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Investor Sentiment and the Cross-Section of Stock Returns

A Study on the Effect of Investor Sentiment in the Norwegian Stock Market

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Abstract

We build a model of investor sentiment for the Norwegian stock market and examine its effect on the returns of various types of stocks following positive and negative sentiment periods. Our sample consists of all listed stocks on Oslo børs per year during the period 1994-2022. The model extends the classic framework of investor sentiment introduced in (Baker & Wurgler, 2006) and employed in subsequent literature. To better suit the Norwegian stock market, we replace some of their proxies with more relevant indicators, including a consumer confidence indicator and the Norwegian economic barometer index. We hypothesize that firms with highly subjective valuations and limited arbitrage opportunities are more likely to be affected by investor sentiment.

Our results show that stock returns in our sample are, on average, influenced by sentiment as expected. However, we identify certain deviations from the findings in (Baker & Wurgler, 2006). Specifically, we observe variations in the impact of sentiment on different portfolios based on firm characteristics. Through analyzing average returns of these portfolios, we make assumptions regarding the presence of sentiment effects in the Norwegian stock market. We find that sentiment influences the returns of portfolios formed on tangibility characteristics as well as those formed on external financing, as expected and in line with previous research. When running regressions examining the effect of sentiment on these portfolios, we experience significance problems with the other characteristics-based portfolios. This is in line with previous literature such as (Concetto & Ravazzolo, 2019; Corredor et al., 2015) who fail to verify the findings that stem from the U.S. stock market, when applied to markets in Europe.

Our research contributes to the literature by building a model of sentiment for Norway using relevant measures grounded in theory and previous literature. By examining the specific context of the Norwegian stock market, our study provides insights into the nuances of investor sentiment and addresses gaps in previous research. These findings enhance the understanding of investor behavior and offer valuable implications for investors and policymakers in the Norwegian financial landscape.

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Contents

Tables

Figures

1. Introduction

In this study, we aim to investigate the role of investor sentiment on cross-sectional returns in the Norwegian stock market in the period 1994-2022. According to (De Long et al., 1990), sentiment affects how individuals trade in the stock market. Sentiment, as defined by (Baker & Wurgler, 2007), is a belief about future cash flows and investment risks that are not justified by the facts at hand. Sentiment is an irrational phenomenon present in the stock market that causes investors to trade in sub-optimal ways, contrasting classical rational economic literature which states markets are efficient and that investors are informed and thus do not trade if stocks are priced correctly according to their fundamental[1] value. The consequences of sentiment can lead to forcing prices of individual stocks away from their fundamentals, which involves systematic mispricing patterns that we hypothesize are present in the Norwegian stock market. While traditional theory of finance is based on rational investors trading based on information which should drive prices of stocks to their fundamental values, the concept of sentiment challenges this view. Our thesis examines the effect of investor sentiment on cross-sectional returns in the Norwegian stock market, by building on the model first introduced in (Baker & Wurgler, 2006) and adapting it to the Norwegian stock market through using a set of sentiment proxies introduced in previous literature, and measuring how these function in our sample. To examine this effect, we form the research question:

"How does investor sentiment affect cross-sectional returns in the Norwegian stock market?"

To answer the research question, we employ methods grounded in previous literature and theory on the field of investor sentiment. We take a cross-sectional approach to measuring patterns of mispricing in stock prices that could stem from investor sentiment. First, through examining previous literature, we find relevant sentiment proxies. Most notably, we employ three of the sentiment proxies found in (Baker & Wurgler, 2006), and add two others based on literature and economic reasoning, which we hypothesize are relevant proxies in the Norwegian stock market. We use Principal Component Analysis to isolate the common variation in these five proxies and build a sentiment index measure

[1] Fundamental value is the discounted cash flow value of an asset, based entirely on the expected return on an investment, thus making it an entirely rational measure of returns for any investment decision.

from this. Subsequently, we follow (Baker & Wurgler, 2006) who group returns variables by different firm characteristics, a method replicated in numerous other studies on sentiment. We use a sorting approach to examine returns of stocks following positive and negative sentiment periods, before employing a time-series regression approach. This allows us to run significance tests on the results uncovered from the sorting approach. We find that firms with a large degree of tangible assets trend positively in terms of returns following positive sentiment periods, while firms with a large degree of research and development trend negatively in terms of returns, following positive sentiment periods. We also find that a high degree of external financing has a negative effect on returns following positive sentiment periods. Overall, we expected to see firms whose valuations are highly subjective and which are difficult to arbitrage to do worse following positive sentiment periods, as is the finding in (Baker & Wurgler, 2006) and subsequent literature. Our findings do not support this. Our analysis experiences issues with statistical significance that makes us unable to claim anything about these effects. This is consistent with others who have attempted the same in European stock markets, such as (Concetto & Ravazzolo, 2019; Corredor et al., 2015).

Our thesis contributes to the literature on investor sentiment in several ways. First, sentiment literature in the Norwegian stock market is limited. While some literature exists, the most recent work does not cover the last few years. Since the pandemic, the share of retail investors active in the Norwegian stock market has increased, and it is of interest to examine whether this leads to increased sentiment in the Norwegian stock market. Second, previous literature in Norway involves using several sentiment proxies which are difficult to obtain for the Norwegian stock market, specifically the closed-end fund discount and the aggregate equity issuance per year, both utilized in (Baker & Wurgler, 2006) for the U.S. stock market and since replicated by others in the Norwegian stock market. Since few closed-end funds exist in Norway, the closed-end fund discount measure is unreliable. Another issue comes from the fact that since Euronext acquired Oslo børs, data on aggregate equity and debt issuance are no longer publicly available. Thus, previous sentiment literature in Norway is difficult to replicate in the present day. Our research then provides a model based on currently available information, which can serve as a basis for sentiment research in Norway going forward.

The rest of the thesis proceeds as follows. In section 2, we present our research question and sub-questions which we hypothesize will be able to answer our main question and examine sentiment in Norway. This section also contains a presentation of our literature review examining the history of investor sentiment and theoretical backgrounds for the sentiment literature in various markets up until today. In section 3, we present the theoretical background to our empirical approach. This section contains our empirical model, a presentation of our grouping of the Norwegian stock market by various characteristics, as well as our model of investor sentiment estimation. In section 4, we present our analysis, starting with empirical tests Here we employ a sorting approach to the stocks in the Norwegian stock market. This conducts a visual check of patterns of returns following positive and negative sentiment periods. To verify the results in the sorting approach, we run time-series regressions to detect the significance of our hypothesis stemming from the previous section, before concluding on our findings in section 5.

2. Research design and Methodology

In this section we will first briefly introduce the Norwegian stock market and outline our research, before introducing our main research question and sub-questions. Then, we will proceed with the literature review where we examine previous literature on the field of investor sentiment. This part will also serve as a basis for presenting our research questions.

The Norwegian stock market consists primarily of industrial stocks and is recognized for its stability, making it an attractive choice for well-informed investors. We will explore this impact through conducting a cross-sectional analysis. In doing so, we will consider the challenge of arbitrage and draw upon existing literature and empirical findings from the U.S. stock market, comparing our results to those of (Baker & Wurgler, 2006). As part of this investigation, we will identify the key components of an investor sentiment index for the Norwegian stock market, inspired by the model by (Baker & Wurgler, 2006) but with local adaptations to fit the Norwegian stock market. We will analyze a time series ranging from 1994 to 2022 with the object of observing the effects of sentiment on cross-sectional returns in the Norwegian stock market. Given the recent volatility and the pandemic's impact on market performance, we aim to examine how investor sentiment affects cross-sectional returns in the Norwegian stock market.

2.1. Research question

To examine the effect of investor sentiment on Norwegian stock market returns, we form a main research question which allows us to uncover whether the effect in Norway is similar to those in other markets, as discussed in (Baker & Wurgler, 2006) and others. Our main research question is thus:

"How does investor sentiment affect cross-sectional returns in the Norwegian stock market?"

To see the relevance of this research question and to form sub-questions which will allow us to answer our main question, we consider previous literature in the field of investor sentiment in the literature review. This will allow us to examine previous findings on investor sentiment and returns in the stock market and to see which potential sentiment proxies are relevant for our study.

2.2. Literature Review

The efficient market hypothesis, founded in classical economic theory, claims that investors are rational actors who trade in the stock market based on rational information. One concept that contradicts the classical theory of rational economic actors is that of investor sentiment. The starting point when dealing with sentiment literature is the separation of noise as opposed to information as a basis for investor behavior. (Black, 1986) claims that investors are subject to noise as opposed to information and that less experienced or simply irrational actors often trade based on noise, confusing it with information. The stock market according to this theory consists not only of rational arbitrageurs who make money on arbitraging stocks which are under- or overvalued relative to their intrinsic value, but also of noise traders that trade excessively and drive prices of stocks away from their intrinsic value. Noise, as opposed to rational information, can be defined as a form of irrational misinformation that drives misinformed traders to make the wrong moves in the stock market, as opposed to making the rational, economically reasonable choice when picking stocks to invest in. A closely related hypothesis following (De Long et al., 1990), which builds on the notion proposed by (Black, 1986), is that investors are exposed to sentiment, that is, they are exposed to a certain form of mood that influences how they trade. Investor sentiment is often linked to psychological biases such as overconfidence, representativeness bias or other misconceptions. These are more actively studied in the field of behavioral economics, specifically behavioral finance, where it is believed to influence the returns of stocks. In recent times, there has been a rise in the amount of literature published in this field, highlighting its growing significance.

The impact of ethics and emotions on financial performance, (Cuomo et al., 2019) , as well as the use of behavioral functions to analyze financial markets, (Khan et al., 2017), has contributed to making behavioral finance a highly relevant research area. Investors form expectations about future cash flows and investment risks based on sentiment, often leading to unjustified assumptions. The theory proposes that rational traders, through diversification and exploiting profit opportunities caused by mispricing, will eliminate sentiment effects, and reach an equilibrium where prices reflect the rationally discounted value of expected cash flows. However, sentiment effects may persist if rational traders cannot fully exploit these opportunities, as discussed in (Stambaugh et al., 2012). They find that high periods of sentiment are associated with anomalies in stock pricing, specifically that mispricing anomalies in stock prices are more frequent following positive sentiment periods. (Mian & Sankaraguruswamy, 2012) utilize the model by (Baker & Wurgler, 2006, 2007) to find that investors react more to earnings announcements in periods of high sentiment than in periods of low sentiment. (Kurov, 2010) confirms that sentiment is influenced by monetary policy, and that market conditions apply, hypothesizing that sentiment is more likely to affect returns in bull markets than in bear markets. (Sun et al., 2016) finds that short-term sentiment indicators can predict returns driven by noise trader behavior.

The significance of whether investor sentiment affects stock prices cannot be overstated, as it has the potential to trigger market bubbles and subsequent significant value losses. (Brown & Cliff, 2004) claim that sentiment is not only a result of individual "noise" traders actions but also linked to the behavior of institutional investors, which is contrary to a lot of the theory on sentiment which links it to irrational trading patterns by misinformed investors. Numerous studies have demonstrated the existence of profitable trading techniques that capitalize on stock price fluctuations resulting from investor sentiment, such as (Baker & Wurgler, 2006) and (Fisher & Statman, 2000). However, the majority of sentiment-related studies concentrate on the U.S. stock market and presume that it is predominantly individual investors who are influenced by sentiment waves and who drive stock prices away from their fundamental values, among others (Kumar & Lee, 2006) who claim sentiment has a role in the formation of returns. (Lee et al., 2002) find that sentiment influences stock market volatility, which again influences returns. New studies keep appearing examining the effect in different markets. These studies suggest that institutional investors exhibit greater rationality in their trading practices, while retail investors are accountable for the impact of sentiment in several markets. While the overall literature is focused primarily on the U.S. stock market and the stock markets of larger economies, the literature on sentiment-driven mispricing in Norway remains relatively limited. As a result of this, it is of interest to verify whether the results obtained from the U.S. market and other large markets, can be transferred to the Norwegian stock market, which remains relatively small compared to other economies. (Concetto &

Ravazzolo, 2019) find their measures of sentiment for the U.S. market does not have the same predictability in European markets. (Corredor et al., 2015) find that sentiment has a greater explanatory power for returns in less developed economies, comparing three Central European economies to larger European economies. (He et al., 2022) finds sentiment measures created from financial newspaper coverage influences returns.

Specifically, the Norwegian stock market may demonstrate different reactions in stock returns in response to investor sentiment, compared to other markets. One crucial difference is that the free float of Norwegian stocks is relatively small, whereas in the U.S. it is approximately 91 %; as discussed in (Ding et al., 2016). In addition, the proportion of retail investors is considerably lower in Norway compared to other developed markets, including the United States (25%), Japan (28%), and the United Kingdom (23%), with only a handful of the Norwegian population being shareholders in comparison. These distinctions raise the question of whether investor sentiment has an impact on the Norwegian stock market. Investors may have incorrect expectations of returns by being too bull or bear which can lead to poorer valuations of assets, causing more incorrect price expectation compared to their fundamental value. This creates the assumption that high (low) sentiment indicates low (high) stock market returns, which can make investor sentiment a projection for future stock returns, (Dergiades, 2012), (Chung et al., 2012). The impact is particularly salient for stock returns that are challenging to assess and difficult to exploit through arbitrage. Studies have shown how investor sentiment can predict stock returns with different use of proxies in their estimate. (Schmeling, 2009) investigates the impact of investor sentiment using a cross-sectional approach on stock returns across 18 industrialized countries, providing evidence of sentiment's predictive power in stock markets. (Bergman & Roychowdhury, 2008) even find that sentiment can be used by corporate managers as a tool in an attempt to affect returns of their own firm through strategic corporate disclosure policy given current sentiment levels, both as a means of reacting to and/or guiding analyst coverage and also as a means of signaling to investors. (Smales, 2017) also finds a link between sentiment and subsequent stock returns, utilizing a measure of fear through the CBOE Volatility Index (VIX) to estimate sentiment and explain returns.

(Baker & Wurgler, 2006) have highlighted profitable strategies that capitalize on stock return fluctuations resulting from sentiment changes. In their study, it was revealed that stock features like firm size, age, and volatility can more strongly influence the impact of sentiment on returns. Specifically, (Baker & Wurgler, 2006) claim that the returns of firms whose valuations are highly subjective and more difficult to arbitrage are more strongly affected by sentiment. To consider the effect of sentiment on these stocks in the Norwegian stock market, we form the following sub-question:

Sub-question 1: The effect of sentiment is stronger for firms whose valuations are highly subjective and more difficult to arbitrage.

When constructing a sentiment measure, the question becomes which proxies to include. Sentiment is not directly observable and is often estimated from indirect measures or proxies that have a theoretically founded correlation with sentiment. The model developed by (Baker & Wurgler, 2006) is a natural starting point. This model is cited and used in most of the subsequent literature which examines the effect of sentiment on cross-sectional returns, also recent models such as (Huang et al., 2015) which finds it is a reliable predictor of stock returns. However, since the model is based on U.S. market proxies, we should make some adaptations to develop a model for the Norwegian market. The question is then which other proxies can be utilized.

(Lemmon & Evgenia, 2006) find that consumer confidence can serve as a proxy for sentiment and that it can forecast returns for small stocks which in our case are relevant as theory suggests these should be more sensitive to sentiment. (Schmeling, 2009) also utilize consumer confidence as a sentiment proxy and constructs a sentiment measure that succeeds in forecasting negative stock market returns across several countries. Both articles use the measure as it is both available in several markets (many developed countries employ a form of consumer confidence indicator in their economy) but also as there is a clear theoretical assumption that consumer confidence is linked to psychological biases such as overconfidence, which again is linked to investor sentiment and excessive trading behavior. (Qiu & Welch, 2006) even find that consumer confidence as a sentiment proxy can outperform other sentiment proxies, such as the closed-end fund discount employed in (Baker & Wurgler, 2006). In a study on the Scandinavian stock markets, (Grigaliūnienė & Cibulskiene, 2010) find that consumer confidence can function as an indicator of sentiment when predicting stock returns. (Fisher et al., 2002) uses consumer confidence as a predictor for negative stock returns. A number of more recent papers also use the measure of consumer confidence as a sentiment proxy. (Sayim & Rahman, 2015) employs the measure for the Turkish market. Since these articles find that consumer confidence can function well as a sentiment proxy, we want to examine whether this proxy can function in our sample. This leads us to the following sub-question:

Sub-question 2: Consumer Confidence Index is a viable proxy for investor sentiment and can predict negative returns.

Another potential influence on sentiment stems from the sentiment of the overall economy. Economic theory suggests consumer behavior is influenced by measures of overall sentiment in the economy. If consumers believe the overall economy has a positive trend, theory suggests spending is increased. To examine whether overall economic sentiment indicators influence investor sentiment, we look for measures of such indicators in the Norwegian economy. One obvious such measure is the Economic Barometer Index ("Konjunkturbarometeret"), in which businesses within the Norwegian industry are asked about their expectations for the period going forward. Since this Barometer Index tends to get substantial media focus, we hypothesize that this can serve as a sentiment proxy, leading to increased speculative demand from retail investors. Since retail investors are often linked to speculative trading in the stock market, we form the hypothesis that this proxy can predict negative stock returns for stocks which are highly affected by sentiment. This measure is a form of survey that is specific to the Norwegain economy, and thus it has less historical foundations in the literature than many of the other relevant sentiment proxies that are often used. However, various forms of expectations about the development of the overall economy do exist in most countries, both from a consumer perspective but also from a business/firm perspective. It is thus interesting to employ such a measure. This leads us to the following sub-question:

Sub-question 3: Norwegian Economic Barometer Index is a viable proxy for investor sentiment and can predict negative returns.

3. Empirical Approach and Data

In the following section, we first present our empirical approach in section. Secondly, we present our data on the Norwegian stock market in which all stocks are grouped by various characteristics, as inspired by (Baker & Wurgler, 2006). Thirdly, we present our data source before moving on to our estimation of an investor sentiment index. When presenting our sentiment index, we also show the sentiment proxies that we employ in our index as well as the background for choosing these proxies. We present the index visually and conduct an eyeball test to see how it lines up against historical accounts of bubbles and shocks in the economy that we hypothesize should correlate with a sentiment levels index.

3.1. Empirical Approach

Theory and previous literature both suggest that investor sentiment may cause systematic mispricing in stock prices. One issue with mispricing is that it is difficult to measure directly. We follow the approach by (Baker & Wurgler, 2006), which is to look for systematic patterns of mispricing correction. Their primary example is that a pattern in which returns on unprofitable growth firms are, on average, especially low when beginning-of-period sentiment is estimated to be high, could represent a correction of a bubble in growth stocks.

We use their empirical framework to measure the cross-sectional impact of investor sentiment on stock returns. To show sentiment-driven changes in cross-sectional predictability patterns, we control for the generic impact of investor sentiment on all stocks and the impact of characteristics across all time periods. Following their model, the analysis is organized around the following predictive specification:

$$E_{t-1}[R_{it}] = \alpha + \alpha_1 T_{t-1} + \boldsymbol{\beta}_1 x_{it-1} + \boldsymbol{\beta}_2 T_{t-1} x_{it-1} \tag{1}$$

where i indexes firms, t denotes time, x is a vector of firm characteristics, and T a proxy for sentiment. The coefficient α_1 picks up the generic effects of investor sentiment, β_1 captures the generic effect on firm characteristics on stock returns and β_2 captures the effect of sentiment-driven mispricing in cross-sectional patterns. Our main interest in this thesis is on β_2. The null hypothesis is that $\beta_2 = 0$, indicating that any nonzero effect is rational compensation for systematic risk. Alternatively, if $\beta_2 \neq 0$, the null hypothesis is rejected as we believe this reveals cross-sectional patterns in sentiment-driven mispricing. The equation utilized is termed by (Baker & Wurgler, 2006) as a "conditional characteristics model", as it adds conditional terms to the original model by (Daniel & Titman, 1997).

3.2. Characteristics and Returns

Our sample of firm-level data are extracted from the Reuters Refinitiv Eikon database. The sample includes all 1008 equities listed on Oslo Børs available in the database during the period 1994-2022.

Table 1 shows summary statistics for the returns characteristics variables based on (Baker & Wurgler, 2006) definitions. To provide a comprehensive overview of trends over time, we also compute subsample means for both the returns and characteristics variables. All variables are winsorized[2] at their 5th and 95th percentiles.

Panel A displays the returns variables. Returns (Rt) are computed monthly. Our sample consists of 70 074 individual returns observations. Average monthly returns over our sample period is 0.31 % and we see from the subsample means that monthly returns on average decrease going from the 1990s and up until 2020. Subsample means for 2022-2022 are also included, but since the timespan is only two years the development after 2020 is still unclear. Our sample period overlaps with (Baker & Wurgler, 2006) for the 19902 and 2000s. Our sample data on the Norwegian stock market seem to have similar development during these decades as in the U.S. stock market, but we observe that our returns are lower than in the U.S. stock market. Following common practice, Momentum (MOM) is defined as the raw return for the 11-month period from 12 through 2 months prior to the observation return. Momentum is not specifically mentioned as a salient characteristic in previous literature, and previous theory does not suggest a direct causal relationship between momentum and the difficulty of valuation or arbitrage. Like (Baker & Wurgler, 2006), we use momentum merely as a control variable to understand the

[2] Winsorization at the 5^{th} percentile involves adjusting all values of a variable which are below the 5^{th} percentile value, to the 5^{th} percentile value. The same goes for values above the 95^{th} percentile, which are adjusted to the 95^{th} percentile value. The method removes the most extreme observations from the sample.

independence of our results from known mispricing patterns. The subsample means have a similar development through the decades as the monthly returns variable.

The remaining panels summarize firm and share characteristics. Shares are grouped according to firm size, risk, profitability, dividends, asset tangibility, growth opportunities and/or distress.

Panel B reports size and total risk characteristics. Size is the logarithm of market equity (ME), defined as the stock price multiplied by the number of common shares outstanding. We match ME to monthly returns from the same period. We see that market equity has a rising trend from the 1990s moving forward, consistent with increased liquidity in the stock market. We see a similar development in the U.S. stock market for the overlapping period with (Baker & Wurgler, 2006). Total risk (σ) is computed as the annualized standard deviation in monthly returns for the 12-month period prior to the observation. We match σ to monthly returns from the same period. Observing our subsample means, we see that volatility has an upward trend moving from the 1990s to the 2000s, before decreasing slightly in the 2010s and again rising upwards from 2020 through 2022. The trend is similar in (Baker & Wurgler, 2006) for the 1990s and 2000s.

Panel C displays profitability characteristics. This includes the ratio of earnings to book equity (E+/BE), which is positive for profitable firms and zero for unprofitable firms. If earnings are positive, earnings, (E), are net income before extraordinary items/preferred dividends, plus deferred income taxes and investment tax credit on income statements, less preferred dividend requirements. Book equity (BE) is total shareholders' equity plus deferred taxes on balance sheets. The profitability dummy variable ($E > 0$) is set to one for profitable firms and zero for unprofitable firms.

Panel D shows dividend characteristics. This includes the ratio of dividends to equity (D/BE). Dividends (D) are determined by multiplying dividends per share (DPS) on the ex-date by the number of outstanding shares, divided by book value of equity. The dividend policy dummy variable (D>0) is set to one for dividend-payers and zero for nonpayers. Like (Baker & Wurgler, 2006), who cite (Fama & French, 2001), we observe that the share of firms that pay dividends is declining over our sample period also in Norway.

Panel E summarizes the characteristics of asset tangibility. We show PPE/A and RD/A. According to (Baker & Wurgler, 2006), asset tangibility can serve as a proxy for the difficulty of valuation. PPE/A represents the proportion of gross plant, property, and equipment to total assets, while RD/A represents the proportion of research and development expenses to total assets.

Panel F represents the characteristics of growth opportunities and distress. These include the book-to-market ratio (BE/ME). This is calculated as the book equity over market equity for the 12-month period prior to the current observation. The external finance characteristic (EF/A) is measured as the ratio of external finance to the total assets. Sales growth (GS) is measured as the percentage change of net sales or revenues over the year, following the approach by (Baker & Wurgler, 2006).

3.3. Data

Our firm-level data is extracted from Reuters Refinitiv Eikon Datastream. The data on Returns Characteristics are measured as monthly time series data on a per share level and aggregated on a stock market level by summing the average of all observations available per month over the period 1994-2022. Table 1 shows the summary statistics for each variable. Each variable is winsorized at the 5^{th} and 95^{th} percentile.

The sentiment proxy data are also from Reuters Refinitiv Eikon Datastream, and these are measured annually across the time period 1994-2022. All measures are winsorized at their 5^{th} and 95^{th} percentiles. By averaging the returns characteristics variables when they are used as dependent variables in our analysis, we are able to remove extreme observations and get a representative sample for each time period. Table 2 shows the distribution of the sample across all firms sorted on market equity (size characteristics).

The data employed in the Empirical Tests chapter, specifically the Fama-French factors (HML, SMB) and momentum (UMD) are extracted from the website of professor Bernt Arne Ødegaard (ba-odegaard.no). These are used merely as control variables to isolate the effect of sentiment on returns.

Table 1

Summary statistics: 1994-2022

Panel A summarizes returns variables. Returns are measured monthly. Momentum (MOM) is defined as the cumulative return for the 11-month period between 12 and 2 month prior to t. Market Equity (ME) is price per share multiplied with number of shares outstanding. Total risk (σ) is the rolling standard deviation for the average return over the 12 month period prior to t. Panel C summarizes the profitability variables. The Earnings-book equity ratio (E+/BE) is defined for firms with positive earnings. Earnings (E+) is defined as income before extraordinary items plus income statement deferred taxes minus preferred dividends. Book Equity is defined as shareholders' equity plus balance sheet deferred taxes. The dummy variable E>0 is equal to one for profitable firms and zero otherwise. Panel D shows dividend characteristics. Dividends (D+) is dividends per share multiplied by shares outstanding. The dummy variable D>0 is euqal to 1 for dividend payers and zero for non-payers. Panel E shows tangibility characteristics. Plant, Property and Equipment (PPE) and Research & Development (RD) are scaled by Total Assets (A). Panel F shows variables used as proxies for growth oppurtunities and distress. The book-to-market ratio (BE/ME) is the log of the ratio of book equity to market equity. External Finance (EF) represents the external financing of the company. GS shows the change in net sales or revenues over the year. All variables are Winsorized at the 5th percentile and 95th percentile.

	Full Sample						Subsample Means			
	N	Mean	Median	SD	Min	Max	1990s	2000s	2010s	2020-2022
					Panel A: Returns					
R_t (%)	70 074	0.31	-0.43	12.80	-80.00	140.00	0.92	0.27	0.02	0.39
MOM_{t-1} (%)	71 670	9.03	2.11	57.18	-100.00	680.27	15.23	7.10	6.10	14.05
					Panel B: Size and Total Risk					
ME_t (1000)	75 721	6 602.91	809.95	33 070.52	0.00	765 631.52	2 161.53	4 912.53	8 448.17	11 212.97
σ_{t-1} (%)	78 304	14.05	10.88	17.34	0.31	890.26	12.81	14.52	13.43	16.05
					Panel C: Profitability					
$E+/BE_t$ (%)	63 891	38.26	11.39	278.49	0.00	12 446.63	23.47	46.09	40.30	34.95
$E>0_t$ (%)	61 551	22.13	0.00	41.52	0.00	100.00	22.42	22.34	21.40	23.33
					Panel D: Dividend Policy					
$D+/BE_t$ (%)	32 356	19.28	3.59	404.61	0.00	19 463.02	5.68	12.03	36.92	9.77
$D>0_t$ (%)	75 019	36.69	0.00	48.19	0.00	100.00	45.17	37.90	34.79	32.87
					Panel E: Tangibility					
PPE/A_t (%)	64 779	70.39	59.26	149.83	-11.05	9 289.71	83.09	59.73	75.58	73.74
RD/A_t (%)	14 738	8.64	2.70	18.20	-18.95	276.62	7.00	8.66	9.49	7.06
					Panel F: Growth Oppurtunities and Distress					
BE/ME_t (%)	75 662	115.10	74.88	306.06	-10 456.85	5 058.31	109.47	114.81	123.27	101.25
EF/A_t (%)	93 963	11.07	2.58	118.89	-6 583.36	1 412.16	11.60	10.70	9.24	16.48
GS_t (%)	87 159	14.18	8.75	72.47	-794.13	900.40	14.20	16.40	10.00	20.23

Table 2

Sample Size and Distribution in Size Deciles

The table shows the number of available observations per year. Our total sample includes 1008 equities, but as only a part of these are present in any given year, we provide an overview of the available equities per year. The total number of observations are given in the N column. The columns "0.1" - "1" show the number of equitities available per year, grouped on market equity deciles. As the number of observations in each decile are approximately evenly distributed, our sample should be representative of the market each given year.

		Market Equity (size) Deciles									
Year	N	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
1994	125	14	11	13	12	13	12	12	13	12	13
1995	118	12	12	12	11	12	12	11	12	13	11
1996	158	16	16	16	15	16	16	15	16	16	16
1997	200	20	20	20	20	20	20	20	20	20	20
1998	224	23	22	22	23	22	22	23	22	22	23
1999	205	21	20	21	20	21	20	20	21	20	21
2000	204	21	20	20	21	20	20	21	20	20	21
2001	201	21	20	20	20	20	20	20	20	20	20
2002	188	19	19	19	18	19	19	18	19	19	19
2003	175	18	17	18	17	18	17	17	18	17	18
2004	187	19	19	18	19	19	19	19	19	19	19
2005	210	21	21	21	22	20	21	21	21	21	21
2006	235	24	23	24	24	24	23	24	25	22	24
2007	262	27	26	26	26	27	25	26	26	26	27
2008	251	26	25	25	25	25	25	25	25	25	25
2009	231	24	23	23	23	23	23	23	25	21	23
2010	235	25	22	24	23	24	23	23	24	23	24
2011	232	25	22	23	23	23	23	23	23	23	24
2012	222	23	22	22	22	22	22	22	22	22	23
2013	215	22	21	22	21	22	21	21	22	21	22
2014	221	23	22	22	22	22	22	22	22	22	22
2015	217	22	22	21	22	22	21	22	21	22	22
2016	216	22	22	21	22	21	22	21	22	21	22
2017	228	23	23	23	22	23	23	22	23	23	23
2018	239	24	24	24	24	24	23	24	24	24	24
2019	241	25	24	25	23	24	24	24	24	24	24
2020	283	29	28	28	29	28	28	29	28	28	29
2021	331	34	33	33	33	33	33	33	33	33	33
2022	257	26	26	25	26	26	25	26	25	26	26

3.4. Measuring Investor Sentiment

Measuring investor sentiment is not straight-forward as investor sentiment is not a directly observable phenomenon. While the concept of sentiment has been controversial in classic economic theory, the field of behavioral finance has established the concept of investor sentiment as an important part of the theory on stock returns. Presently, the issue is more about how to measure investor sentiment than whether it exists or in what form. Previous literature considers multiple variables which can serve as sentiment proxies, none of which are entirely uncontroversial. In line with previous literature, (Baker & Wurgler, 2007) present two distinct approaches for measuring investor sentiment. One is “bottom-up” and utilizes qualitative micro-level data such as investor surveys to exhibit psychological biases such as overconfidence, representativeness bias or conservatism, elaborating on how investors underreact or overreact to past returns or fundamentals. The second approach is “top-down” and macroeconomic and relies on quantitative data. With this method, the movement in market variables, such as price movements and trading patterns, are used to measure investor sentiment. We employ the latter in our research and look for market variables which can serve as sentiment proxies. One concern in that regard is that each individual sentiment proxy alone possesses limited predictive power, primarily since variation in a market variable such as price movements is not all related to one specific factor. Obviously, the movement in share turnover (or liquidity) is not all caused by sentiment, but rather a variety of different factors that all sum to make out the movement in the variable.

To address this issue, we construct a composite sentiment index based on the methodology introduced by (Baker & Wurgler, 2006). The index is constructed from the common variation in several proxies which we hypothesize will have certain shared characteristics with investor sentiment. These proxies include three of the five proxies utilized by (Baker & Wurgler, 2006). We use the annual share turnover (TURN), annual number of IPOs (NIPO), and the annual dividend premium (P^{D-ND}). In addition to these three proxies, (Baker & Wurgler, 2006) employ the closed-end fund discount, the average first-day returns of IPOs, and the equity share in new issues as additional sentiment proxies. However, since the closed-end fund market in Norway is very small, we exclude this proxy due to very limited data. We are unable to use first-day returns of IPOs as data on offer prices is not available on Datastream. The equity share in new issues is also excluded due to poor data availability. In addition to the three available proxies from (Baker & Wurgler, 2006), we add two proxies which we hypothesize will correlate with investor sentiment in the Norwegian stock market, namely the Consumer Confidence Index (CCI) and the Norwegian Economic Barometer Index (NEBI). In the following we will elaborate on how each sentiment proxy is measured.

3.4.1. Potential Sentiment Proxies

Based on previous literature we use five proxies and extract the common variation in these to form a measure of investor sentiment. Below we present the five proxies.

Share Turnover (TURN)

(Baker & Stein, 2004) show that turnover, or simply liquidity, can function as a sentiment proxy. In a market with short-sales constraints, irrational investors participate and add liquidity only when they are optimistic. From this, they argue that increased liquidity is a symptom of overvaluation. More generally, (Black, 1986) claims noise traders who act on noise rather than rational information as a basis for trading in financial markets, can cause systematic mispricing in the stock market. Following these arguments, we employ turnover as a sentiment proxy. TURN is the natural log of turnover, detrended by the five-year moving average.

Number of Initial Public Offerings (NIPO)

The IPO market is often considered to be sensitive to sentiment. In a market with high sentiment, the number of initial public offerings can be viewed as a reaction to increased demand from investors. The number of IPOs is expected to have a positive correlation with sentiment. The data on IPOs are extracted from Reuters Refinitiv Eikon Datastream. We construct the variable as a dummy variable equal to one if a firm’s share price has data in the current period but not in the previous period, and zero otherwise. We then count the number of observations equal to one per month and use this as our indicator of IPOs per month.

Dividend Premium (P^{D-ND})

P^{D-ND} is the natural log of the difference between the average market-to-book ratios of dividend payers and nonpayers. It represents a firm's propensity to pay dividends and can serve as a proxy for a characteristic of safety. An inverse relationship is expected between p^{d-nd} and investor sentiment. (Baker & Stein, 2004) use this variable to proxy for the relative investor demand for dividend-paying shares. Since dividend-payers are generally larger, more profitable firms with weaker growth opportunities, as mentioned in (Fama & French, 2001), the dividend premium can serve as a proxy for the relative demand for this correlated bundle of characteristics, according to (Baker & Wurgler, 2006). Additionally, (Baker & Wurgler, 2004) links the decision to pay dividends to the demand for dividend payers from investors, which we hypothesize is again linked to sentiment. The variable is constructed by the data for all available securities on a monthly basis, and then aggregated to annual data.

Consumer Confidence Index (CCI)

According to (Lemmon & Evgenia, 2006), (Schmeling, 2009) and (Qiu & Welch, 2006), consumer confidence can function as a sentiment proxy. The Consumer Confidence Index in Norway is derived from a quarterly survey ("Forventningsbarometeret") by Kantar TNS for Finans Norge, where consumers are asked a number of questions related to their expectations about the economy and own consumption patterns in the coming period. In this regard the measure can serve as a proxy for sentiment as it should reflect consumption patterns. CCI is expected to have a negative correlation with share returns. We have obtained the data on CCI from Reuters Refinitiv Eikon Datastream and aggregated the quarterly data to yearly data.

Norwegian Economic Barometer Index (NEBI)

We use the Economic Barometer Index as a measure of the overall sentiment in the Norwegian economy. The measure is derived from a survey ("Konjunkturbarometeret") distributed by Statistics Norway in which selected businesses in the industry are asked a number of questions about their expectations about the economy going forward. The index functions as a leading indicator for the Norwegian economy, and we use it as a sentiment proxy because we hypothesize it can influence the behavior of market participants. Positive trends in the economic barometer index can serve as indicators of bullish sentiment, while negative trends can serve as indicators of bearish sentiment. The measure is obtained from Reuters Refinitiv Eikon Datastream.

3.4.2. Constructing a Sentiment Index

In this section we create our sentiment index. Each sentiment proxy will contain a sentiment component as well as idiosyncratic components which are not directly related to sentiment. We use Principal Component Analysis to estimate the sentiment component. Another issue in forming a sentiment index is determining the timing of the variables, specifically if the variables exhibit lead or lag relationships with sentiment. Generally, (Baker & Wurgler, 2006) claim proxies that involve firm supply responses (such as NIPO) can be expected to lag behind proxies based directly on investor demand/behavior (such as P^{D-ND} and TURN).

We form a composite index to capture the common variation in the five proxies, while also including the fact that some variables take longer to show the same sentiment. First, we run a Principal Component Analysis on the five proxies and their five lags. The first PCA accounts for 68.95 % of the variation in the sample. We form a first-stage index with the five proxies and their five lags, and then calculate the correlation matrix between the first-stage index and the five proxies + their lags. We then run a second PCA, defining $SENTIMENT$ as the first two principal components of the correlation matrix between the first-stage index and the five proxies and their lags, rescaling the coefficients so the index has unit variance. This leads to the following index

$$\begin{aligned} SENTIMENT_t = 0.51TURN_{t-1} + 0.49NIPO_{t-1} - 0.19PD - ND_t \\ -0.03CCI_{t-1} + 0.22NEBI_{t-1} \end{aligned} \tag{2}$$

where each of the index components has first been standardized. This index explains 74.55 % of the sample variance, thus we conclude that the index captures most of the common variation. The correlation between the first-stage index and the $SENTIMENT$ index is 0.9630, which indicates little information is lost in dropping the five terms with other time subscripts.

TURN enters with the expected sign and timing. NIPO enters with the expected sign, but not the expected timing. We would expect $SENTIMENT$ and NIPO to be strongly correlated in the same period, but our analysis shows that in fact $SENTIMENT$ and lagged NIPO have a stronger correlation. Since the coefficient on NIPO is significant on the 0.01 % level, we continue to include the proxy in our index. P^{D-ND} enters with the expected sign but not the expected timing. Following the same arguments as with NIPO, we keep the variable in our index.

CCI enters with the expected timing, but not with the expected sign. We would expect movements in consumer confidence to be positively related to movements in sentiment, but in our case the opposite appears to be the case. The negative coefficient is quite weak and is only significant on the 15 % level. NEBI[3] enters with the expected sign and timing and is also significant on the 1 % level. Table 3 shows the coefficients p-values, regression R^2 and RMSE.

An obvious objection to $SENTIMENT$ as measured above is that Principal Component Analysis cannot separate a common sentiment component from a common business cycle component. An example is that the number of IPOs will vary with business cycles for rational reasons, and not necessarily only due to sentiment reasons. Our topic of interest is to detect when the number of IPOs is high for no rational reason. To deal with this, we follow (Baker & Wurgler, 2006) and by forming a second $SENTIMENT$ index by regressing each of the five proxies on a set of macro-economic variables, namely the Consumer Price Index, growth in industrial production, gross domestic product and the policy interest rate. The residuals from these regressions, denoted with superscript ~, can serve as cleaner sentiment proxies. We form an index of the orthogonalized[4] proxies following the same procedure as before, this time keeping the first two principal components of the common variation in the proxies. The resulting index is

$$SENTIMENT_t^{\sim} = 0.63TURN_{t-1}^{\sim} + 0.52NIPO_{t-1}^{\sim} - 0.28PD - ND_t^{\sim}$$

$$-0.11CCI_{t-1}^{\sim} + 0.20NEBI_{t-1}^{\sim} \tag{3}$$

Here, the index explains 71.78 % of the sample variance of the orthogonalized variables. Also, only the first two eigenvalues are above 1. In terms of signs and timing, $SENTIMENT_t^{\sim}$ is similar to $SENTIMENT_t$.

[3] Norwegian Economic Barometer Index, one of our sentiment proxies. Quarterly survey among businesses in the Norwegian industry regarding expectations about economic conditions, indicates optimism or pessimism among businesses in the Norwegian industry.

[4] Orthogonalizing involves standardizing the coefficients by subtracting the mean and dividing by the standard deviation, also known as standardizing the variable. This creates a new variable that has a mean of zero and a standard deviation of one.

Table 4 shows summary statistics and correlation matrices for the sentiment proxies as well as the two indices constructed from the common variation in the proxies. Table 4 indicates that the sentiment proxies overall are slightly less correlated with each other after controlling for the macro-economic variables, even if the coefficients are stronger in the second equation. In the rest of the thesis, we will present the results for both indices just to be sure.

There are obviously other measures that one would want to include in a sentiment index. Data availability and consistent measurement over a long period of time are the main concerns.

Table 3

Table 2 shows the estimation of the investor sentiment index from the common variation in the five proxies. Regressions are shown in equations (1) and (2). Each coefficient p-value is listed in parenthesis. Regression R^2 and Regression Mean Squared Error is displayed below.

	SENTIMENT_t		$\text{SENTIMENT}^{\sim}_t$
	(1)		**(2)**
TURN_{t-1}	0.51	$\text{TURN}_{t-1}^{\sim}$	0.64
	(0.00)		(0.00)
NIPOt-1	0.49	$\text{NIPO}_{t-1}^{\sim}$	0.52
	(0.00)		(0.00)
PDNDt	-0.19	$\text{P D-ND}_t^{\sim}$	-0.28
	(0.00)		(0.00)
CCIt-1	-0.03	$\text{CCI}_{t-1}^{\sim}$	-0.11
	(0.15)		(0.14)
NEBIt-1	0.22	$\text{NEBI}_{t-1}{}^{\sim}$	0.20
	(0.00)		(0.03)
R^2	0.99		0.96
RMSE	0.10		0.22

3.4.3. Does this Index Capture Fluctuations in Sentiment? An Eyeball Test

The main evidence that the indices succeed in capturing sentiment is that they line up quite well with historical bubbles and financial crises. First, we consider the period of 1995-2000. We see that there was a top in sentiment in 1998, which is interesting since the Norwegian economy suffered from an oil price crisis in that year. We also observe a top in 2000, which lines up fairly well with the dot-com bubble burst of that year. Moving onwards, we see an all-time high in the couple of years leading into the financial crisis of 2008, followed by a sharp decline. In the years following 2014 sentiment has been upwards-trending and is positive until the end of the sample period. This also lines up fairly well with the corona pandemic situation, where the interest in trading shares among retail investors with increased disposable income increased a lot.

Overall, $SENTIMENT^{\sim}$ is positive for 1996-1998, 2001, 2005-2009, and 2017-2022. This, we argue, confirms that the measures on the aggregate level seem to correlate with hypothesized positive sentiment periods.

Table 4
Investor Sentiment Data, 1994-2022

Means, standard deviations, and correlations for measures of investor sentiment. In the first panel, we present raw sentiment proxies. TURN is the natural log of turnover. Turnover is the ratio of shares traded to total market value. NIPO is the annual number of initial public offerings. P D-ND is the difference between the average market-to-book ratios of dividend payers and nonpayers. CCI is the consumer confidence index. NEBI is the Norwegian economic barometer survey from business in the Norwegian industry. TURN, NIPO, CCI and NEBI are lagged one year reative to the other measures. In the second panel, we regress each of the 5 proxies on the consumer price index, growth in industrial consumption, gross domestic product and the policy rate issued by the central bank. The orthagonalized proxies, labeled ~, are the residuals from these regressions. P-values are listed in parenthesis.

					Correlations with Sentiment		Correlations with Sentiment Components				
	Mean	SD	Min	Max	SENTIMENT	SENTIMENT~	$TURN_{t-1}$	$NIPO_{t-1}$	$P\ D\text{-}ND_{t}$	CCI_{t-1}	$NEBI_{t-1}$
Panel A: Raw Data											
$TURN_{t-1}$	-0.01	0.27	-0.58	0.50	0.82	0.81	1.00				
					(0.00)	(0.00)					
$NIPO_{t-1}$	22.93	15.60	2.00	68.00	0.86	0.69	0.52	1.00			
					(0.00)	(0.00)	(0.00)				
$P\ D\text{-}ND_{t}$	-0.17	0.26	-0.74	0.22	-0.18	-0.36	0.03	0.00	1.00		
					(0.35)	(0.06)	(0.89)	(0.99)			
CCI_{t-1}	66.54	44.41	-30.82	135.22	0.29	0.10	0.20	0.23	0.34	1.00	
					(0.13)	(0.62)	(0.30)	(0.23)	(0.07)		
$NEBI_{t-1}$	29.40	49.36	-59.30	129.80	0.59	0.44	0.30	0.50	0.04	0.77	1.00
					(0.00)	(0.02)	(0.11)	(0.01)	(0.85)	(0.00)	
Panel B: Controlling for Macroeconomic Conditions											
$TURN_{t-1}$~	0.00	0.92	-1.94	1.70	0.73	0.86	1.00				
					(0.00)	(0.00)					
$NIPO_{t-1}$~	0.00	0.74	-1.59	1.33	0.69	0.74	0.51	1.00			
					(0.00)	(0.00)	(0.01)				
$P\ D\text{-}ND_{t}$~	0.00	1.00	-2.16	1.50	-0.18	-0.36	-0.16	0.07	1.00		
					(0.35)	(0.06)	(0.40)	(0.71)			
CCI_{t-1}~	0.00	0.76	-1.59	1.29	0.22	0.13	0.04	0.32	0.19	1.00	
					(0.26)	(0.51)	(0.82)	(0.10)	(0.32)		
$NEBI_{t-1}$~	0.00	0.80	-2.30	1.28	0.48	0.45	0.22	0.58	0.03	0.70	1.00
					(0.01)	(0.01)	(0.24)	(0.00)	(0.87)	(0.00)	

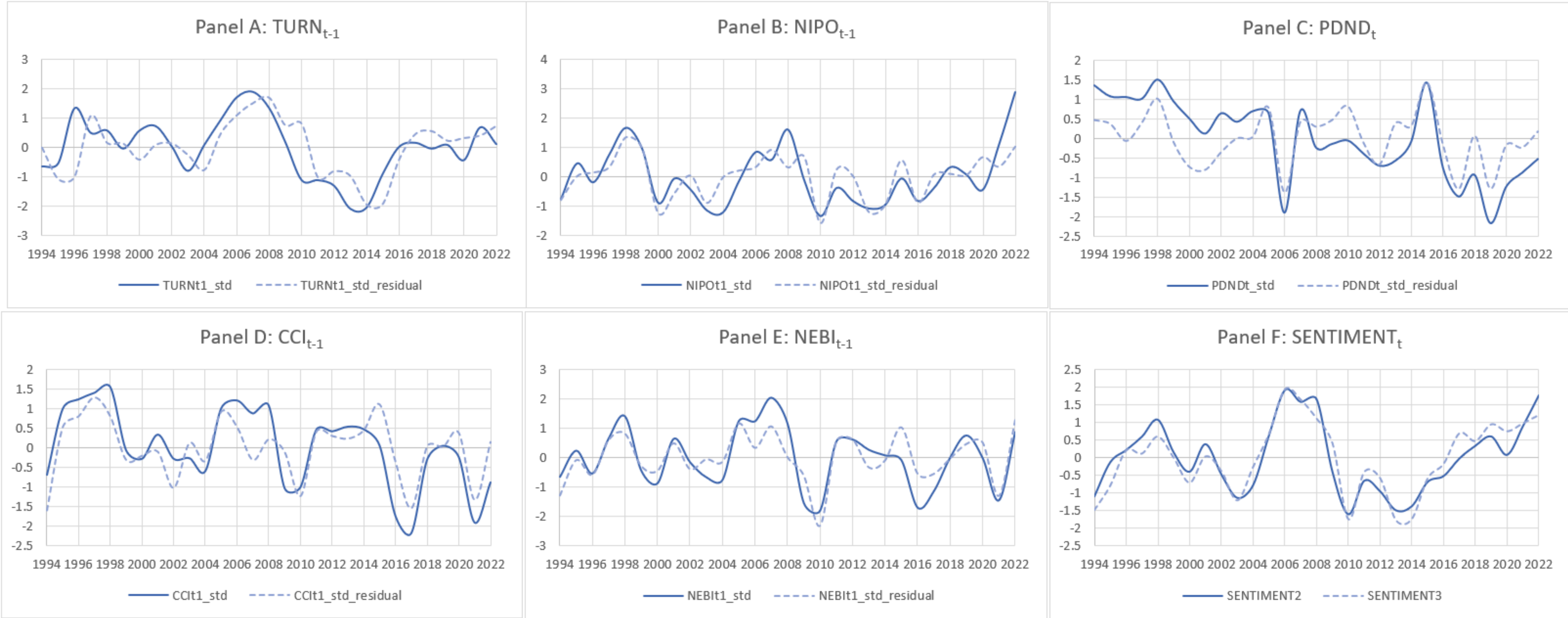

Figure 1: Investor sentiment, 1994-2022

Panel A shows the log turnover. Turnover is the ratio of reported share volume to average shares listed. Panel B shows the annual number of initial public offerings. Panel C shows the dividend premium, given by the difference between the average market-to-book ratios of payers and nonpayers. Panel D shows the Consumer Confidence Index. Panel E shows the Norwegian Economic Barometer Index. All variables have been orthogonalized to have zero mean and unit variance. The solid line shows raw data. All variables have been orthogonalized to have zero mean and unit variance. The solid line in Panel F is a Sentiment Index built from the first two principal components of the common variation in the first-stage index and the five proxies. The dashed line is a Sentiment Index built from the first two principal components of the residuals obtained by regressing the proxies on the consumer price index, growth in industrial production, gross domestic product and the policy interest rate. These may function as cleaner sentiment proxies. In the indices, TURN, NIPO, CCI and NEBI are lagged one year relative to PDND, as discussed in the text.

4. Empirical Tests

In this section we first conduct a sorting approach to look for conditional characteristics of sentiment on returns of various portfolios. The objective is to detect whether the effect of sentiment on portfolios formed on various characteristics, specifically size, risk, earnings, dividend payment, tangibility, growth opportunities and distress. The returns of each portfolio are grouped in deciles and the results are discussed per panel. Next, we conduct formal tests of the preliminary patterns observed from the sorting approach. We do this by forming various long-short portfolios and conducting time-series regressions where we examine the difference in returns across portfolios which are long on high (low) levels of a characteristic and short on low (high) levels of the characteristic.

4.1. Sorts

Following the methodology of (Baker & Wurgler, 2006), table 5 looks for conditional characteristics in a simple, non-parametric way. Each monthly return observation is placed in a bin according to the decile rank that the characteristic takes at the beginning of that month, and then according to the level of $SENTIMENT^{\sim}$ at the end of the previous calendar year. To keep the meaning of the deciles similar over time, they are defined based on all available firms on Datastream trading on Oslo børs in the given month. This gives us an overview of the distribution of the returns of the aggregate market based on the characteristics we have chosen. We calculate an equal-weighted average monthly return for each bin and look for patterns. Like (Baker & Wurgler, 2006), we identify time-series changes in cross-sectional effects from the conditional difference of average returns across deciles.

Figure 2 shows the results of table 5 graphically. The solid blue bars indicate returns following positive $SENTIMENT^{\sim}$ periods, while the solid gray bars indicate returns following negative $SENTIMENT^{\sim}$ periods. The dashed blue lines are the average returns across both periods (positive and negative sentiment the previous year-end), and the solid dark blue line is the difference. $SENTIMENT^{\sim}$ is positive for 1996-1998, 2001, 2005-2009, and 2017-2022. Below we will group the characteristics-based long-short portfolio returns by panel shown in figure 2. Each panel in figure 2 has a corresponding category in table 5, where numeric values are listed.

4.1.1. Panel A: Market Equity (ME)

The first three rows of table 5 show the effect of size, as measured by ME, conditional on sentiment. The same set of variables are shown graphically in panel A of figure 2. Unsurprisingly, larger firms have greater returns than smaller firms both when sentiment the previous year end is positive as well as negative. We are not primarily concerned with the absolute returns distribution over the deciles, but the difference between the deciles conditional on positive or negative sentiment the previous year end. We see that when $SENTIMENT_{t-1}^{\sim}$ is positive, returns average – 2.93 % for the bottom 1 ME decile and 1.57 % for the top 1 ME decile. When $SENTIMENT_{t-1}^{\sim}$ is negative, returns average -1.36 % for the bottom 1 ME decile and 1.89 % for the top 1 ME decile. Our analysis supports (Baker & Wurgler, 2006) that there is a size effect. Specifically, the difference in returns conditional on positive sentiment the previous year-end for firms in the first decile is higher than the difference in returns conditional on negative sentiment the previous year end for firms in the tenth decile. Unlike (Baker & Wurgler, 2006), the difference in returns across the other deciles does not decrease approximately linearly as firm size increases. (Baker & Wurgler, 2006) finds that the difference between returns conditional on previous year-end sentiment is highest for small firms characterized on market equity. Our panel indicates support for this as the bottom 1-2 deciles exhibit the largest difference (dark blue line) between returns. Interestingly, the trend of differences does not decrease approximately linearly as we move up through the deciles as they do in (Baker & Wurgler, 2006). This is primarily due to a low difference for the third decile, otherwise the pattern is similar.

4.1.2. Panel B: Volatility ($\boldsymbol{\sigma}$)

The next three rows of table 5 show the cross-sectional effect of returns volatility conditional on sentiment. The results are also visualized in panel B of figure 2. When $SENTIMENT_{t-1}^{\sim}$ is positive, returns average – 0.11 % for the bottom 1 ME decile and 1.02 % for the top 1 ME decile. When $SENTIMENT_{t-1}^{\sim}$ is negative, returns average 0.58 % for the bottom 1 ME decile and 2.35 % for the top 1 ME decile. (Baker & Wurgler, 2006) find that the returns of high σ stocks are more affected by sentiment in the previous year-end than low sigma stocks. In our sample, the difference in returns conditional on sentiment across deciles does not linearly increase as volatility increases as in (Baker & Wurgler, 2006). Rather, in our sample, the difference in returns of the portfolios formed on volatility tends to increase as their volatility decile rank increases, but not linearly. For the 1st-5th deciles, there is a small difference of about on average 0.5 %. The greatest difference is for the 7th and 10th deciles, with 1.56 % and 1.34 %. Visually panel B confirms the dip on the 7th and 10th deciles. The 8th and 9th deciles exhibit lower differences of 0.62 % and 0.63 % respectively. The pattern in our sample is thus not as clear as in (Baker & Wurgler, 2006). We see that the most volatile stocks (10t decile) exhibit the largest sensitivity to sentiment.

4.1.3. Panel C: Earnings/Book Equity (E/BE)

The next six rows of table 5 examine profitability and dividends. These are also displayed in panels C and D in figure 2. For the average investor, the most salient comparisons according to (Baker & Wurgler, 2006) are those between profitable and unprofitable firms ($E < 0$) and payers and nonpayers ($D = 0$). We show these differences in the right most column, where we average returns across profitable (paying) firms and compare them to unprofitable (non-paying) firms.

First, we consider the portfolios formed on E/BE. We find that when $SENTIMENT_{t-1}^{\sim}$ is positive, the difference in returns across profitable firms average 1.89 % higher than for unprofitable firms. When $SENTIMENT_{t-1}^{\sim}$ is negative, the difference is 1.87 %. These findings are interesting, because we would expect profitable firms to do remarkably better in positive $SENTIMENT_{t-1}^{\sim}$ periods. While (Baker & Wurgler, 2006) find a greater difference in returns across positive and unprofitable firms, the direction of the difference in our analysis is the same as theirs. Curiously, the difference in returns conditional on sentiment tends to be greatest for the most profitable firms (top 1 decile). We also see that returns of portfolios formed on these firms are very different from the portfolios of the 8th and 9th deciles. We are unable to detect errors in returns characteristics variables that explains this. Winsorizing the returns and E/BE variables once more does not yield any large differences in the differences in returns between the 9th and 10th deciles. Thus, it would seem that the returns for the most profitable firms are quite different from the rest of the sample. Furthermore, the direction of differences across the deciles is the opposite of that in (Baker & Wurgler, 2006). Summing up panel C, it appears that unprofitable firms are not particularly sensitive to sentiment the previous year-end. Also, it appears that the portfolios formed on earnings/book equity do not exhibit a clear direction in differences within the ten deciles, however it is interesting that the tenth decile is the most sensitive to sentiment.

4.1.4. Panel D: Dividends/Book Equity (D/BE)

When $SENTIMENT_{t-1}^{\sim}$ is positive, the returns of dividend paying firms are on average 0.79 % higher than the returns of non-paying firms. When $SENTIMENT_{t-1}^{\sim}$ is negative, the returns of dividend paying firms are on average 0.24 % higher than the returns of non-paying firms. Our findings support (Baker & Wurgler, 2006) in that dividend paying firms generally do better than non-payers. One hypothesis is that non-payers do better following high sentiment periods as sentiment correlates with the tendency to speculate. (Baker & Wurgler, 2006) is often cited in the literature for their analysis of investor sentiment and its impact on stock returns. While they may not directly mention the correlation between sentiment and the tendency to speculate, they provide a comprehensive exploration of sentiment's influence on stock market performance. (Fisher & Statman, 2000) examine the relationship between investor sentiment and stock returns, highlighting profitable strategies that capitalize on sentiment-induced stock return fluctuations.

Our findings do not support this hypothesis. Generally, non-payers as well as unprofitable firms are more difficult to value and arbitrage, thus making them more exposed to sentiment fluctuations is the hypothesis and finding in (Baker & Wurgler, 2006). Our eyeball test of the patterns in panels D and E of figure 2 do not reflect this. On the contrary, we find no clear direction of the differences based on any extremities when using the sorting approach. In general, for portfolios formed on dividends, there seems to be a trend of smaller differences in the most extreme deciles (nonpayers, 1st and 10th deciles) as well as the middle (5th) decile. For the other deciles, there are patterns of differences. It seems the differences are largest for the 3rd and 9th deciles. It is difficult to claim anything about the effect of sentiment on dividend payers from this. Firstly, the patterns are unclear. Secondly, since the sorting approach is merely a visual test of returns patterns across different characteristics-based portfolios, we are unable to claim anything about the effect of sentiment on dividend payers vs nonpayers.

4.1.5. Panel E: Plant, Property & Equipment/Total Assets (PPE/A)

The next six rows of table 5 consider asset tangibility characteristics, shown visually in panels E and F in figure 2. We consider the hypothesis by (Baker & Wurgler, 2006) that firms in the lower deciles of asset tangibility may be harder to value. First, we consider PPE/A. In our sample, we find that firms in the lower and middle deciles on average earn higher returns than firms in the top deciles. This makes sense as firms in the top deciles may be larger, more stable firms as they may be steady state firms with more stable returns. Theoretically, these firms should be less affected by sentiment. Overall, the difference between returns following positive and negative sentiment periods (the dark blue line in panel E) seem to be at the greatest in the bottom 1-3 deciles. This supports the hypothesis by (Baker & Wurgler, 2006) that these firms are more affected by sentiment. However, since this approach does not allow for significance testing, we are unable to make the claim that the relationship is as such, but there is a visual pattern that we will explore further in the next section where we form long-short portfolios on the same characteristics.

4.1.6. Panel F: Research & Development/Total Assets (RD/A)

Next, we consider RD/A, shown in panel F of figure 2. The differences across the deciles between returns following positive and negative sentiment periods are quite volatile across the different deciles, as observed by the pattern of the dark blue line in panel F of figure 2. We note that the sample size of RD data is quite low compared to the other categories, which may explain part of this. In (Baker & Wurgler, 2006), the difference is largest between zero-RD firms and the top decile firms. In our sample, the largest difference in returns conditional on sentiment is at its highest for the 7th and 9th deciles. Generally, returns differences conditional on sentiment are higher in the top six deciles compared to the other deciles. This indicates that firms where a research and development make out a larger proportion of total assets, are more affected by sentiment than those where research and development make out a minor proportion of total assets. This makes sense if we consider firms where research and development make out a smaller proportion of total assets as larger firms with a large balance sheet, compared to younger firms with high initial R&D costs, such as growth firms. We will examine this hypothesis further in the next section, where long-short portfolios formed on characteristics are formed.

4.1.7. Panel G: Book Equity/Market Equity

The remaining rows in table 5, which are also shown in panels G, H and I in figure 2, exhibit growth opportunities and distress through the ratio of book equity to market equity, external finance to total assets, and sales growth.

First, we consider the portfolios formed on BE/ME. We observe that the difference in returns conditional on sentiment for firms in the BE/ME distribution is approximately constant across the deciles. (Baker & Wurgler, 2006) find that returns of firms in the bottom 1 and top 10 deciles are more sensitive to sentiment than the others, even though there are low differences in the middle deciles in their research as well. This indicates that average returns conditional on sentiment in Norway do not support the findings in (Baker & Wurgler, 2006).

4.1.8. Panel H: External Finance/Total Assets (EF/A)

For firms in the EF/A sample, displayed in panel H of figure 2, the difference in returns seems to be greatest for the top decile. This makes sense as firms with a high degree of external financing are often firms characterized by being young, unprofitable, in the growth phase or simply financially distressed firms. One would expect these firms to earn lower returns following positive sentiment periods. This is the case in our sample, supporting (Baker & Wurgler, 2006).

4.1.9. Panel I: Growth of Sales (GS)

Looking at the GS sample, shown in panel I of figure 2, firms in the higher deciles of sales growth appear to be more sensitive to sentiment than firms in the low deciles. This finding supports (Baker & Wurgler, 2006), but in their study they also find that the same is true for firms in the low deciles. Subsequently, the shape of differences in their research takes an inverted U shape. We find no indication of this in our sample.

4.1.10. Conclusion from Sorting Approach

Concluding the Sorting Approach section, we note that since this approach is based on creating equal-weighted portfolios of returns for firms based on different characteristics, we are unable to make solid claims about causal relationships. This part has attempted to indicate some patterns. In the next section, we form long-short portfolios on the same firm characteristics and run regressions to examine the differences in returns conditional on sentiment. This allows us to run formal significance tests to examine the effects of sentiment on the returns of these characteristics-based portfolios.

Table 5

Future Returns by Sentiment Index and Firm Characteristics, 1994-2022

For each month, we form 10 equal-weighted portfolios according to characteristics of firm size (ME), total risk (σ), earnings-book ratio for profitable firms (E+/BE), dividend-book ratio for dividend payers (D+/BE), fixed assets (PPE/A), research and development (R&D/A), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth (GS). We also calculate portfolio returns for unprofitable, nonpaying, zero-PPE, and zero-R&D firms. We then report average portfolio returns over months in which SENTIMENT˜ from the previous year-end is positive, months in which it is negative, and the difference between these two averages. SENTIMENT~ is positive for 1996-1998, 2001, 2005-2009, and 2017-2022. Numbers are in percent.

		Decile											Comparisons			
	$\widetilde{\text{SENTIMENT}}_{t-1}$	≤0	1	2	3	4	5	6	7	8	9	10	10-1	10-5	5-1	>0 - ≤0
ME	Positive		-2.93	-1.32	-0.52	-0.44	0.20	0.30	0.65	1.11	1.18	1.57	4.50	1.37	3.13	
	Negative		-1.36	-0.23	0.01	0.92	0.98	1.54	1.22	1.67	1.91	1.89	3.25	0.91	2.34	
	Difference		-1.57	-1.08	-0.53	-1.36	-0.78	-1.24	-0.57	-0.55	-0.74	-0.32	1.25	0.46	0.79	
σ	Positive		-0.11	-0.11	0.15	0.04	0.14	-0.22	-0.65	-0.06	0.30	1.02	1.13	0.88	0.25	
	Negative		0.58	0.64	0.73	0.38	0.85	0.82	0.91	0.55	0.93	2.35	1.77	1.50	0.27	
	Difference		-0.70	-0.76	-0.58	-0.34	-0.71	-1.04	-1.56	-0.62	-0.63	-1.34	-0.64	-0.62	-0.02	
E/BE	Positive	-1.19	0.01	-0.06	0.46	0.02	0.93	1.05	1.69	1.86	2.00	-0.91	-0.93	-1.84	0.91	1.89
	Negative	-0.36	0.64	0.98	1.22	0.91	1.66	1.88	2.03	2.00	3.11	0.74	0.10	-0.92	1.02	1.87
	Difference	-0.83	-0.62	-1.04	-0.76	-0.89	-0.73	-0.83	-0.33	-0.15	-1.11	-1.65	-1.02	-0.92	-0.11	0.02
D/BE	Positive	-0.28	0.81	0.77	0.46	0.98	0.55	0.43	0.35	0.74	-0.08	0.05	-0.77	-0.50	-0.27	0.79
	Negative	0.77	0.83	1.42	1.45	1.52	0.59	1.12	0.91	1.16	0.85	0.21	-0.62	-0.39	-0.23	0.24
	Difference	-1.05	-0.01	-0.64	-1.00	-0.54	-0.05	-0.69	-0.56	-0.42	-0.93	-0.16	-0.15	-0.11	-0.03	0.55
PPE/A	Positive	0.08	0.77	-0.42	0.17	0.72	0.24	0.08	-0.43	0.85	0.01	-0.51	-1.28	-0.74	-0.53	0.07
	Negative	0.75	1.64	1.15	1.79	1.13	1.18	1.05	0.65	0.51	0.52	-0.27	-1.91	-1.44	-0.47	0.18
	Difference	-0.67	-0.88	-1.57	-1.62	-0.40	-0.94	-0.96	-1.08	0.34	-0.51	-0.24	0.64	0.70	-0.06	-0.11
RD/A	Positive	0.00	0.69	1.02	0.64	-0.06	0.64	0.18	-0.85	0.35	-1.13	-0.58	-1.27	-1.22	-0.05	0.09
	Negative	0.80	0.25	1.89	0.95	1.10	0.71	1.12	1.55	1.20	1.60	1.03	0.78	0.32	0.46	0.34
	Difference	-0.80	0.44	-0.87	-0.30	-1.16	-0.07	-0.94	-2.40	-0.85	-2.73	-1.61	-2.05	-1.54	-0.51	-0.25
BE/ME	Positive		2.39	1.22	1.03	0.47	0.23	0.00	-0.07	-0.51	-1.04	-1.30	-3.70	-1.54	-2.16	
	Negative		2.98	1.99	1.88	1.07	1.10	0.81	0.76	0.24	-0.24	-0.51	-3.49	-1.61	-1.88	
	Difference		-0.59	-0.77	-0.85	-0.60	-0.87	-0.81	-0.83	-0.76	-0.80	-0.80	-0.21	0.07	-0.28	
EF/A	Positive		-0.18	0.48	0.12	-0.07	0.37	-0.01	0.39	0.25	0.53	-1.27	-1.09	-1.65	0.56	
	Negative		0.58	0.73	1.15	1.03	0.97	0.98	0.62	1.01	1.12	0.74	0.16	-0.23	0.40	
	Difference		-0.76	-0.24	-1.03	-1.09	-0.60	-0.99	-0.23	-0.76	-0.59	-2.01	-1.25	-1.41	0.16	
GS	Positive		-1.68	-0.82	-0.13	-0.04	0.46	0.50	0.73	0.98	0.72	0.41	2.09	-0.05	2.14	
	Negative		-0.65	0.03	0.01	0.49	0.87	0.97	1.56	1.46	1.88	2.42	3.07	1.55	1.52	
	Difference		-1.02	-0.85	-0.14	-0.54	-0.40	-0.47	-0.83	-0.48	-1.15	-2.01	-0.99	-1.61	0.62	

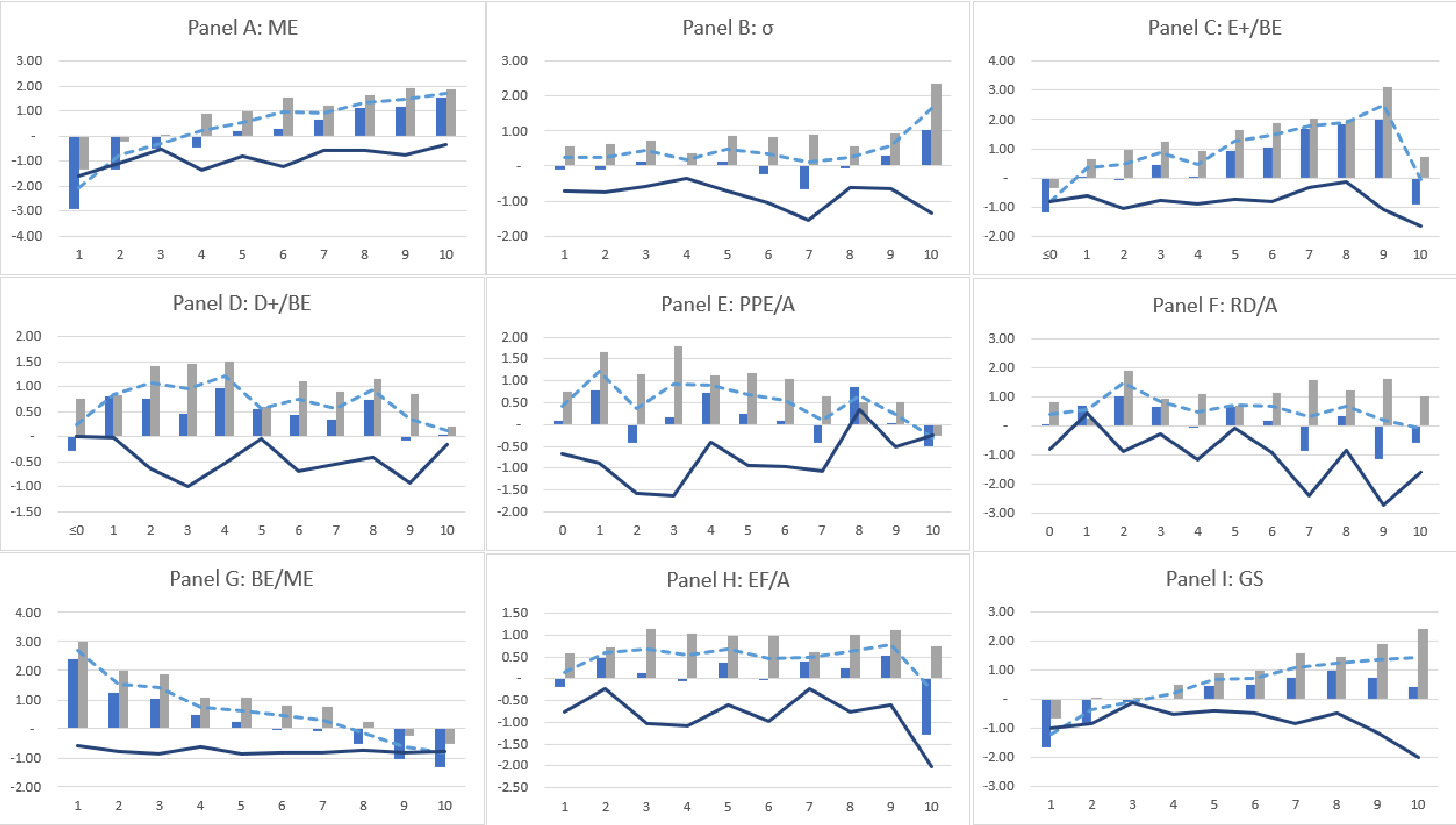

Figure 2. Two-way sorts: Future Returns by Sentiment Index and Firm Characteristics

For each month, we form 10 equal-weighted portfolios according to characteristics of firm size (ME), total risk (σ), earnings-book ratio for profitable firms (E+/BE), dividend-book ratio for dividend payers (D+/BE), fixed assets (PPE/A), research and development (R&D/A), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth (GS). The solid blue bars are returns following positive SENTIMENT˜ periods, and the solid gray bars are returns following negative sentiment periods. The dashed blue line is the average across both periods and the solid dark blue line is the difference. We also calculate returns for unrprofitable firms and nonpayers. Returns are measured monthly and listed in percent. SENTIMENT˜ is positive for 1996-1998, 2001, 2005-2009, and 2017-2022.

4.2. Predictive Regressions for Long-Short Portfolios

As in (Baker & Wurgler, 2006), we examine conditional characteristics effects by using sentiment to forecast equal-weighted portfolios that are long on stocks with high values of a characteristic and short on stocks with low values of the same characteristic. By running regressions of this type, we can conduct significance tests to confirm or reject whether the conditional differences in returns are in fact caused by sentiment or not. Table 6 plots average monthly returns on various long-short portfolios over time.

We hypothesize whether sentiment can predict the various long-short portfolios analyzed in table 6. We run regressions of the type:

$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT_{t-1}^{\sim} + u_i \tag{3}$$

The dependent variable is the monthly return on a long-short portfolio, formed on factors such as SMB, and the monthly returns from January through December of t are regressed on the sentiment index that prevailed at the end of the prior year. Like (Baker & Wurgler, 2006), we want to separate the predictability in our sample from well-known co-movement. We attempt to control for this running the multivariate regression:

$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT_{t-1}^{\sim}$$

$$+\beta_2 RMRF_t + \beta_3 SMB + \beta_4 HML + \beta_5 UMD + u_i \tag{4}$$

The variable RMRF is the excess return of the market over the risk-free rate. The variable UMD is the return on high-momentum stocks less the return on low-momentum stocks, where momentum is measured over months [-12, -2]. We also employ the factors from (Fama & French, 1993), specifically SMB and HML. SMB is the return on portfolios of small and big ME stocks that is separate from HML, where HML is constructed to isolate the difference between high and low BE/ME portfolios. When SMB and HML are dependent variables, they are excluded from the right-hand side of the regression. In table 7, the regressions (1a) - (15a) are conditional on $SENTIMENT_{t-1}$. The regressions (1b) - (15b) are also conditional on $SENTIMENT_{t-1}$, also controlling for RMRF, HML , SMB and UMD. In table 8, regressions (1c) - (15c) are conditional on $SENTIMENT_{t-1}^{\sim}$. The regressions (1d)-(15d) are also conditional on $SENTIMENT_{t-1}^{\sim}$, but we control for RMRF, HML, SMB and UMD.

The correlations of the portfolio returns are shown in table 6. First, we will consider the directions of the correlations to detect whether they correlate as expected. We observe a weak positive correlation between the portfolios formed on ME, based on small-minus-big, and σ formed on high-low. A positive correlation between size and volatility is as expected, and also in line with the finding in (Baker & Wurgler, 2006), although our correlation is 0.23, which is not as strong as their correlation coefficient (0.77). It is significant on the 1 % level. Secondly, portfolios formed on earnings based on profitable minus unprofitable firms, and dividends formed on payers vs. nonpayers, correlate negatively with those formed on market equity. This is also as expected and in line with (Baker & Wurgler, 2006). The correlations are significant on the 1 % level. The portfolios formed on PPE/A based on high-low, correlate weakly positively with ME-based portfolios, but the correlation is not significant. For the portfolios formed on RD/A (high-low) and BE/ME (high-low), there is a very weak positive correlation, significant on the 10 % level, as expected and in line with (Baker & Wurgler, 2006). Portfolios formed on EF/A (high-low) have a positive correlation with those formed on ME, significant and in line with (Baker & Wurgler, 2006).

The portfolios formed on GS based on high-low exhibit a weak negative correlation with those formed on ME, which is the opposite direction of (Baker & Wurgler, 2006). The correlation is significant on the 10 % level. Portfolios formed on BE/ME based on medium-low exhibit a very weak negative correlation with ME-formed portfolios, but the correlation is not significant. Portfolios formed on EF/A based on high-medium correlate positively with ME-based portfolios, significant on the 1 % level. This is in line with (Baker & Wurgler, 2006). Portfolios formed on GS based on high-medium exhibit weak positive correlations with ME-based portfolios, significant on the 1 % level and in line with (Baker & Wurgler, 2006) although our correlation is not as strong as theirs.

Finally, the portfolios formed on BE/ME (high-medium), EF/A (medium-low) and GS (medium-low) all correlate as expected with ME-formed portfolios. The directions are positive for the first portfolio, and negative for the two latter, compared to ME-formed portfolios. These correlations are significant on the 1 %, 5 % and 1 % level respectively and enter as expected in line with (Baker & Wurgler, 2006). We also consider the correlations between the different portfolios formed on BE/ME, EF/A and GS. These are all formed on different characteristics, specifically high-low, high-medium and medium-low. The correlations between these enter with the expected signs and significance level, as in (Baker & Wurgler, 2006).

Having considered the correlations of the different characteristics-based portfolios, we see that the directions of the correlations are as expected and in line with (Baker & Wurgler, 2006).

Table 6
Correlations of Portfolio Returns, 1994-2022

Correlations between portfolios formed on firm characteristics. The sample period includes monthly returns from 1994-2022. The long-short portfolios are formed on firm characteristics: firm size (ME), total risk (σ), profitability (E), dividends (D), fixed assets (PPE), research and development (RD), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth deciles (GS). High is defined as a firm in the top three Oslo børs deciles, low is defined as a firm in the bottom three Oslo børs deciles, and medium is defined as a firm in the middle four Oslo børs deciles.

		Size and Risk		Profitability, Dividends		Tangibility		Growth Opportunities and Distress			Growth Opportunities			Distress		
		ME	σ	E	D	PPE/A	RD/A	BE/ME	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
ME	SMB	1.00														
σ	High-Low	0.23	1.00													
		(0.00)														
E	>0 - <0	-0.42	-0.69	1.00												
		(0.00)	(0.00)													
D	>0 - =0	-0.39	-0.86	0.75	1.00											
		(0.00)	(0.00)	(0.00)												
PPE/A	High-Low	0.05	-0.13	0.11	0.15	1.00										
		(0.40)	(0.01)	(0.04)	(0.01)											
RD/A	High-Low	0.10	0.20	-0.21	-0.22	-0.50	1.00									
		(0.06)	(0.00)	(0.00)	(0.00)	(0.00)										
BE/ME	High-Low	0.10	-0.41	0.31	0.40	0.57	-0.42	1.00								
		(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
EF/A	High-Low	0.17	0.49	-0.47	-0.51	-0.36	0.30	-0.52	1.00							
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
GS	High-Low	-0.10	0.16	0.05	-0.15	-0.16	0.04	-0.19	0.29	1.00						
		(0.08)	(0.00)	(0.37)	(0.01)	(0.00)	(0.46)	(0.00)	(0.00)							
BE/ME	Medium-Low	-0.03	0.06	0.05	0.03	0.39	-0.31	0.63	-0.28	-0.06	1.00					
		(0.57)	(0.29)	(0.38)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	0.27						
EF/A	High-Medium	0.27	0.23	-0.33	-0.33	-0.16	0.13	-0.32	0.71	0.16	-0.31	1.00				
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	0.00	(0.00)					
GS	High-Medium	0.14	0.19	-0.19	-0.26	-0.22	0.13	-0.27	0.34	0.44	-0.27	0.30	1.00			
		(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
BE/ME	High-Medium	0.16	-0.57	0.33	0.47	0.30	-0.20	0.60	-0.36	-0.18	-0.25	-0.08	-0.06	1.00		
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.25)			
EF/A	Medium-Low	-0.13	0.36	-0.19	-0.24	-0.26	0.22	-0.27	0.40	0.16	0.04	-0.36	0.06	-0.38	1.00	
		(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.48)	(0.00)	(0.30)	(0.00)		
GS	Medium-Low	-0.22	-0.01	0.22	0.07	0.03	-0.08	0.04	-0.01	0.63	0.17	-0.10	-0.42	-0.12	0.12	1.00
		(0.00)	(0.91)	(0.00)	(0.18)	(0.58)	(0.17)	(0.45)	(0.87)	(0.00)	(0.00)	(0.07)	(0.00)	(0.03)	(0.04)	

The following analysis, consisting of regressions (1) – (15), acts as a formal test of the preliminary results from the sorting approach in the previous section. In this section we are analyzing the coefficients on sentiment from the long-short portfolio regressions. When we refer to coefficients in the following part, we are referring to the coefficient on sentiment in each regression. All other variables in each regression are either intercept or control variables, employed to test the effect of sentiment on returns. Thus, our main variable of interest in each regression is the sentiment coefficient.

4.2.1. Regressions (1a) - (1d): Portfolios formed on Size Characteristics

We consider the average returns of the long-short portfolios formed on size characteristics, conditional on sentiment. Our size characteristics portfolios are formed based on market equity. These portfolios are long on small firms (bottom three deciles) and short on large firms (top three deciles). Regressions (1a) and (1b) exhibit positive sentiment coefficients, while regressions (1c) and (1d) show negative coefficients. However, none of the coefficients are statistically significant. According to (Baker & Wurgler, 2006), the effect of sentiment on the portfolios formed on size should be negative. In our sample, two coefficients on sentiment are positive, indicating returns on small firms following a positive sentiment period are positive, while the opposite is true for the remaining two coefficients on sentiment. Thus, our hypothesis that large firms are negatively influenced by sentiment is rejected. Why is this the case? There are several possible reasons. Firstly, our sentiment index may not be successful in capturing sentiment in Norway. Secondly, the Norwegian stock market may have different dynamics from the U.S. market. Perhaps in Norway, where the stock market is concentrated around a few stocks with a very high degree of liquidity (the OSEBX index makes out the largest proportion of the market liquidity), increased sentiment leads to more liquidity and positive returns going into these stocks than perhaps smaller stocks. As we saw in panel A of figure 2, following positive sentiment periods, small firms earn particularly lower returns than following negative sentiment periods.

4.2.2. Regressions (2a) - (2d): Portfolios formed on Risk Characteristics

We now consider the average returns of the long-short portfolios formed on risk characteristics, specifically on volatility, or σ. These portfolios are long on high volatility stocks (top three deciles) and short low-volatility stocks (bottom three deciles). (Baker &

Wurgler, 2006) find that sentiment has a positive effect on returns of long-short portfolios formed on volatility. Our analysis does not support this. Firstly, as our regressions exhibit positive sentiment coefficients in regressions (2a) and (2c). However, after controlling for RMRF, SMB and UMD, regressions (2b) and (2d) exhibit positive sentiment coefficients. However, since our coefficients are not significant, we are unable to make a reliable claim about the effect for our sample. There could be several reasons for this. Firstly, our sentiment index may not be successful in capturing the effect of sentiment. Secondly, there could be other dynamics in our sample than in the (Baker & Wurgler, 2006) sample.

4.2.3. Regressions (3a) - (3d) Portfolios formed on Earnings Characteristics

Let's now consider the effect of sentiment on the long-short portfolios formed on earnings characteristics, specifically on earnings. These portfolios are long profitable firms and short unprofitable firms. In (Baker & Wurgler, 2006), sentiment has a positive effect on the returns of profitable firms. In our sample, regressions (3a), (3b), (3c) and (3d) exhibit very weak coefficients. Neither of them are significant, so the effect of sentiment on returns of profitable firms in our regressions is inconclusive and does not support or contradict (Baker & Wurgler, 2006). These regressions show no clear result, and we are unable to draw any conclusions from these. We recall panel C in figure 2 displayed an increase in returns over deciles 1-9, even more positive following negative sentiment periods than positive sentiment periods. Unfortunately, we are unable to verify the finding from the sorting approach in our regressions.

4.2.4. Regressions (4a) - (4d): Portfolios formed on Dividend Characteristics

The next set of regressions, formed on dividend characteristics, are long dividend payers and short nonpayers. The significance of the sentiment coefficients in regressions (4a)-(4d) are particularly low, and we are unable to make any claim about our results compared to (Baker & Wurgler, 2006) in that sentiment has a positive effect on the returns of dividend payers. we recall panel D in figure 2 that shows how dividend payers tend to have positive returns following negative sentiment periods and even lower positive returns following positive sentiment periods. However, the highest average returns of these firms, following negative sentiment periods, belong in deciles 2, 3, 4 and 6 and 9. The largest difference between returns following positive vs. negative sentiment periods lies in deciles 2, 3 and 4, along with decile 9. This distribution of differences in the conditional effect of sentiment is interesting, but it might well just be an entirely natural random distribution of the effect.

4.2.5. Regressions (5) - (6): Portfolios formed on Asset Tangibility

Regressions (5)-(6) are formed on Asset Tangibility characteristics. We cover portfolios based on the ratio of plant, property & equipment to total assets as well as research & development to total assets.

Regressions (5a), (5b), (5c) and (5d) cover portfolios which are long on high-PPE stocks (top three deciles) and short low-PPE stocks (bottom three deciles). All the regression coefficients exhibit positive signs. Regressions (5a), (5b), (5c) and (5d) are all significant on the 1 % level. the sentiment coefficients in regressions (5a) and (5b) are around 0.4, while the ones in (5c) and (5d) are around 0.3. In (Baker & Wurgler, 2006), the regression coefficients on these portfolios are 0.4. Our analysis thus supports (Baker & Wurgler, 2006) and we conclude that the returns of high-PPE stocks are positive over the year following a positive sentiment period. We recall panel E of figure 2, where the difference in conditional effects of sentiment on the returns of these portfolios seems to be present in all deciles but the fourth, eight and tenth. The difference is especially high in the first, second and third deciles, with the fifth-seventh deciles also having quite high differences in returns following positive vs. negative sentiment periods. Following this reasoning we could make the case that returns conditional on sentiment affect firms where tangible assets (PPE) make out a lower proportion of total assets more than firms where PPE makes out a lower amount of total assets. Following positive sentiment periods these firms earn negative or low positive returns, vs. strong positive returns following negative sentiment periods. This could indicate preference for tangibility is lower when sentiment is positive.

The next set of regressions, (6a) - (6d), are long on stocks with high R&D (top three deciles) and short on firms with low R&D (bottom three deciles). All the regressions exhibit negative sentiment coefficients, and they are all significant on the 1 % level. According to (Baker & Wurgler, 2006), the returns on these portfolios should be negatively affected by sentiment. Our results support this. Following a positive sentiment year, the average returns of portfolios which are long high R&D stocks and short low R&D stocks, trend negatively. Looking at panel F of figure 2, we see that the difference in returns conditional on previous end-of year sentiment is particularly large for the seventh and ninth deciles, which could indicate the returns of firms where research and development consists of a large proportion of total assets are more affected by sentiment. Overall, the returns of these firms tend positively as the deciles increase following negative sentiment periods, while the same deciles trend negatively following positive sentiment periods. This could indicate a preference for firms where low research and development make out a lower fraction of total assets, following positive sentiment periods.

4.2.6. Regressions (7) - (9): Portfolios formed on Growth Opportunities and Distress

Regressions (7) - (9) are formed to exhibit characteristics of Growth Opportunities and Distress.

Regressions (7a) - (7d) are long firms with high book-to-market ratios (top three deciles) and short on firms with low book-to-market ratios (bottom three deciles). (Baker & Wurgler, 2006) find a weak positive effect of sentiment on the returns of these portfolios. In our results, regressions (7a) – (7d) have positive coefficients. Regression (7a) is significant on the 10 % level. However, after controlling for RMRF, SMB and UMD in regression (7b), the coefficient p-value drops to 0.17. From this, we have to conclude that the effect of sentiment on returns formed on these portfolios is unclear and that we are unable to make any claim about how our results compare to previous literature. If we consider panel G of figure 2, we see an interesting pattern. The returns of these firms are strongly positive in the bottom decile and exhibit a falling linear trend as we move through deciles and end up on the tenth decile. For deciles 8-10 returns are weakly positive or trend negatively. These firms tend to earn higher returns when sentiment the previous year-end is negative, over positive. Since these characteristics indicate growth opportunities and distress, we could hypothesize that returns are greater for small BE/ME firms than large ones, but since our regressions have insignificant coefficients, we cannot make any such claim.

Regressions (8a) – (8d) show portfolios which are long on firms with a high degree of external financing (top three deciles) and short on firms with a low degree of external financing (bottom three deciles). In all four regressions, the coefficient on sentiment is negative and significant. Regressions (8a), (8b), (8c) and (8d) are all significant on the 5 % level. The sentiment coefficients are in the interval [-0.17, -0.20]. After a positive sentiment period, firms with a high degree of external financing on average earned negative returns over the following year. These results support (Baker & Wurgler, 2006). Looking at panel H of figure 2, we also observe how these firms tend to earn higher positive returns following negative sentiment periods than following positive sentiment periods. Particularly for the tenth decile firms in this group, returns are particularly highly negative following positive sentiment periods. This indicates that the preference for firms with a high degree of external financing are sensitive to variations in sentiment.

Regressions (9a) - (9d) show portfolios which are long on firms with high sales growth (top three deciles) and short firms with low sales growth (bottom three deciles). Like (Baker & Wurgler, 2006), we find that the regression coefficients are negative, but not significant. When considering panel I of figure 2, we see that the returns of firms with a high degree of sales growth tend to have increasingly positive returns as we move up through the deciles, following negative sentiment periods. Interestingly, the effect following positive sentiment periods is the same, but there is a peak at the eight decile which decreases towards the tenth decile. This could indicate that for some reason, the preference for the most growing firms in terms of revenues falls following positive sentiment periods. However, we note that we cannot make a definitive claim as these are only visual patterns and not significance tested as in these regressions.

4.2.7. Regressions (10) – (12): Portfolios formed on Growth Opportunities

To further separate the effect of growth opportunities and distress, we form long-short portfolios on the same variables (BE/ME, EF/A, and GS) but built on Medium-Low or High-Medium instead of High-Low as in regressions (7) - (9).

Regressions (10a) – (10d) are long on firms with a medium market-to-book ratio (middle four deciles) and long on firms with a low market-to-book ratio (bottom three deciles), indicating growth opportunities. In (Baker & Wurgler, 2006) the returns of these portfolios are hypothesized to be positively influenced by sentiment. Our analysis does not support nor contradict this. First, sentiment coefficients in regressions (10a) and (10b) are both negative, although both (10c) and (10d) are positive. Secondly, none of the sentiment coefficients are significant. In accordance with this, we cannot make any conclusion about the effect of sentiment on these portfolios.

The next set of regressions, (11a) – (11d), are long on firms with a high degree of external finance (top three deciles), and short on firms with a medium degree of external financing (middle four deciles), also indicating growth opportunities. In (Baker & Wurgler, 2006), the portfolios of these characteristics are negatively influenced by sentiment. Our analysis shows signs of the same tendency, not for (10a) and (10b), but the signs are indeed negative for sentiment coefficients in regressions (10c) and (10d). Unfortunately, again we have issues with significance. Thus, our results do not support nor contradict (Baker & Wurgler, 2006) for these portfolios.

In regressions (12a) – (12d), we regress portfolios which are long on firms with a high sales growth (top three deciles) and short on firms with a medium sales growth (middle four deciles), again indicating growth opportunities. Like in (Baker & Wurgler, 2006), our regression coefficients on sentiment are negative, but these are not significant in our analysis. While the direction of our regressions supports their results from the U.S. stock market, we cannot make the claim due to the insignificant results.

4.2.8. Regressions (13) – (15): Portfolios formed on Distress Characteristics

Finally, we form regressions formed to exhibit distress characteristics. Regressions (13a) – (13d) are long on firms with a high market-to-book ratio (top three deciles) and short on firms with a medium market-to-book ratio (middle four deciles). In (Baker & Wurgler, 2006), these regressions have negative coefficients, but they experience significance issues and are inconclusive about the effect of sentiment on these portfolio returns. In our analysis, the coefficients on sentiment are positive for all four regressions. Regressions (13a) and (13b) exhibit sentiment coefficients which are significant on the 5 % level. According to these two regressions the resulting effect of sentiment is negative on the returns of portfolios which are long on high market-to-book ratio shares and short medium market-to-book ratio shares. For regressions (13c) and (13d) we have significance issues. Our analysis thus in part claims that returns of these portfolios are positively affected by sentiment. We can make the claim with significance based on the first two regressions, which are based on the non-orthogonalized proxies.

In regressions (14a) – (14d), we form portfolios which are long on firms with a medium degree of external finance (middle four deciles) and short firms with a low degree of external finance (bottom three deciles). All four regressions have negative sentiment coefficients which are significant. For regressions (14a) and (14b) we have coefficients of -0.18 and -0.17, which are significant on the 1 % level. For regressions (14c) and (14d), we have coefficients of -0.11 and -0.10 which are significant on the 5 % and 10 % level. According to these regressions, the conditional effects of sentiment on the returns of these portfolios are negative.

Finally, regressions (15a) – (15d) are long on firms with a medium sales growth (middle four deciles) and short on firms with a low sales growth (bottom three deciles). All our sentiment coefficients are negative, but none of them are significant. In (Baker & Wurgler, 2006) the coefficient on these portfolios are both positive and significant. In our analysis we are unable to verify nor contradict this due to issues with statistical significance.

4.2.9. Conclusions from Time-Series Regressions on Long-Short portfolios

Overall, the results from the regressions of the long-short portfolios show that sentiment has an effect on some of the portfolios formed on firm characteristics, but far from all.

We find that the returns of portfolios which are long on high-PPE firms trend positively following a positive sentiment period. This indicates that firms with a high degree of tangible assets earn higher average returns following a period of positive sentiment. The same is true for firms with a high market-to-book ratio. The conditional effect of returns on portfolios long high BE/ME firms and short on low BE/ME firms is positive.

We also find that the opposite is true for firms with a high degree of research and development. The returns of these firms following a period of positive sentiment trend negatively. The same is true for firms with a high degree of external financing. Following a period of positive sentiment, these firms on average earn lower returns than the ones with a lower degree of external financing. For portfolios which are long firms with a high degree of external financing and short firms with a medium degree of external financing, the conditional effect of sentiment on average returns is negative over the following year.

Our analysis supports that the overall effect of sentiment on stocks in the Norwegian stock market is not significant. Our findings are thus in line with previous research such as (Concetto & Ravazzolo, 2019) who also do not succeed in proving an effect of sentiment on cross-sectional returns in European markets. (Corredor et al., 2015) find that sentiment functions as a predictor for returns in the Czech, Hungarian and Polish markets, but not in more developed European Economies. Their results are not significant in more developed economies. Our results are in line with theirs in that regard.

Table 7

Time-Series Regressions of Portfolio Returns, 1995-2022

Regressions of long-short portfolio returns, first on lagged SENTIMENT alone, then on lagged SENTIMENT and controlling for the market risk premium (RMRF), the Fama-French factors (HML, SMB) and a momentum factor (UMD).

$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT_{t-1} + u_i$$
$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT_{t-1} + \beta_2 RMRF_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + u_i$$

The sample period includes monthly returns from 1995 to 2022. The long-short portfolios are formed on firm characteristics: firm size (ME), total risk (σ), profitability (E), dividends (D), fixed assets (PPE), research and development (RD), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth decile (GS). High is defined as a firm in the top three Oslo børs deciles, low is defined as a firm in the bottom three Oslo børs deciles, and medium is defined as a firm in the middle four Oslo børs deciles. Average monthly returns are matched to SENTIMENT from the previous year-end. The SENTIMENT index is formed based on five proxies that have been orthogonalized to growth in industrial production, the growth in durable, nondurable and services consumption, the growth in employment and the policy interest rate. P-values of each coefficient are listed in parenthesis.

	Size and Risk		Profitability, Dividends		Tangibility		Growth Opportunities and Distress			Growth Opportunities			Distress		
	ME	σ	E	D	PPE/A	RD/A	BE/ME	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
	SMB	High-Low	>0 - <0	>0 - =0	High-Low	High-Low	High-Low	High-Low	High-Low	Medium-Low	High-Medium	High-Medium	High-Medium	Medium-Low	Medium-Low
Regression	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)	(8a)	(9a)	(10a)	(11a)	(12a)	(13a)	(14a)	(15a)
Intercept	-1.31	0.27	1.15	0.25	-0.35	-0.23	-1.25	-0.03	0.93	-0.04	-0.14	0.17	-0.56	0.11	0.63
	(0.00)	(0.11)	(0.00)	(0.01)	(0.00)	(0.24)	(0.00)	(0.72)	(0.00)	(0.00)	(0.08)	(0.01)	(0.00)	(0.07)	(0.00)
$SENTIMENT_{t-1}$	0.03	-0.05	0.03	0.00	0.43	-0.51	0.16	-0.20	-0.07	-0.51	0.01	-0.03	0.17	-0.18	-0.03
	(0.75)	(0.76)	(0.72)	(0.96)	(0.00)	(0.01)	(0.10)	(0.01)	(0.41)	(0.64)	(0.89)	(0.62)	(0.03)	(0.00)	(0.68)
Regression	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)	(8b)	(9b)	(10b)	(11b)	(12b)	(13b)	(14b)	(15b)
Intercept	-1.28	-0.03	1.29	0.40	-0.28	-0.20	-1.13	-0.15	0.82	-0.48	-0.17	0.14	-0.49	0.04	0.56
	(0.00)	(0.89)	(0.00)	(0.00)	(0.05)	(0.65)	(0.00)	(0.12)	(0.00)	(0.00)	(0.04)	(0.05)	(0.00)	(0.54)	(0.00)
$SENTIMENT_{t-1}$	0.03	0.02	0.00	-0.03	0.42	-0.52	0.13	-0.17	-0.04	-0.04	0.02	-0.02	0.16	-0.17	-0.01
	(0.77)	(0.92)	(0.10)	(0.73)	(0.00)	(0.01)	(0.17)	(0.03)	(0.65)	(0.59)	(0.81)	(0.73)	(0.05)	(0.01)	(0.87)
RMRF	0.00	0.06	-0.04	-0.05	-0.01	0.02	0.01	0.00	0.00	0.01	-0.01	0.00	0.00	0.01	0.00
	(0.99)	(0.06)	(0.05)	(0.00)	(0.75)	(0.65)	(0.65)	(0.80)	(0.85)	(0.73)	(0.33)	(0.87)	(0.84)	(0.42)	(0.73)
SMB		0.08	-0.03	-0.02	0.00	-0.06	-0.06	0.05	0.07	-0.01	0.03	0.02	-0.04	0.02	0.04
		(0.04)	(0.15)	(0.26)	(0.93)	(0.24)	(0.03)	(0.01)	(0.00)	(0.46)	(0.07)	(0.13)	(0.03)	(0.14)	(0.01)
HML	0.01		0.00	-0.01											
	(0.78)		(0.82)	(0.49)											
UMD	-0.02	0.07	-0.03	-0.03	-0.04	0.02	-0.03	0.03	0.01	-0.02	0.00	0.00	-0.01	0.02	0.01
	(0.30)	(0.02)	(0.03)	(0.02)	(0.07)	(0.50)	(0.09)	(0.04)	(0.49)	(0.24)	(0.77)	(0.80)	(0.36)	(0.03)	(0.35)

Table 8

Time-Series Regressions of Portfolio Returns, 1995-2022

Regressions of long-short portfolio returns, first on lagged SENTIMENT~ alone, then on lagged SENTIMENT~ and controlling for the market risk premium (RMRF), the Fama-French factors (HML, SMB) and a momentum factor (UMD).

$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT^{\sim}_{t-1} + u_i$$

$$R_{X_{it=High_t}} - R_{X_{it=Low_t}} = c + \beta_1 SENTIMENT^{\sim}_{t-1} + \beta_2 RMRF_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + u_i$$

The sample period includes monthly returns from 1995 to 2022. The long-short portfolios are formed on firm characteristics: firm size (ME), total risk (σ), profitability (E), dividends (D), fixed assets (PPE), research and development (RD), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth decile (GS). High is defined as a firm in the top three Oslo børs deciles, low is defined as a firm in the bottom three Oslo børs deciles, and medium is defined as a firm in the middle four Oslo børs deciles. Average monthly returns are matched to SENTIMENT from the previous year-end. The SENTIMENT index is formed based on five proxies that have been orthogonalized to growth in industrial production, the growth in durable, nondurable and services consumption, the growth in employment and the policy interest rate. P-values of each coefficient are listed in parenthesis.

	Size and Risk		**Profitability, Dividends**		**Tangibility**		**Growth Opportunities and Distress**			**Growth Opportunities**			**Distress**		
	ME	σ	E	D	PPE/A	RD/A	BE/ME	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
	SMB	High-Low	>0 - <0	>0 - =0	High-Low	High-Low	High-Low	High-Low	High-Low	Medium-Low	High-Medium	High-Medium	High-Medium	Medium-Low	Medium-Low
Regression	(1c)	(2c)	(3c)	(4c)	(5c)	(6c)	(7c)	(8c)	(9c)	(10c)	(11c)	(12c)	(13c)	(14c)	(15c)
Intercept	-1.31	0.27	1.15	0.25	-0.35	-0.22	-1.25	-0.03	0.93	-0.51	-0.13	0.17	-0.56	0.11	0.63
	(0.00)	(0.12)	(0.00)	(0.01)	(0.01)	(0.26)	(0.00)	(0.74)	(0.00)	(0.00)	(0.08)	(0.01)	(0.00)	(0.07)	(0.00)
$SENTIMENT^{\sim}_{t-1}$	-0.02	-0.03	0.02	0.02	0.31	-0.54	0.14	-0.19	-0.06	0.04	-0.05	-0.01	0.08	-0.11	-0.04
	(0.85)	(0.85)	(0.81)	(0.78)	(0.01)	(0.00)	(0.15)	(0.02)	(0.47)	(0.63)	(0.50)	(0.83)	(0.31)	(0.05)	(0.57)
Regression	(1d)	(2d)	(3d)	(4d)	(5d)	(6d)	(7d)	(8d)	(9d)	(10d)	(11d)	(12d)	(13d)	(14d)	(15d)
Intercept	-1.28	-0.03	1.29	0.40	-0.27	-0.21	-1.13	-0.15	0.82	-0.48	-0.16	0.14	-0.48	0.03	0.56
	(0.00)	(0.89)	(0.00)	(0.00)	(0.06)	(0.35)	(0.00)	(0.12)	(0.00)	(0.00)	(0.05)	(0.05)	(0.00)	(0.61)	(0.00)
$SENTIMENT^{\sim}_{t-1}$	-0.02	0.15	0.00	-0.01	0.29	-0.54	0.01	-0.17	-0.04	0.03	-0.04	-0.01	0.07	-0.10	-0.03
	(0.81)	(0.93)	(0.99)	(0.95)	(0.01)	(0.00)	(0.24)	(0.05)	(0.65)	(0.69)	(0.56)	(0.90)	(0.40)	(0.09)	(0.71)
RMRF	0.00	0.06	-0.04	-0.05	-0.01	0.02	0.01	0.00	0.00	0.01	-0.01	0.00	0.00	0.01	0.00
	(0.97)	(0.06)	(0.05)	(0.00)	(0.63)	(0.58)	(0.68)	(0.87)	(0.86)	(0.70)	(0.32)	(0.86)	(0.92)	(0.36)	(0.73)
SMB		0.08	-0.03	-0.02	0.00	-0.05	-0.06	0.05	0.07	-0.01	0.03	0.02	-0.04	0.02	0.04
		(0.04)	(0.15)	(0.27)	(0.95)	(0.26)	(0.02)	(0.01)	(0.00)	(0.49)	(0.08)	(0.13)	(0.02)	(0.12)	(0.01)
HML	0.01		0.00	-0.01											
	(0.78)		(0.82)	(0.49)											
UMD	-0.02	0.07	-0.03	-0.03	-0.04	0.02	-0.03	0.03	0.01	-0.02	0.00	0.00	-0.14	0.02	0.01
	(0.29)	(0.02)	(0.03)	(0.02)	(0.07)	(0.51)	(0.09)	(0.05)	(0.50)	(0.25)	(0.79)	(0.81)	(0.34)	(0.03)	(0.36)

5. Conclusions

In this study, we aimed to investigate the impact of investor sentiment on cross-sectional returns in the Norwegian stock market by constructing a comprehensive model based on five underlying proxies: Oslo børs turnover, the number of initial public offerings, the dividend premium, the consumer confidence index, and the economic barometer index for Norway. Our main research question focused on understanding how investor sentiment influences cross-sectional stock returns in Norway. Our findings reveal that sentiment does have conditional effects on cross-sectional stock returns, although not entirely as anticipated. Examining various portfolios based on firm characteristics, we observed intriguing patterns. Our first sub-question was: *"The effect of sentiment is stronger for firms whose valuations are highly subjective and more difficult to arbitrage."*

Addressing our first sub-question regarding the effect of sentiment on firms with highly subjective valuations, we found that our analysis does not fully support the findings of Baker and Wurgler (2006). In fact, when controlling for macro-economic variables, our sentiment index encounters significance issues when estimating the effects of sentiment on returns. This aligns with the findings of (Grigaliūnienė & Cibulskiene, 2010) where Scandinavian stock markets demonstrate contrasting results compared to the U.S. stock market. Consequently, we fail to confirm the hypothesis that sentiment has a stronger effect on firms with highly subjective valuations and greater arbitrage difficulty.

On the matter of our second sub-question regarding the viability of the Consumer Confidence Index (CCI) as a standalone proxy for investor sentiment and its ability to predict negative returns, our analysis reveals issues with its significance. We are unable to establish that the CCI can independently explain the relationship between investor sentiment and cross-sectional returns in the Norwegian stock market. Thus, the CCI lacks the predictive power to consistently forecast negative returns, suggesting a limitation as a reliable proxy for investor sentiment.

Regarding our third sub-question on the viability of the Norwegian Economic Barometer Index as a proxy for investor sentiment and its ability to predict negative returns, our model fails to replicate the previous literature's findings, leading us to reject this hypothesis.

In terms of our contribution to the literature, our study aimed to examine whether the effect of investor sentiment on stock returns in Norway aligns with the findings of (Baker & Wurgler, 2006) and subsequent studies that utilized their model. Our analysis does not support their findings in the Norwegian stock market, despite observing some similar returns patterns. We speculate that the composition of the Norwegian stock market, a significant portion being industrial stocks, oil-related stocks that dominate market liquidity, differs from the U.S. stock market. This disparity might explain the poor fit of the overall classification of firms based on return characteristics to Norwegian stock market data. To address this issue, future research could consider reducing the sample size of stocks or scaling them by industry, potentially revealing patterns consistent with the findings of (Baker & Wurgler, 2006). Our findings are in line with studies such as (Concetto & Ravazzolo, 2019; Corredor et al., 2015) which employ similar models but fail to find significant results in developed European economies.

To expand on our research, it would be valuable to explore different sample segments and assess the effect of sentiment on these segments. While we analyzed the Norwegian stock market as a whole and found unexpected effects for small growth stocks and volatile stocks, investigating specific industries may yield more significant sentiment effects.

In conclusion, the implications of our study demonstrate that the classical investor sentiment model proposed by (Baker & Wurgler, 2006), along with proxies like the Consumer Confidence Index combined with the Norwegian Economic Barometer Index, inadequately explains the impact of sentiment on cross-sectional returns in the Norwegian stock market. While the model demonstrates the effect of sentiment on firms based on tangibility characteristics and external financing as expected, other firm characteristics-based portfolio returns are not significant in our regressions. Consequently, alternative proxies should be utilized when estimating the effect of sentiment on returns for these firms. Our analysis suggests that each measure individually may explain some variation, but combining them into an index, as done in previous literature, fails to provide a good fit.

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