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DOES INVESTOR SENTIMENT MATTER FOR STOCK RETURNS IN THE FINNISH STOCK MARKET?

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ABSTRACT

This study aims to test if investor sentiment affects stock returns in the Finnish stock market. Previous research suggests a negative relationship between sentiment and subsequent returns on stocks that are considered speculative. As the behavioral theories suggest that individual investors are more likely to be subjects to sentiment and act on noise, it is presumable that small stocks, commonly held by individual investors, are more prone to shifts in sentiment. I test whether two confidence measures have an impact on stock returns in Finland, and whether the impact differs between speculative stocks and large bond-like stocks. Additionally, I aim to distinguish the irrational part of sentiment from the sentiment measures and test its possible effects on stock returns.

Investor sentiment and its possible effects on stock returns have been widely discussed in the finance literature. Classical finance assumes that majority of investors are rational utility maximizers who make unbiased estimations about stock returns, and that possible misvaluations are quickly corrected by rational arbitrageurs. Thus, stock prices are unpredictable, valued in accordance with their fundamentals, and always fully reflect all available information in markets. Behavioral finance challenges this view by arguing that psychological and sociological have an important role in the way that investors behave in the markets. Previous findings suggest that investor sentiment may play a role in security market under- and overreactions.

I find that contemporaneous changes in both sentiment measures are positively related to stock returns. Especially indices consisting of small stocks are subjects to shifts in sentiment. Changes in both sentiment indices have only weak forecasting power on the returns of the stock indices. Irrational sentiments show significantly negative effects on subsequent stock returns, but the explanatory power of sentiment is relatively trivial. In addition, I find no evidence that the irrational sentiment would primarily affect speculative stocks.

KEYWORDS: Behavioral finance, Investor sentiment, Overreaction

1. INTRODUCTION

Investor sentiment has been a widely discussed topic in the field of finance for decades. In classical finance the sentiment does not play any part, while stock prices reflect the discounted value of expected cash flows and irrational pricing is quickly washed away by rational arbitrageurs. However, from the behavioral finance perspective, waves of irrational sentiment, for example overly optimistic or pessimistic expectations, can be influential enough to affect asset prices for significant periods of time. There exists no common consensus among academics on how sentiment should be defined. According to DeLong et al. (1990) sentiment is a formation of beliefs about future cash flows and investment risks that are not justified by the facts at hand. Baker and Wurgler (2006), on the other hand, see investor sentiment as a propensity to speculate. Brown and Cliff (2002) state that "sentiment intuitively represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be" (2002: 2).

Investor sentiment is closely related to the concept of noise trading introduced by Black (1986). He asserts that some investors trade on a "noisy" signal that is not related to fundamentals, and that these "noise traders" cause prices to deviate from their intrinsic values. Behavioral theories suggest that psychological and sociological factors play an important role in investors' decision making process and hence in price formation. According to behavioral finance, securities' expected returns are determined by rational risk factors as well as investor misvaluation. (Hirsleifer 2001: 1). Misvaluations appear in the form of over- and underreactions to new information. The empirical findings seem to suggest short-term return continuations and long-term returns reversals, which are against the idea of random walk in stock prices.

Literature regarding the effects of sentiment is controversial. Most studies find that high sentiment, in other words, superfluous optimism is negatively related to subsequent stock returns. It has been suggested that the negative effect is a sign of initial overreaction, which is followed by a correction to fundamental prices. This negative impact of sentiment has shown to be especially pronounced for stocks that are hard to value and arbitrage. In contrast, some research suggests that sentiment has a stronger impact on returns of large and value stocks. These contradictions may be due to the fact that there exists no precise definition, nor measure for sentiment. Hence, the use of different sentiment measures in studying the impacts of sentiment may result in alternating results. Moreover, as sentiment is closely related to behavioral biases and these biases differ among cultures, the effects of sentiment might differ between countries.

In previous research a vast repertory of sentiment measures has been suggested. In this study I test whether the survey measures of Consumer Confidence and Economic Sentiment affect stock returns. Qui & Welch (2006) and Lemmon & Portniquina (2006) suggest that consumer confidence measures are strongly related to other measures of sentiment and play a significant role in financial market pricing.

1.1. Purpose, scope and contribution

The purpose of this thesis is to study the effects of investor sentiment on stock returns in the Finnish stock market during 2001-2014. I test, whether the chosen sentiment measures have an impact on aggregate stock market returns (OMXH-index) in Finland. In accordance with previous research (Fisher & Statman 2003) a negative relationship between sentiment measures and subsequent aggregate stock market returns is expected. Hence, the first hypothesis is:

H1: Consumer Confidence Index and Economic Sentiment Indicator have a negative impact on subsequent aggregate stock market returns in Finland.

More specifically, this study aims to answer the question whether stocks that are considered speculative (e.g. small and growth stocks) are more sensitive to sentiment in contrast to large value stocks. Previous studies suggest that retail investor sentiment primarily affects small stocks as they are disproportionally held by small investors. Thus, firm size is a natural variable to use when studying the relationship between sentiment and stock returns. In addition, small stocks are usually less liquid compared to large stocks, which enhances the impact of sentiment on their returns. The second hypothesis is as follows

H2: The impact of Consumer Confidence Index and Economic Sentiment Indicator is stronger for stocks considered more speculative compared to bond-like stocks.

Previous research [Lemmon & Portinaquina (2006), Chen (2011), Kholdy & Sohrabia (2014)] suggests that investor sentiment is formed on the basis of rational and irrational factors. In this study both survey measures of sentiment are controlled by several macroeconomic factors in order to separate the irrational components of sentiment. After that the impacts of irrational sentiment (adjusted sentiment) on stock returns is tested. Brown and Cliff (2006) and Lemmon & Portinaguina (2006) document that prices of speculative stocks tend to be negatively related to lagged sentiment and this negative relationship is suggested to reflect corrections to an initial overreaction of investors. I observe whether the stock prices in Finland show similar behavior. Hence, the third hypothesis is:

H3: The adjusted sentiments have a stronger negative impact on subsequent returns of stocks that are considered speculative compared to returns of bond-like stocks.

Consumer confidence index and Economic sentiment indicator are used as proxies for sentiment in this study, as prior research suggests that confidence measures are closely related to investors’ market expectations. The predictive power of sentiment on various index returns is tested using a linear regression approach. This study contributes to the previous literature in that the effect of sentiment on stock returns is studied in the Finnish stock market. Moreover, to my knowledge the measures of Consumer Confidence Index (CCI) and Economic Sentiment Indicator (ESI) have not been used as measures for sentiment in Finnish stock markets before. Most previous literature regarding investor sentiment focuses on U.S. stock markets. U.S. stock markets differ from Finnish markets in their magnitude but also in the proportion of retail investors. In U.S, households own approximately 38% of the equity market (The Goldman Sachs Group. Inc. 2013), whereas in Finland, household ownership sums up to approximately 22% (Euroclear Finland 2015). As previous research shows that retail investors are most likely to be affected by sentiment, it is presumable that there are differences in the magnitude of the effect of sentiment depending on the country. Lehman, Chiu & Schaller (2004) suggest that cultural differences might also have a significant role for the relative strength of behavioral biases between countries.

1.2. Structure of the study

The purpose, scope and hypotheses of the study are introduced in the first chapter. Chapter two covers the theoretical background of the subject and introduces the differences between neoclassical finance and behavioral finance approach. Chapter three gives an overview on previous research regarding investor sentiment and its effects on stock returns. Chapter four covers the data and methods used in this study. Chapter five discusses the research results and the last chapter concludes the findings.

2. THEORETICAL FRAMEWORK

2.1. Market efficiency

The efficient market hypothesis (EMH), first introduced by Eugene Fama, claims that security prices fully reflect all available information when trading and information costs are zero. When new information arises, news spread rapidly and is incorporated in the prices without delay. (Fama 1970: 383–384). Hence, changes in stock prices represent the efficient discounting of new information and stock price is based on the expected present value of its dividends, using a constant discount rate (West 1988: 37). If there is incremental risk associated to the expected cash flow, a rational investor will require extra return to compensate for the risk (Martson & Harris 1993: 117). In efficient markets, a large number of well informed, profit maximizing investors do their best trying to forecast future market values of individual stocks. This competition among investors results in a situation where actual prices of individual assets already reflect not only the information based on past events, but also events that markets expect to take place in future. Thus, in efficient markets, price of a security is an accurate estimate of its fundamental value at any given time. (Fama 1995: 76). EMH consists of three forms; the weak form of market efficiency implies that all historical price information is fully reflected in present prices. The second, semi strong form, implies that prices also reflect all public information whereas the third, strongest form, states that prices reflect all information, including inside information. (Bodie, Kane & Marcus 2009: 349, 359.)

EMH is closely connected to the theory of random walk, which implies that past history of stock price series cannot be used to predict future prices of stocks in any relevant way. In other words, stock prices have no memory and the price level of a security should not be more predictable than a series of cumulated random numbers (Fama 1995: 76). As all relevant information is incorporated into stock prices immediately and consecutive price changes are independent, it is impossible for an investor to make a strategy based on technical trading rules that would increase his expected gains (Malkiel 2003: 59). Random walk theory also challenges investment strategies based on company fundamentals. If the theory of random walk holds and if markets are information efficient, there are no additional gains to be made based on the analysis of company fundamentals. As stock prices already reflect all relevant information, a possibility for an investor to earn additional earnings only arises, when he or she has new information about the stock. If the trader has no inside information or other proprietary information regarding the stock, he or she may as well choose a stock portfolio through a random selection. (Fama 1995: 80.)

Market efficiency can be tested using asset pricing models that provide an explanation between risk and asset returns. The most well-known model is the capital asset pricing model (Sharpe 1964, Litner 1965), which is based on the Markowitz mean-variance efficiency model. In this model investors are assumed to be risk-averse with one-period investment horizon, and to care only about expected returns and the variance of returns (risk). Risk averse individuals value a gamble in accordance with its expected return. The risk of an investment is measured by beta, which is the covariance of asset returns with the market returns relative to variance of the market. Additionally, all investors are assumed to have identical assumptions about the distributions of the returns. Investors choose efficient portfolios with given variances based on their individual risk aversion (Fama & French 2004: 49-50). Thus, an investment decision is made so that it maximizes the expected utility of wealth for the investor (Black 1986: 534). Under the standard theory of expected utility, an investor who has to allocate his or her wealth between a safe and a risky asset, will buy some of the asset if the expected (present) value is larger than the price of the asset. Contrariwise, the investor will sell the asset short if the expected value is less than the current price.

As seen above, efficient market theory is based on several assumptions on investor behavior in markets. According to efficient market theory, investors learn to make correct judgments about the influence of new information on the probability distribution of potential stock returns. (Brown et al. 1998: 355.) However, in an uncertain world, it is very difficult to determine the exact fundamental value of a security, and disagreement always exists among market participants. According to Fama (1995) this disagreement gives rise to discrepancies between actual prices and fundamental values. Although discrepancies exist, competition among rational market participants causes stock prices to wander randomly around their fundamental values (1995: 76). Efficient market theory does recognize that some investors might not be fully rational, and that actions of these irrational investors could cause prices to deviate from their fundamental values. However, in the case of mispricing, rational, well informed investors – or ‘arbitrageurs’, will quickly observe the mispricing and drive prices back to their fundamental levels (Delong et. al 1990: 704). Moreover, classical finance sees that overpricing of stocks is as common as underpricing, making them a chance result.

2.2. Behavioral Finance

By the start of the twenty-first century, efficient market theory has lost some of its popularity among academics. Research has shown that stock prices tend to violate the theory on random walk and can be predicted to at least some extent. Behavioral finance takes a wider, social science perspective in studying financial markets and argues that psychological and sociological factors have an important role in explaining some financial phenomena that rational financial models are not able to explain (Shiller 2003: 83). Behavioral finance disregards the traditional assumptions of rationality and utility maximizing investors and uses broader-minded models in studying financial markets (Ritter 2003: 429). Behavioral finance is based on two building blocks: cognitive psychology and limits to arbitrage. Cognitive psychology refers to people's mental processes whereas limits to arbitrage refers to forecasting the circumstances in which arbitrage forces will be powerful and in which they will not be. Behavioral finance is interested in the systematic errors in investors' metal processes that cause individuals to act irrationally in the markets.

As opposed to efficient market theory, behavioral finance asserts that investors act irrationally to the extent that they cause misvaluations in financial markets. Moreover, due to impediments in short selling, arbitrageurs are not always able to step in and drive stock prices back to their fundamentals (Ritter 2003: 430.) Hirshleifer (2001) states that the arbitrage argument of classical finance has two sides: The same way that rational investors arbitrage the mispricing away, irrational investors arbitrage away efficient pricing as well. Miller (1997) states that in the markets with little or no short-selling, an optimistic minority of investors can drive the price of a given security up, since they are the ones who set the demand for the particular security. Additionally, due to some overpowering cognitive tasks, which efficiency would require, all investors might be irrational in some respects (Hirshleifer 2001: 1536.) The next section introduces some of the most well-known psychological biases and their possible consequences for asset pricing.

2.2.1. Psychological biases

A large body of evidence from cognitive psychology experiments shows that people tend to repeat patterns in their behavior. Behavioral finance suggests that heuristics have in important role in investors' decision making processes. Heuristics can be defined as rules of thumb that makes judging a likelihood easier, when the use of cognitive resources is limited. Although rules of thumb can be useful in some tasks, applying them in a wrong context can result in harmful biases. Psychological research has shown that people tend to have similar heuristics and may also be subject to similar biases. Thus, although rational finance theories assume that irrational investors do not affect market prices as their trades cancel each other out, it is possible that a common bias among a large amount of investors is influential enough to move stock prices from their fair values (Hirshleifer 2001).

Overconfidence refers to the fact that people overestimate their own abilities in several contexts. Psychological evidence shows that overconfidence is more predominant in tasks which require judgment and from which the feedback is delayed, in contrast to more mechanical tasks from which the feedback is received immediately. Thus it can be assumed that overconfidence would be present in security valuation, where judgments about uncertain future outcomes are required and feedback is not received immediately (Daniel, Hirshleifer & Subrahmanyam 1998: 1884). Daniel et al. (1998) argue that investors overestimate their own capabilities in valuing securities and underestimate their forecast error. Investors who believe that their valuations of securities are more accurate than they actually are, trade more compared to rational investors. Odean (1998) finds confirming evidence and shows that overconfident investors trade more compared to others and suffer from excessive trading costs, which in turn lowers their expected utility (1998: 1916.)

If over-confident investors fail more than they expect to, one could assume that these investors would learn out of overconfident behavior. Biased *self-attribution* is seen as an important tumbler in people’s learning process, and hence a booster for overconfidence. Self-attribution bias occurs when people take the credit for past success and blame external factors for failure. Daniel et al. (1998) suggest that due to self-attribution bias, investor confidence rises when public information is in line with the investor’s private information, but falls only modestly when public information contradicts private information. This suggests that among overconfident investors new public information can result in further overreaction to foregoing private signal (1998: 1842). *Self-deception*, which is a tendency to grow attachment to activities one has spent resources on, also enhances overconfidence. According to the self-deception theory, people tend to adjust their attitudes to match past decisions in a way that reassures them of their skillful decision making. (Hirsleifer 2001: 11.)

Shefrin and Statman (1985) identify that investors have a tendency to hold on to poorly performing stocks for too long, and sell winning stocks too early. This tendency is called a disposition effect. Self-deception may be a partial explanation for disposition, since realizing losses would indicate a low decision making ability of the investor. Thus, by holding on to a poorly performing stock, an investor does not need to admit his/hers lack of ability in decision making (Hirsleifer 2001: 11). Another explanation for disposition effect may be *conservatism*. Conservatism implies that under some circumstances, investors do not revise their current beliefs in the way that a rational Bayesian would, when faced with relevant new information. According to Hirsleifer (2001) one explanation for conservatism is that processing new information and revising current beliefs is cognitively too costly. People tend to underweight information that is represented in a statistical or abstract form, and overweight information, in which causal relationships are easily observable and the information is simple to process. *Confirmatory bias* is closely related to conservatism. People have a tendency to interpret unclear information in a way that is consistent with their prior beliefs. Contradicting new information is examined with caution and possibly explained as a chance result or faulty data gathering. (2001: 14.)

On the other hand, the biases of *representativeness and salience* imply that people extrapolate too powerfully from patterns in small samples, and overreact to some type of information. For example, under uncertainty, investors tend to believe that an excellent past performance on a given firm is "representative" of the firm's future performance or that a poorly performing company will continue to perform poorly. (Boussaidi 2013: 10). Thus, representativeness heuristics can result in trend chasing, as people believe that trends have systematic causes. *Clustering illusion* appears, when people interpret random clusters as causal patterns and fail to recognize that the occurrences are serially independent. (Hirsleifer 2001: 14.)

As different psychological biases tend to presume different kind of reactions to new market information, the possible effects of the biases should be observed in the setting that they occur in. For example, self-deception may be at its strongest in a stable environment, when an investor has absorbed a perception and is unwilling to admit that he or she has made an erroneous decision. In contrast, in a volatile environment, it might be easier for the investor to admit that different opinions are needed. (Hirsleifer 2001: 14).

2.2.2. Limits of Arbitrage

Efficient market theory asserts that though some investors may be irrational and misevaluate stocks, rational well-informed investors will quickly recognize these mispricings as excess profit opportunities and drive the prices back to their intrinsic values. Thus, arbitrage plays an important role in ensuring market efficiency and keeping prices on their fundamental levels. The simple text-book definition of arbitrage asserts that arbitrage is a risk-free opportunity to simultaneously purchase and sell the same security in two different markets with a different price, and earn a certain gain. However, in reality arbitrage almost always contains a risk. (Shleifer & Vishny 1997: 35). Additionally, whether arbitrage is riskless or risk-free, it requires capital. The larger the observed mispricing, the more capital is needed to correct it. Although the efficient market theory assumes that arbitrage is conducted by all rational market participants, in reality, only relatively few professionals have the information and ability to engage in arbitrage with large positions. Most typically arbitrage is conducted by market professionals who manage other people's money. According to Shleifer & Vishny (1997) arbitrage is especially ineffective in situations where prices are far from their intrinsic values and arbitrageurs are fully invested. When prices further deviate from their fundamental values, people who have provided capital for the arbitrage, observe that the arbitrageur is losing money and will want to bail out. Thus, arbitrageurs may avoid especially volatile arbitrage positions, even if such positions may offer substantial returns. The risk of losses and urge to liquidate the portfolio under the pressure from fund holders prevents arbitrageurs from driving prices to their fundamental levels. (Shleifer & Vishny 1997: 54.)

Another important factor limiting arbitrage is short-sale constrains. According to Miller (1977), when investors differ in their opinions about a value of a risky security, short-sale constrains will cause the price of a security to disproportionately reflect positive information. Hence, as a result of impediments to short-selling, the opinions of bearish investors are not revealed in prices. Short-sale constrains have been found to lead to artificially inflated prices, which are indicated by excessive returns. Stocks that are subject to higher short-sale impediments tend to have lower price efficiency (Saffi & Sigurdsson 2011: 821).

2.3. Noise trading

There exists substantial evidence that many investors do not follow advice of economists to buy and hold the market portfolio. Instead, individual investors fail to diversify their portfolios by holding just a single stock or a small number of stocks. These investors choose their stocks according to their own research rather than the recommendations of professionals (DeLong, Sheifler, Summers Waldmann 1990: 704). Black (1986) defines such investors as “noise traders”. Typically, noise traders are investors with no access to inside information, who irrationally act on noise as if it was information that would give them advantage in the markets. According to Black (1986) noise-trading accounts for a significant proportion of overall trading in securities markets and is essential to the existence of liquid markets. On the other hand, noise trading also generates noise into the prices. Thus, stock prices are formed on the basis of information that rational information traders trade on and noise that noise trader trade on. In other words, a price of a security is always a noisy estimate of its value. (1986: 531)

Black (1986) states that an increase in noise trading makes trading on information more profitable. However, the profit is not guaranteed due to the risk of trading against noise. As the noise in prices increase, information traders take larger positions in order to eliminate the noise. The larger the positions are, the larger the risk becomes, and there will be a limit to how large a position an information trader is willing to take (1986: 531). Similarly, Delong et al. (1990) find that arbitrageurs tend to be risk averse and have moderately short horizons. Thus, they have limitations in taking positions against noise traders (1990: 705). The noise that noise traders generate into prices cumulates over time and stock prices deviate further from their fundamental values (Black 1986: 532). It might take a long time for noise traders to lose their money and during this time, arbitrageurs have to bear fundamental risk while holding the opposite position. The risk might even become more extreme before the noise traders’ beliefs revert, and if the arbitrageurs have to liquidate before the reversion, they suffer losses. The same logic applies to short positions of arbitrageurs. If noise traders’ bullishness increases after arbitrageurs have taken short positions, arbitrageurs have to account for the risk that they have to buy the stock back with a higher price. In sum, arbitrageurs cannot eliminate the mispricing caused by noise traders because noise itself creates a risk. Hence, prices can deviate significantly form fundamental values even though no fundamental risk exists (Daniel et al. 1990: 705-706). Eventually information traders are able to drive the price back to its intrinsic value, but the move is often so gradual that it is hard to observe. Brasky and De Long (1993) propose a model that accounts for the role of noise traders in the markets:

(1) $$p_t = d_t/(r - g_t),$$

Where g_t is the permanent growth rate in dividends from date *t*. This permanent growth rate is the expected average dividend growth rate following date *t*. Despite the fact that g_t is assumed to be constant as of date *t*, the dividend is not fixed. Hence, each day investors revise their estimates of the dividend growth based on new information that arrives to the markets. According to Barsky & De Long (1993), dividend (d_t) and dividend growth rate (g_t) are positively correlated, meaning that when dividend changes, investors generalize this change into the future, causing a positive change in dividend growth rate as well. Hence, the positive change in d_t affects the price not only through the numerator but also indirectly through the growth rate. As g_t is positively affected by d_t, the stock price will grow more proportionately. This model explains why stock prices may overreact to new positive information. (1993: 203).

Daniel et al. (1998) propose a model that accounts for investor confidence and its impact on possible over- and underreactions to public and private information. In their model, overconfidence in the private information results in an initial overreaction in a stock price. Later on, when noisy public information arrives, part of the overreaction in the price is corrected. The overreaction in the stock price gets fully corrected after further public information arrives to the market. The overreaction phase is the impulse response prior to the price peak or through which is followed by a correction phase (1998: 1847). Indeed, many papers (Jegadees & Titman 2009, Moskowitz & Grinblatt 1999, Cooper et. al 2004) show a short-run continuation in stock prices, which violates the theory of efficient markets. These findings are in support of overreaction of market participants.

Barberis et al. (1998) propose an alternative model for overreaction in stock prices. In their model the stock market follows a random walk but an investor is under the clustering illusion, and does not recognize the serial independence of prices. In contrast, the investor falls to the fallacy of representativeness and believes that series of good news are a sign of consistent good performance in the future as well. This bias causes an overreaction described by

(2) $$E(r_{t+1}|z_t = G,_{z-1} = , \dots , z_{t-j} = G) < E\left(r_{t+1}\middle|z_t = B,_{z-1} = , \dots , z_{t-j} = B\right),$$

Where j is at least one and probably higher, $z_t = G$ or $z_t = B$ denotes either good news (*G*) or bad news (*B*) at period t, and $E(r_{t+1})$ is the expected stock return in the period following an announcement. The model implies that series of good news will cause the investor to become overly optimistic, which in turn drives the stock price to unduly high levels. Later on, when new information contradicts investors' optimism, subsequent returns are lower (Barberis et al. 1998: 313).

3. PREVIOUS RESEARCH

As early as in 1936, John Maynard Keynes stated that the market is “subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate where no solid basis exists for a sound calculation.” (1936:154). According to Keynes, although people try to make rational decisions between the alternatives available, and calculate where they can, they often fall back to their motive on caprice, sentiment, or chance (1936: 154). The rational asset pricing models have not left much role for the impact of investor sentiment in the valuation of assets. Miller (1977) provides an alternative view for the neo-classical decision making theory and argues that it is hardly rational to assume that all investors would have the exact same predictions about the future, while it is so hard to forecast; The price of a security should be higher, the greater the difference of opinion about the return from the security. According to Miller (1977), difference of opinion increases with risk, which may result in lower expected return for risky securities rather than high. (1977: 1154-1155.)

Behavioral finance suggests that sentiment of investors is an important factor in the formation of asset prices. Investor sentiment can be defined in various ways. DeLong et al. (1990) see it as a formation of beliefs about future cash flows and investment risks that are not justified by the facts at hand. Baker and Wurgler (2006), on the other hand, see investor sentiment as a propensity to speculate. According to Brown and Cliff (2002) “sentiment intuitively represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be“ (2002: 2). DeBondt and Thaler (1985) suggest that investors are subjects to waves of optimism and pessimism. These waves cause prices to deviate temporarily from their fundamental values and to exhibit mean reversion later on.

Indeed, recent market history has experienced episodes where market prices could not have been set by rational investors, and where psychological factors have played an important role. In October 1987 the Dow Jones industrial Average (DIJA) lost approximately one-third of its value without any substantial change in the overall economic environment. Another example of an extreme episode in the financial markets is the ‘Internet bubble’ in the late 1990s, when the valuations for Internet and related high-tech companies were highly over their fundamentals. (Malkiel 2003: 73.) Individual investors thought that stock market was in a bubble in the late 1990s and early 2000. The deflating market of 2000 and 2001 affected negatively to investor expectations but did not deflate the optimism of investors about their own luck and abilities. Investors tend to form their expectations as if inflated bubbles continued to inflate and deflated bubbles continued to deflate. As the stock market is overvalued, investors expect high returns, while during undervaluation of the markets, investors expect low returns. (Fisher & Statman 2002: 17.)

3.1. Measures of investor sentiment

Investors are not alike and neither are their sentiments. (Fisher and Statman 2000:16). Many papers (Brown & Cliff 2004, Verma & Verma 2007, Kholdy & Sohrabia 2014) suggest that the sentiment of different groups of investors differ from each other. As there is no precise valuation model for sentiment, it is difficult to study the effects of sentiment empirically. On the grounds of previous literature, measures of sentiment can be broadly divided into two groups: direct and indirect measures. Direct measures are obtained using surveys and questionnaires given directly to investors, whereas indirect measures, are financial variables that capture the effects of sentiment to some extent. Commonly used indirect measures are for example closed-end fund discount (CEFD), put-call ratio, Initial public offerings (IPOs), advancing issues to declining issues, and market liquidity. Survey measures of sentiment have been found to be significantly related to indirect sentiment proxies. (Brown & Cliff 2004: 14).

3.1.1. Direct measures of sentiment

Direct measures of sentiment are obtained through surveys and questionnaires, in which investors are asked about their market views. Commonly used survey measures of investor sentiment are the American Association of Individual Investors (AAII) and Investor’s Intelligence (II). In the survey conducted by American Association of Individual Investors (AAII), respondents are asked about their market views for the following 6 months: up, down, or the same. The respondents are random members of AAII, and thus the survey interprets the sentiment of individual investors. Investors Intelligence survey on the other hand can be seen as a sentiment proxy for institutional investors, as it is conducted from market newsletters, mostly written by market professionals. For both of the surveys, the responses are categorized as bullish, bearish or neutral. (Brown & Cliff 2004: 6-7).

Brown and Cliff (2004) study the relationship between the individual sentiment measure of AAII and institutional sentiment measure of II, and find that institutional sentiment is a significant predictor of individual sentiment but not vice versa. (2004: 19-22). Verma & Verma (2007) confirm this finding. Kholdy & Sohrabian (2014) show contradicting results and state that individual sentiment (AAII) has a statistically significant and large impact on institutional sentiment (II). However, they state that past stock returns have affected individual sentiment greater than institutional sentiment.

Fisher and Statman (2000) study the relationship between AAII, II, and the sentiment of Wall Street strategists, who are considered as the most professional large investors. They suggest that sentiment of large investors can be measured by the mean of asset allocation to stocks of Wall Street strategists (2000: 16). They report a strong and statistically significant relationship between the sentiments of individual investors (AAII) and newsletter writers (II). However, the sentiment of Wall Street strategists does not seem to have a strong relation to the two other groups. They find a negative and statistically significant relationship between the sentiment of small investors and S&P 500 returns in the following month. Also, Wall Street strategists' sentiment is found to be negatively related to near future S&P 500 returns. However, the sentiment of newsletter writers does not seem to be correlated with subsequent stock returns. (2000: 18-17).

In addition to investor sentiment indices such as AAII or II, which are based on surveys targeted directly to investors, a number of consumer confidence indices have been used as direct measures of investor sentiment. There is a popular belief that the way people behave as consumers, is linked to the way they behave as investors (Nofsinger 2005: 152). Consumer confidence is measured through surveys that pole a large number of households on their personal financial situation, the present business conditions and job availability. Consumer Confidence Index is then constructed based on these survey responds. Lemmon & Portniaguina (2006) find that consumer confidence does a good job in predicting troughs and peaks in business cycle. Moreover, Fisher and Statman (2003) report that both the consumer confidence survey measures of Conference Board and University of Michigan capture elements of investor optimism. According to them, consumers perceive the economy and stock markets as "two sides of a coin". When consumers have confidence in the economy, they have confidence in the stock market as well, and become bullish (2003: 6). Schmeling (2009) confirms the findings of Lemmon and Portniaguina (2006) at an international level, and reports that investor sentiment, measured by consumer confidence, has a significantly negative effect on future stock returns of the 18 different sample countries.

Fisher and Statman (2003) find a positive and statistically significant relation between the measure of individual investor sentiment (AAII) and the measure of overall consumer confidence (CCI). In addition, they find that the AAII measure of investor sentiment is positively correlated with the consumers' future prospects about the economy. Consumer confidence measures of Conference Board and the University of Michigan both incorporate two components: A present and an expectations component. Present component is estimated based on the responds about the current state of the economy, while expectations component describes the respondents' future prospects about the economy. (2002: 4). Fisher & Statman (2003) report a statistically significant positive correlation between the changes in the expectations component and the present component in both confidence measures. According to Fisher and Statman, it seems like when consumers lose their faith in the present, they lose their faith in the future as well (2003: 5.)

3.1.2. Indirect measures of sentiment

Several different financial variables have been found to reflect investor sentiment. Prior studies suggest that investor sentiment is inversely related to closed-end fund discount (CEFD), which is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices. Hence, high optimism of investors decreases the discount. Qiu & Welch (2006) examine the closed-end fund discount as a potential measure of investor sentiment and find that CEFD does not seem to do well in capturing the effects of sentiment. CEFD neither correlates with direct sentiment measures nor with the excess rate of return on small firms in their sample. According to their results, CEFD has only been able to explain small stock excess returns in Januaries prior to 1985, but not afterwards. (Qiu & Welch 2006: 3.)

Turnover, or more generally liquidity, is also seen as a proxy for sentiment. Short-sales constraints affect the markets so that irrational investors trade and add liquidity only when they are optimistic– thus, liquidity is seen as a symptom of overvaluation. Brown and Cliff (2004) suggest that variables based on market performance may capture the effects of sentiment. They use the number of advancing issues to declining issues as an indirect proxy for sentiment. Additionally, they apply the number of new highs to new lows (HI/LO), which captures the relative strength of the market as proxy for sentiment. Both of the proxies are found to be correlated with direct survey measures of sentiment (Brown & Cliff 2004: 11-15). Investor enthusiasm can also be seen in the IPO market. Exceptionally high first-day returns of IPOs as well as the number of IPOs in a year reflect investor optimism (Baker & Wurgler 2006: 1656). Baker & Wurgler (2006) combine several above-mentioned indirect measures of sentiment into a composite sentiment index using principal component analysis and find that their sentiment index lines up well with important episodes of market booms and crashes. (Baker & Wurgler 2006: 1656)

3.1.3. Rational and irrational sentiment components

Previous studies suggest that investor sentiment is formed on the basis of rational fundamental components as well as irrational noise components. (Lemmon & Portinaguina 2006). Doms & Morin (2004) suggest that consumer confidence contains an irrational component as it responds to the volume of economic news reports rather than to the contents of the news. The conventional wisdom says that individual investors are most likely to be affected by sentiment and institutional investors are seen more as the rational agents with more unbiased estimations of stocks' intrinsic values. (Brown and Cliff 2004: 1.) Brown and Cliff (2004) suggest that the price effects on large stocks are due to institutional investor sentiment while small stocks are affected by retail investor sentiment. However, they find that sentiment is not limited to individual investors. In fact, the strongest relations seem to exist between measures of institutional investor sentiment and returns on large stocks. According to Brown and Cliff (2004), it might be that only institutional sentiment is powerful enough to affect asset prices. (2004: 19-22). Kholdy & Sohrabia (2014) regress survey measures of individual and institutional sentiment on several macroeconomic variables and find that institutional sentiment is formed mostly on the basis of rational fundamentals (64%). In contrast, the economic fundamentals explain only 39% of individual sentiment, pointing out that exuberance has greater impact in forming individual sentiment. (Kholdy & Sohrabian 2014: 854).

Verma & Verma (2007) study the effects of fundamental and noise trading on the conditional volatility of stock returns. Similarly to Lemmon & Portiaguina (2006) they separate the fundamental and irrational components of sentiment. Measuring sentiment by survey measures of AAII (individual sentiment) and II (institutional sentiment) they find that both institutional and individual sentiments are driven by irrational as well as by rational factors. Although both sentiments incorporate irrational parts, the effect of stock market in formation of sentiment is significant only for individual investors. This finding suggests that individual investors are more likely to be positive feedback traders, meaning that they buy rising stocks and sell losing stocks.

The individual sentiment is significantly related to the following factors: business conditions, market excess returns, dividend yield, SMB and HML. Similarly, institutional sentiment is related to dividend yield, SMB and HML. Verma & Verma (2007) find that rational sentiments have more positive effects on stock returns, while irrational sentiments are negatively related to stock returns. In line with behavioral theories, irrational sentiments have asymmetric effects on stock returns. The impact on irrational sentiment is greater when investors are bullish compared to bearish, a finding in line with Brown and Cliff (2005). The rational parts of sentiment do not exhibit any asymmetric effects. (2007: 242.)

Verma, Baklaci and Soydemir (2008) examine the relative impacts of irrational and rational investor sentiment on Dow Jones Industrial Average and S&P500 returns. They find that economic fundamentals, as determinants of stock returns, play an important role in sentiment. The effect of rational sentiment on stock market returns is greater compared to the effect of irrational sentiment. The irrational part of institutional investor sentiment has an immediate positive effect on the returns followed by a negative reversal. Thus, it seems that the excessive optimism drives prices above fundamental values and prices revert back to their intrinsic values shortly after. In contrast to Verma & Verma (2007), past stock returns are found to have an impact on both individual and institutional irrational sentiments. Moreover, it takes longer for rational effects of sentiment to get incorporated in stock prices compared to irrational effects, which implicates the longer time consumed to analyze information based on economic fundamentals.

3.2. Investor sentiment and stock characteristics

According to Miller (1977), market prices do not reflect the expectations of average investors, but of the minority who buy the particular security (1977: 1157). A small group of largely optimistic investors can drive the price of given security up when rational investors are unwilling to sell short (1977: 1154). Baker & Wurgler (2006) assert that short-selling is especially risky for small and new companies, whose future prospects are uncertain. Hence, prices of these types of stocks tend to be more prone to shifts in sentiment, relative to companies with a longer earnings history (Baker & Wurgler 2006: 1646).

In addition to the short-selling argument of Baker and Wurgler (2006), small companies may be more affected by sentiment due to the fact that noise traders are likely to be individual investors and small stocks are disproportionately held by individuals as opposed to institutions (Lee, Shleifer & Thaler 1991). Nagel (2005) finds a strong positive correlation between firm size and ownership by institutions. Chen (2011) tests whether the level of institutional ownership in firm affects the impact of pessimism and shows that consumer confidence does not have a significant effect on the returns of those stocks that are in the highest institutional ownership decile.

Baker and Wurgler (2006) suggest that investor sentiment should have a significant effect on the cross-section of stock returns due to uninformed demand shocks that cause mispricing in the markets. They test if cross-section of subsequent stock returns varies with beginning-of-period sentiment. Investor sentiment is measured by a composite index that captures the common component in six indirect proxies of sentiment. Moreover, these components are regressed on several macroeconomic variables in order obtain a cleaner measure of sentiment and to remove business cycle variation from the proxies. Baker and Wurgler (2006) find that sentiment has significant cross-sectional effects on stock returns in their sample period from 1963 to 2001: When the beginning of period sentiment is estimated to be high (above average) stocks that are young, small, unprofitable, non-dividend paying, highly volatile, extreme growth, and distressed earn relatively low subsequent returns. During low sentiment periods (sentiment index is below sample average), small stock earn exceptionally high subsequent average returns. The results are especially striking when the stocks are sorted based on the age of the firm: When sentiment is positive, investors tend to demand young stocks while during negative sentiment, older stocks become more appealing. During pessimistic periods, youngest stocks earn 0,54% per month less than the oldest stocks. In contrast, during optimistic periods the average monthly returns of youngest stocks are 0,85% higher than the returns to oldest stocks. Baker and Wurgler (2006) conclude that market-wide sentiment is associated with cross-sectional return differences, and that stocks that are hard to arbitrage and value are especially exposed to sentiment. According to Baker and Wurgler (2006), the results cannot purely stem from compensation for systematic risk and rational financial models alone are not able to explain the findings. (2006: 164-1647.)

Kholdy & Sohrabian (2014) study the dynamic interaction between individual investor sentiment and institutional investor sentiment on US stock returns using AAII and II measures of sentiment (2014: 849-850.). As Baker and Wurgler (2006), they focus on the returns of small, volatile, distressed, non-dividend paying, unprofitable and extreme growth securities that have proven to be especially vulnerable to sentiment. Their data spans from January 1990 to December 2010 covering a long bullish period in the 1990s and boom in the turn of the millennium. Kholdy & Sohrabian (2014) find support for the evidence that high irrational sentiment period combined with significant risk of arbitrage results in relatively low subsequent returns on speculative stocks. Their results show that in the period from 2000 to 2010, when the markets were more volatile and short-selling was less risky, sentiment did not have an impact on the returns in their sample. (Kholdy & Sohrabia 2014: 856-859.)

Brown and Cliff (2004) study the impacts of sentiment on U.S. stock returns during 1965-1998 using several indirect and direct (AAII & II) proxies of sentiment. Although, a strong co-movement between all sentiment measures and stock market returns is found, their results show very little evidence that sentiment is capable of predicting subsequent stock returns on a short horizon (2004: 17-18). When they test the predictability on a weekly data, they find no statistically significant results. Albeit sentiment does not seem to have predictive power on stock returns on a short-horizon, it does not imply that sentiment would have no effect on prices at all. It is possible that sentiment drives prices away from their fundamental values for extended periods of time, in which case the effect of sentiment is difficult to observe. Brown and Cliff (2005) test this issue by studying the impact of sentiment on longer horizons and find that high levels of sentiment, result in significantly lower returns over the next 2-3 years. The high optimism has an impact on the aggregate market, but the impact is especially strong in large growth stocks. One standard deviation (bullish) shock to sentiment forecasted 7 % underperformance of the market over the next three years. (Brown & Cliff 2005: 407-408.)

Fisher and Statman (2000) compare sentiment effects of different groups of investors (individual, medium and large), using three different sentiment survey measures, each to represent the sentiment of one group. They find that the sentiment level of individual investors is a reliable contrary indicator for future S&P 500 returns. As opposed to Brown and Cliff (2006), they find no support for the hypothesis that individual investor sentiment affects primarily small stocks (CRPS 9-10 index) whereas institutional sentiment mostly affects the returns of large stocks. In contrast, the sentiment of individual investors seems to have a stronger impact on the returns of large stocks compared to small stocks. Moreover, the sentiment of large investors shows a stronger correlation with the returns of small stocks compared to the returns of large stocks. (2000: 19).

Fisher and Statman (2003) study the impact of sentiment, measured by various consumer confidence indices on U.S stock returns during 1987 and 1998. The relationship between contemporaneous changes in consumer confidence indices and stock returns is positive and highly significant. Thus, confidence moves with stock returns. This finding could be explained by the fact stock returns bring wealth, which in turn boosts confidence. Additionally, Fisher and Statman (2003) test the predictive power of various consumer confidence measures on U.S stock returns. They report similar results to Baker and Wurgler (2006): When sentiment is low in the previous month, stock returns in the following month tend to be positive. The predictive power persists at one-month, 6-month and 12-month horizon. Moreover, the negative relationship is especially pronounced for Nasdaq-US stock returns and for returns of small stocks. However, consumer confidence is not a reliable predictor for S&P500 returns, as the index consists of large cap stocks. Schmeling (2009) shows similar results to those on Fisher and Statman (2003) on an international level. He finds that sentiment, measured by CCI, has a significant effect on returns of small stocks but not for large stocks. Moreover, the impact of sentiment is stronger for value stocks compared to growth stocks. As consumer confidence index rises one standard deviation, aggregate value stock returns decrease by 0,5%, whereas growth stock returns experience a 0,3% decline. This finding is contradicting to that of Brown and Cliff (2005), who find a larger impact of sentiment on growth stocks. Baker and Wurgler (2006), on the other hand, find no disparity between the impact of sentiment on value and growth stocks.

Lemmon & Portniaguina (2006) study the time-series relationship between investor sentiment and stock returns using the survey measure of consumer confidence conducted by the Conference Board (CBIND) and confidence measure conducted by University of Michigan Survey Research Center as proxies for investor sentiment. As in Baker and Wurgler (2006), the two confidence measures are regressed on a set of macroeconomic variables in order to distinguish the irrational element of sentiment from the fundamental part. The residual from the regression is then used as a measure of superfluous optimism or pessimism, which is not based on rational factors. Lemmon & Portinaguina (2006) evaluate the extent to which investor sentiment affects prices of different stocks during times of optimistic and pessimistic appraisals of market conditions by investors during 1956-2002. Specifically, they focus on the differences between the returns of small and large firms (size premium).

The results show that the magnitude of the sentiment effect is different between the two sub periods. During 1956-1977 consumer confidence exhibits no forecasting power on size premium. However, in the latter sub-period, covering 1977–2002, a strong and statistically significant negative relationship between the confidence measures and size premium is found. As confidence measure increases by one standard deviation, the corresponding size premium decreases from 3 % to 5 % over the following quarter. The results are similar for the 6- and 12-month holding periods. (2006: 1513-1514.) While many studies on investor sentiment focus on the direct impact on investor sentiment on stock returns, Yu and Yuan (2011) suggest a mechanism in which sentiment affects the compensation for volatility first and then, in turn, price levels. They argue that high market sentiment reduces risk premiums by activating irrational sentiment traders who demand lower price of risk. Yu & Yuan (2011) find that the mean-variance tradeoff is strongly affected by investor sentiment. Their results show that stock market's expected excess return is positively related to the market's conditional variance in low-sentiment periods but unrelated to variance during high sentiment. The results show that the sentiment effect on the mean-variance trade-off is stronger for equally-weighted index than for value-weighted index. Hence, although sentiment affects also large-cap stocks, the effect is stronger in small stocks. During high sentiment periods the otherwise positive tradeoff is undermined. In addition, during high-sentiment periods, realized variances are much higher compared to their counterparts in low-sentiment periods. The results suggest that stock prices are more volatile in high-sentiment periods compared to low sentiment periods. Their findings are consistent with the large influence of noise traders during high sentiment. (2011: 367, 372-373.)

Strambaugh et al. (2012) study the impact investor sentiment on a variety of market anomalies in cross-sectional stock returns. As in Yu and Yuan (2011), they assume markets to be less rational during high-sentiment periods. In accordance with the lower rationality during high sentiment, anomalies, which stem from overpricing, should be more prevalent during these periods. In contrast to Baker and Wurgler (2006), who suggest that difficulty to value *and* arbitrage certain types of stocks is the main reason for mispricing, Stambaugh et al. (2012) see short selling constraints as the main obstacle in eliminating mispricing. Hence, due to short sale impediments they assume stocks included in the short leg to be more overpriced during high sentiment and returns on the short leg to be lower (higher profits) following high sentiment period.

Additionally, the returns on the long leg of the portfolio should not be very exposed to sentiment since underpricing is less prevalent in the markets than overpricing. (2012: p. 289).

As Baker and Wurgler (2006), Stambaugh et al. (2012) construct a composite sentiment index based on several indirect sentiment proxies. They construct eleven long-short strategies based on well-known asset pricing anomalies and find that the strategies produce significantly positive average return spreads, varying from 0,43% to 1,77 %(2012: 293). They classify each month on the sample period as “high sentiment” or “low sentiment” based on the value of the sentiment index on the previous month. When the sentiment index exceeds (falls below) its median value on the previous month, sentiment is defined as high (low). The average returns are then calculated separately for each high- and low-sentiment month.

The long-short strategies are found to be more profitable following periods of high sentiment. The return spread of the combined long-short strategy is 0,93 % higher following high sentiment, and the result is statistically highly significant. Moreover, the short legs of the portfolios are more profitable following times of high sentiment; all the short legs of the strategies have lower average returns following a high-sentiment month. The short side of the combined strategy has 1,32 % lower monthly returns following high sentiment, in contrast to following low sentiment. This finding indicates that short sale constrains, combined with market-wide sentiment, have a significant impact on mispricing. In addition, the long legs of the strategies do not seem to be exposed to changes in sentiment, which refers to underpricing being less prevalent in the markets. (Strambaugh et al. 2012: 294).

Baker et al. (2012) study sentiment and cross-sections of stock returns. Stocks considered relatively volatile, small, non-dividend paying, distressed, or extreme growth are classified as high sentiment beta stocks, and they are expected to be more pronounced to sentiment. They form portfolios based on four measures; firm size, book-to-market equity ratio and sales growth, which are ought to capture the sentiment beta level of the stock. The stocks are sorted across years based on the level of their total sentiment index (negative or positive) (2012: 283-284). The results indicate that the highest volatility stocks earn 1,34 % less per month when the year begins with a high-sentiment state. This finding supports the correction of sentiment-driven overpricing theory. The top decile of sales growth portfolio has 1.07% lower returns when exiting high-sentiment periods. Also for the bottom decile market equity- portfolio, the difference between the returns in high- and low-sentiment states is 1% per month. (2012: 284.) In line with Baker and Wurgler, (2006) hard to arbitrage and hard to value stocks are found to be especially prone to country's total sentiment. When sentiment is high, future returns of high growth, volatile, and distressed stocks are relatively low. (2012: 272–273).

3.2.1. Market cycles and investor sentiment

According to behavioral theories investors are most optimistic during times of economic expansion. Chung, Hung and Yeh (2012) show that the predictive power of investor sentiment on cross-section of stock returns varies across different market cycle states. They use the sentiment index of Baker and Wurgler (2006) as a proxy for sentiment and test the predictive power of investor sentiment on stock returns on a short-term horizon (2012: p. 218). The market cycle variations are classified to expansion or contraction based on the NBER data and Markov-switching model with time-varying regime transition probabilities are used to estimate economic regimes (2012: 220). In their sample period between 1966 and 2007 they find a positive correlation (0.11) between the NBER recession indicator and the level of investor sentiment. Also the recession regime of the two-state Markov-switching model has a positive correlation with investor sentiment (0,27). Hence, sentiment index by Baker and Wurgler (2006) seems to have a higher average value during recessions compared to expansions. (2012: 223–224).

Chung et al. (2012) construct equally weighted long-short portfolios based on several firm characteristics (market equity, BE/ME, dividend yield, E/P, firm age, return volatility, expense-to-assets, fixed assets, sales growth and external finance-to-assets) that go long in stocks with the high characteristic values and short the stocks with low values. The results show that when sentiment is high, stocks that are either small, high volatility, young, high growth, low-earnings, or non-dividend paying have lower future returns compared to stocks that are large size, old, value, low growth, high dividend yields, high earnings, low volatility, and low intangible asset. These results are consistent with Baker and Wurgler (2006) and Stambaugh et.al (2012). When controlling for the economic regime, the predictive power of investor sentiment is insignificant during the recession states, whereas during expansions sentiment has a strong and statistically significant predictive power. (Chung et al. 2012: 220.)
In addition, Chung et al. test the predictability on investor sentiment on eleven anomaly-based portfolios (Failure probability, Ohlson's O-Score, Net stock issues, composite equity issuance, total accruals, net operating assets, momentum, gross profitability, asset

growth, returns on assets and investments to assets) by going long on the highest performing stocks in each anomaly group and shorting stocks in the lowest performing decile. They find positive and significant coefficients for anomalies associated with Failure probability, Ohlson's O-score, net stock issues, composite equity issuance, net operating assets, gross profitability, and return on assets (2012: p 238). When controlling for the economic regimes, they find that the predictive power of investor sentiment on the returns of the anomalies is economic regime-dependent. Overall, the predictive power is more pronounced during economic expansion states than in recession states. Chung et al. assert that their findings are consistent with theories of overreaction: Sentiment increases with the wave of economic expansion and results in overpricing that is especially significant on stock that are hard to value and arbitrage (2012: 237.)

Chen (2011) investigates if the effect of consumer confidence on stock returns is asymmetric between bull and bear market states and if the decreased level of consumer confidence leads to bearish market state. The sample covers S&P 500 stock index returns during 1978-2009, and consumer confidence is measured using University of Michigan Consumer Sentiment Index (UMCSI). (2011: p. 225). Chen (2011) finds a negative and statistically significant relationship between stock returns and lack of confidence, which supports the theory that investor pessimism has a lowering effect on stock returns. Also, an asymmetric relationship between confidence shocks and stock returns is identified. Lack of consumer confidence has a greater impact on stock returns during bear markets than during bull markets, as expected. Moreover, the impact of market pessimism affects the small stocks greater than large stocks. The negative impact of market pessimism on size premium is evident in both, bull and bear market states, but the impact is greater during bear markets. (2011: p 231–232).

3.2.2. Investor sentiment globally

Earlier findings suggest that the impact of sentiment on stock returns might be correlated with the level of cultural collectivism and institutional quality in a given country, as well as with uncertainty avoidance among individuals. Schmeling (2009) compares the effects of sentiment between the 18 industrialized sample countries. Sentiment-return relation seems to vary quite much between the countries, and there is no evidence that the relation would be connected to the size or location of the country. The strongest negative relationships between sentiment and subsequent stock returns are found in Germany, Italy and Japan, whereas almost no correlation is identified in

Australia, New Zealand and U.K. (2000: 400). Schmeling (2009) finds that the impact of sentiment on future stock returns is strongest over the forecast horizon of one to six months and decreases over longer horizons. The results are in line with theoretical considerations of the impact of noise traders: Noise trading effects diminish over longer period of time as limits to arbitrage become weaker. Differences between the sentiment-return relations among the sample countries are examined by dividing the countries into subsets according to their exposure to the aforementioned determinants. The results show that countries with high level of collectivism and uncertainty avoidance experience larger effects of sentiment on returns compared to individualistic and low uncertainty avoidance countries. The sentiment-return relation is considerably stronger in countries where herding and overreaction is more pronounced. Moreover, a higher level of institutional quality weakens the impact of sentiment on stock returns. (2009: 404-406).

Bathia & Bredin (2013) study the relation between investor sentiment and stock market returns on G7 countries, using direct surveys measures as well as several indirect financial measures as proxies for sentiment. Using monthly data from 1995 to 2007, they find that investor sentiment has a significant negative effect on stock returns and the effect of sentiment is stronger for value stocks compared to growth stocks. The effect of survey sentiment varies between the sample countries. In USA, only growth stocks and aggregate stock market are affected by survey sentiment, while in Canada the effect exists for value and growth stocks as well as for the overall market. The predictive power of survey sentiment on overall market returns is present also for France, Germany and Italy on a one month-forecast horizon. Interestingly, survey sentiment has no predictive power for Japan and UK on the same forecast horizon. The impact of survey sentiment on returns is found to reduce gradually beyond the one-month forecast horizon. According to Bathia and Bredin (2013) these dissimilarities between the sample countries may be due to the differences in the survey structures and the number of participants. The effect of consumer confidence index is consistently observed in all the sample countries in contrast to the indirect measures (CEEF discount and equity fund flow).

Also Baker, Wurgler & Yuan (2012) find evidence that investor sentiment affects stock returns globally. They study the global and local components of investor sentiment on six major stock markets; Canada, France, Germany, Japan, United Kingdom and the U.S. They construct a local sentiment index for each sample country, as well as a global index that combines all the local indices. Their results show that global sentiment seems to be a contrarian predictor for country level returns. When global sentiment index increases by one standard deviation, the value-weighted market returns in the next year are 5,4 % lower, and the equal-weighted market returns 5,6 % lower. In addition, a country's local investor sentiment index seems to be a contrarian predictor of market returns, though not as strong as global sentiment. A one standard deviation increase in total investor sentiment is associated with 3,5 pp lower value-weighted returns per year and 4,3 % lower equal-weighted returns. Baker et al. (2012) conclude that both global and local components of sentiment predict the returns of high-sentiment beta portfolios that include high volatility stocks, or stocks of distressed small and growth companies. Sentiment seems to be contagious across markets and international capital flows is one of the mechanisms through which it emerges. (2012: 286.)

4. DATA AND METHODS

4.1 Return data

The sample period covers fourteen years, from January 2001 to December 2014. This period is chosen partly because of limitations in the availability of the data. Also, the period is interesting in a sense that it covers the crash of the dot.com boom in the beginning of 2000 as well as the sub-prime crisis which started in September 2007. The return data consists of eight Morgan Stanley Capital International (MSCI) indices and OMX Helsinki All-Share index. The MSCI indices are: MSCI Finland Small, MSCI Finland Large, MSCI Finland Growth, MSCI Finland Value, MSCI Finland Small Growth, MSCI Finland Large Growth, MSCI Finland Small Value and MSCI Finland Large Value. As a general benchmark index for the Finnish stock market, I use The OMX Helsinki All-Share Index, which includes all the shares listed on the Helsinki Stock Exchange.

The MSCI indices measure the performance of 50 stock markets across the world. The indices are calculated daily in US dollars and in local currency. Valuation ratios for the indices (P/E, P/CE, P/BV, Return on Equity and dividend yield) are calculated on a monthly basis and the market value is calculated each day. Free-float stands for the proportion of the shares of a security, which are freely available for trading in the market. Free float is an important matter when constructing an investable index. The combined market capitalization of firms in MSCI indices represents approximately 85% of the free float adjusted market capitalization in each country. MSCI total return indices, which are used in this study, measure the price performance of markets with the income from constituent dividends.

MSCI Value and Growth indices are a sub-set of the MSCI Standard indices. Till May 2003 both of the indices were based on price to book value, which was used to divide the MSCI standard country indices into value and growth style indices. After May 2003, the original methodology was changed to a more complex one. Since June 2003 Value and Growth index have been calculated using eight variables. Value index is based on book value to price ratio, 12-month forward earnings to price ration and dividend yield. Growth index on the other hand is determined by long-term forward earnings per shares (EPS) growth rate, short term forward (EPS) growth rate, current internal growth rate, long-term historical EPS growth trend and long-term historical sales per share growth trend. MSCI Finland Small index, on the other hand, tracks the performance of small cap stocks. The MSCI World Small cap index was launched on Jan 01, 2001, which limits the availability of the data. It includes securities with a market cap between 200-1500 million US dollars. (Thomson Financial Limited 2005.)

OMX-Helsinki (OMXH) index was established in December 1990 with a base level of 1000. OMXH is an all-share index that incorporates all the stocks listed on Helsinki Stock Exchange. Thus, it aims to reflect the current state and changes in the market. As the main purpose of the index is to mirror the population of shares representing the index, the index does not comply with liquidity and stability requirements. Hence, the index itself may not be easy to replicate in a portfolio against the pricing of the shares. One must account for the fact that because of the lack in liquidity requirements, the index level may lag due to infrequent trading in the underlying shares. (Nasdaq 2014: 3).

The maintenance of the OMXH-Index shares is carried out on a daily basis, in order to sufficiently reflect the ongoing changes in outstanding shares and listed companies. In this study, the total return index is used. The total return index reflects changes in market value of Index Shares during the trading day. The index value reflects ordinary and extraordinary dividends. The reinvestment of extraordinary dividend is done by subtracting the extraordinary dividend from the price on the ex-dividend date. By performing this adjustment, the dividend in all index shares is reinvested in proportion to their respective gains. The number of shares of a company used in the index, is the current outstanding number of shares. In case of such corporate actions that cause adjustments in the index, the number of shares is changes so that it fully reflects the the new market capitalization of the company in the index. (Nasdaq 2014: 13-16).

As Table 1 shows, returns on small stocks have had a higher performance compared to large and value stocks. The size effect described by Banz (1981) can be seen in the Finnish markets. MSCI Small Value index has been superior to all other indices with average monthly returns of 1,14%. Also MSCI Small stock index has outperformed most of the indices. MSCI Large Growth returns have the largest standard deviation, whereas standard deviation is smallest for the MSCI Small and MSCI Small Value index returns.

Skewness measures the asymmetry of the return series around its mean, thus for the normal distribution, skewness is zero. Kurtosis on the other hand measures the peakedness or flatness of the distribution of the series. Kurtosis for the normal distribution is 3. The results indicate negative skewness for large growth, small growth, small, and large value index returns. Skweness is especially strong for the returns of the large growth index, which implicates that the returns have a long left tail. For the large value, OMXH, and Small Value and Value index returns skewness is positive, indicating a long tail to the right. Moreover, all returns series exhibit excess kurtosis, which means that their distribution is more peaked that the Gaussian distribution. The Jarque-Bera statistic describes, if the series is normally distributed. For Jargue-Bera test, the null is that the series is normally distributed. Thus, small probability values from the Jargue-Bera test lead to rejection of the null. The results indicate that none of the return series is normally distributed. To account for this issue, logarithm returns are used. All the index returns are logarithmized the following way

(3) $$R_{log} = \ln (P_t/P_{t.1}) = \ln(P_t) - \ln(P_{t-1}),$$

where P_t is the price of the index at time t and $P_{t-1}$is the price of the index in subsequent period.

Table 1. Descriptive statistics of the average monthly returns of each sample index. The returns are expressed in percents.

	Growth	Large Growth	Large Value	OMXH	Small Growth	Small	Small Value	Value	Large
Mean	0,23	-0,04	0,41	0,31	0,33	0,96	1,14	0,41	-0,04
Median	1,06	1,13	0,93	1,04	1,32	0,96	1,51	0,73	0,62
Maximum	37,01	32,03	37,27	29,25	19,18	27,88	31,51	33,19	35,32
Minimum	-35,02	-0,44	-21,76	-26,88	-27,16	-20,00	-19,08	-17,09	-33,01
Std. Dev.	0,10	0,11	0,08	0,08	0,07	0,06	0,06	0,07	0,10
Skewness	-0,25	-8,55	0,44	0,03	-0,78	-0,17	0,15	0,47	-0,04
Kurtosis	5,43	5,72	5,12	5,56	4,17	5,28	6,50	5,26	4,88
Jarque-Bera	42,92	69,63	36,83	46,03	26,58	37,09	86,33	41,95	24,81
Probability	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Sum	0,39	-0,72	0,69	0,51	0,55	1,61	1,92	0,70	-0,07
Sum Sq. Dev.	1,70	1,93	1,10	0,95	0,91	0,66	0,64	0,83	1,63
Observations	168	168	168	168	168	168	168	168	168

4.2 Consumer Confidence Index and Economic Sentiment Indicator

Consumer confidence index (CCI) is constructed based on a qualitative consumer survey, which describes the views and intentions of consumers related to economic matters. Consumer Confidence survey was first introduced in November 1987, when the data was collected twice per year. Since 1995 the data has been collected monthly in accordance with the harmonized EU data collection method. The Consumer Survey is a telephone interview, in which the respondents are asked about the development of their own and Finland's economic situation. The survey consists of 17 EU harmonized questions in addition to Statistics Finland's own questions, which are made monthly or quarterly. The questions include backward looking questions as well as questions about the future prospects about economy related matters (see Appendix 2.)

In most of the questions, respondents can choose their answer among five options: "got/get a lot better"(++), "got/get a little bit better"(+). "stayed/stay the same" (=), "got/get a little worse" (-), "got/get" a lot worse (--), or "cannot say" (N) (European Commission 2016). The characteristic value index is then derived from the percentage distribution of the responses. The figure describes the average opinion of the respondents at any given time. The arithmetic mean of the four most central balance figures (EU Harmonized questions 2,4,9 and 13) is called the Consumer Confidence indicator. The questions are:

1. What will your own economic situation be like in 12 months' time compared to present?
2. What will Finland's economic situation be like in 12 months' time compared to present?
3. What will be the number of the unemployed in Finland in 12 months' time compared to present?
4. How likely are you to be able to save money within the next 12 months?

The survey also aims to depict the household's intention of making purchases, saving and raising loans. Survey data consists of a random sample of 2350 individuals that changes completely every month. The target area is the whole country, thus, the sample represents all Finnish households. The interviewees are private persons permanently living in Finland and aged 15 to 84. The surveys are carried out during the first two or three weeks of the month and the results are published in Finland on the 27th day of the survey month. The response data of the Consumer Survey are expanded to the whole population with weighting coefficients, which correct the impact of non-response and enhances the statistical accuracy of the data. A number of studies have shown that consumer data can predict the economic behavior of consumers rather accurately. The results of the survey are strongly correlated with inflation, unemployment, private consumptions and GDP. (Official Statistics of Finland (OSF) Updated 02.06.2015)

Economic Sentiment Indicator (ESI) is composite indicator that consists of five sectoral confidence indicators with different weights: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator and Retail trade confidence indicator. The surveys are conducted on a monthly basis. The industry monthly questions regard production, employment expectations, order-book levels, stock of finished products and selling price. Construction indicator is based on questions regarding trend of activity, order-books, employment expectations, price expectations, and factors that limit building activity. Retail sales monthly questions concern business situation, stocks of goods, order's placed with suppliers and firm's employment. Services monthly questions regard business climate, evolution of demand, evolution of employment and selling prices whereas financial services monthly questions concern business situation, evolution of demand as well as employment. (European Commission 2016.)

Approximately 135 000 firms and more 40 000 individuals are interviewed every month across the EU. For Finland the monthly sample size regarding the industry confidence measure is 700 firms. Service confidence measure is based on the answers of 800 firms, Retail Trade surveys cover the responses of 500 firms and Construction confidence measure is based on the answers of 160 firms. Confidence indicators are arithmetic means of seasonally adjusted balances of responses to a number of questions. The balances are calculated as the difference between positive and negative answers. The results of the surveys are published monthly on the second-last working day. The questions of the monthly surveys are in Appendix 1. Majority of the questions are asked on a monthly basis but additional questions are added to the surveys regarding industry, construction and among consumers. (European Commission 2016.)

Almost all of the questions are qualitative nature and the respondents are asked to choose from three optional answers: "increase" (+), "remain unchanged" (=), "decrease" (-); or

"more than sufficient (+)", "sufficient" (=), "not sufficient" (-); or "too large(+)", "adequate" (=), "too small" (-). In some questions the respondents may choose from broader set of options; “got/get a lot better”(++), “got/get a little bit better”(+). “stayed/stay the same” (=), “got/get a little worse” (-), “got/get” a lot worse (--), or “cannot say” (N). (European Commission 2016.)

4.2.1 Controlling for macroeconomic factors

Prior research shows that sentiment proxies are highly correlated with macroeconomic factors. Lemmon & Portniaguina (2006) find that their measure of consumer confidence is strongly correlated with contemporaneous macroeconomic variables and contains information about the future macroeconomic conditions (2006: 1511-1522). Table 2 shows the correlations between the macroeconomic variables and sentiment measures used in this study.

Table 2. Correlations between the macroeconomic variables. Bold entities represent statistical significance at a 10% level or less. Probability values are in parenthesis, below the correlation estimates. CCI is the consumer confidence index, ESI is the economic sentiment indicator, RATE is the 3-month Euribor rate, GDP is the moving average on quarterly change in GDP, UNEMP is the current unemployment rate and INDPRO is the growth in industrial production.

	CCI	ESI	CPI	RATE	DUNEMP	MAVGDP	DDIV	INDPRO
CCI	1,00							

ESI	**0,83**	1,00						
	(0,000)	-----						
CPI	**-0,34**	**-0,23**	1,00					
	(0,000)	(0,003)	-----					
RATE	**0,28**	**0,31**	**0,19**	1,00				
	(0,000)	(0,000)	(0,014)	-----				
DUNEMP	**-0,59**	**-0,71**	**0,14**	**-0,27**	1,00			
	(0,000)	(0,000)	(0,063)	(0,000)	-----			
MAVGDP	**0,51**	**0,72**	-0,05	**0,52**	**-0,66**	1,00		
	(0,000)	(0,000)	(0,540)	(0,000)	(0,000)	-----		
DDIV	0,07	**0,16**	**0,16**	**0,17**	**-0,13**	**0,25**	1,00	
	(0,386)	(0,039)	(0,044)	(0,028)	(0,099)	(0,001)	-----	
INDPRO	**0,24**	**0,25**	**-0,13**	-0,01	**-0,15**	0,10	-0,09	1,00
	(0,002)	(0,001)	(0,090)	(0,863)	(0,060)	(0,194)	(0,221)	-----

Despite some dissimilarities in the surveys that ESI and CCI are based on, the measures are strongly positively correlated (0,83). Both sentiment measures show also strong correlations with the macroeconomic variables. The 3-month Euribor (RATE) is strongly positively correlated with both measures of sentiment. Additionally, growth in GDP is positively related to CCI and ESI. Inflation and unemployment rate, on the other hand, exhibit a negative correlation with both sentiment measures, which is rational since inflation and unemployment can be interpreted as negative indicators for the overall economic development. Negative correlation between the sentiment measures and unemployment is especially strong. This finding is not surprising, since questions regarding unemployment play an important role in the surveys that CCI and ESI are based on. Dividend yield does not show a significant correlation with consumer confidence, while it is positively correlated with ESI. Additionally, Industrial production growth shows positive correlation with both sentiment measures.

Following Chen (2011), Lemmon & Portniaguina (2006) and Kholdy & Sohrabia (2014) both of the sentiment indices are regressed on a set of macroeconomic variables in order to distinguish the irrational part of the overall-sentiment. The residual from these regressions is then used as proxy for irrational part of sentiment. Naturally, one must consider that there might be an important rational factor, which has not been included in the regression. However, after adjusting both sentiment measures on the macroeconomic variables, sentiment can be interpreted as a cleaner proxy of irrational sentiment. Macroeconomic variables used in this study are as follows: inflation, described by the monthly change in consumer price index (CPI), change in 3-month Euribor (RATE), change in the monthly industrial production growth (INDPRO), change in the monthly unemployment rate (UNEMP), moving average on quarterly GDP growth (GDP), and monthly dividend yield of OMXH25-index (DIV). Data of the macroeconomic indicators is downloaded from the official website of Bank Of Finland, Statistics Finland and Eurostat. In addition, data for the dividend yield is downloaded from Bloomberg data base. The data consists of monthly observations excluding quarterly GDP growth. The regression is performed the following way

(4) $$\mathrm{ADJSENT_t} = c + \beta_1 \times \Delta\mathrm{UNEMP_t} + \beta_2 \times \Delta\mathrm{RATE_t} + \beta_3 \times \Delta\mathrm{INFL_t} + \beta_4 \times \Delta\mathrm{INDPRO_t} + \beta_5 \times \Delta\mathrm{GDP_t} + \beta_6 \times \Delta\mathrm{DIV_t} + \beta_7 \times \Delta\mathrm{UNEMP_{t-1}} + \beta_8 \times \Delta\mathrm{RATE_{t-1}} + \beta_8 \times \Delta\mathrm{INFL_{t-1}} + \beta_{10} \times \Delta\,\mathrm{INDPRO_{t-1}} + \beta_{11} \times \Delta\mathrm{GDP_{t-1}} + \beta_{12} \times \Delta\mathrm{DIV_{t-1}} + \varepsilon_t, ,$$

where, $ADJSENT_t$ is Economic Sentiment Indicator or Consumer Confidence index, $\Delta UNEMP_t$ is the change in monthly unemployment rate, $\Delta RATE_t$ is the change in 3-month Euribor, $\Delta INFL_t$ is the change in inflation measured by consumer price index, $INDPRO_t$ is the change in industrial production growth, and ΔGDP_t is the change in gross domestic production growth (moving average), and ΔDIV_t is the change in monthly dividend yield.

4.3. Regression approach

The impact of consumer confidence index and economic sentiment indicator on stock returns is studied using Ordinary Least Squares (OLS) approach. Simple linear regression model is an econometric model used to investigate the relationship between the chosen economic variables. OLS is a method used to estimate the unknown parameters in a linear regression model. OLS determines the line of best fit in a linear regression model and minimizes the sum of squared residuals (Hill & al.1997:51). The fitted line is

(5) $$\hat{y} = b_{1+}\, b_2\, x_t$$

and the vertical distances from each point to the fitted line are the least squares residuals, are given by

(6) $$\mathrm{e_t} = \mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t} = \mathrm{y_t} - \mathrm{b_1} - \mathrm{b_{2t}}.$$

OLS makes several assumptions regarding the ordinary least-squares estimates of its parameters, which are also known as the Gauss-Markov conditions. Violation of these conditions is likely to cause biased parameter estimates or biased estimates of the standard errors of sample statistics. In these cases, making any valid statistical inferences about the results is misleading. (Allen 1997: 181-182.) Under the Gauss-Markov assumptions of the linear regression model, the estimators b_1 and b_2 have the smallest variance of all linear and unbiased estimators of b_1 and b_2, thus they are the best linear unbiased estimators of b_1 and b_2. (Hill & al.1997: 77). The Gauss-Markov conditions are as follows (Woolridge 2013: 59- 60).

1. Linearity in parameters $y = \beta_O + \beta_1 x + u$

2. The expected value of the error term is zero for all observations E (u|x) = 0

3. Homoscedasticity: The conditional variance of the error term is constant in all x and over time Var(u|x) =σ^2

3. Error term is independently distributed and not correlated: Cov ($\varepsilon_{i,}\varepsilon_j$) = E ($\varepsilon_i$, ε_j)= 0, i$\neq j$

4. X_i is uncorrelated with the error term since x_i is deterministic.

T-test was used to test the statistical significance of the results. T-test follows the student t-distribution and the t-value of the least square estimate is obtained by

(7) $$t = {(\hat{\beta} - \beta_0)}\Big/{SE(\hat{\beta})},$$

where $\hat{\beta}$, is the estimated coefficient, β_0 is the slope of the regression, and $SE(\hat{\beta})$ is the standard deviation of $\hat{\beta}$. The null hypothesis is that $H_0 : \hat{\beta} = 0$, and the alternative is $H_1 : \hat{\beta} \neq 0$. If the t-statistics exceeds the critical value, null hypothesis is rejected and coefficient is said to be significantly different from zero. (Hill& al. 1997: 105.)

The coefficient of determination, denoted R^2, indicates the goodness of fit on the OLS regression line on the data. R^2 is the ratio of the explained variation in *y*, which is explained by *x*. The coefficient of determination can be defined as

(8) $$R^2 = SSE/SST = 1- SSR/SST,$$

Where SSE is the explained sum of squares, SST is the total sum of squares and SSR is the residual sum of squares. If R^2 equals 1, this indicates that all the data lie on the same line, thus OLS provides a perfect fit for the data. (Woolridge 2013:3 7-38).

4.4. Preliminary tests

Ordinary Least Square (OLS) assumes that the means and variances of the variables being used in the model are constant over time. If the means and variances change over time, the variables are defined as non-stationary or unit root variables. In contrast, stationary process can be defined so that it has a mean, variance and autocorrelation that are constant over time. Running regressions with nonstationary data can result in misleading results and spurious regressions. In spurious regressions R-square values and t-statistics no longer follow usual distributions and appear larger. Therefore, testing of unit roots of the series is a precondition for using OLS method. (Glynn, Perera & Verma 2007: 65.) The stationarity of the data is tested using Augmented Dickey-Fuller

(ADF) test, which is an extension of the popular Dickey-Fuller and allows for the possibility that the error term is autocorrelated. Considering the autoregressive model

(9) $$Y_t = \rho Y_{t-1} + e_{t,} \; t = 1,2 \ldots,$$

Where Y_0=0, ρ is a real number and $e_{t,}$ is a sequence of independent normal random variables with mean zero and variance, σ^2. The non-stationarity (with intercept) can be tested by the equation

(10) $$\Delta y_t = \alpha + \theta y_{t-1} + \varepsilon$$

The null hypothesis that H_0: $\theta = 0$ against the alternative H_1: $\theta < 0$. If we reject the null, we conclude that the series is stationary. The Augmented Dickey-Fuller test (with intercept) on the other hand is done following the equation:

(11) $$\Delta z_t = \alpha_0 + \theta z_{t-1} + \alpha_1 \Delta z_{t-1} + \alpha_2 \Delta z_{t-2} + \cdots + \alpha_p \Delta z_{t-p} + a_t,$$

where p is the number of augmenting lags and θ is the ordinary least squares estimate. The number of lags is determined by minimizing the Akaike information criterion. The same null hypothesis applies to Augmented Dickey-Fuller test, H_0: $\theta = 0$ against the alternative H_1: $\theta < 0$.

Results from the Augmented Dickey-Fuller test are shown in Table 3. Unemployment rate (UNEMP), 3-month Euribor (RATE), and inflation are non-stationary at levels. Adding a trend does not change the results. Industrial production growth (INDPRO) and dividend yield are both integrated at I(0). For CCI and ESI null of a unit root is rejected at 5 % and 10% level respectively, when only an intercept is included in the equation. By adding a trend, both series incorporate a unit root. Thus, the results for ESI and CCI are not clear judging by the Augmented-Dickey Fuller test. However, all the variables which are non-stationary at levels become stationary when first differenced. It is a commonly known fact that many unit root tests fail to reject the null of a unit root for economic time series. The standard conclusion is that most economic time series incorporate a unit root. However, in many unit root tests, such as Augmented Dickey Fuller and Phillips-Perron, unit root is the null to be tested. As the classical economic hypothesis testing is performed so that the null is accepted, unless there is strong evidence against the null, it is likely that unit root tests are not powerful against the relevant alternative (Kwiatkowski et al. 1992: 160).

Table 3. Augmented Dickey-Fuller unit root test including an intercept, and intercept and trend. Lag length criteria is based on automatic Akaike information. Table presents p-values and bolded values denote statistical significance at 10% level or less.

	Intercept	Trend and intercept
UNEMP	0,387	0,906
ESI	**0,060**	0,154
CCI	**0,047**	0,138
INDPRO	**0,000**	**0,000**
RATE	0,399	0,196
GDP	**0,072**	**0,060**
INFLATION	0,256	0,494
DIV	**0,023**	**0,045**

In the case of CCI and ESI, it is clear that these series do not incorporate a unit root in the long-run and that the unit root is only due to a finite sample; both confidence indicators are arithmetic means of seasonally adjusted balances of responses to a number of questions, and the balances are calculated as the difference between positive and negative answers. In order to further test, if the series contain a unit root, I apply the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. KPSS is a stationarity test, which differs from Augmented-Dickey fuller test in so that the null of to be tested is that the series does not contain a unit root. Hence, the series y_t is assumed to be (trend-) stationary. The KPSS is based form the OLS regression of y_t on the exogenous variable x_t:

(12) $$y_t = x_t'\delta + u_t$$

The LM statistic is defined the following way:

(13) $$LM = \sum_t S(t)^2/(T^2 \int 0),$$

where $\int 0$ is an estimator of the residual spectrum at frequency zero and $S(t)$ is a cumulative residual function.

(14) $$S(t) = \sum_{r=1}^{t} \mho_r$$

Based on the residuals $\mho_t = y_t = x_t'\delta(0)$. (Kwiatkowski et al. 1992: 163-165). Test results from the KPSS test of stationarity are presented in Table 4. The results show that stationarity (with intercept) is rejected for unemployment rate (UNEMP), 3-month Euribor (RATE), and for growth in GDP. When trend is included, unemployment rate, rate, inflation, and dividend yield seem to be nonstationary. However, all the nonstationary series become stationary after first differencing.

Table 4. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test of stationarity. Bandwidth Newey-West automatic using Bartlett kernel. Results are given including an intercept (first row) and including and intercept and trend (second row). Asymptotic **c**ritical values *) are denoted below the table. Bolded values denote that the null of stationarity is rejected at 10% level or less.

	UNEMP	ESI	CCI	INDPRO	RATE	GDP	INFLATION	DIV
Intercept	**0,481**	0,240	0,330	0,169	**0,910**	**0,403**	0,283	0,153
Trend and intercept	**0,272**	0,113	0,092	0,057	**0,154**	0,058	**0,124**	**0,122**

*) KPPS Critical values (intercept)		KPPS Critical values (trend and intercept)	
1% level***	0,739	1% level***	0,216
5% level**	0,463	5% level**	0,146
10% level*	0,347	10% level*	0,119

OLS includes an assumption that the error terms are homoscedastic meaning that the conditional variance of the error term is constant, thus E(ε_i^2) = σ_t^2. If this does not hold true, the error term heteroscedastic. Heteroscedasticity has serious consequences for the OLS estimator and it results in false estimated standard errors. This, on the other hand, implies that the confidence intervals and hypotheses test become unreliable. Additionally, OLS method requires that there exists no serial correlation. Serial correlation means that the residuals of the variables are correlated with their own lagged values. This is a statistical problem, since it violates the standard assumption that error terms are uncorrelated. Serial correlation can result in invalid standard errors and t-statistics as well as biased coefficients. In the case of lagged dependent variables, coefficients may be biased and inconsistent. Time series data typically exhibits some unknown form of serial correlation and heteroscedasticity. In these cases, it is essential to use covariance matrix estimators that are able to consistently estimate the covariance of the model parameters. Heteroscedasticity and serial correlation in the regressions is taken care of by using HAC Newey-West (1987) procedure, which can be used when the Gauss-Markov assumptions do not apply. HAC Newey-West procedure estimates heteroscedasticity and serial correlation consistent standard errors (Müller 2014: 311).

4.4.1. Granger causality and Toda-Yamamoto procedure

One of the most common ways to test causality between variables is the Granger-Causality test by W. Grager (1969). Granger (non-) causality provides a definition for causal ordering of time series, which implies a parametric model for stationary processes. Granger causality is widely used to explore causal ordering of variables given multivariate time series (Yue et al. (2015). Granger causality test is based on the Vector Auto-regressions (VAR) frame work, where the null hypothesis is formulated as zero restrictions on the coefficients of the lags of a subset of the variable. Let X_t and Y_t be two stationary series with zero means. The simple causal model can be put in the following form

(15) $$X_t = \sum_{i=1}^{m} a_i X_{t-i} + \sum_{j=1}^{n} \beta_j Y_{t-j} + \mu_{1t}$$

(16) $$Y_t = \sum_{i=1}^{m} c_i X_{t-i} + \sum_{j=1}^{m} \delta_j Y_{t-j} + \mu_{2t} ,$$

Where disturbance terms μ_{1t} and μ_{2t} are assumed to be uncorrelated white-noise series. In equations X and X, *m* can equal infinity, but in practice, given the finite sample, *m* is assumed to be shorter than the given time series. Equation 13 states that Y_t is causing X_t provided β_j does not equal zero. Similarly in equation 14, X_t is causingY_t given that c_i is not zero. In the case that both of these events occur, there exists a feedback relationship between $X_t$and Y_t. (Granger 1969: 431.)

The usual Wald test statistic for Granger non-causality, based on levels estimation, has a nonstandard asymptonic distribution, and depends on nuisance parameters in general, if the process is integrated in the first order. Thus, problem in testing Granger non-causality occurs, if the series is integrated in different orders. As seen from the Augmented Dickey-Fuller test results in Table 3 and from the KPSS results in Table 4, series used in this study seem to be integrated in different orders. Toda & Yamamoto (1995) propose a way to overcome this problem by using a method that is applicable whether the VAR's are stationary, integrated of an arbitrary order or cointegrated of an arbitrary order. (Toda & Yamamoto 1995: 226-227.) By using the Toda & Yamamoto method one can apply the usual lag length selection procedure to a possibly integrated or cointegrated VAR. After choosing a lag length k, one can estimate a (k + $d_{\max}$)th-order VAR, in which $d_{\max}$is the maximal order of integration that is suspected to occur in the process. The coefficient matrices of the last $d_{\max}$ lagged vectors in the model are ignored and the linear on non-linear restrictions on the first k coefficient matrices can be tested using the standard asymptonic theory. (Toda & Yamamoto 1995: 246.)

I test for the Granger non-causality by first estimating the following VAR-model.

(17) $$Y_t = a_0 + a_1 Y_{t-1} + ... + a_k Y_{t-k} + b_1 X_{t-1} + ... + b_k X_{t-k} + u_t$$

(18) $$X_t = c_0 + c_1 X_{t-1} + ... + c_k X_{t-k} + d_1 Y_{t-1} + ... + d_k Y_{t-k} + v_t$$

With the null H_0*:* $b_1 = b_2 = ... = b_0 = 0$, which implies that X_t does not cause Y_t. Similarly testing the H_0: that $d_1 = d_2 = ... = d_0 = 0$ implies that Y_t does not cause X_t. According to the unit root test results, the maximum order of integration in the series is 1, thus *m=1*. In accordance with Toda-Yamamoto (1995) procedure a VAR-model is set in the levels of the data.

Table 5 shows the lag-length criteria used in the VAR-model. It is important to determine the number of lags *(k)* in an appropriate manner, as results from the Granger-causality test depend heavily on the number of lags given. Each of the criteria suggests lag order of two for the VAR-model. However, the results from LM serial correlation test show that the residuals are serially correlated, which results in that the VAR-model is not well-specified.

Table 5. Lag order selection criteria. * denotes lag order suggested by the criterion: sequential modified LR test statistic (LR) , Final prediction error (FPE), Akaike information criterion AIC, Schwartz information criterion(SC) and Hannan-Quinn information criterion (HQ).

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1970,73	NA	6,4E-25	-24,50	-24,29	-24,41
1	2317,03	**640,67***	**3,82e-26***	**-27,31***	**-24,78***	**-26,28***
2	2390,60	125,99	7,1E-26	-26,72	-21,86	-24,75
3	2481,36	142,95	1,1E-25	-26,34	-19,15	-23,42
4	2567,38	123,65	1,9E-25	-25,90	-16,39	-22,04
5	2665,29	127,27	2,9E-25	-25,62	-13,78	-20,81
6	2772,54	124,68	4,5E-25	-25,44	-11,28	-19,69
7	2906,15	136,95	5,7E-25	-25,60	-9,11	-18,91
8	3043,17	121,61	8,3E-25	-25,80	-6,99	-18,16

The results of LM serial correlation test suggests that the residual autocorrelation can be taken care of by increasing the lag order to *k=12*. Hence, lag order is increased in order to obtain a well-specified model. After estimating VAR-model with suggested appropriate lag-length, Granger-Causality Block Exoqeneity Wald-test is applied. Additional lag (*m=1*) is added to the model as an exogenous variable, so that Wald-statistic has it usual asymptonic chi-square null-distribution. The results for the Granger-causality test are shown in the next section.

5. RESEARCH RESULTS

Firstly, I test for the Granger-Causality between the sentiment measures and stock returns. Granger-Causality is a simple way to test time-series dependencies between the chosen variables. As stated earlier, the series is integrated in different orders. Hence, instead of using the traditional Granger-Causality test, I apply the Toda-Yomamoto (1995) method. The results are shown in Table 6.

Table 6. Granger-Causality Block Exoqeneity Wald-test. Causality between the sentiment measures and index returns. Bolded p-values denote statistical significance at 10% level or less.

	Growth	Large	Large Growth	Large Value	Small	Small Growth	Small Value	Value	OMXH
CCI→r	0,750	0,888	0,236	0,937	**0,009**	**0,001**	0,279	0,491	0,567
r→CCI	0,446	0,817	0,965	0,916	0,200	0,647	0,542	0,699	0,512
ESI→r	0,684	0,774	0,529	0,781	**0,008**	0,138	0,182	0,478	0,533
r→CCI	0,526	0,190	0,901	0,733	0,715	0,547	0,444	0,996	0,273

Results from the Granger-Causality test indicate that there does not exist two-way causality between the sentiment measures and stock returns in any case. Consumer confidence granger-causes returns of small and small growth indices at 1% level, but there exists no feed-back effect from the returns back to CCI. In addition, Economic sentiment indicator granger-causes the returns of the small index, but is itself not caused by the returns on the index. Hence, the past levels of consumer confidence and economic sentiment incorporate information that is useful in predicting returns on small stock and small growth stocks, but the past stock returns do not seem to have any predictive power on levels of sentiment. These findings supports the view that consumers primarily hold small stocks, as consumer confidence only affects returns on those indices. However, it seems past stock returns are not an essential factor in the formation of confidence. Moreover, it is interesting to note that according to the results there appears to be no dependency between the sentiment measures and OMXH-index. This finding does not support the second hypothesis that sentiment would have an influence on the aggregate market returns. On the other hand, these findings give support for the first hypothesis that the impact of sentiment has a stronger effect on the returns of small stocks, while the results show causality running from sentiment only to the returns of small stocks. The results here are partially in line with Brown and Cliff (2004), who find that causality runs from sentiment to small stocks but not to large stocks. However, they also find causality running from small and large stocks to sentiment, which is contradicting to my results. Also Schmeling (2009) finds two-way causality between confidence measures and stock returns for aggregate market as well as for value and growth stocks.

5.1. Stock returns and changes in sentiment

To investigate the impacts of sentiment on stock returns further I test, if changes in the sentiment measures affect the returns of the stock indices. Following Fisher and Statman (2000), I take the first difference of Consumer Confidence Index and Economic Sentiment Indicator and run the following regression

(19) $$R_t = c + \beta_1 \Delta SENT_t + e_t,$$

where R_t is the (log) return of a chosen stock index $\Delta SENT$ is the change in either CCI or ESI, and e_t is the error term.

The results for the impact of contemporaneous change in CCI or ESI are seen in Table 7. As seen in Panel A, contemporaneous changes in CCI have a statistically significant impact on Small, Growth and Small Value index, which are considered to be more speculative compared to large and value stock indices. This finding is in line with Fisher and Statman (2003) and Brown and Cliff (2004). The R-squares of the regression show that the variance of Consumer Confidence index explains 6 percent of the variance of the Small index returns and 5% of the variance of Small Growth and Small Value index returns.

Changes is Economic Sentiment Indicator, on the other hand, have a statistically significant impact on all the index returns at a 10% level or less. Additionally, contemporaneous changes in ESI seem to have significant effect on stock returns in general as the impact is statistically significant for OMXH-index returns. The R-square of the regression shows that variance in ESI explains 7% of the variance of OMXH-index returns. In addition, changes in ESI explain 8% of the variance of Value index. The results suggest that ESI incorporates more explanatory power on all the index returns compared to CCI, as the R-squares are higher in every case and the coefficients are more significant. ESI is based on a variety of different confidence indicators and the surveys are targeted to firm managers, whereas consumer confidence surveys are targeted to households who are more likely to be small stock holders.

Table 7. Monthly index returns (log) regressed on contemporaneous changes in CCI and ESI. Bold entities represent statistical significance at 10% percent level or less. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level, *** Statistically significant at 1 % level.

	Panel A			Panel B		
	c	ΔCCI	R2	c	ΔESI	R2
Growth	-0,003	0,000	0,00	-0,002	**0,007****	0,04
	(-0,34)	(0,14)		(-0,29)	(2,20)	
Large	-0,006	-0,002	0,00	-0,005	**0,006***	0,03
	(-0,75)	(-0,72)		(-0,60)	(1,90)	
Large Growth	-0,001	-0,001	0,00	0,000	**0,006****	0,03
	(-0,55)	(-0,32)		(0,01)	(2,02)	
Large Value	0,001	0,000	0,00	0,001	**0,004***	0,02
	(0,14)	(-0,17)		(0,23)	(1,88)	
Value	0,002	0,001	0,00	0,002	**0,006*****	0,08
	(0,34)	(0,61)		(0,47)	(4,75)	
Small	0,008	**0,006****	0,06	0,008	**0,005*****	0,07
	(1,49)	(2,12)		(1,68)	(3,14)	
Small Growth	0,001	**0,007****	0,05	0,001	**0,006*****	0,07
	(0,15)	(2,08)		(0,19)	(3,12)	
Small Value	**0,010***	**0,006****	0,05	**0,010***	**0,005*****	0,07
	(1,88)	(2,17)		(1,78)	(2,71)	
OMXH	0,000	0,002	0,00	0,001	**0,006*****	0,07
	(0,06)	(0,70)		(0,18)	(3,00)	

Many papers show evidence that survey measures of sentiment exhibit forecasting power on stock returns. The forecasting ability of changes in two sentiment measures is tested with a forecast horizon of one month and two months. The equation can be put in the form of

(20) $$R_t = c + + \beta_1 \Delta SENT_{t-1} + e_t,$$

where R_t is the (log) return of a chosen stock index $\Delta SENT_{t-1}$ is the change in either CCI or ESI with the chosen forecast horizon and e_t is the error term. As the results in Table 8 show, changes in both sentiment measures appear to have some forecasting power on the stock index returns. CCI in the previous month has a positive and statistically significant impact on the returns of Small Growth index, Small index, and Small Value index. These results support the findings of Fisher and Statman (2003), who report that the predictive power of sentiment is especially pronounced for return s on small stocks. Additionally, Schmeling (2009) finds that consumer confidence predicts returns on small stocks on a short-horizon. They, however, report a negative relationship between sentiment and subsequent stock returns, which is in support of the investor overreaction theory. The same effect is not observed here. As seen in Table 8, the R-squares reveal that the variation in sentiment, measured by CCI and ESI, explains the variation in stock returns very modestly, thus the predictive power is relatively weak. The unexpected sign of the sentiment coefficient may be explained by the weak overall explanatory power of sentiment.

Table 8. Monthly index (log) returns are matched with the change in CCI (Panel A) and ESI (Panel B) in the previous. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level.

	Panel A			Panel B		
	c	ΔCCI_{t-1}	R2	c	ΔESI_{t-1}	R2
Growth	-0,002 (-0,20)	0,000 (-0,05)	0,00	-0,002 (-0,24)	-0,003 (-1,23)	0,01
Value	0,002 (0,32)	0,003 (1,36)	0,01	0,002 (0,29)	0,001 (1,15)	0,00
Large	-0,004 (-0,59)	0,000 (-0,02)	0,00	-0,005 (-0,59)	-0,003 (-1,16)	0,01
Large Growth	0,000 (-0,39)	-0,002 (-0,34)	0,00	-0,003 (0,00)	**-0,004*** (-1,76)	0,01
Large Value	0,002 (0,27)	0,002 (0,83)	0,00	0,002 (0,27)	0,001 (0,80)	0,00
OMXH	0,001 (0,22)	0,001 (0,80)	0,00	0,001 (0,179	-0,001 (-0,45)	0,00
Small Growth	0,002 (0,27)	**0,004**** (2,11)	0,02	0,002 (0,25)	**0,003*** (1,89)	0,02
Small	0,008 (1,35)	**0,004**** (2,27)	0,02	0,008 (1,39)	**0,003***** (3,27)	0,03
Small Value	0,010 (1,66)	**0,004**** (2,15)	0,02	0,010 (1,54)	**0,003***** (2,91)	0,02

Results are similar in the case of ESI; a positive change in ESI in the previous month has a positive and significant impact on the returns of small growth, small and small value indices. ESI has only significant negative impact on the returns of large growth index. Again, all though the estimates of sentiment are statistically significant, the R-squares show that ESI has almost no explanatory power on the returns of the indices. Again, it is not surprising that the estimates of CCI and ESI are positive, on the contrary to what was expected, since their impact on returns is so modest in general. When the forecast horizon is extended to two months, forecasting power of ESI disappears. ESI seems to have a statistically significant negative impact only on the returns of Large Value stocks. Nevertheless, the result is significant on a 10% level, which indicates that it may be solely due to chance. The results are similar to Fisher and Statman (2000) who were also not able to find a significant forecasting power of changes in sentiment on stock returns.

Table 9. Monthly index (log) returns are matched with the change in CCI (Panel A) and ESI two months before. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level.

	Panel A			Panel B		
	c	ΔCCI_{t-2}	R2	c	ΔESI_{t-2}	R2
Growth	0,001 (0,15)	0,003 (0,93)	0,00	0,001 (0,08)	-0,003 (-0,88)	0,01
Value	0,003 (0,48)	0,000 (0,21)	0,00	0,002 (0,39)	-0,002 (-1,45)	0,01
Large	-0,002 (-0,26)	0,000 (-0,03)	0,00	-0,002 (-0,32)	-0,005 (-1,58)	0,02
Large Growth	0,003 (0,39)	0,002 (0,81)	0,00	-0,001 (-0,12)	-0,003 (-0,98)	0,01
Large Value	0,001 (0,21)	-0,002 (-0,70)	0,00	0,001 (0,16)	**-0,003*** (-1,85)	0,02
OMXH	0,003 (0,55)	0,001 (0,58)	0,00	0,003 (0,45)	-0,002 (-1,02)	0,01
Small Growth	0,003 (0,50)	0,001 (0,81)	0,00	0,003 (0,46)	0,000 (0,14)	0,00
Small	0,008 (1,32)	0,002 (1,20)	0,00	0,008 (1,25)	0,000 (-0,07)	0,00
Small Value	0,010 (1,50)	0,002 (1,03)	0,00	0,009 (1,61)	0,000 (0,24)	0,00

5.2. Adjusted sentiment and stock returns

Prior literature suggests that consumer confidence might incorporate a component which is not explained by rational fundamentals. Thus, when using the raw sentiment indices as explanatory variables for stock returns, one cannot be sure of whether the results are due to correlation of the sentiment indices with business cycle. In order to address this issue, both confidence indices are regressed on a set of macroeconomic variables and their lagged values to account for the issue that some proxies might take longer to affect consumer confidence. The variables are chosen following Lemmon & Portniaguina (2006) and Chen (2011), who find that a substantial amount of consumer confidence is explained by macro fundamentals. Table 9 describes the results of the equation for CCI and Table 10, for ESI.

Table 10. Economic Sentiment Indicator regressed on macroeconomic factors. Entities in middle represent coefficients for each independent variable. Right hand side of the table represents t-values of the coefficients. $\Delta UNEMP_t$ is the monthly change in unemployment rate, $\Delta INFL_t$ is the monthly change in CPI, $\Delta RATE_t$ is the change in 3-month Euribor rate, ΔGDP_t is a moving average of the change in quarterly GDP growth, ΔDIV is the monthly change in OMXH25 dividend yield, and $\Delta INDPRO_t$ is the change in industrial production growth. Bolded values indicate statistical significance at 10% or less. * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level. $\overline{R^2}$= 0,74.

Variable	Coefficient	t-statistics
C	**103,47*** **	131,56
$\Delta UNEMP_t$	**-18,13*** **	-2,79
$\Delta RATE_t$	**13,84*** **	5,84
$INDPRO_t$	0,14	0,86
ΔDIV_t	0,82	1,07
GDP_t	**0,58** **	2,36
$\Delta INFL_t$	0,61	0,95
$\Delta RATE_{t-1}$	**4,67* **	1,74
$INDPRO_{t-1}$	0,09	0,53
ΔDIV_{t-1}	0,31	0,43
GDP_{t-1}	-0,12	-0,60
$\Delta INFL_{t-1}$	**-2,17*** **	-3,11
$\Delta UNEMP_{t-1}$	**-27,18*** **	-4,28

The adjusted R-square of the regression is 0,74 for Economic Sentiment Indicator and 0.62 for Consumer Confidence, indicating that variation in the macroeconomic fundamentals explain a significant proportion of the variation in both sentiment measures. Moreover, the estimates of the macro variables are consistent with the economic intuition that counter-cyclical factors decrease confidence in the economy and pro-cyclical factors increase it; the estimates of interest rate and unemployment are negative whereas GDP-growth has a positive sign. Following Chen (2011) the residual of the regression is then treated as the irrational measure of sentiment, in other words, the adjusted sentiment. It is likely, that the residual of the regression incorporates other rational factors that have not been included in the regression. However, the residual is treated at least a cleaner measure of irrational sentiment.

The change in 3-month Euribor seems to have the strong impact on ESI, both on a contemporaneous level and in the previous month. Also the growth in GDP has a positive impact on ESI on a contemporaneous level. Contemporaneous unemployment as well as lagged unemployment have a strong negative impact on economic sentiment. Additionally, lagged inflation appears to affect ESI negatively.

Table 11. Consumer Confidence Index regressed on macroeconomic factors. Entities in middle represent coefficients for each independent variable. Right hand side of the table represents t-values of the coefficients. $\Delta UNEMP_t$ is the monthly change in unemployment rate, $\Delta INFL_t$ is the monthly change in CPI, $\Delta RATE_t$ is the change in 3-month Euribor rate, ΔGDP_t is a moving average of the change in quarterly GDP growth, ΔDIV is the monthly change in OMXH25 dividend yield, and $\Delta INDPRO_t$ is the change in industrial production growth. Bolded values indicate statistical significance at 10% or less. * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level. $\overline{R^2}$= 0,62.

Variable	Coefficient	t-statistics
C	**14,59*** **	19,79
$\Delta UNEMP_t$	**-14,77** **	-2,42
$\Delta RATE_t$	**11,62*** **	5,23
$INDPRO_t$	-0,02	-0,14
ΔDIV_t	-0,12	-0,16
GDP_t	**0,53** **	2,29
$\Delta INFL_t$	0,48	0,80
$\Delta RATE_{t-1}$	-0,77	-0,31
$INDPRO_{t-1}$	0,10	0,64
ΔDIV_{t-1}	-0,35	-0,52
GDP_{t-1}	**-0,36** **	-1,99
$\Delta INFL_{t-1}$	**-2,01*** **	-3,07
$\Delta UNEMP_{t-1}$	-5,29	-0,89

Comparing the results in Table 10 and 11, the macroeconomic variables seem to do a better job in explaining ESI compared to CCI. The adjusted R-square shows, that the macro variables explain approximately 62% of the variation in the level on CCI. As ESI, Consumer Confidence is positively affected by the contemporaneous change in 3-month Euribor (ΔRATE_t) and the contemporaneous growth in GDP. The contemporaneous growth in unemployment rate has a negative impact on CCI. The negative effect is not surprising as the growth in unemployment is one of the key factors determining the level on consumer confidence indicator. In addition, the lagged inflation has a significantly negative impact on the level of consumer confidence.

Figures 1 and 2 show the adjusted ESI and CCI over the sample period. Both figures line up well with recent booms and crashes in the markets. The crash of the dot-com boom in the beginning of 20th can be seen in as a substantial decrease in confidence in the beginning of 2001. Another notable decline in the adjusted CCI can be observed in the middle of 2007, when the subprime crisis escalated. Adjusted CCI also experiences a sharp rise around 2010, which is followed by a major decline in 2011, which might reflect consumers' views about the unstable financial situation in Europe at that time. The sub-prime credit crisis in the US affected the in financial sectors especially in Europe. The deterioration of the in the financial sectors of the US and Europe destabilized national financial systems all over the world and led to the global financial crisis. (Moshirian 2011: 510.)

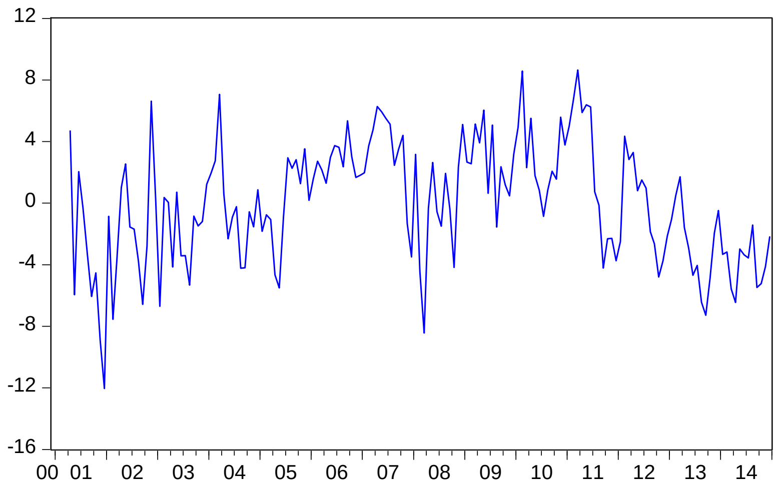

Figure 1. Adjusted Economic Sentiment Indicator over the sample period from January 2001 to December 2014.

Comparing the figures of adjusted sentiment measures, CCI exhibits larger deviations during the overall sample period compared to ESI. This might be due to the fact that consumer confidence surveys are targeted to households, whereas economic sentiment survey is mostly targeted firm managers. Consumers might not be as consistent in their economic views and expectations, compared to managers. As in the case of adjusted CCI, adjusted measure of ESI also shows a sharp decrease during 2001, when the dot-com boom deflated. Another notable decline in the index is seen during the financial crisis in 2007-2008. Compared to adjusted CCI, economic sentiment does not drop as strongly in the beginning of 2011, although it does experience several downward shifts.

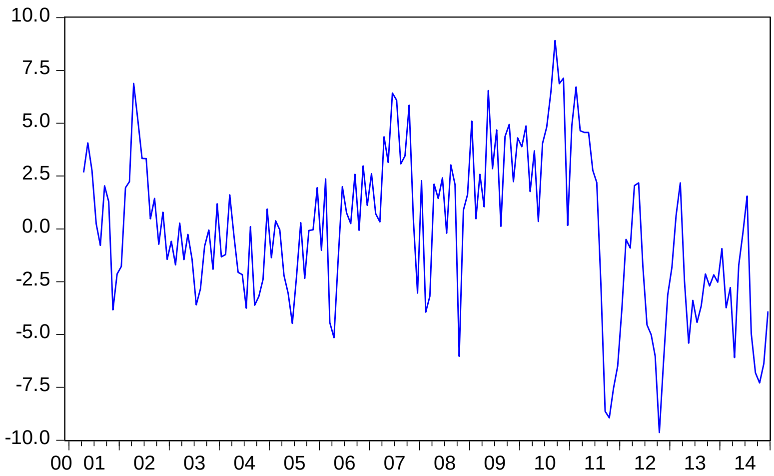

Figure 2. Adjusted Consumer Confidence Index over the sample period from January 2001 to December 2014.

Next we address if the adjusted sentiment indices have forecasting power on the returns of the stock indices. This regression is performed the following way:

(21) $$R_t = c + \beta_1 ADJSENT_{t-1} + e_t,$$

where R_t is the return (logarithm) of a given index at time t and $ADJSENT_{t-1}$ is the lagged value of the adjusted measure of consumer confidence or economic sentiment indicator. Special attention is paid on the coefficient sign of β_1, which implicates if subsequent returns are negatively related to increase in previous sentiment. Table 12 summarizes the results for the impact of adjusted sentiment with one-month lag on stock index returns. As shown in Panel A, adjusted consumer confidence has virtually no effect on any of the index returns on a one month-forecast horizon. Adjusted CCI has a negative effect on the returns of the value index. However, the effect is significant only on a 10% level. As with adjusted CCI, adjusted ESI does not seem to have an impact on most of the index returns. An increase in adjusted ESI in the previous month is negatively related to the returns of large value and value indices. The results show that adjusted ESI explains the variation in returns of large value and value index modestly, as the R-squares of the regressions are 2% and 3 % respectively.

Table 12. Index returns regressed on adjusted CCI (Panel A) and adjusted ESI (Panel B) with a one-month forecast horizon. Bold entities represent statistical significance at 10% level or less. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level, *** Statistically significant at 1 % level.

	Panel A			Panel B		
	C	$Adj.CCI_{t-1}$	R2	c	$Adj.ESI_{t-1}$	R2
Growth	-0,002	-0,001	0,00	-0,002	-0,002	0,01
	(-0,20)	(-0,65)		(-0,21)	(-0,86)	
Large	-0,004	-0,002	0,00	-0,004	-0,003	0,02
	(-0,54)	(-1,04)		(-0,54)	(-1,48)	
Large Growth	-0,003	-0,001	0,00	-0,003	-0,002	0,00
	(-0,36)	(-0,60)		(-0,36)	(-0,78)	
Large Value	0,001	-0,002	0,01	0,001	**-0,003***	0,02
	(0,13)	(-1,45)		(0,13)	(-1,79)	
OMXH	0,001	-0,001	0,01	0,001	-0,002	0,01
	(0,21)	(-1,13)		(0,23)	(-1,22)	
Small	0,008	-0,001	0,00	0,008	0,000	0,00
	(1,16)	(-0,70)		(1,16)	(-0,36)	
Small Growth	0,003	0,000	0,00	0,003	0,000	0,00
	(0,44)	(-0,27)		(0,43)	(-0,11)	
Small Value	0,009	-0,001	0,01	0,009	0,000	0,00
	(1,32)	(-0,90)		(1,32)	(-0,35)	
Value	0,002	**-0,002***	0,01	0,002	**-0,003****	0,03
	(0,39)	(-1,76)		(0,40)	(-2,10)	

Results in Table 13 show that when the forecast horizon is extended to two months, adjusted consumer confidence has a statistically significant negative impact on the returns of large value index and small value index. Hence, as the investor sentiment increases, returns on large and small value index decrease. Adjusted CCI no longer impacts the value index returns, as it did on a one-month forecast horizon. Again, the R-squares implicate that variation in adjusted CCI on a two-month forecast horizon explain only 3% and 2% of the variation in large value index and small value index respectively. On the contrary, adjusted ESI maintains it explanatory power on large value and small value index. An increase in adjusted ESI results in a 0,5 % decrease in the returns of large value index. Moreover, the variance in adjusted ESI explains 6% of the variance in large value index returns. For small index and small value index, an increase in adjusted ESI leads to 0,3% and 0,2% decrease in their returns, respectively.

Table 13. Index returns regressed on adjusted CCI (Panel A) and adjusted ESI (Panel B) with a two-month forecast-horizon Bold entities represent statistical significance at 10% level or less. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level.

	Panel A			Panel B		
	c	$Adj.CCI_{t-2}$	R2	c	$Adj.ESI_{t-2}$	R2
Growth	-0,001	-0,001	0,00	-0,001	-0,001	0,02
	(-0,13)	(-0,67)		(-0,13)	(-0,54)	
Large	-0,004	-0,002	0,01	-0,004	-0,003	0,02
	(-0,47)	(-1,28)		(-0,48)	(-1,58)	
Large Growth	-0,003	-0,001	0,00	-0,002	-0,001	0,00
	(-0,29)	(-0,47)		(-0,30)	(-0,28)	
Large Value	0,001	**-0,004****	0,03	0,001	**-0,005*****	0,06
	(0,09)	(-2,18)		(0,09)	(-4,37)	
OMXH	0,002	-0,002	0,01	0,002	-0,002	0,02
	(0,29)	(-1,55)		(0,27)	(-1,61)	
Small	0,007	-0,002	0,02	0,007	**-0,003***	0,03
	(1,12)	(-1,65)		(1,09)	(-1,92)	
Small Growth	0,003	-0,002	0,01	0,003	-0,002	0,01
	(0,38)	(-1,18)		(0,36)	(-1,14)	
Small Value	0,009	**-0,002***	0,02	0,009	**-0,002***	0,02
	(1,32)	(-1,73)		(1,28)	(-1,73)	
Value	0,002	-0,003	0,02	0,002	-0,002	0,06
	(0,45)	(-2,09)		(0,27)	(-1,61)	

On a three-month forecast horizon adjusted CCI does not have explanatory power on any of the returns as seen in Table 14. Adjusted ESI, on the other hand, retains its explanatory power on the large value index returns on 10% significance level. An increase in ESI decreases the subsequent monthly returns on the large value index by 0,3 %. Schmeling (2009) finds that the impact of sentiment on future stock returns decreases with forecast horizon. The same effect is present here: When the forecast-horizon is extended to three months, the forecasting power of CCI disappears completely and ESI shows only weak forecasting ability on the returns of large value index. The returns that ESI seems to affect consistently are the returns on the large value index.

Table 14. Index returns regressed on adjusted CCI (Panel A) and ESI (Panel B) with a three-month forecast horizon. Bold entities represent statistical significance at 10% level or less. The standard errors are estimated with HAC Newey-West procedure (Newey-West automatic bandwidth and lag length). * Statistically significant at 10% level, ** Statistically significant at 5% level,*** Statistically significant at 1 % level.

	Panel A			Panel B		
	c	$Adj.CCI_{t-3}$	R2	c	$Adj.ESI_{t-3}$	R2
Growth	0,001	-0,001	0,00	0,000	0,001	0,00
	(0,07)	(-0,62)		(0,04)	(0,68)	
Large	-0,002	-0,001	0,00	-0,002	0,000	0,00
	(-0,34)	(-0,69)		(-0,34)	(0,16)	
Large Growth	-0,001	-0,001	0,00	-0,001	0,002	0,01
	(-0,13)	(-0,47)		(-0,12)	(1,02)	
Large Value	0,001	-0,002	0,01	0,001	**-0,003****	0,02
	(0,18)	(-1,16)		(0,18)	(-1,98)	
OMXH	0,003	-0,002	0,01	0,003	0,000	0,00
	(0,51)	(-1,11)		(0,47)	(-0,21)	
Small	0,008	-0,003	0,02	0,008	-0,002	0,02
	(1,26)	(-1,57)		(1,21)	(-1,58)	
Small Growth	0,004	-0,002	0,01	0,003	-0,002	0,01
	(0,49)	(-1,15)		(0,46)	(-0,91)	
Small Value	0,010	-0,003	0,03	0,009	-0,003	0,03
	(1,44)	(-1,62)		(1,38)	(-1,59)	
Value	0,003	-0,002	0,01	0,003	-0,002	0,01
	(0,57)	(-1,46)		(0,53)	(-1,63)	

All in all, the results from the predictive regressions are in line with Brown and Cliff (2004), and suggest that sentiment, after controlling for macroeconomic factors, shows only weak predictive power on stock returns on short-horizons. Although, an increase in sentiment on previous periods seems to have negative impact on returns in subsequent periods, the explanatory power is weak in all cases. The negative effect of adjusted sentiment appears to be strongest on a two- month forecast horizon. More over the results from the predictive regressions are somewhat conflicting: Adjusted Consumer

Confidence Index shows weak forecasting power only on returns of the Value Index. On a 2-month forecast-horizon however, an increase in adjusted CCI has a negative effect on Large Value and Small Value index returns. Thus, there seems to be a lack of consistency in the effect, and the negative impact is not more prone for returns on small stocks.

The negative effect of adjusted Economic Sentiment Indicator on the index returns seems to be stronger compared to adjusted CCI. Nevertheless, the results differ with the chosen forecast horizon. As adjusted CCI, adjusted ESI has a negative impact on value index returns on a one-month forecast horizon in addition to large value returns. On a 2-month forecast horizon the negative effect on value returns disappear, but the effect remains for large value returns. Moreover, adjusted ESI shows a negative impact on the returns of small index and small value index. When the forecast horizon is extended to three months, adjusted ESI has a negative impact on the returns of large value stocks. Hence, adjusted ESI seems to have negative consistent impact only on the returns of large value stocks.

6. CONCLUSIONS

The aim of this study was to investigate the impact investor sentiment, measured by Consumer Confidence Index and Economic Sentiment Indicator, on stock returns in Finnish stock markets. I test whether stocks that are considered speculative are more prone to sentiment compared to bond-like stocks. Additionally, the impact of sentiment on aggregate stock market returns is tested. In this study, the proxy for aggregate market return in Finland is the OMX-Helsinki index. Previous literature suggests that confidence measures of sentiment are strongly correlated with macroeconomic fundamentals but might also incorporate an irrational component. Following Lemmon & Portniaguina (2006) and Chen (2011) both sentiment survey measures were regressed on a set of macroeconomic variables in order to distinguish the irrational part of sentiment, and to test whether irrational sentiment has any impact on returns of the indices. More specifically, if there exists a negative relationship on a short-horizon between irrational sentiment and subsequent returns on stocks that are considered speculative.

The results show that neither Consumer Confidence Index nor Economic Sentiment Indicator has an impact on the aggregate stock market returns. Although, changes in Economic Sentiment Indicator are positively correlated with contemporaneous returns on OMXH, Consumer Confidence Index does not seem to have any effect on aggregate stock market returns. Additionally, results from the Granger-causality test show that neither sentiment index granger-causes returns on OMXH. Hence, the results do not support the first hypothesis that there would exist a negative relationship between the sentiment measures and subsequent aggregate stock market returns.

Previous studies, such as Fisher and Statman (2001, 2003) and Brown & Cliff (2004), find a strong positive correlation between stock returns and changes in survey measures of sentiment. In line with their findings, I find that contemporaneous changes in both sentiment measures are positively correlated with stock returns. However, the magnitude of the sentiment effect differs between the two survey measures. Contemporaneous changes in CCI as well as changes in CCI in the previous month affect only the returns of Small, Small Growth and Small Value indices. Moreover, the results from the Granger-Causality test show that CCI granger-causes solely the returns of Small and Small growth index. Thus, the second (alternative) hypothesis is accepted in the case of Consumer Confidence Index. The results are not as clear for Economic Sentiment Indicator: Contemporaneous changes in ESI are positively correlated with all index returns. Unlike changes in CCI, changes in ESI affect the overall market returns - OMXH-index. Moreover, a change in ESI in the previous month shows a positive impact on Small, Small Growth and Small Value indices, but also negative effect on the returns of Large Growth index. On a two-month forecast horizon, a change in ESI has a negative impact on returns on the Large Value index. Results from the Granger-Causality test indicate that the level of ESI granger-causes only the returns of small stocks. Hence, although ESI seems to affect also returns on indices that are not considered speculative, the impact is stronger and more consistent in the case of speculative stocks. These findings are in line with the second hypothesis. In accordance with Fisher and Statman (2000), the changes in the two sentiment proxies show only weak forecasting power on the returns of the indices.

After controlling for macroeconomic factors, both of the adjusted sentiment indices appear to have negative effects on subsequent returns. This finding might refer to an initial overreaction and subsequent correction move, suggested by behavioral theories. On a one-month forecast horizon the negative impact of sentiment is significant only for the returns of Large Value and Value indices, which are not considered speculative. The negative effect of the adjusted sentiment appears to be strongest on a two-month forecast horizon. An increase in the level of adjusted ESI decreases returns on the Large Value-, Small-, and Small Value indices. Similarly, an increase in adjusted CCI is associated with a decrease in returns of Large Value and Small Value indices. On a three-month forecast horizon, adjusted CCI does not have any impact on any index returns. Adjusted ESI, on the other hand, retains its negative impact on Large Value index returns. These findings are partially in line with Schmeling (2009), who finds that consumer confidence has a stronger negative relation with value stocks compared to growth stocks. However, Schmeling (2009) also finds that small stocks are affected by sentiment whereas large stock are not, which is conflicting to my results.

Although, there exists a negative relation between adjusted sentiments and subsequent returns on some indices, the findings do not support the third hypothesis that adjusted sentiment would primarily affect speculative stocks. Moreover, the R-squares implicate that the explanatory power of sentiment on stock returns is relatively trivial. In accordance with Brown and Cliff (2004), the results show very little evidence that sentiment is capable of predicting stock returns on a short-horizon. On the other hand, the lack of ability to predict the index returns on a short horizon does not mean that sentiment would not have any impact on returns. It is possible that the impact of sentiment is implemented gradually on the returns, which makes it hard to identify the effect. Hence, for further research, it would be interesting to test if the adjusted measures of these sentiment indices have stronger impact on a longer horizon. Additionally, one must consider if the negative effect of adjusted sentiments on subsequent stock returns stems from actual irrational sentiment, or if there is some underlying macroeconomic factor not captured by the model that causes the effect. Moller, Norholm, and Rangvid (2014) show that consumer confidence is a strong predictor of stock returns, but the information concerning expected returns is due to its correlation with the business cycle. Thus, for further research more sophisticated models are needed to clarify this matter.

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APPENDICES

Appendix 1. Economic Sentiment Indicator monthly survey questions

Type of survey	**Monthly questions**
Industry	Production, past 3 months Production, next 3 months Total order books Export order books Stocks of finished products Selling prices, next 3 months Firm's employment, next 3 months
Construction	Building activity, past 3 months Factors limiting building activity Overall order books Firm's employment, next 3 months Selling prices, next 3 months
Retail trade	Business activity, past 3 months Business activity, next 3 months Stocks of goods Orders placed with suppliers, next 3 months Firm's employment, next 3 months Selling prices, next 3 months
Services	Business situation, past 3 months Demand/Turnover, past 3 months Demand/Turnover, next 3 months Firm's employment, past 3 months Firm's employment, next 3 months Selling prices, next 3 months
Consumers	Financial situation, past 12 months Financial situation, next 12 months General economic situation, past 12 months General economic situation, next 12 months Consumer prices, past 12 months Consumer prices, next 12 months Unemployment, next 12 months Major purchases of durable consumer goods, current environment Major purchases intentions, next 12 months Savings, current environment Savings intentions, next 12 months

Reference: European Commission 2016

Appendix 2. Consumer Confidence Index monthly survey questions

The following 17 EU harmonised questions are included in the Consumer Survey each month (approximate translations from Finnish):

1. What is your present economic situation like compared to 12 months ago?
2. What will your own economic situation be like in 12 months' time compared to present?
3. What is Finland's present economic situation like compared to 12 months ago?
4. What will Finland's economic situation be like in 12 months' time compared to present?
5. What are the consumer prices like now compared to 12 months ago?
6. By how many per cent have the consumer prices changed during the last 12 months?
7. How will consumer prices change within the next 12 months?
8. By how many per cent will the consumer prices change during the next 12 months?
9. What will be the number of the unemployed in Finland in 12 months' time compared to present?
10. Is it now a favourable or unfavourable time to purchase consumer durables?
11. Are you going to spend more or less money on consumer durables over the next 12 months compared to the last 12 months?
12. Is this a favourable time to save money?
13. How likely are you to be able to save money within the next 12 months?
14. What is your household's present financial situation?
15. How likely is your household to purchase a car within the next 12 months?
16. Is your household going to purchase or build a dwelling within the next 12 months?
17. How likely is your household to spend a large amount of money on basic repairs to your dwelling in the next 12 months?

Besides the EU harmonized questions, some Statistics Finland's own questions are made monthly or quarterly. They are the following:

Statistics Finland'

1. Is your household planning to buy a new or used car?
2. How are you going to finance the purchase of the car (two main modes of financing)? (quarterly)
3. How are you going to finance the purchase of the dwelling (two main modes of financing)? (quarterly)
4. Is your household going to use money on the following items within the next 6 months: dwelling repair and maintenance, home furnishing, holiday home, entertainment electronics, household appliances, hobby and sports equipment, vehicles (excl. car), holiday travel in Finland, holiday travel abroad?
5. For what purpose are you saving money? (quarterly)

6. How are you going to invest your savings? (quarterly)
7. Is this a favourable time to raise a loan?
8. Is your household planning to raise a loan during the next 12 months?
9. For which purpose are you going to raise a loan? (quarterly)
10. How likely are you to be thrown into unemployment within the next 12 months?
11. Which of the following equipment does your household have (25 equipment: entertainment electronics, information technology, telephones, car)? (quarterly)
12. How have you invested your savings (at the moment of the interview)? (quarterly)

Classification items, which characterise the respondent and his or her household, are also included in the questionnaire (monthly):

1. How many members belong to your household?
2. How many adults/children (4 age groups) are there in your household?
3. How many of the members of your household go to work regularly?
4. Which is your municipality of domicile at present?
5. What is the form of tenure of your household's dwelling?
6. What is your primary activity at present?
7. What is your occupation?
8. Have you had occupational training for your (present) job?
9. What is the gross income of your household?

The basic information of the respondent, e.g. age, gender and sample municipality, are always found in the original sampling data. In addition, each person's education code is drawn from the Register of Completed Education and Degrees. Different regional classifications can be formed with the help of the municipality code.

Reference: Official Statistics of Finland (OSF)