MSc. Finance Thesis

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Investor Sentiment: An empirical study on Swedish Industries

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Abstract

We decompose the monthly Swedish consumer confidence index into a rational part based on fundamentals and an irrational part based on exogenous, irrational beliefs. Subsequently, we investigate the impact of investor irrationality and its short-term predictability on industry returns in Sweden. In addition, we provide an explanation to the reason some industries are more prone to investor sentiment than others. We predict that young industries that are complex and characterised by risky projects, dependence on intangible assets, and that have high growth potential are more exposed to investor sentiment than mature and core-industries with stable cash flows. We provide evidence of a short-term predictability of investor sentiment on future industry returns on the Swedish stock market. Also, in line with our predictions, we find that small industries, that experience high growth, that are dependent on intangible assets, and have more volatile cash flows are more exposed to investor sentiment. However, we find that core-industry returns, contrary to the other industries, have a positive relationship with last period investor sentiment.

Keywords: Investor sentiment, consumer confidence, industry returns, irrationality, Sweden.

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1. Introduction

Through the eras, traditional financial theories have been dominating the literature. Nevertheless, since the emergence of behavioural finance, an increasingly growing interest is accorded to the way decision-making among investors is affected by irrationality, a term that surged due to the inconsistencies and failure of the classical financial models in explaining bubbles, crashes and financial crises. For instance, the crash of 1987, the dotcom bubble and the financial crisis 2007/2008 all indicate that asset prices, contrary to what has been claimed by the classical financial theories, possibly deviate from fundamentals; in addition, there is a wide documentation in the financial empirical literature regarding deviations of stock prices from their equilibrium (Anderson, Darras, & Zhong, 2003) (Becchetti, Rocci, & Trovato, 2007) (Berk & Stanton, 2004) (Shiller, Kon-Ya, & Tsutsui, 1996).

In order to understand financial markets, neoclassical finance theory puts in place a key assumption stipulating that investors are rational; that expected utility theory is employed in evaluating payoffs, and Bayes' theorem is applied to make inferences and predictions (Montier, 2002). Nonetheless, since the emergence of behavioural theory, findings indicate that investors are found to violate the rationality assumption (Baker & Wurgler, 2006), (Baker & Wurgler, 2007), (Tvede, 2002), (Wilkinson & Klaes, 2012). While undertaking investment activities, investors may take fundamentals explaining changes in stock prices into account, but also tend to follow trends, over-react to news, give importance to less relevant (or irrelevant) information, and seem not to follow established rules while making predictions and inferences; thus, distorting prices from equilibrium. This characterises investor sentiment, a term relating broadly to the attitudes of investors towards the financial market, but which universal definition remains unclear and undecided upon.

During the last two decades, extensive research has been conducted on the effect of investor sentiment on individual stock returns, including Brown and Cliff (2004), Baker and Wurgler (2006), and Tetlock (2007). This interest in investor sentiment has also generated a considerable body of research concerning investor sentiment proxies as for instance Spiegel (1997), Berk and Stanton (2004), and Qiu and Welch (2006) to state a few. However, little importance is accorded to the impact of investor sentiment on industry returns. Similar to firms where the impact of investor sentiment is already established, different industries also vary in terms of characteristics; thus, it would be of interest to see whether differences in these characteristics result in different industry exposures to investor sentiment. Our paper attempts to fill this gap by establishing a relationship between investor sentiment and the cross-industry deviations of returns in Sweden. Indeed, a very limited number of papers address this specific research question. Yang and Sheng (2014) investigate the relationship between investor sentiment and Chinese industries. Sayim, Morris, and Rahman (2013) focus on five US industries, and investigate investor sentiment's effect on industry returns and volatilities by using an indirect approach, while no literature seems to accord interest to any of the European industries. For the sake of our paper and for clarity purposes, we define investor sentiment as ***"Beliefs** that are exogenous to fundamentals, and that are based on irrational reasoning".* Concretely, this research aims at decomposing the consumer confidence index (CC) into a rational part based on fundamentals and an irrational part of sentiment based on exogenous, irrational beliefs to investigate the impact of investor irrationality and its short-term predictability on industry returns in Sweden. In addition, we provide an explanation to the reason some industries are more prone to investor sentiment than others. Unlike most of the related literature such as Baker and Wurgler (2006), a monthly proxy is constructed rather than a yearly one, focusing our analysis on the short-term predictability of investor sentiment.

In essence, the hypothesis of the paper is that investor sentiment should affect some industry returns more than others'. We believe that young industries that are complex and characterised by risky projects, dependence on intangible assets, and that enjoy high growth potential are more exposed to investor sentiment than mature with stable cash flows and core-industries. The idea is that, on the one hand, core-industries such as *industrials* in Sweden are of greater importance to the economy, are well understood, and obtain more attention and coverage by professionals than other industries. On the other hand, industries in an early stage in the life cycle, with high growth, risk, and complexity to understand and predict, are more exposed to subjectivity in their valuation process as more assumptions are made, creating more room for uncertainty and exogenous sentiment.

In our results, we find that some industries are more prone to investor sentiment than others. The most exposed to investor sentiment are *Consumer goods, Leisure goods, Household goods, Software & Computer services* and *Support services*, while the least exposed include *Real estate, Healthcare* and *Mining*. In this paper, we reach several conclusions that may enhance the understanding of efficient markets and the impact of investor sentiment. Primarily, in contrast to Brown and Cliff (2004), we provide evidence for a short-term predictability of investor sentiment on future industry returns on the Swedish stock market. Additionally, we confirm the hypothesis that industries that are small, that experience high growth, that are more dependent on intangible assets, and have more volatile cash flows are more exposed to investor sentiment. We also provide new evidence that core-industry returns have, contrary to the other industries, a positive relationship with last period investor sentiment. Practically, these findings may be of interest for traders and portfolio managers although transaction costs might diminish potential gains from trading on investor sentiment.

The subsequent chapters of the paper develop and illustrate theoretical predictions in more detail. In Chapter 2, we discuss the theoretical background to investor sentiment, Chapter 3 presents previous literature in the field of investor sentiment. Chapter 4 encloses investor sentiment proxies, and models our measure of investor sentiment to later develop the method for measuring the predictability of investor sentiment on industry returns. The same chapter concludes with the method used to classify industries and illustrates the relationship between investor sentiment and some susceptible investor sentiment-prone industry characteristics. Following, Chapter 5, presents the data used to conduct the research. In Chapter 6, we conduct empirical tests on our data, and present the findings of the research, to also provide an analysis of the results. The paper concludes with contributions and potential future areas of research.

2. Theory

This chapter provides a theoretical background to investor sentiment starting with a broad discussion about the classical financial theory and its premises. The section then narrows gradually down to the principles of behavioural finance theory to further define investor sentiment and explain its theoretical cross-sectional effect on industry returns.

2.1 Theoretical background

Pertinent to all sciences and with the premise to explain relationships between phenomena, the use of models and thus underlying assumptions are required. Within finance, both the classical and behavioural theories share the same purpose of shedding light on the investor decision-making process, yet the underlying assumptions differ. Nonetheless, as the Nobel laureate Milton Friedman (1953) once stated; “The relevant question to ask about the “assumptions“ of theory is not whether they are descriptively “realistic”, for they never are, but whether they are sufficiently good approximations for the purpose at hand”.

2.2 Classical financial theory

The main concepts underlying the classical financial theory derive from the assumption that individuals, or economic agents, conduct rational and utility maximising decisions. The classical approach of rational agents is applied to all parts of financial economics including agent’s investment decision-making process (Wilkinson & Klaes, 2012). The application of classical financial theory to asset pricing and financial markets can be summarised with two main conclusions.

Firstly, financial markets are efficient information-wise; in other words, traded securities completely reflect all available information at any time. The concept of efficient markets is a widely discussed and researched subject, and was first introduced by Fama (1965). Succeeding on Fama’s work on efficient markets, Roberts (1967) defines the today well-known term *efficient market hypothesis* (EMH). In accordance with EMH, stock prices should only reflect the fundamental value of the underlying asset, which would be the value of the expected discounted future cash flows. Changes in the asset prices would only occur as a result of newly released information (Zhang, 2006). As a result of this, future stock prices follow a sub martingale, that is to say, prices are hence unpredictable (Samuelson, 1965). The premises of efficient markets can mathematically be presented using the following formula:

$$P_t = E_t \, [P_{t+1}{}^* | I_t]$$

where the price of the asset at the current time t is the expected value of the price of an asset P at any future time, e.g. t+1, given all current information. The second main concept concludes that all participating agents are rational. This premise is directly in line with the efficient market hypothesis. As stated earlier, it entails that all economic agents make rational and utility maximising decisions (Zhang, 2006). Following the concepts of the traditional theory, it can be concluded that financial markets must be arbitrage-free if we assume that markets are frictionless. Any divergence from the fundamental price, as a result of suboptimal trades by agents based on irrational beliefs, would quickly diminish due to arbitrageurs. Hence, there should be no sustained impact on asset prices as a result of irrational agents.

2.3 Behavioural Finance

The failure of the classical financial theory to explain stock prices deviations from their fundamentals as well as market bubbles and crashes has surged the development of new financial models. These models attempt to explain changes in stock prices using psychological behaviours rather than classical theory. Although behavioural finance is considered as an evolving discipline, Adam Smith, the father of economics wrote already in 1759, *"The Theory of Moral Sentiments",* providing insights related to the role of emotions in making decisions (Smith, 1759). Likewise, behavioural models consider the effect of investor sentiment on the decision-making process while investing (Barberis & Thaler, 2003), (De Long, Shleifer, Summers, & Waldmann, 1990). Perfect rationality is no longer a valid assumption; instead, investors' own sentiment often leads to biased and irrational investment decisions. In their papers, De Long, Summers and Waldman (1990) show that investor sentiment does affect the stock price equilibrium, that assets mostly traded by individuals are more influenced by sentiment, and the high transaction costs make it harder to conduct arbitrage.

Introducing the notion of noise traders, Albert Kyle (1985) and Fischer Black (1986) use the latter term to refer to traders lacking information and investing without taking fundamental data into account. These traders, while making investment decisions follow trends and rumours, over-react to news and events, and often give more importance to less relevant information rather than focus on fundamental drivers of asset prices; thereby affecting asset prices from equilibrium (Black, 1986).

In the attempt to thwart the EMH that posits that mispricing will be completely offset by aggressive arbitrageurs, the noise trader model is developed. This model motivates that taking into account investors' risk aversion and tendency to have short-horizons, exposure to undiversifiable risk may discourage investors to conduct arbitrage. Moreover, since noise traders' expectations about asset returns are driven by their sentiment, which itself, due to the tendency to follow trends, is correlated across noise traders, risk cannot be diversified away (De Long, Shleifer, Summers, & Waldmann, 1990), (Fama & French, 1993). The noise trader model implies then that asset prices can deviate from the fundamentals.

2.4 Investor sentiment

Despite the common use of "investor sentiment" in many renown papers including Baker and Wurgler (2007), Baker and Wurgler (2006), Shefrin (2007), Qiu and Welch (2006), Brown and Cliff (2004), Qiu and Welch (2004) and Daniel, Hirshleifer, & Subrahmanyam (1998) to explain the movements in stock prices or to measure it, no general definition of investor sentiment is universally used. Among the different definitions is the propensity to speculate, which is introduced by Aghion and Stein (2004) as "a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker & Wurgler, 2007), or model-specific investor biases where bias is the tendency to make decisions based on beliefs (Shefrin, 2007). While some papers do provide definitions, other simply use the term without providing one or refer to it as investor optimism, pessimism, or the tendency to trade on market noise while disregarding fundamentals. Surprisingly, after two decades of being given importance in the financial literature, the formal definition of investor sentiment remains unclear, and thus for the sake of this paper, the definition below is constructed to support our purpose. The traditional view suggests that a rational investor makes decisions based on fundamentals; the way investor sentiment is viewed in this paper is that investors make investment decisions not only by considering fundamental drivers of prices, but also by unconsciously taking into account their own exogenous beliefs that arise from ignoring fundamentals and following trends and irrational beliefs instead.

Formally, our definition of investor sentiment summarises as follows;

***"Beliefs** that are exogenous to fundamentals, and that are based on irrational reasoning."*

In other words, a change in investor sentiment is unrelated to changes in the present value of all future cash flows. Thus, is can be considered as a completely irrational part.

2.5 Investor sentiment and industry returns

In accordance with behavioural theory, we arrive at the conclusion that mispricing is induced by misinformed, biased or exogenously influenced demand that cannot be completely offset by arbitrage. Also, Baker and Wurgler predict and successfully show that sentiment does have a cross-sectional effect when demand for certain stocks is sentiment-influenced (Baker & Wurgler, 2006). Similarly, in the context of our paper, we predict that on the one hand, certain industry returns should as well be affected by sentiment-based demand shocks. That is to say, industries that are relatively new, more volatile, complex to understand and value due to risky projects, high dependence on intangible assets and Research & Development, and that have high growth potential should be more exposed to investor sentiment effect than other more established, mature industries with stable cash flows. On the other hand, core-industries; the ones crucial for national economic growth, might not be as, or not at all affected by investor sentiment as they are of greater importance, and obtain more attention and coverage by professional analysts. Additionally, we predict that the relationship between investor sentiment and future industry returns should be negative.

The reasoning behind our prediction is derived from the idea that the higher the subjectivity in determining the value of a firm, the more assumptions need to be made, the more subject to exogenous sentiment the valuation will be. Starting from the fact that industries are composed of companies of different growth cycles, earnings histories, risk, size, and complexities, we consider that an industry with many subjectively valued firms is more influenced by investor sentiment than an industry with mostly stable firms that have a traceable cash flow history, moderate future growth and less room for assumptions that increase uncertainty. Similarly, one could think of it from arbitraging perspective; it goes in line with theory that the same type of firms; young, unprofitable, volatile with high growth prospects, are harder to conduct arbitrage on (D'Avolio, 2002). Meaning that an industry mostly composed of this type of firms is more exposed to speculation and risk, and seizing arbitrage opportunities may then be more costly, disabling some arbitrageurs to undertake arbitrage, and thus preventing prices from converging back towards equilibrium. The rationale behind our prediction of a negative relationship is derived from the idea that high investor sentiment results in contemporaneously, unjustifiable, increases in asset values. This temporary increase in asset prices will later be adjusted down by market participants resulting in a negative relationship.

3. Evidence

The following chapter presents previous literature in the field of investor sentiment. Due to the limited number of research concerning the effect of investor sentiment on industry returns specifically, the focus will be on investor sentiments impact on the aggregated stock market or portfolios of stocks. Nevertheless, the most relevant works involving industries are also presented.

Extensive research is being done on the subject of investor sentiment and its impact on asset prices. Research mostly revolves around investor sentiment impact on the aggregated stock market return or portfolios sorted after specific characteristics. However, due to the complexity of measuring investor sentiment and lack of a universally accepted proxy, there is a wide range of methodologies used. The two primary methods used in previous research to measure investor sentiment are the direct method involving surveys to subtract investor sentiment, and the indirect method involving using observable economic variables (Brown & Cliff, 2004), (Brown & Cliff, 2005).

One of the most renowned papers is Baker & Wurgler (2006), where they show that beginning of period investor sentiment does impact the cross-section of future stock returns. They measure investor sentiment using a direct approach where they include, among other variables, the closed-end fund discount. They identify specific characteristics of firms that are more subject to investor sentiment. These characteristics include age, size, growth and distressed firms. Continuing on their work, and using the same proxy, Baker and Wurgler (2007) increase the understanding of investor sentiment by showing the predictability of investor sentiment on future stock returns both for the individual stocks and for the aggregated market. Similarly to Baker and Wurgler, Brown and Cliff (2004) show that investor sentiment contemporaneously positively correlates with aggregated stock returns. They find limited evidence for any short-term predictability in returns. Brown and Cliff also conclude that both the direct and indirect approaches yield similar results. The results from Baker & Wurgler and Cliff & Brown are in line with earlier research of Neal & Wheatley (1998) that found a relationship between investor sentiment and future returns. Neal and Wheatley used an investor sentiment proxy consisting of three different variables including the close-end fund discount, a ratio of odd-lot sales to purchases and the net mutual fund redemptions.

Contrary to the work of Baker and Wurgler, Qiu and Welch (2006) argue that the use of CEFD as a variable is not a valid proxy for investor sentiment, and Huang, Jiang, Tu, and Zhou (2014) construct an investor sentiment measure that they refer to as "aligned sentiment index". Making use of an indirect method, they extract common components that are the most relevant to expected stock returns from several proxies by making use of PLS, the partial least squares method (Huang, Jiang, Tu, & Zhou, 2014). By removing the common noise part of the different proxies, Huang, Jiang, Tu, and Zhou (2014) find that the "aligned sentiment index" does have a statistically greater predictive power on the aggregated stock market than any individual approximation of investor sentiment. Albeit this argument, both Baker and Wurgler (2006) and Qiu and Welch (2006) papers derive similar conclusions by stating that investor sentiment does have a contemporaneous impact on stock returns.

Direct measures are used by several other researchers following Qui and Welsh's work including Schmeling (2008), Zouaoui, Nouyrigat, & Beer (2011) and Sayim, Morris, & Rahman (2013). Schmeling (2008) uses CC as a proxy and concludes, in line with earlier research, that investor sentiment negatively forecasts future aggregate stock. Schmeling also finds that countries which stock markets are more affected by herd-like behaviour and subject to less market integrity are more likely to show negative results to investor sentiment. In their paper, Zouaoui et al (2011) find that investor sentiment does have an explanatory power in regards to predicting stock market crises, and reiterate Schmeling's conclusions that countries more prone to herding are affected by investor sentiment. Continuing on their own work, Brown and Cliff (2005) deepen the knowledge of investor sentiment by using a direct measure that includes published analyst newsletters. They investigate investor sentiment and its impact on deviations for the intrinsic value for the aggregated stock market. Brown and Cliff find in their paper that investor sentiment predicts deviations over the next one to three years. Their findings support the controversial conclusion that investor irrationality is a factor that impacts asset valuation. Alternative measures of investor sentiment also lead to similar results. Tetlock (2007) uses media coverage as a proxy for investor sentiment; more precisely, he uses the daily Wall Street Journal column. He finds that a relationship between future stock returns and weak media coverage does exist and that media coverage can be used as a proxy for investor sentiment.

The little importance accorded to industries is covered by less iconic journals where, for instance, Sayim, Morris, & Rahman, (2013) investigate the impact of investor sentiment using the American Association of Individual Investor Index as a proxy for investor sentiment on the stock returns and volatilities on a limited number of US industries. They find a significant relationship between investor sentiment and stock return and volatility. In another paper, basing their work on one of the pioneering papers in the literature, Huang, Yang, and Sheng, (2014) use the principal component analysis to indirectly proxy investor sentiment in order to establish a relationship between industry returns and investor sentiment. Findings indicate that for all chosen industries, there is a positive contemporaneous relationship between industry returns and investor sentiment, but a negative relationship once a lag is introduced. More specifically, they find that industries closely related to the Chinese national economy, such as fishery, animal husbandry and extractive industries are less affected by investor sentiment than non-core industries.

Due to the limited amount of research conducted within this area, this paper attempts to fill the gap in the research literature by investigating the predictability of investor sentiment on industry returns in the Swedish stock market. The paper draws from earlier work by Baker & Wurgler (2006) with regards to the method of investigating investor sentiment predictability, and from Qui & Welch (2006) and Zouaoui et al (2011) with respect to the chosen proxy for investor sentiment.

4. Method

This chapter first walks the reader through two popular investor sentiment proxies and the rationale behind discrediting one of them. The second section defines consumer confidence index in detail to later decompose it and retrieve our investor sentiment variable from it. Later, we present our three-step model with the aim of explaining the effect and short-term predictive power of investor sentiment on industry-returns. Finally, we classify industries into characteristics that should, according to theory and to our reasoning, indicate a relationship in order to reaffirm the relationships found earlier.

In our attempt to study the effect and predictability of investor sentiment on future industry returns, investor sentiment is first modelled. By regressing fundamental variables on the consumer confidence index, we treat the residuals from the regression as a variable representing investor sentiment, a sentiment that is considered irrational since it is not based on fundamentals. We then set up a three-step model to separately test the effect and the predictive power of investor sentiment, Fama French three-factor model, and the aggregated variables on industry returns.

4.1 Investor sentiment proxies

Several proxies have been developed to measure investor sentiment. The one that Baker & Wurgler use is one of the most widely adopted proxies. By using the principal component analysis, Baker and Wurgler include several variables in their investor sentiment proxy including Closed-End Fund Discount, NYSE share turnover, the number of IPOs, average first-day return on IPOs, equity share in new issues, and finally the dividend premium. The stated variables would provide a proxy for investor sentiment; for instance, high number of IPOs, average first-day return, turnover, and dividend premium would indicate high investor sentiment. One of the most used and discussed proxy is the Closed-End Fund Discount; the difference in price between the underlying asset and security price of the currently traded closed-end fund. The idea is that, if retail investors hold closed-end funds disproportionally, the average discount on close-end equity funds may be a sentiment indicator (Baker & Wurgler, 2006). However, Qiu & Welch (2006), Ross (2005), Spiegle (1997) and Berk and Stanton (2004) question the efficiency of the CEFD as a proxy. Claiming that other than CEFD being held unevenly by investors, other factors such as transaction costs or time-varying liquidity premium, for instance could contribute to the difference between the selling and fundamental price (Ross, 2004). Lee, Shleifer and Thaler (1991) also consider that most importantly, transaction costs could influence CEFD. In addition to that, Spiegel (1997) and Berk and Stanton (2004) underlined that CEFD follows a time-pattern. Another argument is that CEFDs could misrepresent retail investors; unusual investors such as trust accounts could hold CEFDs for instance (Ross, 2004).

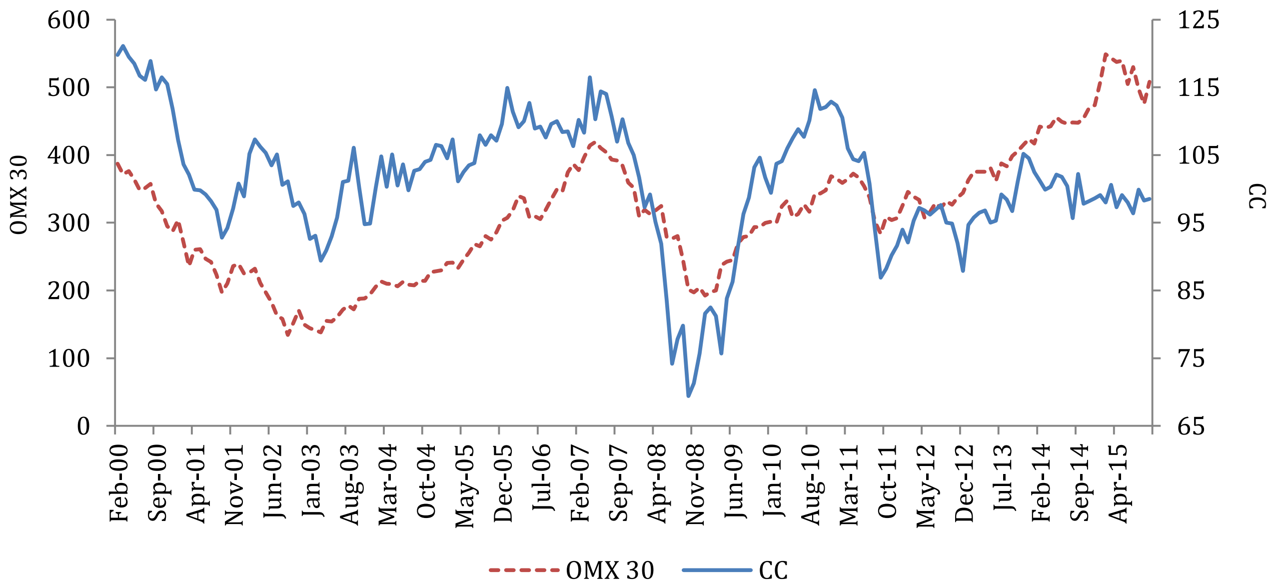
Other scholars opted for a more direct alternative measure of investor sentiment; attitude surveys, which have been conducted since the late 80's by Robert Shiller. These surveys ask respondents about their attitudes toward the economy, which provides a purer insight into irrationalities. In our context, the attitude survey CC is used where the respondents are households. They are asked about their attitudes about the economy and provide us with an insight into how rational or irrational investors are. In order to validate the reliability of CC surveys, Qiu and Welch 2006 use the UBS/Gallup survey - an investor confidence survey directly related to investors' attitudes toward the financial market in the US, as a proxy for investor sentiment, and compare the correlation of both CEFD and CC surveys with the direct measure UBS/Gallup. Their study shows that CEFD is reliable only in Januaries yet only until 1987, it is not correlated with UBS/Gallup, and is thus not a good proxy for investor sentiment while CC is. CC shows to be a reasonable proxy as changes in CC are strongly correlated to changes in the direct measure, UBS/Gallup, although CC does not include direct questions about securities prices (Qiu & Welch, 2006).

Consumer confidence surveys are tested and used in several published papers including Lemmon and Evgenia (2006), Qiu and Welch (2006), Ho & Hung (2009), and Zouaoui, Nouyrigat, & Beer (2011), which is the measure we rely on this paper. In order to directly proxy investor sentiment, we use the monthly CC survey for Sweden. This direct approach regresses the CC index on macroeconomic fundamentals in order to decompose the CC into two parts. We base our rational part on the following fundamentals; CPI; the monthly consumer price index, GDP; Gross Domestic Product, IP; industrial production, SEK; Swedish Krona Trade-Weighted Index, SPREAD; the spread between 10-year and three-month government bond, and EXPENDIT; household expenditures, and investor sentiment, the exogenous part would then be based on irrational beliefs, which is captured by the residuals.

4.2 Consumer confidence

Statistics Sweden (SCB) are the providers of the CC survey (Konjunkturbarometern Hushåll). The survey was initiated in the beginning of 1973 and was then released quarterly; however, starting in 1993, the survey is available on a monthly basis. The index is compiled by 1500 interviews of randomly selected Swedish households. The participating individuals are between the ages of 16 and 84. The data is collected during the first 15 days of the month, and the survey is seasonally adjusted and published at the end of the same month. The participating households are asked questions on both a macro and micro level, including their view on their own financial situation, inflation, changes in interest rate and household spending. Questions also relate to their view of the economy as a whole. In total, there are 19 questions. Two of the questions require precise number estimation (forward, looking and backward looking inflation estimations), the other questions are answered by a scale of one to six. The questions are split between forward and backward looking with a time frame of 12 months. A complete list of the questions asked is presented in Appendix A1. Despite the lack of questions directly related to asset prices, plotting the CC and the OMX 30 over the past 16 years co-movements between the variables can easily be observed. An illustration is shown below.

Figure 1. OMX 30 & Consumer Sentiment



The chart depicts monthly observations of the Swedish stock market index, OMX 30, and the Swedish consumer confidence survey from February 2000 to October 2015. Based on the chart, it is clear that the two variables follow similar trends.

4.3 Modelling exogenous investor sentiment

To retrieve our investor sentiment variable, the CC index is adjusted with eight different economic fundamental variables. This is done in order to separate the origin of variations in CC between the rational part, which is based on fluctuations in macroeconomic fundamentals, and changes purely based on investor's exogenous irrational beliefs, the investor sentiment. Thus, we perform the adjustment on CC index by regressing the fundamental variables on CC as shown in equation (1). We then use the residuals from the regression as a proxy for the irrational beliefs; in other words, the part of the CC that cannot be explained by rational factors - investor sentiment.

$$CC_{i,t} = \alpha + \beta_j \sum_{j=1}^{J} \mathrm{FUND}_{i,t}^{j} + \varepsilon_{i,t} \tag{1}$$

where the CC is the consumer confidence, FUND represents the eight different fundamental variables and $\varepsilon_{i,t}$ is the residual that represents the irrational part, also referred to as investor sentiment.

Strictly speaking from an econometric point of view, residuals from a BLUE (best linear unbiased estimator) OLS regression are to be only white noise, and thus show no form of pattern. However, from a financial perspective, we have no desire to create an IID variable; rather we want to remove the rational part of the CC and save the remaining part as investor sentiment. Therefore, necessary adjustments will be made if problems with the residuals appear. This topic is covered later in the paper. In equation (1), none of the independent variables are lagged. By doing this, we implicitly assume that households react instantaneously to changes in macroeconomic fundamentals. This assumption is both in line with methods used by previous research Zouaoui, Nouyrigat, & Beer (2011), and is reasonable to assume considering that households are an integrated part of the economy.

The rationale for the inclusion of each fundamental variable is based on the actual questions asked in the CC survey, fundamentals suggested by previous research and well recognised macroeconomic variables that are documented to have an impact on stock returns. The eight fundamentals include the following: change in inflation, GDP growth, industrial production growth, the Swedish trade-weighted exchange rate, changes in unemployment rate, the term spread between the ten-year and the three-month Swedish government bond, a dummy variable for recessions and growth in household spending. Baker and Wurgler (2006) used growth in industrial production, household spending, and the dummy variable for recession. Zouaoui, Nouyrigat, and Beer (2011) also use these variables. We include the term spread based on Fama (1990), who also recommends using industrial production. The rationale behind using these variables is their close link to stock market performance. We also include changes in unemployment, inflation and GDP due to their presence in the questionnaire. We base the inclusion of the Swedish trade-weighted exchange rate on research by Solnik (1974) and Adler and Dumas (1984).

4.4 Predicting industry stock returns

In order to test the predictability of investor sentiment on industry return, and later be able to see the impact of the irrational sentiment on the sensitivity coefficients, three regressions are performed. The initial regression involves the direct impact of investor sentiment on industry returns; in this regression, we use the investor sentiment proxy constructed in the previous section as a regressor on all of the 25 industry returns separately as follows:

$$IND_{i,t} = \alpha + \beta_1 SENT_{t-1} + \varepsilon_{i,t} \tag{2}$$

where IND is the monthly stock return for the respective industry and SENT is the investor sentiment variable retrieved from equation (1). In this regression, investor sentiment is lagged since the purpose is to investigate if it has a forecasting power on industry returns.

To be able to compare the impact on industry returns of both the irrational investor sentiment and well-known variables with a strong explanatory power on returns separately, we run a second regression. In this step, we use the Fama French Three-Factor Model to explain co-movements in industry returns. The Three-Factor Model includes small stocks minus big stocks SMB, high minus low book to market ratios HML, and excess return on the market portfolio, OMXER.

$$IND_{i,t} = \alpha + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 OMXER_t + \varepsilon_{i,t} \tag{3}$$

The last step involves a regression where both investor sentiment and the Fama French factors are included as depicted in equation (4). From the regression output, by examining the changes in Fama French coefficients, we will be able to determine if sentiment does play a role in explaining industry returns; a change in coefficients would indicate that SENT has an explanatory power. Additionally, comparing the adjusted coefficients of determination, adjusted $\mathbf{R}^2$ values, also provides insights into the extent of investor sentiment impact.

$$IND_{i,t} = \alpha + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 OMXER_t + \beta_4 SENT_{t-1} + \varepsilon_{i,t} \qquad (4)$$

4.5 Industry Classification

In order to further analyse and confirm the sensitivity of industry stock returns with respect to SENT, industry characteristics that would be more prone to investor sentiment are identified. These characteristics are based on the theoretical discussion presented earlier, and include risk, size, growth, and valuation subjectivity, and industries are classified accordingly. More detail regarding the characteristics is presented in the next chapter. Industries are sorted from high to low with respect to each characteristic. Based on our theoretical argumentation, we predict that high risk and growth, small and complex industries to value would be more affected by investor sentiment than other more stable, predictable or core-industries.

5. Data

The following chapter describes the data used in every step of our model, specifies the time span covered by our paper and the provenance of each dataset. It starts with the description of the data used in modelling investor sentiment including consumer confidence index and the fundamental variables. Next, we point out the way some missing data points were generated. The last section presents the industries chosen, and demonstrates how data on Fama French Three-Factor variables are constructed for the Swedish Market.

5.1 Data description

Our dataset extends over sixteen years of monthly data, 2000 until 2015; thus, after calculating changes, the first monthly observation is lost, and we are left with monthly observations from February 2000 until October 2015. The first part of the study involves modelling investor sentiment. The Swedish CC survey conducted by Konjunkturinstitutet, the National Institute of Economic Research was published by Statistics Sweden, SCB, and the underlying index is retrieved from Thompson Reuters database. Eight fundamental variables are used including CPI; the monthly consumer price index, GDP; quarterly Swedish Gross Domestic Product, IP; Swedish industrial production, SEK; monthly Swedish Krona Trade-Weighted Index, SPREAD; the spread between 10-year and three-month Swedish government bond, and EXPENDIT; household spending constructed by adding together quarterly observations of durable goods, non-durable goods and services. While all stated variables so far originate from SCB and are retrieved from Datastream, other variables include UNEMPL; unemployment rate taken from Eurostat, and SWEREC; a binary variable indicating recession for Sweden retrieved from Economic Research – Federal Reserve Bank of St.Louis. All variables are adjusted for inflation and seasonality.

5.2 Cubic spline Interpolation

Our model makes use of monthly observations; however, household expenditure and GDP variables are published quarterly, and need hence to be transformed, or “split” into monthly observations in order to use consistent time-intervals. Cubic spline interpolation is performed for that purpose using Matlab. Mathematically, interpolation is a method used to construct new data points from a set of known actual data points. In our analysis, Cubic spline interpolation is used rather than polynomial interpolation as the former uses low-degree polynomials in each interval to estimate smooth data points, and is found to yield similar results while having smaller errors (Columbia Economics LLC, 2010). Cubic spline interpolation is then defined as a piecewise continuous curve traversing known values (Utah Education). In our case, the known values on the curve are quarterly observations, and monthly observations are estimated to connect the quarterly data-points. The same operation is performed for all of GDP, durable goods, non-durable goods and services. This practical method comes with a limitation; using interpolated data in our regressions may introduce serial correlation in our regressors since observations interpolated will be linked by a cubic polynomial (Utah Education). To take this limitation into account, we control for serial autocorrelation by using the Newey-West, HAC, standard errors as they are robust to cubic splines induced autocorrelations (Westerlund, 2005).

5.3 Industries and Fama French Three-Factor Model

In the second part of our model where we test the predictability of investor sentiment on industry returns, we performed the analysis on 25 Swedish industry indices namely; *Financial services*, *Software & Computer services*, *Electronic & Electrical equipment*, *Technology*, *Technology hardware & Equipment*, *Healthcare*, *Pharmaceuticals & Biotech*, *Industrials*, *Construction & Materials*, *Industrial goods & services*, *Support services*, *Financials*, *Leisure goods*, *Travel & Leisure*, *Telecommunications*, *Mobile telecom*, *Food producers*, *Retail*, *Consumer services*, *General retailers*, *Personal & Household goods*, *Mining*, *Forestry & Paper*, *Real estate*, and finally *Consumer goods*. All industry indices are provided by NASDAQ OMX NORDIC, and are retrieved from Thompson Reuters database for the same sixteen-year period. In our three-step model, we use Fama French Three-Factor model where SMB; average return on three small portfolios minus the average return on three big portfolios, HML; average return on two value portfolios minus the average return on two growth portfolios, and OMXER excess returns on the Swedish market are constructed manually using the following formulas suggested by (Fama & French, 1993);

$$SMB = \frac{(Small\ Vaule + Small\ Neutral + Small\ Growth)}{3} - \frac{(Big\ Value + Big\ Neutral + Big\ Growth}{3}$$

$$HML = \frac{(Small\ Vaule + Big\ Value)}{2} - \frac{(Small\ Growth + Big\ Growth}{2}$$

Later, in our attempt to illustrate industry return sensitivity to investor sentiment, we classify the 25 industries using four characteristics. Size is based on the market capitalisation of each industry divided by the number of firms in the industry, risk is based on standard deviation of industry returns for the whole sample period, growth is proxied using price to book ratios, and valuation complexity using PP&E/Assets; where the measures are calculated for each industry based on, to limit the repetitive work, the yearly observation from 2015. Price to book ratio is a widely used proxy for growth given that a high value indicates high growth (Koller, Goedhart, & Wessels, 2015). To support the use of PP&E/Assets as a measure of valuation complexity, we also assume that industries with a low ratio of property plant and equipment relative to total assets have substantial intangible assets.

6. Empirical Findings

Shedding light on our findings, this chapter commences by presenting the results from the modelled investor sentiment variable, and later performing a non-statistical investigation of our hypothesis before turning to the formal model. The remaining sections focus on a proper statistical examination of the predictability of investor sentiment on near future industry returns. Starting by first presenting and analysing outcomes from the three-step regression model, we subsequently attempt to explain the differences in results by categorising industries into investor sentiment-prone characteristics.

The first part of the analysis extracts investor sentiment from the Swedish consumer confidence index. The regression output below from equation (1) exhibits the regression results[1]. Out of the eight fundamental variables used, GDP growth is significant at a 1% level while changes in industrial production and unemployment are significant at 5% level, and the recession variable SWEREC and household expenditures are significant at 10% level. Change in inflation, the interest rate spread and the trade-weighted exchange rate are not significant. The residual from the regression, that is the irrational part is saved and plotted on the next page together with the market index.

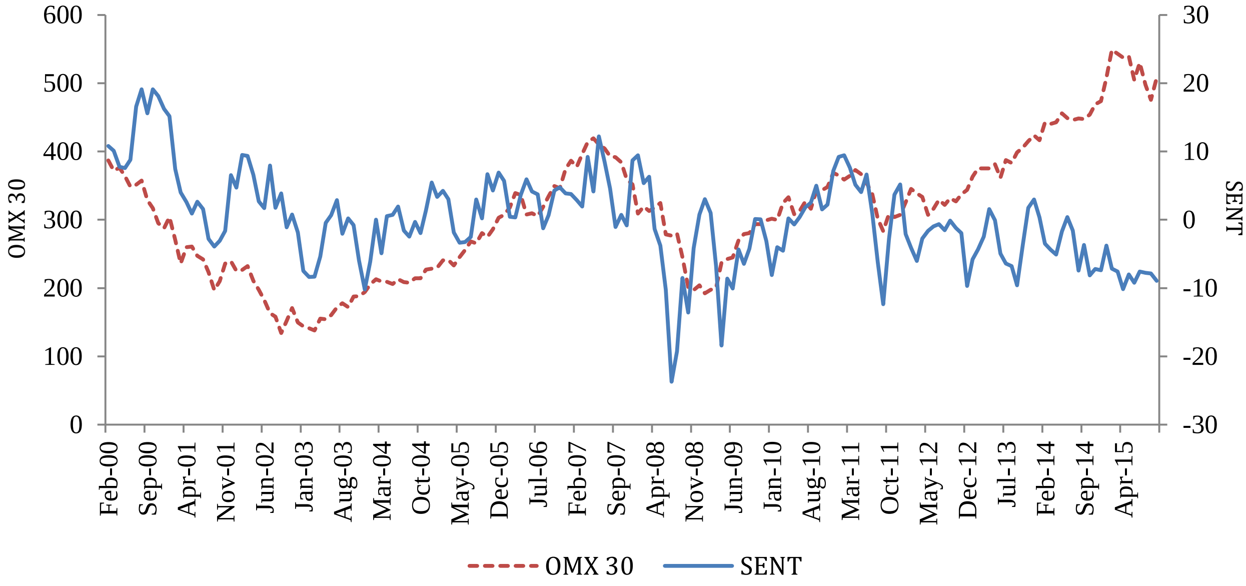
Table 1. Output from Regression equation 1

Variable	Coefficient	P-value
C	101.8162	0.0000
DCPI	-17.3552	0.8611
DGDP	1121.9600	0.0000
DIP	31.3968	0.0208
DSEK	-28.1108	0.5462
DUNEMPL	-19.6622	0.0398
SPREAD	-129.1694	0.3333
SWEREC	-4.9545	0.0617
DEXPENDIT	526.1367	0.0566

The table depicts the reslut from regression 1. Out of the eight fundamental variables used, change in inflation, the interest rate spread and the trade-weighted exchange rate are not significant.

[1] To adjust for autocorrelation, the common Cochrane Orcutt Iterative Procedure is not used as it removes autocorrelation, which is not desired for the purpose of our paper as mentioned earlier. Therefore, Newey-West Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors are used for all regressions where heteroscedasticity and autocorrelation is present. We use the following formula to compute the variance covariance matrix: $Cov(\boldsymbol{b}) = N(\boldsymbol{X'X})^{-\mathbf{1}}\boldsymbol{S}(\boldsymbol{X'X})^{-\mathbf{1}}$ (Westerlund, 2005).

Figure 2. OMX 30 & Investor Sentiment

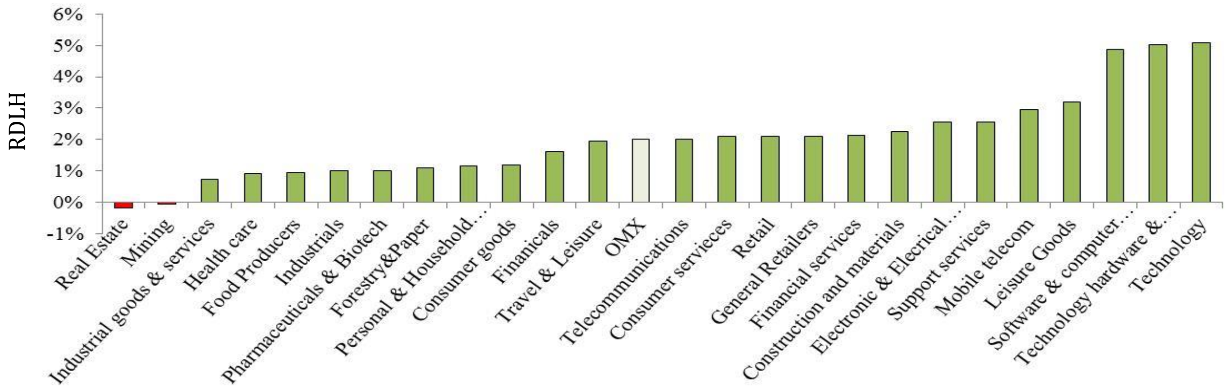


The chart depicts monthly observations of the Swedish market index, OMX 30 and the investor sentiment proxy from February 2000 to October 2015. By observing the chart it is apparent that the two variables follow a similar trend. However, the investor sentiment proxy, SENT, appears to be more volatile. Sentiment above null is considered high sentiment period and sentiment below null is considered low sentiment period

Based on the chart above, it is clear that the variable SENT and the OMX market index follows similar trends. However, SENT appears to be more volatile. We note that average sentiment is naturally zero; therefore, sentiment above null is considered as a high sentiment period and sentiment below null is considered a low sentiment period. Average high/low sentiment is calculated to be +5/-5, while the highest sentiment in our sample period is +19 during the Dot-Com bubble in year 2000, and the lowest sentiment is -23 during the collapse of Lehman Brothers end of 2008. What is interesting is the apparent diversion of the two variables at the end of 2012.

In order to study the predictability of investor sentiment on industry returns, we start with a non-statistical examination of our hypothesis. We do this by comparing the difference between average monthly returns following high sentiment periods and low sentiment periods, referred to as RDLH (Return Difference Low minus High) later in the text. Following our earlier theoretical reasoning that high contemporary investor sentiment leads to lower industry returns next period and vice versa, we would expect the difference to be positive if investor sentiment has an explanatory power on industry returns. The chart on the following page, Figure 3, shows that the difference in average returns is positive for most of the industries as well as for the aggregated market, OMX. This indicates that average monthly return following a high sentiment period is lower compared to a low sentiment period. Of the 25 selected industries, 23 excluding OMX show positive differences. This provides us with an initial indication of a relationship between investor sentiment and future industry returns that is in line with our hypothesis as well as earlier research. *Software & Computer services, Technology hardware & equipment*, and *Technology* industries appear to be the most subjective to investor sentiment, while *Real estate* and *Mining* the least. A potential reason the *Real estate* industry is not exposed to investor sentiment effect could be the high reliance on tangible assets that may make the valuation straightforward and relatively easy to conduct. The *Mining* industry also seems insensitive to investor sentiment, which can potentially be explained by its apparent link to the commodities market; a positive performance by commodities market implies a good industry performance.

Figure 3. Difference in average returns between low/high sentiment periods



The chart depicts the difference in average returns between low/high sentiment periods for all industries over the 16 year period. The chart provides an initial indication of a negative relationship between investor sentiment and future returns for nearly all industries. Only for Real estate and Mining industries are the average monthly returns following low sentiment periods lower compared to returns following high sentiment period.

The method used in the previous section allows for a graphical illustration of the RDLH. We now use the three-step regression approach presented earlier to conduct a proper statistical investigation. This allows us to formally test the significance, and conduct an econometric analysis of the results. Results from the first regression, equation (2) are presented in Table 2 on the next page. They indicate that 96% of the industries, 24 out of 25, show a negative relationship between industry returns and last period investor sentiment with the exception being *Real estate*. Out of these, 42% or 10 of the industries, are both significant and negatively correlated with lagged investor sentiment; confirming that a high period investor sentiment is followed by a lower industry return.

Table 2. Three-step Model Regression 1 results (Equation 2)

Industry	SENT	Industry	SENT
Construction and materials	-0.0009	Mining	0.0000
Consumer goods	-0.0008	Mobile telecom	-0.0032**
Consumer services	-0.0013**	Personal & Household goods	-0.0007
Electronic & Electrical equipment	-0.0011	Pharmaceuticals & Biotech	-0.0008
Financial services	-0.0009	Real estate	0.0007
Financials	-0.0008	Retail	-0.0014*
Food producers	-0.0003	Software & computer services	-0.0040**
Forestry & Paper	-0.0007	Support services	-0.0020**
General retailers	-0.0014*	Technology	-0.0041***
Healthcare	-0.0005	Technology hardware & equipment	-0.0040***
Industrial goods & services	-0.0002	Telecommunications	-0.0018*
Industrials	-0.0003	Travel & Leisure	-0.0009
Leisure goods	-0.0031***		

The table portrays results for all industries. Based on the results, there appears to be a negative relationship between investor sentiment and future industry returns. Out of the 25 tested industries, ten of them show significant negative results from the SENT variable.
Sig 10%*, Sig 5%**, Sig 1%***

The first regression over the predictability of investor sentiment supports findings of Figure 3 that investor sentiment appears to have a negative relationship with future returns for a majority of the industries. The industry that shows the strongest predictability towards investor sentiment appears to be the *Technology* sector. One possible explanation for the result could be the *Technology* sector's dependence on complex assets that are hard to value, making the sector sensitive to investor's irrational beliefs.

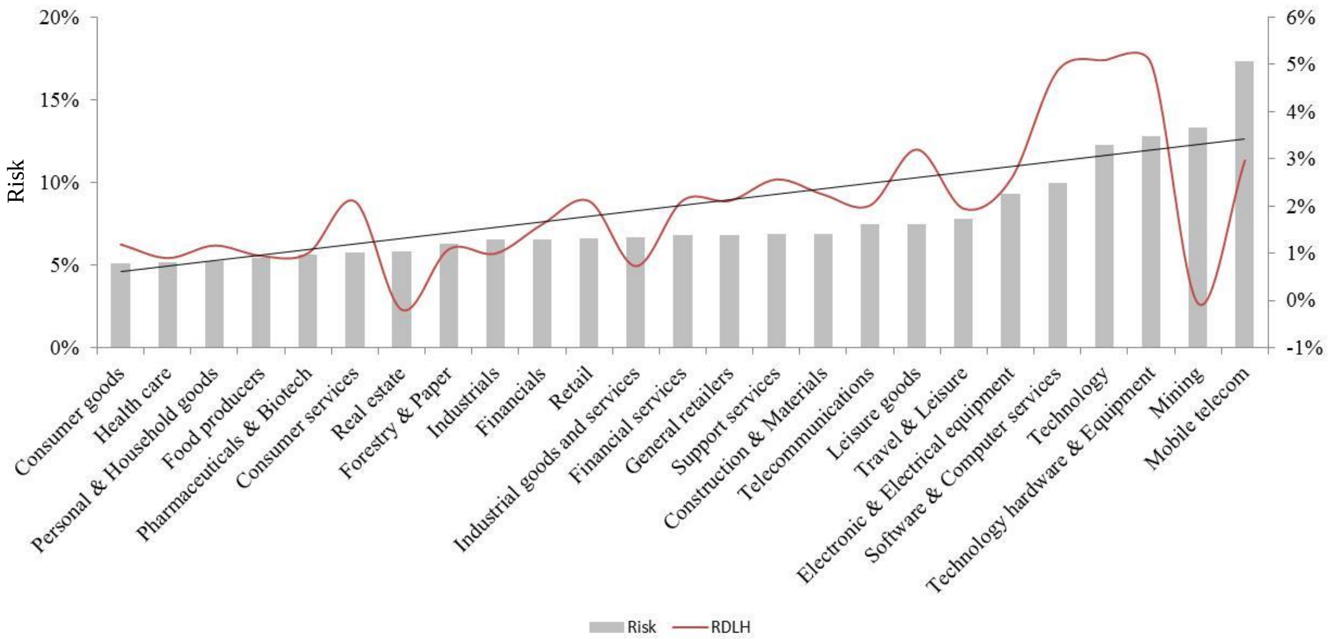
The second regression, equation (3), tests the contemporaneous relationship between Fama and French three factors and industry returns. The output is shown in Appendix A2, and indicates that in line with classical financial theory, Fama and French Three-Factor model does have a contemporaneous explanatory power on returns in general and industry returns in particular. Comparing regression one and two in our three-step model, it is clear and expected that the adjusted $\mathbf{R}^2$ values increase sharply. The adjusted $\mathbf{R}^2$ values increase from a range of 0.1-7% when only the SENT variable is included to 20-80% for the Three-Factor model. This result would indicate that the rational factors used by classical financial theory have a more substantial and significant explanatory power compared to investor sentiment; thus indicating that industries are more rational than irrational, which is clearly expected.

Combining investor sentiment variable and Fama French Three-Factor model in the third and last step of our model, equation (4), we check the robustness of the predictability of investor sentiment on industry returns. Results in Appendix A3 show that after adding the investor sentiment variable SENT, 11 industries show the expected negative relationship between investor sentiment and industry returns one period ahead. Out of these industries, five are both negative and significant. We also observe that, when the investor sentiment variable is added to the regression equation, and when it is significant, coefficients for Fama and French Three-Factor model all decrease. Regarding the explanatory power of the regression, when investor sentiment variable is added in the last step, the adjusted $\mathbf{R}^2$ values slightly increase for 11 out of 25 industries. However, all adjusted $\mathbf{R}^2$ values for industries where investor sentiment together with OMXER, SMB and HML are significant do increase. This result would indicate that the Fama and French Three-Factor model can be improved by including an irrational variable for certain industries. In other words, it appears that investor irrationality does impact industry returns while controlling for well-known stock-return co-moving variables. Additionally, The drop in significance of the SENT in the last step of the model, equation (4), could potentially be explained by the fact that by including the classical factors explaining stock returns, the Fama French Three factor model, irrational behaviour could reside in it, leading therefore to a double counting of the irrationality factor.

What is interesting to note is that for the *Industrials* and *Industrial goods & Services*, the inclusion of Fama French three factor model make the SENT coefficient positively significant. This result is especially interesting as it contradicts our own hypothesis of a negative relationship as well as previous literature. Although earlier research has not investigated investor sentiment and its impact on Swedish industry returns, most papers where a relationship has been found concluded that it was negative. One possible explanation for the appearance of a positive coefficient is the close link between the *Industrials* sector and the aggregated Swedish economy. The Swedish economy is heavily dependent on the *Industrials* sector, and can thus be seen as a core industry. Increases in industry returns related to *Industrials* could be highly correlated to improvements of the economy as a whole, resulting in a rational increase of future expected cash flows. In other words, a new equilibrium price is achieved, and the market will thus not readjust the price.

By classifying industries according to sentiment-prone characteristics; risk, size, growth, and complexity as discussed earlier, we can attempt to explain why the results differ among industries. This allows us to understand whether industry characteristics can explain the subjectivity of certain industries to investor sentiment. Figure 4 below sorts industries by risk, and shows a clear positive trend in RDLH with *Mobile Telecom*, *Mining*, and *Technology* industries having the highest volatilities and *Consumer goods, Healthcare, and Personal household* showing the lowest volatilities. By looking at the chart on industry volatilities, Figure 4, the clear positive trend in RDLH indicates that the riskier an industry, the more subjective it is to investor sentiment. This finding is in line with our theoretical hypothesis that more volatile cash flows increase the difficulty of valuation of an industry, which results in more subjectivity that allows for irrational behaviour to impact the price. However, the *Mining* industry appears to clearly break the positive trend. Despite being the second most volatile industry, it shows a RDLH of -0,6%. One possible explanation of this anomalous behaviour could be that the *Mining* industry is heavily dependent on changes in commodity prices as mentioned earlier. Hence, the subjectivity on the valuation is relatively limited, in other words, if commodity prices increase, valuations increase and vice versa.

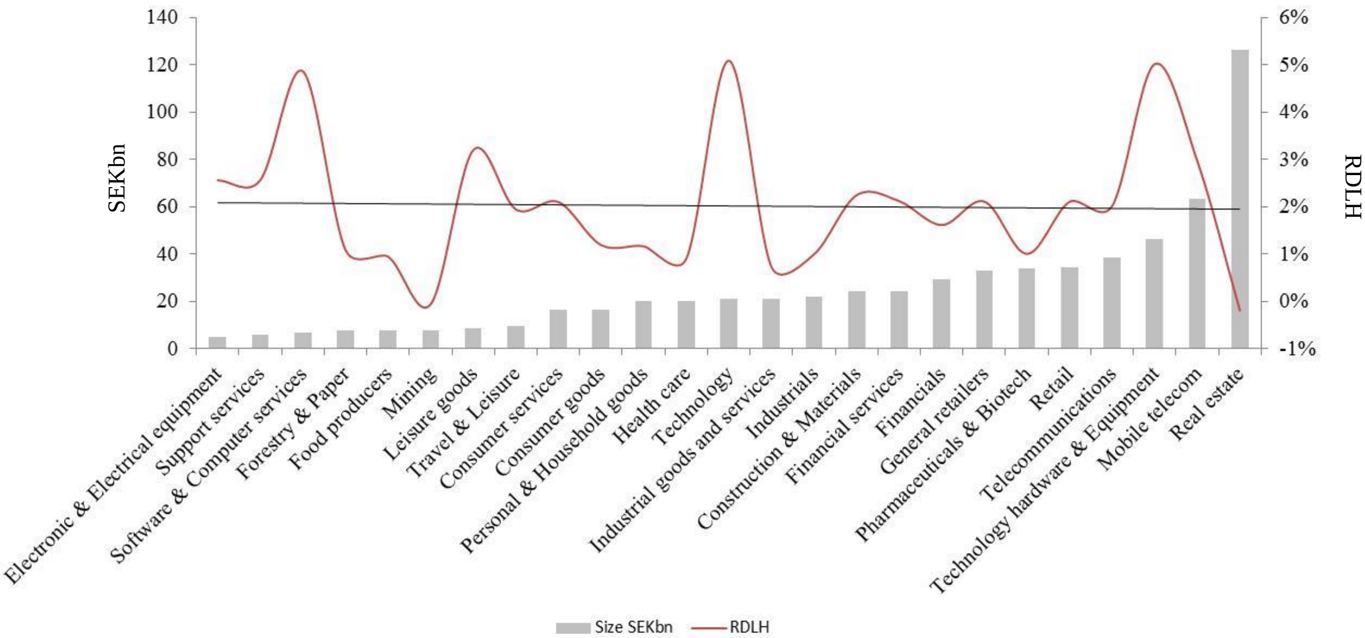
Figure 4. Industry classifications by Risk



The figure sorts all industries by the risk characteristics together with each industry RDLH. The chart shows a positive trend in RDLH. The clear trend in RDLH indicates that the riskier an industry, the more subjective it is to investor sentiment.

Figure 5 sorts industries by size using the average firm market capitalisation as a proxy. The figure shows a slight negative relationship between industry size and RDLH with *Banks*, *Real estate* and *Mobile telecom* being largest industries and *Electronic & Electrical equipment*, *Support services* and *Software & Computer services* being the smallest industries. This negative line indicates that the larger the firm is within an industry, the less impact we expect from investor irrational beliefs. The negative slope does then support our hypothesis.

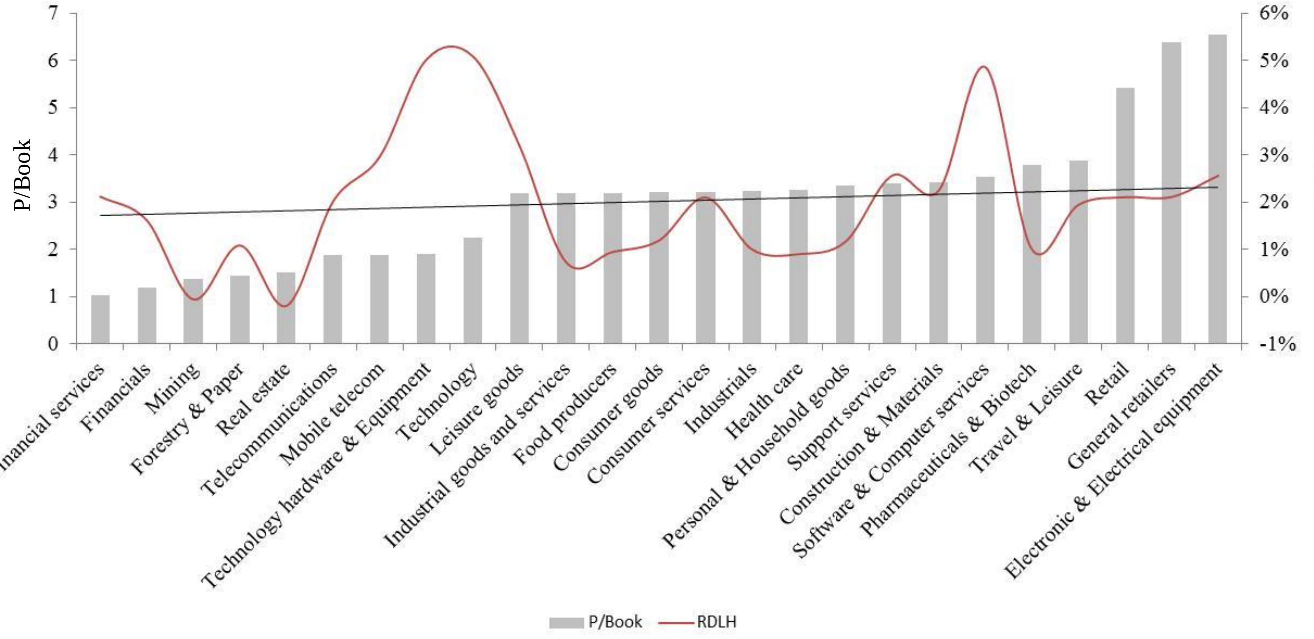
Figure 5. Industry classifications by Size



The figure sorts all industries by the size characteristics together with each industry RDLH. The figure shows a slight negative relationship between industry size and RDLH. This negative line indicates that the larger the firm is within an industry, the less impact from erroneous beliefs from investors can be expected.

Figure 6 on the following page sorts industries by the growth proxy, Price to Book ratio. Similarly to the Size chart, the growth chart depicts only a slight relationship between Price to Book ratio and RDLH. However, in this case the relationship is positive. *Electronic & Electrical equipment, General retailers, Retail and Travel & Leisure* all show the highest growth while *Financial services, Financials and Mining* experience the lowest growth. This result supports the hypothesis presented earlier that high growth industries would be more prone to irrational investor behaviour primarily due to the complexity to value high growth firms.

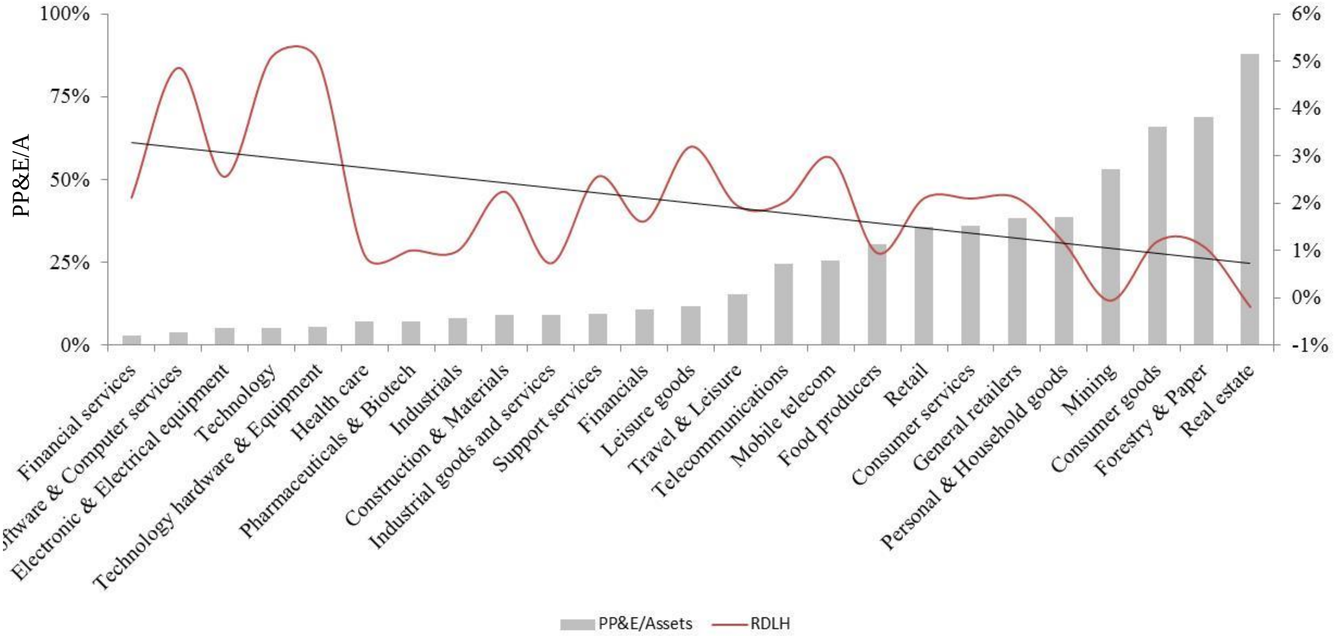
Figure 6. Industry classifications by Growth



The figure sorts all industries by the growth characteristics together with each industry RDLH. The chart depicts a slight positive relationship between the growth characteristics proxy Price to Book ratio and RDLH. This result supports the hypothesis presented earlier, that high growth industries would be more prone to irrational investor.

Figure 7 presented next sorts industries by the complexity characteristics that we proxy using the PPE/TotalAssets ratio. The figure shows a clear negative relationship between RDLH and PPE/TotalAssets with *Real estate, Forestry & Paper, and Consumer goods* with the highest PPE/TotalAssets ratio and *Financial services, Software & Computer services and Electronic & Electrical equipment* having the lowest ratio. As stated earlier, we assume that a larger proportion of PP&E would result in less subjectivity in valuation resulting in the industry being less exposed towards price changes based on irrational investors. The chart clearly shows a negative relationship, which yet again supports our hypothesis. However, it is noteworthy to recognise that the PP&E/ASSET ratio is subject to different forms of accounting principles as well as sensitivity towards yearly changes. This is especially the case for *Industrials* where PPE does not fully include all tangible assets; thus, underestimates the proportions of PPE. Hence, the chart underestimates the negative relationship between RDLH and PP&E/ASSETS.

Figure 7. Industry classifications by Complexity



The figure sorts all industries by the complexity characteristics, proxied by the PPE/TotalAssets ratio, together with the each industry RDLH. The figure shows a clear negative relationship between RDLH and PPE/TotalAssets with Real Estate, Forestry & Paper, and Consumer goods with the highest PPE/TotalAssets ratio and Financial Services, Software & Computer services and Electronic & Electrical Equipment having the lowest ratio. The chart clearly shows a negative relationship, which yet again supports our hypothesis.

The relationship between RDLH and average firm size within the industry and Price/Book is not as apparent as for the Risk and Complexity charts. This is most likely a result of the proxy used that may not be as robust as risk and complexity proxies. This might be due to the fact that the size and Price/Book variables are computed using 2015 year-end data, and are thus more sensitive towards yearly changes, while the Risk proxy is computed over the whole sample, and the Complexity proxy is more stable over time. However, since many of the characteristics are closely related to each other, the results clearly supports our hypothesis that industries that are small, experiencing high growth, more dependent on intangible assets and have more volatile cash flows are more subject to investor sentiment. The chart below summarises the slope of the fitted line for each characteristic.

Table 3. Industry characteristics

Characteristics	Slope
Risk	0.0012
Size	-0.0001
Growth	0.0002
Complexity	-0.0011

The table portrays the slope of the fitted lines for each characteristic. Based on the result, it is clear that the strongest relationship is found between RDLH and the two variables characteristics risk and complexity.

7. Conclusion

Using a direct approach and extracting our measure from the Swedish consumer confidence index, this paper models investor sentiment for two primary reasons; the focal aim is to examine investor sentiment short-term predictability on Swedish cross-industry returns, and subsequently investigate factors affecting industry sensitivity to investor sentiment. Our paper sheds light on several important conclusions that may enhance the understanding of efficient markets and the way investor sentiment impacts industry returns. Principally, we provide evidence for the short-term predictability of investor sentiment on future industry returns on the Swedish stock market, contradicting findings from Brown and Cliff (2004) that limit the predictability to long-term. We find that for some industries, and in line with literature, there exists a negative relationship between investor sentiment and next-month industry return. An additional finding after categorising industries into investor sentiment-prone characteristics is the verification of the earlier presented hypothesis. We found that small industries that experience high growth, that are heavily dependent on intangible assets, and have more volatile cash flows are more exposed to investor sentiment. Results from the industry classification indicate the following; on the one hand, *Consumer goods, Leisure goods, Personal & Household goods, Software & Computer services* and *Support servic*es constitute the list of the most investor sentiment-prone industries. On the other hand, the least exposed industries include *Real estate, Healthcare* and *Mining*. This paper also discerns new evidence; that industries core to the Swedish economy, as opposed to other industries, seem to have a positive relationship with last-month investor sentiment, which can potentially be explained by these industries' close link to the aggregate economy. Practically, these findings may be of interest for traders and portfolio managers although transaction costs might diminish potential gains from trading on investor sentiment.

Seeming overlooked in the literature and with our study being conducted, investor sentiment impact on industry returns is granted various avenues of future research. An important result that might be worthy of further investigating is the behaviour of core industries with regard to investor sentiment; interesting enough, these industries are found to be affected differently in Sweden. Another research path that could potentially contribute to a deeper understanding of the subject is to further analyse different factors that make industries more disposed to investor irrationality. To broaden the research field, and verify the consistency of the predictive power of investor sentiment on industry returns, a cross-border comparison may also be of interest, as one could reason that financial markets in developed countries should react differently to investor sentiment than emerging markets.

8. Appendix

A1. Consumer Confidence questionnaire

Fråga	Svarsalternativ					
1 Hur är Ditt hushålls ekonomiska situation för närvarande jfr med för 12 mån sen?	mycket bättre	något bättre	ungefär lika	något sämre	mycket sämre	vet inte
2 Hur tror Du att Ditt hushålls ekonomiska situation är om 12 mån?	mycket bättre	något bättre	ungefär lika	något sämre	mycket sämre	vet inte
3 Hur tycker Du att den ekonomiska situationen är i Sverige för närvarande jfr med för 12 mån sen?	mycket bättre	något bättre	ungefär lika	något sämre	mycket sämre	vet inte
4 Hur tror Du att den ekonomiska situationen är i Sverige om 12 mån?	mycket bättre	något bättre	ungefär lika	något sämre	mycket sämre	vet inte
* 5a. Hur tycker Du att priserna i allmänhet (dvs de svenska konsumentpriserna) har utvecklats de senaste 12 månaderna?	stigit mycket	stigit ganska mycket	stigit något	varit ungefär oförändrade	sjunkit	vet inte
* 5b/c Hur många procent tycker Du att priserna i allmänhet (dvs de svenska konsumentpriserna) har förändrats de senaste 12 månaderna?		____ %				
* 6b Jämfört med de senaste 12 månaderna, hur tror Du att priserna i allmänhet (dvs de svenska konsumentpriserna) kommer att utvecklas de närmaste 12 månaderna?	stiga snabbare	stiga i samma takt	stiga långsammare	vara i stort sett oförändrade	sjunka	vet inte
* 6c/d. Hur många procent tror du att priserna i allmänhet (dvs de svenska konsumentpriserna) kommer att förändras de närmaste 12 månaderna?		_____%				
7. Hur tror Du att arbetslösheten kommer att utvecklas under de närmaste 12 mån?	öka mycket	öka något	vara ungefär som nu	minska något	minska mycket	vet inte
8. Tycker Du att det i dagsläget är fördelaktigt för folk i allmänhet att göra stora inköp, som exempelvis möbler, tvättmaskiner, tv osv.?	ja, det är rätt tidpunkt	varken rätt eller fel tidpunkt	Fel tidp., inköpet bör ske senare	vet inte		
9. Hur mycket pengar tror Du att Ditt hushåll kommer att använda till inköp av sådana kapitalvaror under de närmaste 12 mån jfr med de senaste 12 mån?	mycket mer	något mer	ung. lika mycket	något mindre	mycket mindre	vet inte
10. Mot bakgrund av det allmänna ekonomiska läget, hur tycker Du att det är att spara för närvarande? Som sparande räknas även minskning av eventuella lån.	mycket fördelaktigt	ganska fördelaktigt	varken eller	ganska ofördelaktigt	mycket ofördelaktigt	vet inte
11. Hur troligt är det att Ditt hushåll kommer att kunna spara något under de närmaste 12 mån? Som sparande räknas även minskning av ev. lån?	mycket troligt	ganska troligt	inte särskilt troligt	inte alls troligt	vet inte	
12. Vilket av följande påståenden beskriver bäst Ditt hushålls nuvarande ekonomiska situation?	vi sparar mycket	vi sparar något	vi går ungefär jämnt upp	vi skuldsätter oss/utnyttjar sparade medel i begränsad utsträckning	vi skuldsätter oss/utnyttjar sparade medel i stor utsträckning	vet inte
13. Hur troligt är det att Ditt hushåll köper eller byter bil under de närmaste 12 månaderna?	mycket troligt	ganska troligt	inte särskilt troligt	inte alls troligt	vet inte	
14. Kommer Ditt hushåll att bygga eller köpa ett hus eller en lägenhet inom de närmaste 12 mån? (avsett som permanentbostad, fritidshus eller för uthyrning)	ja, absolut	ja, troligen	troligen inte	absolut inte	vet inte	
15. Hur troligt är det att Ditt hushåll kommer att använda någon större summa pengar för förbättringar av bostaden/fritidshuset under de närmaste 12 mån?	mycket troligt	ganska troligt	inte särskilt troligt	inte alls troligt	vet inte	
16. Har risken för att Du själv ska bli arbetslös under de senaste 12 mån …?	ökat mycket	ökat något	är ung. som nu	minskat något	minskat mycket	vet inte
18a/c. Idag är den rörliga räntan för bostadslån … procent. Hur hög tror Du att den rörliga boräntan är om 1/2/5 år?	____%	vet inte				

The table depicts all questions asked in the original monthly consumer confidence survey. Two of the questions require precise number estimation (forward, looking and backward looking inflation estimations), the other questions are answered by a scale of one to six. A translation in English can be requested from the authors.

A2. Output from Three-step model regression 2 (Equation 3)

Industry	OMXER	SMB	HML	R^2	Industry	OMXER	SMB	HML	R^2
Construction and materials	1.0990***	0.3592***	0.2584***	0.6680	Mining	1.6104***	0.9514***	0.4179**	0.3889
Consumer goods	0.8163***	0.391***	0.2352***	0.6609	Mobile telecom	1.4351***	0.2720	-1.1840***	0.3654
Consumer services	0.6964***	0.1724*	-0.2333**	0.5149	Personal & Household goods	0.7947***	0.4006***	0.2895***	0.5977
Electronic & Electrical equipment	1.3365***	0.3950***	0.1420	0.5602	Pharmaceuticals & Biotech	0.4531***	0.1582	0.0891	0.1586
Financial services	1.1534***	0.2191***	0.0948	0.8276	Real estate	0.8086***	0.5569***	0.3312***	0.5287
Financials	1.1521***	0.1107**	0.4245***	0.8474	Retail	0.6206***	0.0846	-0.3120**	0.3716
Food producers	0.4865***	0.3910***	-0.1842	0.2649	Software & Computer services	1.2376***	0.4665***	-0.8691***	0.7044
Forestry & Paper	0.8354***	0.2470**	0.4164***	0.4584	Support services	0.9366***	0.2210**	0.0545	0.5270
General retailers	0.6254***	0.0657	-0.3205**	0.3648	Technology	1.2211***	-0.6987***	-0.8069***	0.7599
Health care	0.5270***	0.2562***	0.0236	0.2756	Technology hardware & Equipment	1.2243***	-0.8305***	-0.7874***	0.7459
Industrial goods and services	1.1577***	0.3643***	0.2066***	0.8066	Telecommunications	0.7264***	-0.1529	-0.1015	0.3874
Industrials	1.1567***	0.3550***	0.2207***	0.8395	Travel & Leisure	0.9433***	0.4577**	0.0971	0.3853
Leisure goods	0.6510***	0.6088***	-0.4021*	0.3013					

The table portrays the contemporaneous relationship between Fama and French three factors and the industry returns. The output indicates that in line with classical financial theory, Fama and French Three-Factor model does have a contemporaneous explanatory power on returns in general and industry returns in particular. Comparing regression one and two, it is clear and expected that $\mathbf{R}^2$ values increase sharply. The $\mathbf{R}^2$ values increases from a range of 0.1-7% when only the SENT variable is included to 20-80% for the Three-Factor model.

Sig 10%*, Sig 5%**, Sig 1%***

A3. Output from Three-step model regression 3 (Equation 4)

Industry	SENT	OMXER	SMB	HML	R^2	Industry	SENT	OMXER	SMB	HML	R^2
Construction and materials	-0.0002	1.0979***	0.3620***	0.2657***	0.6665	Mining	0.00065	1.6222***	0.9166***	0.2964	0.3829
Consumer goods	-0.0006*	0.8124***	0.4006***	0.2610***	0.6652	Mobile telecom	0.00124	1.44290	0.2523	-1.23561	0.3641
Consumer services	0.0001	0.6970***	0.1708**	-0.2375*	0.5124	Personal & Household goods	-0.0007*	0.7903***	0.4119***	0.3186***	0.6029
Electronic & Electrical equipment	0.0002	1.3378***	0.3916***	0.1330	0.5580	Pharmaceuticals & Biotech	-0.00054	0.4497***	0.1669	0.1115	0.1578
Financial services	0.0005	1.1566	0.2108	0.0733	0.8291	Real estate	0.00054	0.8119***	0.5483***	0.3090***	0.5295
Financials	0.0001	1.1529***	0.1088	0.4197***	0.8467	Retail	0.00015	0.6215***	0.08209	-0.3184**	0.3684
Food producers	0.0003	0.4883***	0.3866***	-0.1958**	0.2620	Software & Computer services	-0.0011*	1.23097	0.48340	-0.82549	0.7074
Forestry & Paper	-0.0006	0.8314***	0.2572**	0.4426***	0.4596	Support services	-0.0010*	0.9305***	0.2367***	0.09495	0.5328
General retailers	0.0002	0.6270***	0.0618	-0.3305**	0.3619	Technology	0.00068	1.2254***	-0.7098***	-0.83536	0.7599
Health care	-0.0001	0.5266***	0.2573**	0.0263	0.2717	Technology hardware & Equipment	0.00101	1.2307***	-0.8467***	-0.8292***	0.7470
Industrial goods and services	0.0008***	1.1627***	0.3514***	0.1736***	0.8114	Telecommunications	-0.00020	0.7251***	-0.14966	-0.09327	0.3844
Industrials	0.0008**	1.1609***	0.3442***	0.1929***	0.8430	Travel & Leisure	-0.00024	0.9418***	0.4615***	0.10694	0.3823
Leisure goods	-0.0024***	0.6358***	0.6477***	-0.3020***	0.3401						

The table depicts the result from regression 3 (equation 4) where both the investor sentiment variable and the Three-Factor model is included. The result show that after adding investor sentiment variable, 11 industries show the expected negative relationship between investor sentiment and industry returns one period ahead. We also observe that, when investor sentiment variable is added to the regression equation, and when it is significant, coefficients for Fama and French Three-Factor model all decrease. Regarding the explanatory power of the regression, when investor sentiment variable is added in the last step, $\mathbf{R}^2$ values slightly increase for 11 industries out of 25 industries.. This result would indicate that the Fama and French Three-Factor model can be improved by including an irrational variable for certain industries. What is interesting to note is that for the industrials and *Industrial goods & Services*, the sign of the SENT coefficient is positive and significant.

Sig 10%*, Sig 5%**, Sig 1%***

9. References

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