
NAV_{it}	Net asset value

Research has found that closed-end funds are, at least with regards to the United States, disproportionately held by retail investors. Retail investors are also the most prone to hold sentiment towards the market. Thus, the average discount on closed-end equity funds can act as a proxy for investor sentiment – whereunder a high discount reflects bearish sentiment, and a low discount reflects bullish sentiment.[57]

4.2.2 Swedish Data

Amongst Swedish investment companies, it is common practice to account for the net asset value of the fund's assets in each quarterly report, and using the formula in Table IX, each investment company's closed-end fund discount can be easily derived using their respective market capitalization (or stock price if the company quotes the net asset value per share) on the date of valuation of the fund's underlying assets. We manually collect the net asset value of investment companies Investor, Kinnevik, Industrivärden, Latour, Melker Schörling and Lundbergföretagen from their interim and annual reports, and each firm's market capitalization and stock price from their reports and from the Thomson Datastream database.

Some of these firms are represented during the entire sample period, and some firms are represented during the majority of the latter part of the sample period. After calculating the quarterly closed-end fund discount for each firm and quarter, we value-weight them together by their quarterly market capitalization.

Our calculated closed-end fund discount is plotted in Figure III below. The closed-end fund discount bears some irregularities, but some periods of supposedly high and low sentiment can be separately identified. During the heights of the IT bubble, the closed-end fund discount is initially very high, then plummets just before the bubble bursts, and as the bubble

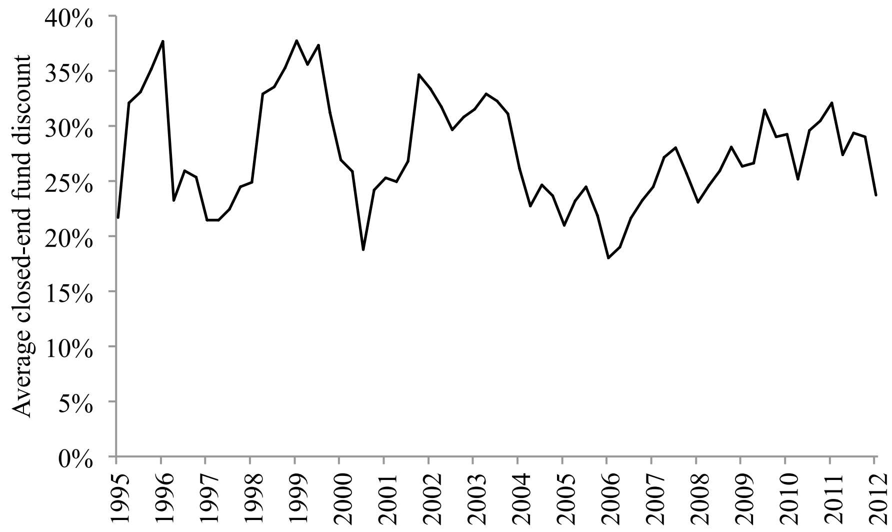
[57] Lee, Shleifer & Thaler (1991)

bursts, the discount peaks yet again. Then follows a number of years of a relatively low discount, and following the 2008 financial crisis we can see a moderate increase, from approximately 20% just before the crisis to approximately 30% in the years following the crisis.

Figure III

Average Closed-end Fund Discount 1995 – 2012

The closed-end fund discount has been calculated quarterly for Investor, Kinnevik, Industrivärden, Latour, Melker Schörling and Lundbergföretagen. The discounts have then been value-weighted based on each investment company's market capitalization.



Source: Quarterly earnings reports, Thomson Datastream

4.3 Option Implied Volatility

4.3.1 Economic Intuition

Inverting an option pricing model, such as the Black-Scholes formula, to yield implied volatility as a function of options prices is a common index used to measure investors' consensus view on the expected future stock market volatility. The Chicago Board Options Exchange's market volatility index (the ”VIX”), which is precisely such an implied volatility index, is commonly referred to as the ”investor fear gauge”. The VIX spikes during periods of market turmoil, and the underlying logic is that if expected market volatility increases, investors will demand higher rates of return on stocks, causing stock prices to fall. Hence, a high (low) implied volatility implies that investors are pessimistic (optimistic) about the future of the stock market.[58]

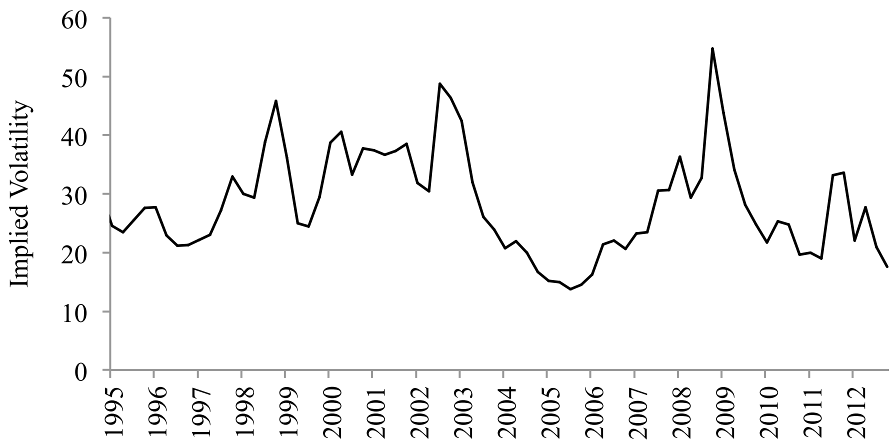
4.3.2 Swedish Data

Deriva Financial Services, an affiliate to the Nordnet Group, calculates the option implied volatility of the OMXS30 index on a daily basis. Deriva Financial Services has very kindly shared this index with us. As the index is computed on a daily basis, we compute the quarterly average option implied volatility.

Figure IV

Option Implied Volatility of the OMXS30 1995 – 2012

Depicted below is the quarterly average option implied volatility of the OMXS30, courtesy of Deriva Financial Services. The implied volatility is calculated on call options on the OMXS30.



Source: Deriva Financial Services

As stated in section 4.3.1 above, high volatility is coincident with high degrees of market turmoil. In our sample period, the OMXS30's volatility spikes the last quarter of 2008, during which the OMXS30 suffered a 14% decline, while the volatility is at is lowest during the years prior to said crisis. The latter years of the IT bubble are coincident with relatively high degrees of volatility, even though the stock market was rising, possibly implying that investors were becoming increasingly nervous about the persistence of the "new economy".

[58] Whaley (2000)

4.4 IPO Volume and First-day Returns

4.4.1 Economic Intuition

IPO volume often fluctuates considerably over time, and it appears that the demand for capital is not the sole driver of IPO volume.[59] Figure V illustrates the quarterly number of IPOs on the Swedish stock market. A substantial amount of research suggests that IPO volume is related to some form of investor irrationality. The underlying logic why investor sentiment should affect IPO volume is quite simple. During periods of high sentiment, investors are overly optimistic and overvalue firms, thus lowering the costs of going public. During periods of low sentiment, investors are overly pessimistic and undervalue firms, thus raising the costs of going public. Firms exploit the prevailing investor sentiment by raising new equity during periods of high sentiment, and IPOs therefore tend to appear in waves.[60]

Researchers have not been able to solve the financial puzzle of the large first-day IPO returns (especially persisting in the U.S. during the 1990s) by ways of information asymmetry, legal costs or other rational explanations. Consequently, the field of behavioral finance has provided evidence supporting the case of investor sentiment affecting the first-day returns.[61] Following a similar logic of that of IPO volume, during periods of high (low) sentiment, the overvaluation (undervaluation) of firms generates high (low) average first-day returns of newly listed companies.[62] IPO volume and first-day returns have also shown to have a strong positive correlation.

4.4.2 Swedish Data

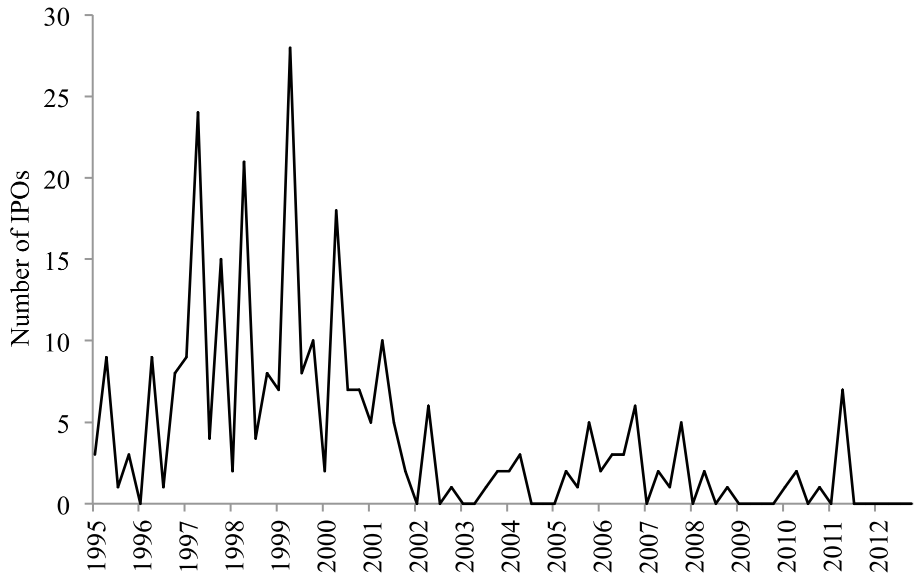
We manually collect IPO volume data from Nasdaq OMXs website. Only ”pure” IPOs are included, hence we exclude transfers between Nasdaq OMX lists or from other stock exchanges in Sweden, secondary listings and mergers and acquisitions. We collect introduction prices primarily from the Swedish Tax Authority's database, and end-day stock prices through Nasdaq OMX's website. If we are unable to find introduction prices from the Swedish Tax Authority, or end-day stock prices from Nasdaq OMX we manually search for press releases and articles in the Affärsdata database covering the price and performance of the introduced stock.[63]

[59] Berk & DeMarzo (2011), pp. 787 f.
[60] Lowry (2003) and Baker & Wurgler (2007)
[61] Zhang (2008)
[62] Ljungqvist, Nanda & Singh (2006), Lowry (2003) and Baker & Wurgler (2007)
[63] Nasdaq OMX's website does not cover historical stock prices of delisted stock.

Figure V

IPO Volume 1995 – 2012

Depicted below is the quarterly IPO volume on the Nasdaq OMX stock exchanges. Only "pure" IPOs are included, as defined above.



Source: Nasdaq OMX

Our IPO volume time series consist of 289 IPOs spread over the 72 quarters. The most active years are during the heights of the IT bubble, 1997 – 2000, during which more than half of the IPOs in our time series took place. One anecdotal example is the IT consultancy firm Framtidsfabriken, run by IT-guru Jonas Birgersson, which was listed on the O-list in June 1999 at an introduction price of 125 SEK. At the end of the day, the stock had risen to 156 SEK, a first-day return of almost 25%.

The last ten years the number of IPOs on the Swedish market has stagnated severely, and during 2012 not a single firm brought their shares to the public market[64]. During the first nine years of our time-series, 240 IPOs took place, compared to 49 IPOs during the last nine years. Research on U.S. data have found a similar "IPO bubble" during 1997 – 2000,[65] but while the U.S. IPO market has somewhat bounced back since the IT bubble burst, the Swedish IPO market has remained on a very low level.

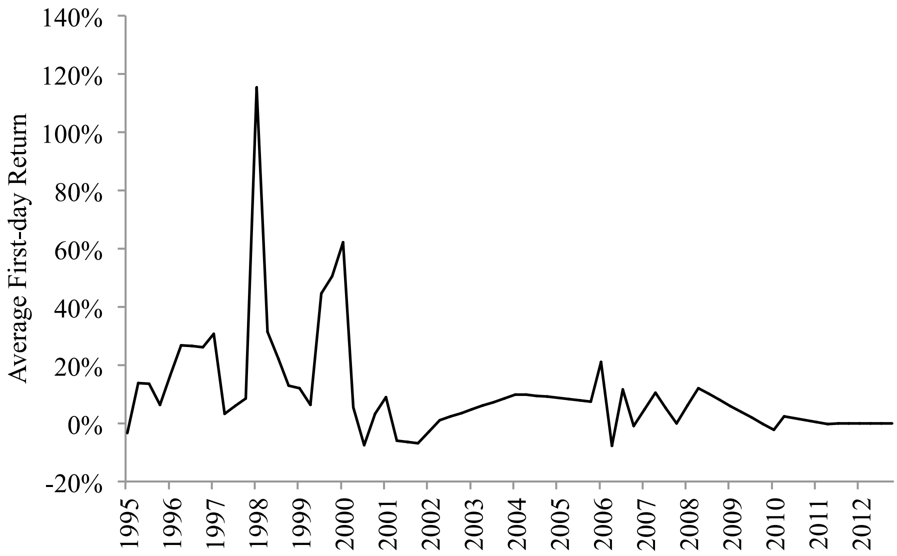
[64] With the exception of listings on NGM Equity, Aktietorget and First North.

[65] Lowry, Officer & Schwert (2010) *"The variability of IPO initial returns"*

Figure VI

IPO First-day Returns 1995 – 2012

The figure depicts average quarterly IPO first-day returns on the Swedish stock market. We interpolate linearly between missing or equal to zero data points.



Source: Nasdaq OMX, Swedish Tax Authority

Both our IPO volume and IPO first-day return time series have the ambition to be exhaustive. Of the 289 identified IPOs, we have been able to compute the first-day returns of 150 IPOs. The primary reason to this incompleteness is our exclusion of spin-offs and equity carve-outs as well as difficulties in finding either introduction prices or historical stock prices. The reason of the exclusion of spin-offs and equity carve-outs from the IPO first-day return time series, is the difficulties in computing the returns when a specific introduction price is not set. The IPO first-day returns peak, just as IPO volume, during the IT bubble. During the second quarter of 1998, the stock of biotechnology company BioGaia and IT consultancy firm Prevas rose more than 50% during their first day listed on the Stockholm stock exchange.

4.5 Consumer Confidence

4.5.1 Application

Consumer and investor surveys of various forms have been used as proxies for investor sentiment. Nowadays, a number of surveys also attempt to specifically measure investor sentiment in a more direct manner.[66] It has been shown that consumer confidence indicators correlate especially strong with the returns of small stocks, and other stocks primarily held by retail investors.[67]

For these reasons, we apply a similar proxy, the Swedish National Institute of Economic Research's Consumer Confidence Indicator (the "CCI"). The CCI is composed of a number of questions concerning the survey participan's personal finances, the Swedish economy and whether now is a good time to buy consumer durables. Very similar questions are asked in the surveys employed in previous research, thus we believe that the CCI may work well as a proxy for investor sentiment on the Swedish market as well. Criticism against the use of consumer surveys as a proxy for investor sentiment primarily concerns the sometimes backward-looking character of the survey questions and the blurry relationship between consumer expectations and investor beliefs.[68]

4.5.2 Swedish Data

As the CCI is computed on a monthly basis by SCB, we calculate its quarterly averages. The CCI is plotted below in Figure VII. What stands out is the extreme drop in consumer confidence during the 2008 financial crisis, a decrease almost twice as large as the one following the burst of the IT bubble. This is especially due to the consumers beliefs about the future of the Swedish economy which was at its lowest during the last quarter of 2008, rather than their beliefs about the future of their personal finances, which was at its lowest during the second quarter of 1995. This could be partially explained by the differences in character of the crisis of the early 1990s and the crisis of 2008, and how it affected Swedish consumers' personal finances. In 1995, during the aftermath of the early 1990s crisis, the repo rate exceeded 8% in order to fight inflation, while the Riksbank lowered the repo rate from 4.75% to 0.25% in just one year during 2008 – 2009 in order to stimulate the Swedish economy.[69]

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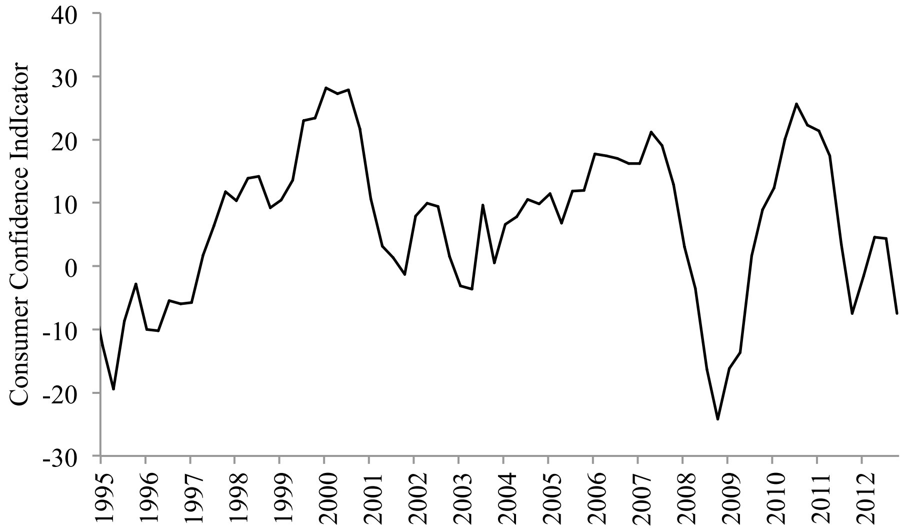
[66] Such as the American Association of Individual Investors' *Sentiment Survey*, Colliers International's annual *Global Investor Sentiment Report*, UBS/Gallup's *Survey of Investor Sentiment* and the Yale School of Management's *Stock Market Confidence Index*.
[67] Qiu & Welch (2006)
[68] Zhang (2008)
[69] Sveriges Riksbank's website, "The Repo rate"

Figure VII

Consumer Confidence Indicator 1995 – 2012

The CCI is calculated as an average of the balances for four questions on personal finances and the Swedish economy at present and in the next twelve months, respectively, and for the question whether now is a good time to buy consumer durables.



Source: National Institute of Economic Research

4.6 Data Quality

We have collected data on our proxy variables from a wide variety of databases and sources, and a majority of the data collection has involved manual entries, calculations and adjustments. Hence, there is a wide array of possible mistakes and errors. Although we have been as careful as possible in handling the data, we cannot rule out the occasional typo and miscalculation. The probability of human error is especially high with regards to the closed-end fund discount, IPO volume and IPO first-day returns, which all have involved rather extensive manual data processing. With regards to the closed-end fund discount, we have relied on each investment company's published net asset value. Thus the calculated discount may, on a firm level, reflect the market's disbelief of the firm's own net asset value calculation rather than factors ascribed to investor sentiment.

5 Data Collection – ERC Study

In this section we account for our data collection in compiling the sample used in the earnings response tests. We also describe how the raw data has been processed and discriminated, and how many earnings announcement have been dropped in accordance with each individual criterion.

5.1 Earnings Announcements

We collect earnings announcements and consensus forecasts using press releases from News Agency Direkt's service SME Direkt. SME Direkt is a widely used financial consensus service in the Nordic stock markets, and first started publishing consensus forecasts in 1994 – thus supplying consistent and comparable coverage for our entire sample period of 20 quarters. Some of SME Direkt's press releases lack the précise date of the earnings announcement. In such cases, we use the Affärsdata database and locate the date of announcement manually through press releases. If we cannot specify the date of announcement, we drop the observation from our sample. Some of SME Direkt's press releases also cover firms from other Nordic countries than Sweden. In uncertain cases, we assert whether the firm is listed on the Stockholm stock exchange, and drop all observations of earnings announcements from firms not listed on the Stockholm stock exchange. SME Direkt applies a different profit measure for banks, namely earnings before interest and taxes (EBIT). Notwithstanding this difference in accounting variable, we include earnings announcements from banks in our sample without distinction.

Two selection criteria are imposed by SME Direkt during our sample period, criteria which we otherwise would have imposed ourselves. First, only firms listed on the Large, Mid and Small Cap lists (A or O-list for quarters prior to 2006) are included. The argument for this restriction, on behalf of our study, is that smaller firm's stock, listed on e.g. NGM Equity, Aktietorget and First North, may face problems with illiquidity and therefore may not incorporate accounting information into market prices as fast as necessary for the purpose of our study.[70] Second, SME Direkt does not provide consensus forecasts for real estate and investment companies. Possibly because the value of these firms is more strongly related to the value of each firm's underlying assets rather than to each firm's earnings.

[70] Bodie, Kane & Marcus (2011), pp. 334 ff.

Further, SME Direkt performs a number of adjustments in their data processing. They adjust the firms' earnings for a number of special items, such as unanticipated restructuring costs and capital gains, the common practice in earnings response studies.[71]

Unfortunately, the firms followed by SME Direkt are not identical during all quarters in our period of interest. As a result, not all companies are represented in all quarters. Our argument for including all available announcements, even though each quarter bears a unique set of companies, is that we believe that our sampled pool of firms is large enough to iron out the lion's share of firm-specific effects. A similar method has also been applied in previous research.[72]

5.1.1 Sample Selection and Data Cleaning

The raw data collected from SME Direkt consist of 943 earning announcements with actual and estimated EBT from 121 companies spread over our sample period of 20 quarters. We then impose further restrictions.

First, the average unexpected earnings are higher during the periods of high sentiment than during the periods of low sentiment. In order to have two more comparable sample sub-sets, we remove earnings announcements with unexpected earnings in the five highest (lowest) percentiles during periods of high (low) sentiment. Second, we remove earnings announcements with negative EBT. Research has shown that losses are less informative than profits for investors when evaluating the firm's future prospects, since investors always hold a liquidation option, i.e. investors always have the possibility to sell the stock.[73] Third, we windsorize earnings announcements with unexpected earnings exceeding 100%, replacing unexpected earnings exceeding 100% with 100%, to avoid the pitfall of the declining marginal response to unexpected earnings mentioned in section 2.2.2.

After these measures, our dataset consist of 814 announcements, 365 of which during high sentiment with an average unexpected earnings of -0.01% and 449 during low sentiment, with an average unexpected earnings of 0.02%. Of the 814 announcements, 464 consist of positive unexpected earnings, while 350 consist of negative unexpected earnings.

[71] Livnat & Mendenhall (2006) and Mian & Sankaraguruswamy (2012)
[72] Mian & Sankaraguruswamy (2012)
[73] Hayn (1995) *"The information content of losses"*

Table X

Data Cleaning and Summary Statistics

Initial data-set	943 announcements	
1. Mean nearing	48 announcements dropped	
2. Negative EBT	81 announcements dropped	
3. Windsorizing	5 announcements windsorized	
Final data-set	814 announcements	
High sentiment	365 announcements	
Average UX	-0.01%	
Low sentiment	449 announcements	
Average UX	0.02%	
Median announcements per quarter	42.5 (Q1 2003 and Q4 2008)	
Most announcements per quarter	64 (Q3 2011)	
Least announcements per quarter	13 (Q4 2002)	
	High sentiment	*Low sentiment*
Good News	198 observations	266 observations
Bad News	167 observations	183 observations

5.2 Market Data

We collect daily data on adjusted stock prices and quarterly data on market capitalization for each firm in our earnings announcement sample during the entire sample period from the Thomson Datastream database. The stock prices are adjusted for splits and dividends. If a firm has more than one class of stock, we use the class with the highest turnover, i.e. the firm's common stock (Swe. "B-aktie"). In order for us to estimate stock returns using the single-index model, we collect daily price index data on the OMXS30 from the Thomson Datastream database.

5.3 Data Quality

As mentioned above in section 5.1, SME Direkt is a widely used financial consensus service, and we have no apparent reason to distrust the data derived from their press releases. Our primary alternative to using SME Direkt was the financial magazine Affärsvärlden's Stock Indicator (Swe. ”Aktieindikator”), which is a data source a number of theses have utilized. In our evaluation of the two possible data sources, we chose SME Direkt because of its more straight-forward presentation of the data, as well as its superior reputation as a source of consensus estimates. Nevertheless, all data, approximately 5000 data points, have been manually inserted into Excel spreadsheets. Such manual processing of data will inevitably result in a few mistypes. We have consciously cross-checked every single press-release, but we cannot with full confidence rule out any and all typos.

6 The Swedish Sentiment Index

In this section we present our sentiment indices and discuss their reliability and validity. We use the following acronyms for our proxy variables; *DVIS* (option implied volatility), *CCI* (consumer confidence index), *CEFD* (value-weighted closed-end fund discount), *TO* (detrended logarithm of MSEK turnover), *IPOV* (IPO volume) and *IPOR* (IPO first-day return).

6.1 The Indices

We have constructed two indices, one in which we use factor analysis (the ”FA Index”) and one in which the proxies are equally weighted (the ”EW Index”). The indices are plotted on page 44.

Table XI

Sentiment Proxies Correlation Matrix

The correlations presented below have been calculated using the residuals from regressing each proxy on our set of macroeconomic variables.

	DVIS	*CCI*	*CEFD*	*TO*	*IPOV*	*IPOR*
DVIS	1					
CCI	0.1788	1				
CEFD	0.1384	0.1792	1			
TO	-0.0235	0.1436	-0.1014	1		
IPOV	-0.0209	0.0166	-0.2809	0.5343	1	
IPOR	0.0090	0.0069	-0.0388	0.3343	0.5504	1

Before controlling for macroeconomic factors, all proxies correlate in the expected directions. After controlling for macroeconomic factors, all proxies correlate in the expected directions with the exception of CCI, which correlates positively with DVIS and CEFD.

The FA Index is presented numerically in Table XII below. Each individual proxy bears the expected sign. The smaller coefficients on DVIS and CCI can be partially explained by the larger variance in these proxies than in the four other proxies. The first principal component explains more than 33% of the sample variance of the proxies. This can be compared with the monthly forty-year sentiment index of Baker and Wurgler, where the first principal component explains 53% of the sample variance.[74]

Table XII

The Factor Analysis Index

Presented below are the results from the factor analysis. First is the component equation from the first principal component. Below is the percentage of variance in the proxies explained by the first and second principal component.

$$SENT_t = -0.067DVIS_t + 0.052CCI_t - 0.347CEFD_t + 0.750TO_t + 0.888IPOV_t + 0.737IPOR_t$$

Principal Component	*% of Variance Explained*
1st	33.676%
2nd	22.255%

In Table XIII below, the averages of each standardized proxy are presented by FA Index quartile, where the 1st quartile represents the 18 most pessimistic quarters, and the 4th quartile represents the 18 most optimistic quarters. All proxies' averages follow the expected distribution, with the exception of CCI, where the mid-quartile quarters have, on average, higher CCI scores than the 4th quartile. A deviation from the expected that cannot be explained by any single particular outlier. All other proxies show an expected pattern, where an optimistic (pessimistic) quarter is represented by a low (high) stock market volatility, a low (high) average closed-end fund discount, high (low) stock market turnover and high (low) IPO volume with high (low) IPO first-day returns.

Table XIII

Proxy Averages by FA Index Quartile

	Quartile			
	1st	*2nd*	*3rd*	*4th*
DVIS	0.50	-0.22	-0.18	-0.11
CCI	-0.39	0.15	0.25	0.00
CEFD	0.35	0.25	-0.29	-0.31
TO	-0.65	-0.11	-0.05	0.80
IPOV	-0.80	-0.63	-0.15	1.57
IPOR	-0.34	-0.37	-0.13	0.84

[74] Baker & Wurgler (2006)

6.2 An Ocular Inspection

As investor sentiment is in itself unobservable, it is quite hard to test whether we have succeeded or not by merely observing the indices. However – an ocular inspection of the indices and whether they line up with more anecdotal evidence of bubbles and crashes is at least one form of evidence of our achievements. Overall, during our sample period, sentiment is high during 1996 – 1999 and relatively high during 2005 – 2007.

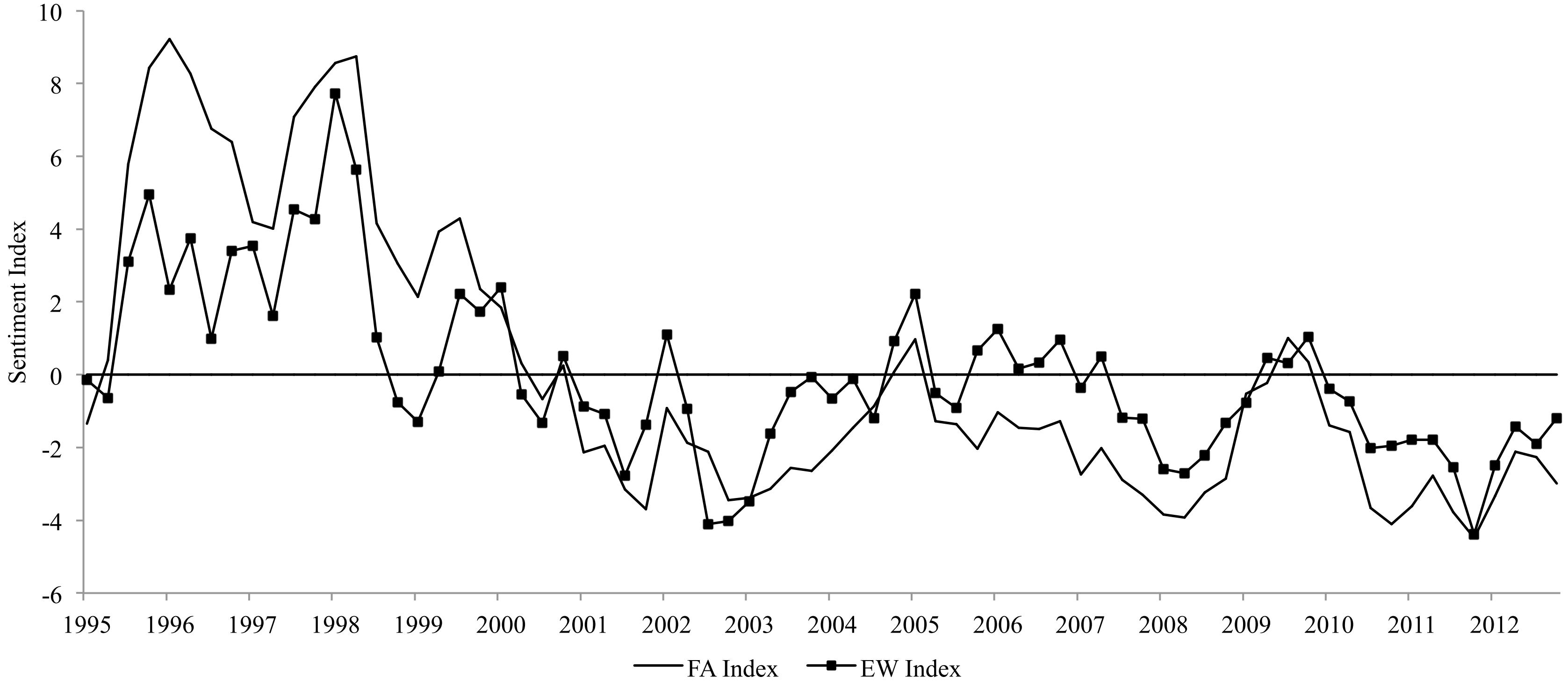
The first major bubble, in our sample period is the IT bubble during the mid-late 1990s. Both the FA Index and the EW Index captures this period of exuberance, as well as the subsequent and inevitable crash in the early 2000s, with a further decrease during the turmoil following the September 11 attacks in 2001. The two later crises we briefly mentioned in the introduction of this paper – the financial crisis of 2008 and the ongoing European sovereign-debt crisis are not as contrasted in our indices, but they are still quite easily observable. Both indices gradually decrease during the years before and during the financial crisis of 2008, possibly implying that the crisis was more anticipated than the burst of the IT bubble. Measures taken by the Swedish government and Riksbank then propel Swedish investor sentiment upwards in 2009 – 2010. As the European sovereign debt crisis unfolds in the aftermath of the 2008 crisis, sentiment again drop to new lows.

> *”When will the IT bubble burst? A stupid question when the Internet is in its early stages and we stand in front of a development that is hard to grasp. SEB’s message to its clients is crystal clear.”*
>
> Göteborgs-Posten, January 23rd 2000

Before questioning the lack of contrast in the indices during the 2000s, one should bear in mind that Sweden was not as affected by these crises as it was by the IT bubble. Nevertheless, the indices’ highs of the 1990s, in part due to the relatively extreme IPO volumes and first-day returns, makes the following highs and lows seem relatively modest. This invites a questioning of whether IPO volume and first-day returns is a suitable proxy for Swedish investor sentiment, or if its variations are due to other factors not identified or controlled for.

Figure VIII

The Swedish Sentiment Indices



However, we must bear in mind that the OMXS30 peaked in the late 1990s, and is yet to return to the levels reached during the peak of the IT bubble. Also, the index constructed by Baker and Wurgler bears a similar pattern – extreme highs in the late 1990s and early 2000s followed by a big dotcom-infused drop and subsequent subdued ups and downs during the 2000s, albeit Baker and Wurgler's index does not have the same high levels during 1995 – 1998 as our indices do.[75] It should also be noted that Sweden was not possessed by the same exuberance during the years prior to the 2008 financial crisis as was the case in the U.S., or as Sweden was during the days of the IT bubble – whereunder the ”new economy” was an unquestioned paradigm.

The FA Index and the EW Index follow each other quite closely, with a positive correlation of 0.8590. For the remainder of this study, we focus on the FA Index. For the purpose of the study of the Swedish stock market's response to earnings news, we have identified ten quarters of high and low sentiment respectively. These quarters, and their score on the FA Index are presented in Table XIV below.

Table XIV

Quarters of the Earnings Response Study

The quarters have been picked on the basis of their score in four indices, the FA Index, the EW Index, an index similar to the EW Index but with 50% smaller weights on the proxies IPO volume and first-day return and finally an equally-weighted index without the IPO proxies. Hence, the score on the FA Index only reflect one of the selection criteria.

High Sentiment		*Low Sentiment*	
Quarter	*FA Index*	*Quarter*	*FA Index*
1997 3rd Quarter	7.0857	2002 3rd Quarter	-2.1188
1997 4th Quarter	7.9089	2002 4th Quarter	-3.4512
1998 1st Quarter	8.5556	2003 1st Quarter	-3.3743
1998 2nd Quarter	8.7502	2008 1st Quarter	-3.8380
1999 2nd Quarter	3.9333	2008 2nd Quarter	-3.9213
1999 3rd Quarter	4.2898	2008 3rd Quarter	-3.2377
1999 4th Quarter	2.3505	2008 4th Quarter	-2.8570
2000 1st Quarter	1.8413	2011 3rd Quarter	-3.7743
2009 3rd Quarter	1.0046	2011 4th Quarter	-4.4881
2009 4th Quarter	0.3551	2012 1st Quarter	-3.3312
Average Score	4.3814	*Average Score*	-3.4137

[75] Baker & Wurgler (2007)

7 Results of the ERC Study

In this section, we present the results of our various tests using the earnings response coefficient and the event study methodology. Our tests have been described previously under section 3.2.4.

7.1 Earnings Response Coefficients

Below in Table XV and Table XVI we present our results from our six tests, using two different normal performance models and three different event windows.

Table XV

Single-Index Normal Performance Model

$CAR_{it} = UX_{it}$

Presented below are the results of the regression above using the single-index normal performance model where $E(R_{it}) = \alpha_{it} + \beta_{it}R_{OMX,t}$. The results from all three event windows are presented. For the purpose of presentation, the coefficient on UX_{it} is called ERC. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that the ERC = 0 are in parentheses.

		Good News		*Bad News*	
		High	*Low*	*High*	*Low*
+/- 10 days	*ERC*	0.2468	0.1764	-0.0651	0.0781
		(0.27%)	(0.04%)	(24.52%)	(22.19%)
	Adjusted R^2	0.0428	0.0563	0.0130	0.0099
+/- 5 days	*ERC*	0.1536	0.1281	-0.0159	0.0680
		(0.48%)	(4.37%)	(53.21%)	(13.22%)
	Adjusted R^2	0.0355	0.0449	0.0013	0.0141
+/- 1 day	*ERC*	0.2053	0.0631	0.0031	0.0826
		(0.03%)	(15.39%)	(88.89%)	(3.77%)
	Adjusted R^2	0.0601	0.0092	0.0002	0.0224
	Observations	198	266	167	183

Table XVI

Simple Normal Performance Model

$CAR_{it} = UX_{it}$

Presented below are the results of the regression above using the simple normal performance model where $E(R_{it}) = R_{OMX,t}$. The results from all three event windows are presented. For the purpose of presentation, the coefficient on UX_{it} is called ERC. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that the ERC = 0 are in parentheses.

		Good News		*Bad News*	
	Sentiment	*High*	*Low*	*High*	*Low*
+/- 10 days	*ERC*	0.3362	0.0835	0.0059	0.1830
		(0.00%)	(9.77%)	(89.72%)	(2.22%)
	Adjusted R^2	0.0804	0.0169	0.0001	0.0676
+/- 5 days	*ERC*	0.2078	0.0844	0.0199	0.1116
		(0.02%)	(19.02%)	(49.90%)	(1.31%)
	Adjusted R^2	0.0588	0.0231	0.0022	0.0415
+/- 1 day	*ERC*	0.2394	0.0498	0.0149	0.0851
		(0.03%)	(26.78%)	(48.29%)	(3.33%)
	Adjusted R^2	0.0467	0.0160	0.0000	0.0389
	Observations	198	266	167	183

Common for *all* of the six tests is that the ERC for good news is higher during periods of high sentiment than during periods of low sentiment, and that the ERC for bad news is higher during periods of low sentiment than during periods of high sentiment. In general, the single-index model generates higher (lower) ERCs for good (bad) earnings news. The adjusted R^2 follows the strength of the ERC, in most of our tests the value relevance, or information content, of the earnings announcements is higher for good (bad) earnings news during periods of high (low) sentiment. Focusing on the tests with a three-day event window, the ERC for good news is 0.2053 using the single-index model and 0.2394 using the simple model during periods of high sentiment, compared to the ERCs of 0.0631 and 0.0498, respectively, during periods of low sentiment. The ERCs for periods of high sentiment are both significant on the 0.03% level, while the ERCs for periods of low sentiment are statistically insignificant. The ERC are not significantly different from zero using the single-factor as well as the simple model during periods of high sentiment, compared to the ERCs of 0.0826 and 0.0851, respectively, during periods of low sentiment, both significant at levels lower than 4%, while the ERCs for periods of high sentiment are not statistically significant.

7.2 Test of Coefficient Differences

The regressions presented in Table XV – XVI support our hypothesis that the market reacts more strongly to good news during periods of high sentiment and to bad news during periods of low sentiment. To further test whether the ERCs are significantly different from each other, we perform another regression, using an interaction variable constructed by multiplying the unexpected earnings with a sentiment dummy variable, whereby differences can be more apparently revealed.

Table XVII

Dummy Test of ERC Differences

$$CAR(-1;+1)_{it} = UX_{it} + SentD_i + UX_{it}SentD_{it}$$

Presented below are the results from the regression above. The coefficient on UX and UXSentD is called ERC and ERC * SentD for presentation reasons. SentD is a dummy variable equal to 1 if the earnings announcement is released during a quarter of high sentiment and equal to 0 if it is released during a quarter of low sentiment. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that each $\beta = 0$ are in parentheses.

	Good News		*Bad News*	
Model	*Single-Index*	*Simple*	*Single-Index*	*Simple*
ERC	0.0631	0.0498	0.0517	0.0579
	(15.36%)	(26.76%)	(0.15%)	(0.02%)
SentD	-0.0060	-0.0083	0.0168	0.0215
	(45.27%)	(31.41%)	(1.97%)	(0.23%)
*ERC * SentD*	0.1421	0.1896	-0.0036	0.0737
	(3.13%)	(0.40%)	(87.89%)	(72.30%)
Adjusted R^2	0.0540	0.0589	0.0512	0.0648
Observations	464	464	350	350

Using both the single-index model and the simple model, the ERC for good news is higher during periods of high sentiment, significant at the 3.13% and 0.40% level respectively, in line with our hypothesis. Focusing on the single-index model, the aggregate ERC for good news is 0.1361 higher during periods of high sentiment.[76] Thus, we can reject the null hypothesis that the ERCs for good news are equal during periods of high and low sentiment. For bad news, the results are highly insignificant.

A simple example can help make this finding more tangible. Suppose a firm reports quarterly earnings of 1 250 MSEK, while the analysts' consensus forecast was 1 000 MSEK. If sentiment is high, during the three days centered around the earnings announcement the firm's stock will earn a cumulative abnormal return of approximately 5%. If sentiment is low, the cumulative abnormal return will only be 1.5%.

Table XVIII

Full Index Test of ERC Differences

$CAR(-1;+1)_{it} = UX_{it} + SentFA_i + UX_{it}SentFA_{it}$

Presented below are the results from the regression above. The coefficient on UX and UXSentFA is called ERC and ERC * SentFA for presentation reasons. SentFA is the score on the FA Index the quarter the earnings announcement is released. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that each β = 0 are in parentheses.

	Good News		*Bad News*	
Model	*Single-Index*	*Simple*	*Single-Index*	*Simple*
ERC	0.1364	0.1394	0.0560	0.0628
	(0.00%)	(0.00%)	(0.03%)	(0.00%)
SentFA	-0.0007	-0.0009	0.0009	0.0015
	(44.09%)	(34.10%)	(25.36%)	(6.87%)
*ERC * SentFA*	0.0214	0.0255	-0.0087	-0.0078
	(1.66%)	(0.65%)	(5.40%)	(5.81%)
Adjusted R^2	0.0542	0.0550	0.0541	0.0725
Obervations	464	464	350	350

If we instead of a dummy variable use the full FA Index, the results are more appealing due to the increased nuance in the degree of sentiment. The results, presented in Table XVIII above, indicate that the ERC for good news is in general higher than the ERC for bad news, and that the ERC for good news increases as sentiment increases, while that the ERC for bad news increases as sentiment decreases. The results on behalf of bad news are only significant at levels between 5.40% and 5.81%, but these significance levels are well below 5% when performing a one-sided t-test.

[76] Calculated as 0.1421 – 0.0060.

The R^2s are on level with those in the previous tests, showing no apparent difference in the information content of good and bad earnings deviations respectively.

Table XIX

Mian & Sankaraguruswamy Model

$CAR(-1;+1)_{it} = Bad_{it} + Good_{it}UXit + Bad_{it}UX_{it} + Good_{it}UX_{it}Sent_t + Bad_{it}UX_{it}Sent_t$

Presented below are the results from the regression above. UX is called ERC for presentation reasons. Good and Bad are dummy variables equal to 1 if the unexpected earnings deviation is positive (negative). Sent is our FA Index. The total earnings response coefficient for good news is Good * ERC + Good * ERC * Sent, while the total earnings response coefficient for bad news is Bad + Bad * ERC + Bad * ERC * Sent. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that each β = 0 are in parentheses.

	Single-Index Model	*Simple Model*
Bad	-0.0437	-0.0439
	(0.00%)	(0.00%)
*Good * ERC*	0.1308	0.1323
	(0.01%)	(0.01%)
*Bad * ERC*	0.0590	0.0675
	(0.01%)	(0.00%)
*Good * ERC * Sent*	0.0181	0.0213
	(0.46%)	(0.15%)
*Bad * ERC * Sent*	-0.0117	-0.0124
	(0.10%)	(0.01%)
Adjusted R^2	0.1426	0.1730
Observations	814	814

In Table XIX above are the results of another test of the ERC variation between periods of high and low sentiment. The estimated coefficients indicate that the ERC for good news is 0.2101 when sentiment is high, and 0.0690 when sentiment is low, while they indicate that the ERC for bad news is 0.0551 when sentiment is low, and -0.0358 when sentiment is high.[77]

[77] We use the single-index model and the average FA Index score during the ten quarters of high and low sentiment, respectively.
I.e. the ERC for good news during high sentiment is 0.1308 + 0.0181 * 4.3814 while the ERC for bad news during low sentiment is -0.0437 + 0.0590 - 0.01167 * -3.4137.

7.3 Firm Size

Presented below in Table XX are our results from performing the same regressions as in Table XV above using the single-index normal performance model, but dividing the sample by firm size.

Table XX

ERCs by Firm Size

$CAR_{it} = UX_{it}$

Presented below are the results from the regression above, divided into four regressions for each event window; good news for large firms during high sentiment, good news for small firms during high sentiment, bad news for large firms during low sentiment and bad news for small firms during low sentiment. UX is called ERC for presentation reasons. Heteroskedasticity-robust *p*-values for a two-tailed t-test of the null hypothesis that the ERC = 0 are in parentheses.

		High & Good		*Low & Bad*	
		Large	*Small*	*Large*	*Small*
+/- 10 days	*ERC*	0.2735	0.3372	0.1957	0.1524
		(12.36%)	(4.34%)	(4.76%)	(12.24%)
	Adj. R^2	0.0209	0.0721	0.0418	0.0294
	Obs.	61	48	37	43
+/- 5 days	*ERC*	0.2394	0.1428	0.0704	0.1177
		(2.97%)	(15.48%)	(22.02%)	(10.64%)
	Adj. R^2	0.0525	0.0211	0.0000	0.0250
	Obs.	61	48	37	43
+/- 1 day	*ERC*	0.2443	0.2107	0.1493	0.0643
		(0.01%)	(1.95%)	(0.03%)	(17.81%)
	Adj. R^2	0.1119	0.1201	0.0779	0.0079
	Obs.	61	48	37	43

For each unique quarter, we divide all reports into those stemming from the firms with market capitalization in the top 25 percentiles and those stemming from firms with market capitalization in the bottom 25 percentiles. We believe this is more precise than dividing the entire sample, regardless of quarter, based on its market capitalization.

Due to smaller firm's stock's lower liquidity, we apply all three of our event windows. The ERC is seemingly larger for larger firms when employing a three-day event window, while longer event windows, allowing for stock price drifts due to lower stock liquidity, tend to increase the ERC for smaller firms relative to that of larger firms. In aggregate, no conclusive inference can be drawn.

8 Analysis and Discussion

The results presented above implies that there exists a significant difference in the stock market's response to earnings announcements in periods of high versus low sentiment. For positive earnings news, when firms' reported earnings exceed the market's expectations, there is a significantly larger market response impounded into stock prices in times of high sentiment than in times of low sentiment. For negative earnings news the situation is the opposite in most of our tests – the response is significantly higher in times of low sentiment than in times of high sentiment. In this section, we analyze and discuss our results.

8.1 Measuring Investor Sentiment

8.1.1 Theoretical Pitfalls

The theory of investor sentiment is a controversial field of research as is behavioral finance in general. Opponents argue that capital markets does follow the efficient market hypothesis, and that discovered market anomalies can be explained within the context of an efficient market with rational investors.[78] In accordance with the efficient market hypothesis, investors incorporate all available information into the market prices unbiased and rationally, with no "emotions" involved. This suggests that there is no such thing as investor sentiment on aggregate and no persistence of noise traders on the market.

However, a vast amount of research has observed market anomalies that can be explained by non-rational behavior. An entirely efficient market would not allow for bubbles to build and burst. In our study, we have so for taken the notion of noise traders and investor sentiment as exogenous. Now is the time to question this notion. If proponents of the efficient market are correct, observing and measuring investor sentiment would be impossible, and the backbone of our study would be broken. A non-existence of investor sentiment would mean that we have simply measured some – by us directly unobservable – economic factor that can be placed within an efficient market context. As researchers have, in their beliefs, found substantial evidence for both the existence and the non-existence of investor sentiment, one could settle with the notion that investor sentiment is as hard to prove as it is to disprove.

[78] C.f. Fama (1998)

All six of our proxy variables are established indicators of investor sentiment within the field of behavioral finance. One should note however, that the economic intuition behind the proxies is formed in a U.S. context. We have no apparent reason to disbelieve that the same logic applies in a Swedish context, but our proxies can be disputed on these grounds.

To our knowledge, no similar study has been conducted on Swedish data, thus the validity of the proxies has not been tested in a Swedish context. We have, since no contrary opinion is to find, assumed that these proxies also are applicable on Swedish data. A number of arguments can be directed against this assumption. The Swedish closed-end fund discount is based on a handful of investment firms, wherein – despite their often broadly diversified portfolios – firm-specific factors cannot be completely ruled out. Also, the Swedish IPO market does not seemingly behave in a similar way as the U.S. market. One should note that the Swedish stock market is a much smaller marketplace than the U.S. stock market, and Swedish firms may lack U.S. firms' inclination towards public equity financing. Our IPO time series show extreme highs during the heights of the IT bubble, but the Swedish IPO market has severely cooled off during the 2000s. While the low IPO volume during the last years may be something of a puzzle, we strongly believe that the extreme volumes during the IT bubble can be strongly ascribed to high levels of investor sentiment. It seems quite obvious that the Swedish market, as the U.S. market, experienced an IPO bubble during the years 1997 – 1999, and that this bubble was inflated by the irrational exuberance connected with going public during this period.

8.1.2 Empirical Pitfalls

Given that investor sentiment exists in the stock market the problem of observing, measuring and quantifying it remains. We use six proxies in our attempt to solve this problem, all of which, as stated above, have been proven in several studies to be affected substantially by investor sentiment. We believe that averaging out six proxies into a composite index is superior to using a single proxy, as it enables us to remove some of the noise inherent in the proxies. After regressing each proxy on a set of macroeconomic indicators, applying factor analysis we still find that more than 33% of the sample variance in the proxies can be explained by a single unexplained factor. In our resulting sentiment index, each proxy enters with the expected sign, and our index ocularly aligns with well-known bubbles and financial crises.

Notwithstanding the above, there is still a possibility that our macroeconomic indicators are inadequate, and that the common variation revealed in our factor analysis is simply another macroeconomic factor that we have not controlled for.

8.2 Generalizability

The results from our study are broadly in line with those of the study on U.S. data conducted by Mian and Sankaraguruswamy. This implies similarities in investor sentiment's effect on the stock market's response to earnings news in Sweden and the U.S. However, previous research has also found that the relationship between earnings announcements and investor sentiment also depends on the size, age, volatility and distress risk of the individual firm. With the exception of size, we have not examined or controlled for such factors. This suggests that we should be cautious concerning whether we can apply these findings on any and all types and categories of stocks.

8.3 Reliability

In our study, we apply two different models of measuring each stock's normal performance and three different lengths of event window. All test setups point in a similar direction, and our tests are the most statistically significant using a three-day event window, the predominant choice in previous studies. Our single-index normal performance model is however righteously subject to criticism due to relatively short estimation window, but it renders similar results as the more simple normal performance model across the board.

8.4 Validity

Our study depends on our sentiment index in two different ways. First, the study depends on whether we have evaded the empirical pitfalls of the sentiment index, i.e. whether the twenty quarters of especially high and low sentiment actually were quarters of especially high and low sentiment. Second, and more fundamentally, the study depends on whether we have evaded the theoretical pitfalls of the sentiment index. If there is no such thing as investor sentiment, bearing in mind that periods of high and low sentiment are in general, inevitably, synonymous with highs and lows of the Swedish economy in general, we have not measured whether the market responds differently to earnings news during periods of high and low sentiment. Rather, we have measured whether it responds differently during highs and lows of the Swedish business cycle. Even though our results could still be considered an interesting market anomaly if this were the case, we would not have measured what we set out to measure.

9 Conclusions

Studies on stock price reactions to earnings announcements generally follow the paradigm of the efficient market hypothesis. This study however, shows that behavioral aspects can successfully be incorporated into Swedish capital market research in financial accounting.

We construct a composite sentiment index, based on six proxies for investor sentiment, proponed in previous research, and find a common component not attributed to macroeconomic factors. We then examine how the Swedish stock market reaction to earnings announcements shifts with investor sentiment. Our results show that the Swedish stock market reacts stronger to good news during periods of high sentiment, as well as to bad news during periods of low sentiment. This is uniform with the idea that investors place increasingly optimistic valuations on securities as sentiment increases, and increasingly pessimistic valuations as sentiment decreases. We cannot conclude whether the effects are stronger for smaller stocks. Our results also imply that the Swedish stock market ascribes earnings announcements larger value relevance if the earnings deviation is positive during periods of high sentiment, and negative during periods of low sentiment.

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