Sentiment-Indices on Financial Markets: What do they measure?

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Abstract

Sentiment indices based on investor sentiment surveys attempt to measure the stock market sentiment. The literature on these indices focusses mainly only whether investor sentiment influences the financial markets or not. But the term “sentiment” gets never defined in the literature. Therefore it is unclear what is measured by sentiment indices, whether it is really sentiment or something different.
This article closes this gap in the literature by using psychological definitions about feelings to explain what might be meant by ”market sentiment”. I show the usefulness of these definitions with data from the German sentiment index “Sentix”.
My contribution is threefold : 1. I present a simple concept of sentiments in general. 2. I relate short and long term sentiment indices to two distinct parts of sentiments, emotion and mood. Their commonly observed statistical properties are in line with the definitions of emotion and mood. And 3. I extract two factors representing investor emotion and mood across all markets in the dataset. These results are stable across markets and model specifications in the Sentix dataset.

Keywords: sentiment indices, investor sentiment, factor analysis, psychological analysis, financial markets
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1 Introduction

1.1 Aim of the paper

Sentiment indices try to measure the stock market sentiments. Usually one tries to measure the impact of observed sentiment on the stock market, but there is usually no definition of "sentiment". Therefore it has remained unclear what the sentiment proxies used in articles like Baker and Wurgler (2007) or Neal and Wheatley (1998) are proxies for. In this article I attempt to close the gap and relate the sentiment data to an appropriate theory of sentiments. Once this gap is closed, a better understanding of investor sentiment and its influence on financial markets is possible.

The German sentiment index "Sentix" serves as my data for the analysis. I use definitions from economic psychology about feelings to explain what might be meant by "market sentiment". These definitions provide the background to my analysis of the sentiment data. Based on the definitions I derive hypotheses about the statistical properties of sentiment indices, given that they really resemble feelings of the investors' and not something different. The hypotheses allow me to explain some features of sentiment data which have been observed in the literature by e.g. Schmeling (2007) or Klein and Zwergel (2006). I combine the psychological theory and the statistical results for a better understanding of the qualitative and quantitative differences between short and long term investor sentiment. During my analysis I will split up the term "sentiment" into two parts, emotion and mood. Emotion stands for the short term sentiment and mood for the long term sentiment. Via factor analysis I extract two (latent) factors from the sentiment data which I interpret as investor emotion and investor mood.

To give more justification why sentiments matter in financial markets and why it is important to understand the nature of sentiments, I discuss shortly the psychology of financial markets based on Tuckett (2009) and Tuckett and Taffler (2008). These articles show why waves of optimism and pessimism are an implicit feature of trading on financial markets.

One result of this article is a well defined concept of (investor) sentiment which removes the shaky ground on which previous analysis have rested. It becomes now possible to test possible sentiment proxies against this concept to make sure that these proxies really measure sentiment and not something else. Successfully testing possible sentiment proxies may lead to more solid conclusions about the relationship between investor sentiment and financial markets. The concept can also act a starting point for further research about the properties of investor sentiment. The result is in a step further into understanding investor behaviour on financial markets.

The results offer also new possibilities for the work of behavioural economists. It seems plausible to look for meaningful behavioural results even in ordinary time series measuring sentiments on financial markets. Without a proper understanding of what is measured by sentiment indicators or sentiment proxies, researchers can not infer for example the informational content of investor sentiment. Therefore they work with measures which they don't understand. So they can not fully understand the relation between investor sentiments and returns.

In the next section I will discuss the status quo of sentiments in economics together with a short literature review. Following this review I will elaborate on sentiment indices in general with some discussion of the potential problems when using this kind of data. In section 2 I will introduce the psychological definitions of sentiments, present my hypothesis based on these definitions and give some background information why sentiments play a crucial role in financial markets. The data set and its limitations will be discussed next in section 3. The hypotheses will be tested in section 4 with some extensions of the analysis in section 5. I will answer some issues raised by reviewers in section 6 and final remarks will be in section 7.

1.2 Literature review

Until now the literature on sentiment indices has been mainly focused on discussing the empirical effects of investor sentiment in relation to the stock market development. The theoretical foundation of sentiment is left out by all articles known to me. In dealing with investor sentiment two branches of literature emerged: 1. Articles using market variables as proxies for investor sentiment and 2. articles using investor sentiment surveys.

Neal and Wheatley (1998) started the first branch and they use three popular market ratios as indicators of investor sentiment. Baker and Wurgler (2007) and Finter et al. (2010) use a similar way to approach market sentiment. They use the Principal Component Analysis (PCA) to construct a sentiment indicator based either typical sentiment proxies (Baker and Wurgler (2007)) or macro-adjusted market variables (Finter et al. (2010)). Baker and Wurgler (2007) and others as well take the origin of investor sentiment as exogenous and focus instead on its empirical effects.

Articles like Brown and Cliff (2004), Klein and Zwergel (2006), Schmeling (2007), Hengelbrock et al. (2011) and Lux (2011) belong to the second branch and use explicitly sentiment data sets, but do not explore, what is actually measured by these data sets (investor sentiment surveys).

Klein and Zwergel (2006), Schmeling (2007), Heiden et al. (2011) and to some extent Finter et al. (2010) and Lux (2011) use the Sentix data set. While all these articles investigate the predictive power of sentiment indices for the stock market with more or less the same results [1], they provide some interesting information concerning the nature of sentiment data.

For example for Heiden et al. (2011) the Sentix dataset is not useful for their analyses, because it contains no reliable information. This finding is in contrast to articles like Klein and Zwergel (2006) or Schmeling (2007), which use the Sentix data set successfully. That's a hint to be cautious with using the Sentix data. Schmeling (2007) addresses also the question of statistical stability of the results. Private investors seem to begin learning from sentiment surveys at the end of Schmeling's study. Accordingly, if these surveys become more available and more known then this knowledge could trigger a change of behaviour, which could lead to a loss of some of the validity these results.

Heiden et al. (2011) found some evidence for sample dependent performance of private sentiment regarding future returns. They find some evidence for a "home-grown" bias as the institutional investors in their sample are unable to forecast the direction of the USD/JPY market. Their dataset consists primarily of German investors. Hence this composition of the panel might be the cause for the poor predictive performance of the institutional investors.

The problem with all of the above mentioned articles is that they take the data as given. None of them explore or explain further what investors' sentiment is through an appropriate economic or psychology theory. Although Baker and Wurgler (2007) discuss at length why and how certain proxies might be useful to measure investor sentiment [2], they still do not explain what investor sentiment is or what they mean by this term. If psychology is used in articles on financial economics then they usually refer to over and under reaction, see e.g. Daniel et al. (2004). This lack of clarity on the term "investor sentiment" is a bit puzzling given the rich literature on investor sentiment. To really justify the usage of investor sentiment for predictions or explaining market behaviour, one needs to know what investor sentiment is and why it should matter. Otherwise the results of these articles might be based on pure chance, spurious correlation, etc.

1.3 The status quo of sentiments in economics

Sentiments and emotions are supposed to play no role in the economic activity at least according to the classical assumption of rationality as in microeconomics. Especially since the advent of the efficient market hypothesis in the theory of financial markets and the rational expectations hypothesis, sentiments are ruled out by definition. Feelings or sentiments should occur only as noise if occurring at all,

[1] In short: Private investors resemble noise trader whereas institutional investors resemble smart money like in De Long et al. (1990).

[2] See section "Measuring Investor Sentiment" in Baker and Wurgler (2007).

because people are assumed to use all the information available to them correctly, therefore evaluate and process them rationally.

According to the rational expectations hypothesis, all information will always be processed so that on the average the right expectation is always formed. Distortions by feelings of euphoria or fear would at best have only a short time impact on one's behaviour and therefore play no role in the long run. According to the efficient market hypothesis by Fama (1970), the prices on the stock markets provide all the available information and therefore are always right. Systematic errors of judgement would not exist if all investors were rational.

If nevertheless investors display irrational behaviour, you have to distinguish between seemingly irrational behaviour and really irrational conduct according to standard game theory. Seemingly irrational behaviour is to force rational investors to act in a way so that the seemingly irrational investors get an improved result, which is why their behaviour is only apparently irrational. An example for seemingly irrational behaviour is self-restraint of their decision-making opportunities.

Truly irrational behaviour is systematically wrong behaviour, which contributes not a benefit increase. In the common financial market models this behaviour is adopted over again to justify deviations from the efficient market hypothesis, herd behaviour and creation of bubbles.But the argumentation is restricted mostly to the adoption of irrational behaviour, but not to the explanation. Only the reaction of rational investors to this deviant behaviour is usually investigated. Examples include models with "chartists" and "fundamentalists". Chartists could theoretically also be regarded as *sentiment trader*, since they use different statistical indicators such as moving averages of past and current yields on orient in order to act on the markets. The selection of the analytical instruments also depends on personal preferences of the agents and how confident the trader is towards certain chart techniques. Consequently, they must rely ultimately on their feelings for their decisions. Therefore, one can understand chartists as sentiment trader like in the models of e.g. De Long et al. (1990), although it is not stated explicitly. Indirectly the idea of sentiment traders has already been introduced in the literature.[3]

Sentiment is just accepted as a fact which you have to take somehow into account in models about financial markets, so that these models represent reasonably accurate the reality in the financial markets. Another way is trying to explain the dynamics of sentiment. Behavioural economics can not or almost nothing contribute to their explanations. Deviations from rational behaviour are examined and compared with the results of experimental economics. Knowledge of systematic biases is extracted from these experiments, but a more detailed explanation for the results of such as e.g. Prospect Theory is still missing.

[3] See Baker and Wurgler (2007) for a further elaboration on this finding.

Even in the context of agent-based modelling, which explicitly tries to take into account the heterogeneity of people, sentiments are not or only insufficiently explained. I could not find a single model which explicitly considered sentiment on financial markets and models them.

Little has been done to give sentiments a foundation in economic theory despite their use in financial economics.

1.4 Sentiment indices in general

A sentiment index can be any kind of available data as long as someone is convinced that these data depict the market sentiment. There is no official definition. The most natural way to obtain sentiment indices is to ask market participants for their feelings/sentiments about the future development of certain markets or the economy in general. Examples for this way of creating sentiment indices are in Germany the Ifo Business Climate Index by Ifo Institute for Economic Research in Munich and the GfK (Society for Consumer Research) Consumer Climate.

The literature on sentiment indices uses different kinds of market numbers/available market data of which the authors think that their data resembles market sentiment. Hence the indices can be composed of everything. As market sentiment is not properly defined there's no absolute way to tell which market number depicts market sentiment or not. The sentiment indices are used by investors to get more informations about other investors assessment of the market. The economics literature is mainly interested in the predictive power of sentiment indices rather than using this information for being active on the market itself.

Problems with sentiment data

There are some problems with sentiment data based investors surveys. The question is how representative the surveyed investor sentiment is for the overall investor sentiment. An accurate overview of the participants in these surveys usually does not exist, at least not freely available. Therefore it stays unclear whether you can generalize the results and to what extent you can draw valid conclusions from the available data sets on the "true" market mood. Baker and Wurgler (2007) warn also regarding the use of investor sentiment surveys in general:

> "The bad news is that each part of this chain is also subject to confounding influences. Economists always treat surveys with some degree of suspicion, because of the potential gap between how people respond to a survey and how they actually behave."

Another problem arises when participants outside the panel attempt to draw conclusions on the behaviour of participants in the stock market from the panel results.

This attempt could be an incentive to conceal the true investor view on the stock market, which would lead to a decrease of explanatory power of the statistical results regarding the forecasting possibilities of sentiment data. This risk exists only with a sufficiently large popularity of sentiment data.

It is difficult to explore whether or to what extent different investment motives play a role in the valuation of market information, which leads to the observed sentiment. A first idea might be to separately consider institutional and private investors. However, this separate consideration has to be incomplete since institutional investors often pursue multiple strategies or investment motives or make both long term and short term investments. Without knowing how much money the private investors put into a stock market, a similar behaviour can not be excluded. Especially institutional investors can influence by their investment strategies markets and the mood of the markets which they communicate through their answers in the sentiment surveys. Sentiment data also give no hint on the influence of cross-linking between the panellists and therefore herd behaviour regarding investment opinion and behaviour is not observable. Hence these latent processes must lead to a cautious interpretation of sentiment data in general, where sentiment data might be every data which capture the mood or feelings of people. [4]

But besides all these problems let's assume for my analysis the following: Many institutional investors like banks, insurance companies, etc. take part in these surveys. They have such a large amount of capital so that they can influence together each market. Therefore the behaviour of these investors forms a good, representative overview of the "actual" market behaviour or situation.

2 Psychological definitions of sentiments

2.1 Definition of sentiments

There is a lack of clarity how sentiment is defined in the literature on investor sentiment. Articles on sentiment indicators like e.g. Klein and Zwergel (2006) or Schmeling (2007) don't provide a definition of investor sentiment, but rather seem to assume some common understanding about the term "sentiment" that is enough to work on market sentiments. Hence they speak about only investor sentiment in terms of short term and long term sentiment. This terminology defines sentiments only with respect to the forecast period for the stock market under consideration. Short term sentiment usually relates to forecasting the stock market development over a period of one week up till one month, whereas long term sentiment usually relates to forecasting periods ranging from three to six months. Nothing is said by

[4] See Bollen et al. (2011) as an example of predicting stock market returns with Twitter tweeds.

this terminology about the expected (statistical) properties of the observed time series nor what sentiments are besides some observable time series.

Therefore I assume market sentiment to be some kind of latent process. This latent process might be the overall emotional state of the market or of the investors. The definition of emotions resorts to the realm of psychology therefore I introduce in this section economic psychological definitions about feelings in general and their properties instead of talking about emotions or sentiments directly I rely for the psychological description of feelings and hence sentiments on the definitions by Werth (2007) page 158: [5]

> "Feeling is the colloquial term for the following terminology:
>
> - Affect is the generic name of a wide range of emotions which includes both emotions and moods.
> - Emotions are strong feelings which are directed toward an object or a person.
> - Moods are feelings which are less intense than emotions and do not necessarily have an object instance. They often have unknown causes and last longer."

As a consequence emotions are rather short living feelings, which disappear as soon as the object or person goes out of mind. Moods might resemble some kind of baseline or average feeling , because they are not necessarily connected with an object and last longer. I will a make difference between emotions and moods from now on. However in everyday language, these terms are used almost interchangeably. The above definitions provide no explanation whether emotions contain information or specifically whether (investor) sentiment data generally contains information about the stock market. Emotions are triggered by the availability of information, general knowledge, our imagination and the conceivability of a certain event. One can distinguish between the implications of an action or the assessment of the expected output and the search for causes of action or attribution as a trigger for feelings.[6]

"**Cognitive trigger of a feeling:** Cognitively triggered feelings are the result of an interpretation and explanation of an event by the person.[7]."

Consequently, feelings always represent expectations, although not necessarily rational expectations like in the hypothesis of rational expectations. If the sentiment data actually reflect the sentiments of market participants regarding future market

[5] This definition and all the following citations from Werth (2007) are translated by the author.

[6] See Werth (2007) p.169.

[7] See again Werth (2007) p.169

developments and then those feelings express interpretations of their available information. In consequence, the sentiment data could be used as a proxy or indicator of unobservable expectations or ideas. If sentiment data inadequately foresee the development of stock markets, feelings or sentiments might still have an influence and explanatory power for the development of the stock market. Probably the panellists have had insufficient information or have been subject to a systematic error in their analysis. Likewise, feelings expressed by sentiment data do not necessarily correlate positively with or cause the activities of panellists on the stock market. On the other hand a good predictive ability of stock market development maybe points on a correct interpretation of the information by the panellists.

2.2 Hypotheses about sentiment data

Hypothesis I : Descriptive statistical properties

Short term sentiments should show higher volatility/standard deviation, more extreme values and shorter autocorrelation in comparison to long term sentiments.
Emotions are strong, but rather short term feelings. Therefore data representing emotions should show more volatility than data representing moods. The short term sentiment can therefore be considered an expression of momentary feelings. I expect the short term sentiment to have a small lag order, both by the means of the autocorrelation function (ACF) and to those of the partial autocorrelation function (PACF). The short term nature and the greater swings of emotions lead to stronger fluctuations = higher volatility of the short term feelings or sentiments. On the other hand I expect the long term sentiment to have a much higher lag order in terms of autocorrelation and a lower volatility than the short term sentiment. This behaviour is due to the long lasting and less volatile nature of moods as defined in the section before.

Hypothesis II : Factor Analysis

Two latent factors should be extractable via factor analysis from the sentiment data, which represent overall emotion and mood across markets.
The question behind this hypothesis is if the investors' sentiment of a market is driven by forces unique to this particular market or is it driven by forces similar across markets? If it is driven by forces similar across markets then common (latent) factors might drive the individual market sentiment. As the participants are asked to share their opinions about the short and the long run, there should be two common factors or maybe even only one factor which drives the market sentiment as described by the sentiment indices. Therefore I suppose that one factor contains most of the variance or information from the short term sentiment but only little variance of the long term sentiments. This factor would be a proxy for overall market or investors' emotion. Vice versa the other factor should include most of the variance of the long term sentiment, but only little variance of the short term.

This factor could be interpreted as a proxy market or investors' mood. Theses two factors together should take the main part of the variable variance.

2.3 Background information: the psychology of financial markets

I present shortly the most important results for this article from Tuckett (2009) and complete the summary with references to Tuckett and Taffler (2008) which deal both with the psychology of financial markets. These articles provide a deeper understanding of why - despite the rationality paradigm - emotions play a critical role in the stock market. According to Tucket market participants build an emotional connection similar to a marriage to an investment. You project love and hate on this so called "fantastic object". [8] In addition, they also believe in a good cover story. Therefore everything seems to be different from before. The investor considers himself as very intelligent, because he invests in this "fantastic object" [9]. Another characteristic of bubbles in financial markets is the predominance of group think [10], leading to the exclusion of critics. Tuckett also speaks of a "Divided State of Mind". Only positive information is processed in the development process of a bubble. Negative emotions and information are stored apart from your mind. In contradiction to common believes a bubble bursts when existing (negative) information is reassessed. [11] New information doesn't lead to the burst of the bubble as opposed to common sense, but negative information and emotions are no longer mentally suppressible. This conclusion is true only besides corruption and criminal activity prior to a bubble burst. As a result of this "Divided State of Mind" after the bursting of a bubble the investor tries to avoid the admission of being guilty for taking part in this bubble. Especially if he faces own losses, as it is not in line with the image of being a smart investor not a dumb one like the others, who did not see this investment opportunity. So he tries to stick to the cover story of him being a smart guy. Instead other causes such as market constraints, poor advice, criminal activity, etc. were named. Tuckett derives his conclusion from three common characteristics of financial assets which help to show how the above described phenomena can emerge. These properties provide an explanation for their formation modelling approach:

1. Financial assets are perishable or discontinuous. They can trigger strong emotions, be it fear, panic in value losses as well as euphoria, triumph feel

[8] For more detailed explanation of the term "fantastic object", see Tuckett and Taffler (2008).
[9] Compare it with the euphoria during the dotcom bubble (Tuckett (2009) page 5) or during the euphoria surrounding CDOs
[10] See definition of group think in Tuckett (2009) Page 4.
[11] See Tuckett and Taffler (2008) page 89 and Tuckett (2009) page 5, where he describes the information regarding dotcom companies had not changed. These companies would not be profitable for years as it was clear by looking at their balances.

with appreciation. Feelings must play a role in investment decisions, since investment decisions are made under uncertainty and without feelings the actions of the players are practically pointless. [12]

2. Financial assets are abstract and have no intrinsic value. This property is unlike other assets such as a car which can be driven even if resale value declines due to new car models. Moreover, the value of financial assets is directly linked to the time and to expectations about the evolution over time. Therefore, the decision to purchase an asset must be justified again and again. In other words: the investment has to be bought again and again from the new.

3. It is very difficult to make valid conclusions about whether an investment was justified with respect to the buying, holding or selling expense/ the investor was successful. A good performance in a period does not necessarily indicate a good performance of the investment / investor in the next period. In principle, such a performance evaluation is always dependent on the context in which it takes place like time, market conditions, investment strategy, etc.

Due to the unknown development on the financial market, people try to use every piece of information e.g. economic models for financial markets or sentiment data to cope with their insecurity and lack of understanding of financial markets. This usage of data is independent of any real (accountable) gain from doing so.

Further examples of the influence of emotions on the stock market

There are more examples of the influence of emotions on the stock market. Feelings affect thinking styles.[13] Positive mood leads to more creative solutions, but they are risky, while negative mood leads to more cautious thinking. Presumably phases of positive mood should correlate with the development of new investment instruments and be associated with increased risk-taking. Conversely, a negative mood leads to flee to safer, lower-risk investments.

Summary

A psychological definition of sentiments is possible, an economic one is not. Statistical properties of the sentiment indices can be derived from the definitions. Tuckett shows how far financial markets are determined by sentiment. For a detailed understanding of financial markets, the use of sentiments is necessary. However, still there are no models of financial markets which model explicitly the development of the sentiments and their impact on financial market development.

[12] No feelings = no subjective benefit assessment = no motivation for action / value of the utility function is 0.

[13] Werth (2007) p.181

3 The dataset

Sentix is a provider of sentiment indices, which are obtained weekly via e-mail survey. It distinguishes between institutional investors such as banks, insurance and investment companies as well as private investors. Only people confirmed to work for an institutional investor in the right section of the company are counted as institutional investors in the Sentix survey. Private investors can be anyone who is interested in participating in this survey. Investors participate on a voluntary basis and are asked to share their assessments of the development of different markets, whether they expect a positive, neutral or negative development. From their answers an index is constructed as a so-called *bull-bear-spread* (Brown and Cliff (2004)) with S being the sentiment index, n^+ the number of positive answers, n^- the number of negative answers and n^0 the number of neutral answers.

$$S = \frac{n^+ - n^-}{n^+ + n^- + n^0}$$

There is also distinction between the short run (1 month) and long run (6 months) sentiment. [14] The data is collected since 2001. On average, 800 people per week took part in the surveys at the end of 2010.[15] The Sentix indices were obtained via Datastream for the period from the 28.11.2002 to 04.11.2010 which equals to 415 data points per sentiment index. This range covers the time from two years after the New Economic Bubble burst until two years after the beginning of the current financial crisis. I will focus only on the sentiment data related to common stock market indices.

4 Tests of Hypotheses

This section deals with tests of the hypothesis from section 2.2. The time horizon goes from 28.11.2002 till 04.11.2010 which equates 415 data points for each index. At first I present the results of descriptive analysis and then the results of the factor analysis.

[14] This distinction is set by Sentix in their survey question. An example survey can be found here http://www.surveymonkey.com/s/R5FBHLP.

[15] See Heiden et al. (2011) for a slightly longer description of Sentix data as well as their (German) FAQ http://sentix.de/index.php/en/Terms/faq.html(Accessed on 11.06.2013 20:36).

4.1 Descriptive Analysis

The descriptive analysis in table 1 as well as some time series analysis including Granger causality tests were made with the program JMulti. [16] Table 1 reports the means, standard deviations and (partial) autocorrelations for the whole sample.
The results from the descriptive analysis are in line with the first hypothesis from section 2.2. Short time sentiments have always higher standard deviation and a wider range in the extreme values than long term sentiments except for one case. The means are also closer to zero. The differences in means and standard deviations between short and long term sentiments are always significant, no matter if you compare long and short term sentiment for the same stock index or for different stock indices. This result seems to fade out over time as T-Tests for the means over different time periods suggest.[17] Therefore the prediction of mean closer to zero for the short term sentiment regarding the mean of the long term sentiment seems to be false. The result for the standard deviation is stable across different time periods.[18] I observe low autocorrelation for short term sentiment and high autocorrelation for long term sentiment as already predicted. This finding is in line with Schmeling (2007) and others observations of long term sentiment being a highly persistent variable. This result confirms the predictions about the statistical properties of long term sentiment data. The value of the partial autocorrelation is usually two, independent of the kind of sentiment. So only the first two lags contain information for any kind of sentiment. An AR(2) model seems to be enough for modelling the data generating process of any sentiment in the Sentix database.
Tables 2 and 3 show the correlations between the variables from table 1. The correlation between the short term sentiment variables is usually quite high with a range from around 0.85 (NIKKES1 and TECDXS1) to 0.98 (e.g. DAXINS1 and TECDXS1). The relations between the long term sentiments is also quite high with correlation coefficients starting from 0.77 (NASDQS6 and ESX50S6) to 0.95 (TECDXS6 and DAXINS6).
The correlation coefficients between long and short are usually below 0.20, so the correlation is rather weak. This observation is even the case for sentiments from the same stock market index, see e.g. the correlation between the two DAX sentiment indicators (DAXINS1 and DAXINS6) is only 0.17 which is a rather weak correlation. There are only positive correlation coefficients. So on average the sentiment indicators move in the same direction. Hence the conclusions made for one market may as well hold for another market. The high correlations between all the long term sentiment variables and between all the short term sentiment variables provide a good starting point for a factor analysis. This pattern hints to

[16] www.jmulti.de and Lütkepohl and Krätzig (2004)
[17] See Appendix **??** for some example results for the DAX.
[18] See again section A.1 for some example results.

Table 1: Descriptive Statistics

Variable	Mean	Min	Max	Std. Dev.	ACF	PACF
DAXINS1	0.05401	-0.4689	0.5916	0.21764	4	2
DAXINS6	0.10074	-0.1471	0.4140	0.11604	17	2
TECDXS1	0.03326	-0.5130	0.5536	0.21641	5	2
TECDXS6	0.07361	-0.2420	0.3923	0.11356	15	2
ESX50S1	0.05017	-0.4564	0.5652	0.21172	5	2
ESX50S6	0.10150	-0.1426	0.3993	0.11263	21	2
SP500S1	0.01732	-0.4815	0.4855	0.20311	4	2
SP500S6	0.02087	-0.1874	0.3337	0.08720	10	2
NASDQS1	0.01599	-0.4706	0.4790	0.20354	4	2
NASDQS6	0.02423	-0.2070	0.3405	0.09105	10	2
NIKKES1	0.06785	-0.4229	0.5514	0.19764	31	12
NIKKES6	0.15244	-0.1848	0.5717	0.16621	36	2

I used sentiment indices for the following stock markets:
DAX (= DAXINS), TecDAX (short TECDX), Euro Stoxx 50 (short ESX50), Nikkei 225 (short NIKKE), Standard & Poor's 500 (short SP500), Nasdaq (short NASDQ)
Variable names: xxxS1 = short term sentiment; xxxS6 = long term sentiment
(P)ACF = last significant lag according to (partial) autocorrelation function
Comment on NIKKES6: Non-stationary variable according ADF and KPSS tests

Table 2: Correlations of all variables: Part 1

	TECDXS6	TECDXS1	DAXINS6	DAXINS1	ESX50S6	ESX50S1
TECDXS6	1.0000					
TECDXS1	0.2030 (0.0020)	1.0000				
DAXINS6	0.9528 (0.0000)	0.0831 (1.0000)	1.0000			
DAXINS1	0.1706 (0.0319)	0.9892 (0.0000)	0.0793 (1.0000)	1.0000		
ESX50S6	0.9264 (0.0000)	0.1067 (1.0000)	0.9731 (0.0000)	0.1065 (1.0000)	1.0000	
ESX50S1	0.1753 (0.0220)	0.9618 (0.0000)	0.0943 (1.0000)	0.9736 (0.0000)	0.1174 (1.0000)	1.0000
NIKKES6	0.6593 (0.0000)	0.2263 (0.0002)	0.6403 (0.0000)	0.2170 (0.0005)	0.7033 (0.0000)	0.2401 (0.0000)
NIKKES1	0.2576 (0.0000)	0.8435 (0.0000)	0.1726 (0.0272)	0.8422 (0.0000)	0.2300 (0.0001)	0.8393 (0.0000)
SP500S6	0.7999 (0.0000)	0.1873 (0.0082)	0.8099 (0.0000)	0.1890 (0.0071)	0.7951 (0.0000)	0.1876 (0.0080)
SP500S1	0.1216 (0.8717)	0.9754 (0.0000)	0.0232 (1.0000)	0.9827 (0.0000)	0.0549 (1.0000)	0.9588 (0.0000)
NASDQS6	0.8334 0.0000	0.2042 (0.0018)	0.8150 (0.0000)	0.1865 (0.0088)	0.7781 (0.0000)	0.1871 (0.0083)
NASDQS1	0.1312 (0.4904)	0.9756 (0.0000)	0.0269 (1.0000)	0.9754 (0.0000)	0.0520 (1.0000)	0.9488 (0.0000)

The variable names refer to the same sentiment variables as in table 1.
Significance levels are in (...) brackets.

Table 3: Correlations of all variables: Part 2

	NIKKES6	NIKKES1	SP500S6	SP500S1	NASDQS6	NASDQS1
NIKKES6	1.0000					
NIKKES1	0.5699	1.0000				
	(0.0000)					
SP500S6	0.4633	0.1997	1.0000			
	(0.0000)	(0.0028)				
SP500S1	0.1845	0.8335	0.1806	1.0000		
	(0.0103)	(0.0000)	(0.0143)			
NASDQS6	0.4361	0.1920	0.8947	0.1913	1.0000	
	(0.0000)	(0.0054)	(0.0000)	(0.0058)		
NASDQS1	0.1592	0.8163	0.1859	0.9917	0.2192	1.0000
	(0.0753)	(0.0000)	(0.0092)	(0.0000)	(0.0004)	

The variable names refer to the same sentiment variables as in table 1.
Significance levels are in (...) brackets.

two latent variables or processes which drive the assessment of the stock markets in the long and the short term. Long and short term predictions are only weakly connected with each other even for the same markets. Besides the results from the factor analysis and the interpretations given there, I have no further explanation for this pattern, especially since this pattern is stable over time.

4.2 Factor Analysis

Just to give you a short reminder about what Factor Analysis (FA) does[19]: The FA is a special case of the Structured Equation Modelling (SEM). In SEM you try to model the causal relationship between unobservable latent variables whose outcomes are the observable, measurable variables.

The idea of FA is now that you have observable, correlated variables whose variability can be explained by linear combinations of latent (unobserved) variables called factors and some error term. The number of factors is potentially lower than the number of observable variable. In my case I assume in section 2.2 that the variation in the twelve used sentiment indices can be explained by two factors. One factor explains most of the variation in the short sentiment and the other one explains most of the variation in the long term sentiment. The factor analysis extracts these factors and their so-called loadings. The loadings represent the

[19] The description of Factor Analysis was requested by one reviewer. However factor analysis is standard method in multivariate analysis. Hence I give only a rather short description and leave out the details.

correlation of a factor with a measurable variable. In my case the correlation between a sentiment index and a factor.

The FA contains of two steps: The first one is to extract the factors and the loadings to explain the variation in the observables. The number of factors can be determined by various rules. One criterion is to use factors which have an eigenvalue higher than 1. An eigenvalue greater than 1 means that this factor captures more variation than a single observable variable. This criterion is also called the Kaiser Criterion. I use this criterion for my analysis. Other criteria might be based on prior knowledge about the right number of factors or the wish to factors which account at least for a certain amount of variation e.g. 80% or 90%. After the numbers of factors has been decided, the factors usually need to be rotated to get factor loadings which provide good interpretation possibilities.

I used the principal component factor method in STATA as it returns the most interpretable results. Other methods tend to extract / favour more factors without adding enough variance to justify the choice of more than two factors. Table 4 shows the obtained factors and factor proportions of the factor analysis.

Table 4: Obtained factors and factor proportions

Factor	Eigenvalue	Proportion
Factor 1	6.33188	**0.5277**
Factor 2	4.2441	**0.3537**
Factor 3	0.83221	0.0694
Factor 4	0.25456	0.0212
Factor 5	0.12289	0.0102
Factor 6	0.06577	0.0055
Factor 7	0.059	0.0049
Factor 8	0.04711	0.0039
Factor 9	0.0165	0.0014
Factor 10	0.01549	0.0013
Factor 11	0.00715	0.0006
Factor 12	0.00335	0.0003

Two factors account for ca. 88 % of the observed variance. Therefore two latent variables explain the overall variance of the sentiment indices. The rest of the variation is split upon 10 additional factors with none of them having an eigenvalue close to 1 and so accounting for not more variation than a single sentiment index would do. Without using a proper rotation method the results of the factor analysis are difficult to interpret. Hence I show in table 5 the factor loadings after applying the Varimax rotation methods [20].

[20] There are many more rotation methods available like for example Quartimax or Promax as an oblique rotation method, but the results don't change significantly Therefore I present only the results from Varimax.

Table 5: Factor loadings after rotation with Varimax

Variable	Factor 1	Factor 2	Uniqueness
DAXINS1	0.9870	0.0825	0.0191
TECDXS1	0.9830	0.0945	0.0247
ESX50S1	0.9719	0.0936	0.0466
SP500S1	0.9879	0.0453	0.022
NASDQS1	0.9813	0.0500	0.0345
NIKKES1	0.8744	0.2135	0.1899
DAXINS6	-0.0170	0.9741	0.0508
TECDXS6	0.0860	0.9596	0.0191
ESX50S6	0.0169	0.9663	0.066
SP500S6	0.1078	0.8799	0.2142
NASDQS6	0.1165	0.8789	0.214
NIKKES6	0.2118	0.6960	**0.4708**

The variable names refer to the same sentiment variables as in table 1.

The high uniqueness[21] for long term Nikkei sentiment indicates a rather bad explanation of the observed variance by the obtained factors. The other sentiments like the long term S&P 500, the long term NASDAQ and the short term NIKKEI sentiment show a uniqueness of maximum 0.2. So roughly 20% of the observed variance is still unexplained by the two obtained factors. Two factors are enough to explain most of the variation of the sentiment indices according to my hypothesis from section 2.2. This hypothesis is in line with the data for most of the indices, but not for all.

I could increase the number of factors in my analysis to lower the proportion of unexplained variation (uniqueness). But if I increase the number of factors without being able to give meaningful interpretations to these additional factors, then I have the risk of overfitting my model to the data. Therefore I keep working with the two factors instead of adding more factors. [22]

[21] "Uniqueness" in the third column refers here to the percentage of variance of a variable which is not captured by the model in the factor analysis. The higher uniqueness the less appropriate the model is for this variable. In my case the model consists of two factors explaining the twelve sentiment indices.

[22] Nevertheless I took a look at what happens if I use more than two factors (not shown here). I used four instead of two factors. The additional factors number three and four account together for roughly eight percent of the data variation. So overall these now four factors explain roughly 97% of the data variation. This addition reduced the proportion of unexplained variance for all sentiment indices under 5%. Therefore the additional factors capture the variation of sentiment indices which had high uniqueness in the case of only two factors. However the interpretation of these additional factors is rather difficult, because there are only a few high loadings with no easily interpretable pattern as in case of the first two factors.

As in section 2.2 already predicted all the short term sentiments load high [23] on the first factor while the long term sentiment loads low[24] on the first factor and vice versa for the second factor. Now the long term sentiments display a high loading while the short term display a low loading. The sign of the low factor loadings is not informative as the values are close to 0.

These results allow me to interpret the two factors as investor emotions and moods, where the first factor represent the investor emotions and the second one the investor moods.[25]

My interpretation is based on combining my hypothesis from section 2.2. The short term sentiment represents investors' emotions and the long term sentiment investors' mood.

The exact reason is up to speculation. To answer this question in more detail I'll probably have to consult the psychology literature on emotions. However I am not too sure whether the connections between sentiments/feelings and time series data (sentiment indices) have been drawn before. Therefore I have to leave the answer to this question for further research.

One consequence of my interpretations for economist is to take "sentimental" data (e.g. investor sentiment) more serious, as these data can contain economical valuable information. Another one is the ability to test proposed sentiment proxies whether they really measure sentiment or to which kind of sentiment they belong to. Knowing to which kind of sentiment a proxy belongs to helps you to understand the observed behaviour of this proxy and might allow you even predictions about future trends. However for investors my interpretation should not have any further implications than already mentioned for the economists. These indices are mainly used by investors to learn something about the current market situation and maybe the predictions of others. Therefore, using my interpretations instead of the current existing ones won't tell them a completely new story or change the way they use these indices.

The assessment of the investors when they answer the survey questions is driven not only by an individual assessment of every item (e.g. DAX, S&P 500), but also by overall assessment of the whole economic situation relevant to the individual investor. That's another interpretation of my results.

The short term sentiment index might not really showing the emotions of investors, as one reviewer put forward. However the 1M is the shortest available sentiment from Sentix. Therefore it is as close as possible concerning resembling

[23] Factor loadings close to 1.
[24] Factor loadings close to 0.
[25] The interpretation of extracted factors is determined by the choice of the interpreter and nothing is proven by the above results due to the nature of factor analysis, but at least some hints can be extracted.

emotions. Cognitively there should be no big difference between one week and one month ahead planning but one month and six month makes a difference.

There is no different pattern occurring in the dataset although AnimusX used one week as the short term and three months as the long term sentiment, according to the results of combining AnimusX and Sentix in my diploma thesis. As long as the time horizons for the indices resemble a range which is cognitively perceived as near and far future, it should not matter that much whether the short sentiment is for one month or one week ahead as well as whether the long term sentiment is for three or six months ahead.

To test my interpretation of short sentiment as emotion one could create daily sentiment indices, as suggested by a reviewer. However creating daily sentiment indices based on the same people for the weekly sentiment indices might not work due to time constraints and might result in a worse quality of the index and/or less answered survey questionnaires. The idea behind this e-mail based survey weakly is to keep the required amount of time and effort as low as possible to guarantee a high participation rate and good quality of the index. The surveys are supposed to be filled out during Friday and Sunday. So the participants have some time to make their assessments before the next trading week starts.

5 Extensions

In this section I will briefly discuss some things which are not important for my main results but might be still of interest.

5.1 Data description

There exist also another dataset of sentiment indices for the German stock market "AnimusX", which Lux (2011) used. I make the factor analysis only for a combination of the sentiment indices related to the DAX and not for other indices due to the focus on the German market of AnimusX in its questionnaires. The results of the factor analysis displayed a high uniqueness of the AnimusX variables, which usually indicates an inappropriate model. Therefore I do not show the results here. Via datastream Sentix offers also sentiment indices for Euro-Bund-Futures and two exchange rates. The Bund sentiments have not been used yet. Heiden et al. (2011) use the two exchange rates sentiments, namely the EUR/USD and USD/JPY. The results for the descriptive analysis are the same as for the stock index sentiments. Unfortunately I could not use them in a factor analysis with the stock index related sentiments as they display a too high uniqueness.

5.2 Additional Tests

I tested the stationary of all sentiment indices with ADF- and KPSS tests, but the variables appear to be stationary for common significant levels. I also checked if the normality assumptions holds which I need to conduct valid Granger causality tests in a VAR framework. For the whole sampling period none of the sentiment indices follow a normal distribution, as table 6 indicates. The existence of the normal distribution for the sentiment data would be good for the validity of tests which are based on the assumption of the normal distribution as the data generating process, e.g. Granger causality tests. On the other hand sentiment data might the representation of summing up individual, small, independent and identically distributed pieces of information [26]. So there isn't probably any dominant process generating the sentiment and the observed sentiment data could be as well as just be approximated as some normally distributed random numbers. In a way the normal distribution is the "no information distribution". This interpretation possibility arises from the definition of the normal distribution. The normal distribution can

Table 6: Results of Jarque-Bera-Tests

Variable	Test Statistic	P-Value	Skewness	Kurtosis
DAXINS6	23.7967	0	0.5822	3.085
DAXINS1	10.0822	0.0065	-0.1297	2.2857
ESX50S1	10.049	0.0066	-0.1526	2.3054
ESX50S6	14.8255	0.0006	0.4434	2.7494
NASDQS1	10.1965	0.0061	-0.168	2.3136
NASDQS6	83.4031	0	0.7895	4.5113
NIKKES1	6.0595	0.0483	-0.1828	2.538
NIKKES6	12.6004	0.0018	0.1744	2.2254
SP500S1	10.5434	0.0051	-0.1712	2.3023
SP500S6	119.8184	0	0.8875	4.9269
TECDXS1	10.8873	0.0043	-0.2272	2.3542
TECDXS6	19.1986	0.0001	0.4882	3.3825

The variable names refer to the same sentiment variables as in table 1.
Test Statistic = value of the test statistic
The Jarque-Bera test statistic is χ^2 distributed.

be the result of the sum of independent, identically distributed, relative to the total negligibly small shocks. The distribution of Sentiments is not stable over time. Normality appears only roughly in the period between 2004 and 2008 according to additional skewness-kurtosis tests, Shapiro-Wilk and Shapiro-Francia-tests for normality for different time horizons. [27] Exactly in this period everything was

[26] Whereas information may refer to any variable generating sentiment.
[27] See Appendix A.2 for example results for the DAX sentiments.

more or less normal after the New Economy bubble and before the current financial crises appeared on the screen. Before and after this period I observe non-normality for all sentiment indices. There are tests for Granger causality which don't need the normality assumption [28]. But these tests are not implemented in common statistical packages. Therefore I assume that the violation of the normality assumption does not have a big influence on the validity of my results.

5.3 Granger causality

One short and one long term sentiment seem to cause all the other sentiments as results from an omitted Forecast Error Variance Decomposition show. For example the DAX sentiments seem to cause all other sentiments when I run Granger causality tests after a VAR estimation with all sentiment indices. This result is reasonable if the knowledge about the German stock market is the basis for accessing the potential performance of all other stock markets. Maybe some kind of home-grown bias or starting point bias is the reason for this pattern.

5.4 Factor Analysis

Unfortunately I can't say anything about the overall relationship between investor moods and emotions. The factors are assumed to be uncorrelated in the basic setting. The results from oblique rotation methods seem to be preferable as they allow for correlation among the factors. However the correlation is rather weak between the two factors as table 7 shows. If I interpret the factors as overall investor moods and emotions then the results indicate a rather weak relationship between investor moods and emotions. The results remain stable if I change variable combinations and factor extraction methods.[29] Unfortunately Granger causality

Table 7: Correlation matrix of the Promax rotated common factors

Factors	Emotion	Mood
Emotion	1	
Mood	.1703	1

Emotion refers to the first factor and Mood to the second factor.

tests in a VAR (2) framework with the predicted factors give no significant result as table 8 shows. Overall investor long term sentiment (mood) does not help to predict overall investor short term sentiment (emotion).

[28] See Hacker and Hatemi-J (2006) as an example.

[29] STATA offers four different methods for extracting factors.

Table 8: Granger causality tests for the predicted rotated factors

Variable	helps predicting	test statistic	P-Value
Emotion	Mood	0.8477	0.4288
Mood	Emotion	1.9851	0.1380

Emotion refers to the first factor and Mood to the second factor.

6 Discussion/Additional Comments

In this section I discuss some issues raised by reviewers.

6.1 Missing Literature on Consumer Sentiment and the Sentiment vs. Economic Fundamentals Debate

As mentioned by one reviewer there is much literature about consumer sentiment. However, in the literature about sentiments in the financial markets this literature is commonly not mentioned. Hence, I did not consider it initially. After reviewing some articles from this literature I still believe that the role of sentiments on financial markets is a bit different from the one on the consumer markets. Hence, I decided not to review these articles here.

While on the consumer market the sentiment of an individual consumer has no/little impact on the resources available to another consumer and the decision making process. However on financial markets the investors compete against each other for return. If sentiment data allows them to get further information about the potential decisions (e.g. to invest or not to invest) of other investors, then they can adjust their own behaviour accordingly and improve their profit. This feature of sentiment data is absent in the case of consumer sentiment. In that case sentiment might be a relevant decision variable for the amount of consumer spending, but the spillover to other consumers is not as important in the consumer market as on the financial market.

This article also does not aim to add something to the sentiment vs. economic fundamentals debate. The purpose of this article is to give sentiment data a psychological foundation. The only thing that this article might add to the debate, is the notion how fundamentals are part of the judgement process that finally leads to sentiments. As stated by Mehra and Martin (2003):

> The fact that sentiment measures are [...] watched both in the financial press and by many serious economic analysts suggests they may be useful in sharpening the assessment of agents for the current state of the economy as measured by the behavior of aggregate income. The empirical result here indicating that sentiment measures lose

> their statistical significance in predicting current spending once one controls for the influences of the current state of the economy on spending suggests that these sentiment measures may have value as a summary statistic for the future course of consumption. (section 3, last parapgraph)

This quote shows several things:

1. Consumer sentiment does not provide more information about the future state of the economy than the economic fundamentals. Consumer sentiment appears to function as an aggregate of economic fundamentals.

2. The quote is in line with the definition of sentiment [30] as the result of judging an information set which contains economic fundamentals among other variables.

3. One benefit of sentiment indices in general (consumer, financial, etc.) is that they are easier and faster to measure than the underlying economic fundamentals and other factors.

The question whether stock markets or financial markets in general are governed by economic fundamentals or by investor sentiment is not touched by this article. However I believe that due to the inherent uncertainty in financial markets (as mentioned in section 2.3) sentiments will always play an important role. Economic fundamentals will be always a good starting point for analysis, but the more the outcome on a certain financial market depends on whether other investors buy or sell the less important economic fundamentals get and it all reduces to who plays best on this market. Who is best able to read the signs of the others and who is not.

6.2 Sample Selection

Everyone who likes to participate in the Sentix survey can register themselves on the Sentix website. If you register yourself as an institutional investor, they will try to confirm whether you are really representing an institution link an investment bank, pension fond, etc. Hence there is no special sampling process nor an underlying population of which the participants are sampled. They are in principle self selected. The individual information are aggregated by just calculating the bull-bear-spread for existing answers. There is no special aggregating scheme involved.

[30] See section 2.1.

6.3 Correlation between Sentiment Indices and Stock Market Indices

I tried to set up a graphical analysis between the sentiment indices and their underlying stock market indices as recommended by a reviewer, but the graphs didn't give a clear picture nor did they add new information. Hence I don't present them here. Instead I put tables with the correlations between the sentiment indices and the stock market indices and their log-returns in the appendix.

As you can see in tables 21 – 26 in the appendix section A.3 the correlations are in most of the cases not high (usually not higher than 0.2), despite being significant. Hence there are at best only weak ("current time") correlations between the sentiments and the underlying stock market indices.

Given the nature of sentiment indices, there are three types of correlations of interest for articles like this one:

1. Correlations of sentiments with stock market indices from the same week.[31] Significant and high correlations of this kind would be rather surprising, given that sentiment indices are meant to predict future developments.

2. Correlations of sentiment indices with the stock market developments during the sampling week and/or some time before. The sentiment indices should be rather correlate with the stock market developments during the sampling week and/or before, since this is the time when the assessment of the stock market is formed. This kind of correlation gives hints how much the future assessment of the stock markets as represented by the sentiment indices is influenced by the past stock markets results.

3. Correlations between the sentiments indices and the time periods they try to predict. In terms of predictive power the correlations between the sentiment indices and the one month (short term sentiment) or six months (long term sentiment) ahead stock market indices are important.

So when you do correlation analysis with sentiment indices there is the problem of the right time periods with which you want to correlate the sentiment indices with the stock market indices. Dependent on the question you want to answer, one of the three types of correlations mentioned above will be appropriate. Non of these proposed correlations can actually answer the question how well the sentiment indices proxy the underlying stock market indices, since sentiment indices are meant for predicting the future development and not for proxying the current one. It is more important how well sentiment indices are correlated with future decisions and actions on the stock markets than how well their movements proxy the stock market movements.

[31] These are the correlations I report in this article.

6.4 Causal Link between Sentiment Indices and Stock Market Indices

This kind of analysis has already been done in the literature of sentiments on financial markets in articles like Schmeling (2007) or Lux (2011). The results in this literature are mixed. Depending on the time horizon [32] and model [33] sentiments influence the return significantly or not. The existing literature usually aims to find Granger causality from the sentiment indices to the stock returns and not "strict" causality. Without going into too many details about the problem of causality in empirical data, let's keep in mind that Granger causality is weaker concept than "strict" causality which asserts functional relationship between two objects.

To find "strict" causality between sentiments and not just Granger causality we would need solve several problems. As we deal with aggregate data like stock prices, returns, sentiment indicators, etc. we can hardly make inference on the underlying micro level. Even if we find a "strict" causal link on the macro level between sentiments and stock market returns, then this observed "causality" might be still only a statistical artefact due to the involved aggregation scheme. To avoid this inference problem, we would need to measure the actual influence of sentiment on the investment decision of a single investor. As far as I know this kind of analysis does not exist.

So the focus in the literature is whether sentiment data help to predict stock markets or not (Granger causality). Whether sentiments in fact cause the movements of stock markets independently from the movements of market fundamentals is not important for investors. Only the potential informational content of sentiment data is important and *not* the potential causal influence, since it may help to improve trading strategies. As long as sentiment data aggregate existing information or add new information, they are useful for investors. Even if sentiment data contained no "real" information, as long as enough participants on the financial markets believe in the credibility of this data, it will be useful for investors.

Like I already mentioned above, the financial market is different from the consumer market. Seemingly stable causal behavioural relationships on the financial market tend to vanish, once everybody tries to exploit these relationships to make more profit if they are not supported from forces outside of the market. This is not the case on consumer markets.

Hence, I am rather sceptical about the benefit of estimating the (causal) influence of market fundamentals and sentiment data on stock market movement. Any causal relationship found might be spurious as well or vanish if it becomes widely known. At the moment we don't have an explicit knowledge about how and why people make certain decisions on the financial market. All we have are

[32] short or long term sentiment; How many periods of returns (ahead) are to be explained.

[33] One equation to test whether sentiment indices influence average returns over several periods estimated via OLS, VAR(X) model with sentiments and returns, etc.

information on market fundamentals, sentiment data and maybe even some data about the motivation and goals of investors, but this data can provide us only up to a certain degree with information about the cause of an investment decision. And investment decisions cause the market movements. Hence, I prefer to look at the weaker concept of predictability instead of causality.

Of course, sentiments as measured by the sentix survey might be just a proxy of market fundamentals or rather an interpretation of the market fundamentals. Like I described in section 2, feelings represent/are created as/by an interpretation/evaluation of an event/information. Hence observable market fundamentals are judged and interpreted by investors. These interpretations form their sentiment, so sentiment indices might only measure an average interpretation of market fundamentals. But this “finding” is exactly one of my points why sentiment data might contain useful information about the further development of a stock market index.

To verify my idea about information being aggregated in the sentiment indices I should probably estimate a regression with the sentiment indices as the dependent variable and the market fundamentals as the independent variables to determine how strong the influence of the market fundamentals on the sentiment indices is. However, this analysis might be worth another paper. Evidence from articles on consumer sentiment like Mehra and Martin (2003) point already towards this possible result.

6.5 Results of Factor Analysis

The results of the factor analysis seem to be kind of obvious given the results of the correlation analysis. However, the interpretation of the correlations and the factor analysis is driven by the proposed theoretical properties of the sentiment data. Hence, the factor analysis helps to see these properties more clearly than by just looking at the correlation matrix. The factor analysis acts here as a tool to expose the theoretical predictions differently and to lay the ground for further analyses.

6.6 Confirmatory vs. Exploratory Factor Analysis

It should be feasible to make a confirmatory analysis on a different dataset. The analysis would take the results of the already presented exploratory factor analysis and the psychological definitions of sentiments as input for the model to be constructed and confirmed. However, I am sceptical whether the confirmatory analysis would provide any more useful information for investors than the exploratory one besides maybe a confirmation of the previous results. Both analyses – confirmatory and exploratory – rely for the same data on the same information from the same covariance matrix. The only real differences between to the two analyses are the restrictions on the covariance matrix and the goals of the analyses. If I added additional variables and estimated a latent variables model then I would end up probably with a new model, which might require adding another theory. Also, I accounted already for the relationships between the factor through an oblique rotation in the factor analysis. Therefore, I doubt to get any new relevant results from this exercise.

7 Conclusion

I have shown for the first time what might be meant by stock market or investor "sentiment" using sentiment data from Sentix. The current literature on investor sentiment has treated this sentiment as given rather than explaining it. Articles on investor sentiment derived their results using a concept which they don't define but instead seem to use some kind of common sense for the definition of sentiment.

However using a not well defined concept leads to not knowing what one is actually measuring by the investor sentiment surveys or by the proxies for investor sentiment. The internal validity is therefore low for these articles.

Therefore all conclusions drawn in the articles on investor sentiment might be based on something which looks like sentiment, but is in fact something else. So these conclusions are at least questionable regarding their explanatory power for the influence of investor sentiment on the financial markets.

I could not find any economic theories explaining or defining investor sentiment. Therefore I had to turn to the economy psychology literature for the definition of sentiments. This fact clearly shows how important it is to use theories from other related fields such as psychology to explain economic behaviour.

To define sentiment as a statistical, measurable concept I translate verbal psychological definition into predictions about statistical properties for time series data which is supposed to resemble sentiment. This concept is my first part of contribution to the literature.

The explanation of systematic differences in the order autocorrelation, standard deviation and extreme values between long and short sentiment is the second of part of my contribution to the literature. I explain theses systematic difference with the difference between emotion and mood whereas both terms are summed up in the common sense as sentiment. To further support this result I extract two latent factors from the set of all twelve sentiment indices via factor analysis which I interpret as hints to the existence of moods and emotions in the overall sample.

Investor sentiment really contains information and is not irrational, random, neural activity, but rather an assessment of the current situation given the uncertainty of financial markets. Hence it may be possible to model investor sentiment as the result of evaluation of market signals under uncertainty or something similar.

It should also be possible to look for factors influencing investor sentiment in an experimental setting, maybe something along the line like Enke and Zimmermann (2013).

According to my definition of sentiment, the short and long term sentiment indices indeed measure the two components of (investor) sentiment, emotion and mood. As a consequence we now have a well defined concept for investor sentiment. This concept removes the shaky ground on which previous analysis have rested. It's now possible to test possible sentiment proxies against this concept to make sure that these proxies really measure sentiment and not something else.

The concept allows also predictions about a proxy variable depending on whether this proxy resembles emotion or mood.

The way I use here the connection between verbal definitions in psychology or of psychological phenomenon's and observed statistical properties can be used likewise in different contexts, especially in the realm of behavioural economics. This connection would help to understand economic or statistical patterns or data which make no sense in the realm of standard economic theory. The result of this connection is a more intense connection between economic and psychology theory even outside the realm of behavioural finance or behavioural economics.

The psychological definitions also allows seeing sentiment data as the aggregate outcome of a latent information valuation process. If we understood better which information really matter in the assessment process of future stock returns, then we could understand financial markets better and learn how to influence them better e.g. to make better policies for the financial markets. It now seems possible and plausible to look for meaningful results related to behavioural economics even in ordinary time series which e.g. measure sentiments on financial markets.

A word of caution at the end: The above results have to be validated first for different sentiment time series. Only then I can be sure that my results are not due to overfitting of my definitions to the data or other problems, but are really general. Nevertheless the first step on the road for a better understanding of investor sentiment has been made.

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A Appendix

In this appendix I present the results of additional tests, which are mentioned in section 4.1. The purpose of these tests is to show whether the differences in mean and variance proposed in section 2.2 between short term and long term indices are stable over time.
The additional normality tests are shown to indicate whether the sentiment indices resemble rather noise than real information. This stems from the discussion of the normal distribution being the "no information distribution" in section 5.2.

A.1 Additional Tests for Equality of Mean and Variance

The time periods for the following tests were derived a) by stability analyses with CUSUM and Chow tests for structural breaks and b) as these periods split the sample into three historical distinguishable times .

The period 1/99 equals to the period from 28th November 2002 to 14th October 2004. In this period the aftermath of the dotcom bubble burst is still present on the stock markets. The period 100/300 equals to the period from 21st October 2004 to 21st August 2008. In that time the stock markets behave relatively normal (no huge swings). And the period 301/415 equals to the period from 28th August 2008 to 4th November 2010. This period covers the starting of the recent financial crises and the following two years. Hence a period with a lot of uncertainty and insecurities on the stock market.

The tests are conducted on the *sentiment* data for all stock indices *not* on the stock indices itself.

Table 9: Two-sample t test with unequal variances in 1/99

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DAXINS6	99	0.0765465	0.00867	0.0862658	0.0593411	0.0937519
DAXINS1	99	-0.040904	0.0202493	0.2014779	-0.0810881	-0.00072
combined	198	0.0178212	0.0117555	0.1654141	-0.0053615	0.0410039
diff		0.1174505	0.0220273	0.0738827	0.1610183	

diff = mean(DAXINS6) - mean(DAXINS1) t = 5.332
Ho: diff = 0 Welch's degrees of freedom = 133, 473

Table 10: Two-sample t test with unequal variances in 100/300

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
DAXINS6	201	0.1399303	0.0073632	0.1043917	0.1254108	0.1544499
DAXINS1	201	0.0961672	0.0157856	0.2237988	0.0650397	0.1272946
combined	402	0.1180488	0.0087667	0.1757718	0.1008143	0.1352832
diff		0.0437632	0.0174184	0.0094776	0.0780488	

diff = mean(DAXINS6) - mean(DAXINS1) t = 2.5125
Ho: diff = 0 Welch's degrees of freedom = 283, 928

Table 11: Two-sample t test with unequal variances in 301/415

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
DAXINS6	115	0.0423861	0.01104	0.1183909	0.0205159	0.0642563
DAXINS1	115	0.0530348	0.0181853	0.1950156	0.0170098	0.0890597
combined	230	0.0477104	0.0106196	0.1610546	0.0267858	0.0686351
diff		-0.0106487	0.0212741	-0.0526135	0.0313161	

diff = mean(DAXINS6) - mean(DAXINS1) t = -0.5005
Ho: diff = 0 Welch's degrees of freedom = 189, 279

Table 12: Two-sample t test with unequal variances

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
DAXINS6	415	.0977795	.0055338	.1127319	.0869017	.1086573
DAXINS1	415	.0515159	.0106747	.2174595	.0305326	.0724992
combined	830	.0746477	.0060617	.174637	.0627495	.0865459
diff		.0462636	.0120238		.0226515	.0698757

diff = mean(DAXINS6) - mean(DAXINS1) t = 3.8477
Ho: diff = 0 Welch's degrees of freedom = 622, 533

Table 13: Variance ratio test for DAXINS6 == DAXINS1 in 1/99

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DAXINS6	99	0.0765465	0.00867	0.0862658	0.0593411	0.0937519
DAXINS1	99	-0.040904	0.0202493	0.2014779	-0.0810881	-0.00072
combined	198	0.0178212	0.0117555	0.1654141	-0.0053615	0.0410039

ratio = sd(DAXINS6) / sd(DAXINS1) f = 0.1833
Ho: ratio = 1 degrees of freedom = 98, 98

Table 14: Variance ratio test for DAXINS6 == DAXINS1 in 100/300

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DAXINS6	201	0.1399303	0.0073632	0.1043917	0.1254108	0.1544499
DAXINS1	201	0.0961672	0.0157856	0.2237988	0.0650397	0.1272946
combined	402	0.1180488	0.0087667	0.1757718	0.1008143	0.1352832

ratio = sd(DAXINS6) / sd(DAXINS1) f = 0.2176
Ho: ratio = 1 degrees of freedom = 200, 200

Table 15: Variance ratio test for DAXINS6 == DAXINS1 in 301/415

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DAXINS6	115	0.0423861	0.01104	0.1183909	0.0205159	0.0642563
DAXINS1	115	0.0530348	0.0181853	0.1950156	0.0170098	0.0890597
combined	230	0.0477104	0.0106196	0.1610546	0.0267858	0.0686351

ratio = sd(DAXINS6) / sd(DAXINS1) f = 0.3686
Ho: ratio = 1 degrees of freedom = 114, 114

Table 16: Variance ratio test for DAXINS6 == DAXINS1

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DAXINS6	415	.0977795	.0055338	.1127319	.0869017	.1086573
DAXINS1	415	.0515159	.0106747	.2174595	.0305326	.0724992
combined	830	.0746477	.0060617	.174637	.0627495	.0865459

ratio = sd(DAXINS6) / sd(DAXINS1) f = 0.2687
Ho: ratio = 1 degrees of freedom = 414, 414

A.2 Additional Normality Tests

Table 17: Skewness/Kurtosis tests for Normality in 1/99

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj. $\chi^2(2)$	Prob > χ^2
DAXINS6	99	0.4388	0.9343	0.62	0.7349
TECDXS6	99	0.0182	0.1963	6.72	0.0348
ESX50S6	99	0.7462	0.8591	0.14	0.9341
NIKKES6	99	0.0054	0.0443	10.09	0.0065
NASDQS6	99	0.9154	0.0858	3.05	0.2182
SP500S6	99	0.6516	0.3389	1.14	0.5647
TECDXS1	99	0.3519	0.0057	7.66	0.0217
DAXINS1	99	0.9293	0.0149	5.71	0.0577
ESX50S1	99	0.7818	0.0161	5.65	0.0593
NIKKES1	99	0.4432	0.1151	3.16	0.2063
NASDQS1	99	0.8023	0.0061	6.98	0.0306
SP500S1	99	0.7783	0.0155	5.7	0.0578

Table 18: Skewness/Kurtosis tests for Normality in 100/300

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj. $\chi^2(2)$	Prob > χ^2
DAXINS6	201	0.3004	0.2906	2.21	0.3307
TECDXS6	201	0.7038	0.1278	2.49	0.2879
ESX50S6	201	0.2604	0.0444	5.3	0.0707
NIKKES6	201	0.3939	0.7899	0.81	0.6683
NASDQS6	201	0.4222	0.0958	3.46	0.1776
SP500S6	201	0.6085	0.0877	3.21	0.2005
TECDXS1	201	0.1153	0.0013	11.2	0.0037
DAXINS1	201	0.2137	0.0005	11.94	0.0025
ESX50S1	201	0.1799	0.0009	11.1	0.0039
NIKKES1	201	0.0321	0.2418	5.83	0.0542
NASDQS1	201	0.3163	0.0077	7.54	0.023
SP500S1	201	0.2624	0.0025	9.31	0.0095

Table 19: Skewness/Kurtosis tests for Normality in 301/415

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj. $\chi^2(2)$	Prob > χ^2
DAXINS6	115	0	0.0003	35.09	0
TECDXS6	115	0	0.0002	36.26	0
ESX50S6	115	0	0.0003	34.32	0
NIKKES6	115	0.0002	0.0171	15.66	0.0004
NASDQS6	115	0	0.0002	34.38	0
SP500S6	115	0	0.0001	35.65	0
TECDXS1	115	0.3117	0.2452	2.43	0.2972
DAXINS1	115	0.2869	0.249	2.52	0.284
ESX50S1	115	0.2663	0.2166	2.83	0.2435
NIKKES1	115	0.1851	0.1594	3.82	0.1478
NASDQS1	115	0.2078	0.0904	4.54	0.1033
SP500S1	115	0.1982	0.1262	4.09	0.1294

Table 20: Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj. $\chi^2(2)$	Prob > χ^2
DAXINS6	415	0.0000	0.7576	15.38	0.0005
TECDXS6	415	0.0011	0.2048	11.07	0.0039
ESX50S6	415	0.0008	0.2742	11.16	0.0038
NIKKES6	415	0.1262	0.0000	26.62	0.0000
NASDQS6	415	0.0000	0.0002	31.19	0.0000
SP500S6	415	0.0000	0.0000	37.57	0.0000
TECDXS1	415	0.0734	0.0002	15.09	0.0005
DAXINS1	415	0.3382	0.0000	17.55	0.0002
ESX50S1	415	0.2524	0.0000	16.70	0.0002
NIKKES1	415	0.1285	0.0107	8.32	0.0156
NASDQS1	415	0.2006	0.0000	16.33	0.0003
SP500S1	415	0.1952	0.0000	17.42	0.0002

A.3 Correlation Tables

Table 21: Correlations of DAX Index and Log Return with corresponding sentiments

Variables	DAX	DAXINS6	DAXINS1	DAX Log Return
DAX	1.0000			
DAXINS6	0.1450	1.0000		
	(0.0031)			
DAXINS1	0.1975	0.0799	1.0000	
	(0.0001)	(0.1045)		
DAX Log Return	0.0322	0.0923	0.1485	1.0000
	(0.5136)	(0.0606)	(0.0025)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (...) brackets.

Table 22: Correlations of TECDAX Index and Log Return with corresponding sentiments

Variables	TECDAX	TECDAX Log Return	TECDXS6	TECDXS1
TECDAX	1.0000			
TECDAX Log Return	0.0675	1.0000		
	(0.1702)			
TECDXS6	0.2037	0.0826	1.0000	
	(0.0000)	(0.0932)		
TECDXS1	0.2206	0.1501	0.2057	1.0000
	(0.0000)	(0.0022)	(0.0000)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (...) brackets.

Table 23: Correlations of EUROSTOXX 50 Index and Log Return with corresponding sentiments

Variables	EUROSTOXX	ESX50S6	ESX50S1	EUROSTOXX Log Return
EUROSTOXX	1.0000			
ESX50S6	0.2946	1.0000		
	(0.0000)			
ESX50S1	0.2263	0.1184	1.0000	
	(0.0000)	(0.0160)		
EUROSTOXX Log Return	0.0534	0.0934	0.1595	1.0000
	(0.2781)	(0.0575)	(0.0011)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (...) brackets.

Table 24: Correlations of NIKKEI 225 Index and Log Return with corresponding sentiments

Variables	NIKKEI	NIKKES1	NIKKES6	NIKKEI Log Return
NIKKEI	1.0000			
NIKKES1	0.2929	1.0000		
	(0.0000)			
NIKKES6	0.4544	0.5718	1.0000	
	(0.0000)	(0.0000)		
NIKKEI Log Return	0.0557	0.2462	0.1051	1.0000
	(0.2578)	(0.0000)	(0.0325)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (...) brackets.

Table 25: Correlations of NASDAQ Index and Log Return with corresponding sentiments

Variables	NASDAQ	NASDQS1	NASDQS6	NASDAQ Log Return
NASDAQ	1.0000			
NASDQS1	0.2538	1.0000		
	(0.0000)			
NASDQS6	0.2456	0.2163	1.0000	
	(0.0000)	(0.0000)		
NASDAQ Log Return	0.0805	0.0239	0.0271	1.0000
	(0.1019)	(0.6280)	(0.5819)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (...) brackets.

Table 26: Correlations of S&P 500 Index and Log Return with corresponding sentiments

Variables	SP500	SP500S1	SP500S6	SP500 Log Return
SP500	1.0000			
SP500S1	0.1844	1.0000		
	(0.0002)			
SP500S6	0.1772	0.1782	1.0000	
	(0.0003)	(0.0003)		
SP500 Log Return	0.0588	0.0327	0.0144	1.0000
	(0.2329)	(0.5076)	(0.7702)	

The variable names refer to the same sentiment variables as in table 1 in section 4.1.
Significance levels are in (. . .) brackets.