Can Sentiment Predict Stock Returns?

- Evidence from the Swedish stock market

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Abstract

Motivated by existing evidence of the importance of psychology and its impact on investors' decision-making behavior, I investigate the Swedish stock market and the implications that investors' sentiment has on the cross-section of returns. Following the methodology applied by Baker and Wurgler (2006), I construct a composite index and employ this in a bivariate portfolio-level analysis. The results indicate that sentiment exhibit a conditional effect on speculative stock characteristics and their average returns. This reveals that sentiment indeed has some predictive power of the cross-section of returns, which is of great concern for investors, as it can assist in taking the right action when detecting anomalies in these proxies for sentiment.

Keywords: Investor sentiment, cross-section of stock returns, Swedish stock market, conditional performance

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1. Introduction

The extensive research that has been conducted during recent years, within the field of behavioral finance, all point to the same overall conclusion: psychology matters. It matters for investors, for the stock market and for anyone who tries to understand the behavior of either of these. The traditional framework, in which the stock market is typically viewed (i.e. the efficient market hypothesis (EMH)), is not successful in explaining the market completely, neither the cross-section of returns nor the irrational behavior of investors. However, when one account for how irrationality is created through individuals' psychology, and for the impact that psychology has on the stock market through the concept of *limits to arbitrage*, it all adds up more neatly (Barberis and Thaler, 2003).

Limits to arbitrage is the general term for any obstacle that stands in the way of arbitrage behavior to effectively bring a mispricing back to fundamental value (Shleifer and Vishny, 1997). This obstacle can be several things, like too high a cost of the arbitrage strategy or the requirement of closing a position prematurely. It can also be solely psychological. A typical example is when noise traders drive down prices below the securities' fundamental value. Arbitrageurs would normally have explored the opportunity to buy low, however, there is nothing guaranteeing that noise traders' expectations will revert back to the mean just yet. Therefore, arbitrageurs face a risk, known as *noise trader risk* (DeLong et al., 1990).

Psychology and behavior thus have a great influence on the stock market. However, this effect is not generic. For instance, Shiller and Pound (1989) find that the *word-of-mouth effect* amongst investors is not equally large across securities. They say that "only certain stocks are 'interesting'". A question that naturally arises is then, what stocks are interesting? Thaler and Ziemba (1988) draw similarities between the stock market and horse race betting. The so-called *favorite-longshot bias* constitute the tendency to favor lottery-like bets with a high outcome, in spite of a low probability to achieve said outcome. Baker and Wurgler (2006) incorporate this aspect into their study about sentiment and the cross-section of returns. They suggest that speculative stocks are of particular interest for investors and, as such, are more prone to be affected by sentiment. They define speculative stocks as those that are hard to evaluate and hard to arbitrage. To know if a specified type of security is hard to evaluate, one should look for certain characteristics within the firm that issued the security. These are, to name a few, firms that are new to the market, firms that are more volatile and firms with an extreme growth potential. Baker and Wurgler (2006) apply this analysis on the U.S. market and sort stocks into deciles of characteristics and then according to sentiment being positive or negative. They find that this conditional analysis reveals patterns that are concealed in an unconditional analysis. In particular, they find that young stocks are more popular when sentiment is positive, whereas old stocks are more popular when sentiment is negative. The same goes for other characteristics such as size, volatility, profitability and dividend policy. Regarding growth stocks, they find a u-shaped pattern across deciles, since firms with extremely low sales growth can be viewed as firms in distress, whereas firms with extremely high sales growth can be viewed as so-called high-flyers. Stable firms are thus found in the middle deciles, hence, a u-shaped pattern. Finally, Baker and Wurgler find that returns following periods of negative sentiment are higher than returns following periods of positive sentiment, across all cross-sections of returns. This means that, securities that possess speculative characteristics are more popular in times when sentiment is high and less so in times when sentiment is low.

Intrigued by their findings, I apply the same methodology onto a new market, namely, Sweden. This market is to this date, and to my knowledge, uninvestigated with regard to this sort of study. I also capitalize on Baker and Wurgler's idea of a composite index as an indicator for sentiment. Using principal component analysis, I construct an index based on the variation in five proxies for sentiment. These are the turnover ratio, the number and first-day returns of IPOs, the equity share in new issuance and the dividend premium. The analysis is then carried out as a bivariate portfolio sorts, conditioning on both deciles of characteristics and on sentiment being positive or negative during the previous period of time. I find that there is a size effect in periods of both positive and negative sentiment, but the effect is more pronounced in periods of negative sentiment. Similar to Baker and Wurgler's findings on the U.S. market, I find that there is also a conditional effect of age on stock returns in Sweden. When sentiment is negative, older firms seem to generate smaller returns than younger firms. This can be interpreted as investors seeming to prefer older firms when sentiment is low, which is coherent with the idea that investors seek to invest in stable and mature companies in times of uncertainty. When sentiment is positive, however, this is true only for the absolute top and bottom decile. It seems to me that the effect of positive sentiment on age is concentrated to the very youngest, which is also in line with BW's findings. This result is fascinating, since age is typically not viewed as having an unconditional effect. This means that a characteristic that previously was thought to not have any explanatory power over stock returns now delivers evidence to the contrary. These are the results that Baker and Wurgler find most exceptional and remarkable in their analysis on the U.S. market in 2006. It is therefore exciting that the same results can be applied on the Swedish market as well.

I also find evidence that strengthens the notion that investors demand firms with higher values of tangible assets in times of uncertainty, indicating that a high value of tangibles is a sign of a mature and stable company. Similarly, I find that investors refrain from investing in companies that could be viewed as in distress, whenever sentiment is negative. These last two features are represented by characteristics such as retained earnings and sales growth. Further, my results indicate that the effect of sentiment varies across deciles. For instance, the effect is larger for stocks in the top deciles of volatility, then it is for stocks in the lower deciles. Finally, across nearly all cross-sections, returns following periods of negative sentiment are higher than returns following periods of positive sentiment. This means that, when times are bad, investors are less willing to invest in stocks that exhibit one or more of these characteristics, than they would if times are good. This is the most consisting pattern that I find across the conditional portfolio sorts.

To add robustness to the test, I also conduct regressions on various long-short portfolios and sentiment. The long-short portfolios are conditional on each characteristic and most of them are constructed as *high minus low*, where high consists of the top deciles and low consists of the bottom deciles of each characteristic. I also regress Fama French factors against the sentiment index. The Fama French factors covers different geographic and demographic areas of which Sweden is a part. The regressions roughly support my findings from the portfolio sorts, however, there is a shifting degree of significance across my results.

The paper is organized as follows. Section 2 summarizes previous research conducted within the field and explains certain key concepts in behavioral finance. Section 3 describes the data used to carry out the analysis and section 4 takes you through the methodology employed. Section 5 discusses the result of the study, whilst section 6 provides a final conclusion and a summary of the main findings.

2. Previous research

The introduction pinpointed that psychology matters, for the individual investor as well as for the stock market as a whole. But why, exactly, does it matter?

A person's psychology unfolds itself in multiple ways. There is a huge amount of studies examining how it affects us and, in particular, our decision-making. Kahneman and Tversky (1979) criticizes the expected utility theory with *the prospect theory*. They propose that individuals place greater weight on perceived gains than they do on perceived losses, even if the gains and losses are equal in size. Shefrin and Statman (1985) takes certain insights from the prospect theory and puts them into a wider view. They conclude that investors sell assets that have increased in value and keep those that have decreased in value, labeling this behavior *the* *disposition effect*. Shiller and Pound (1989) investigates *the contagion effect*. They find that investors generally do not get interested in stocks by reading about them alone but mainly due to an interpersonal communication. This indicates that *the herding behavior* is important in explaining investor decision-making. Benartzi and Thaler (1995) argues that *myopic loss aversion*, which is a combination of loss aversion and a short evaluation period, can partly explain the equity premium puzzle, a consequence of investors' choosing.

Through this widespread effect on decision making and thus behavior, investors' psychology influences the stock market. Black (1986) classifies noise trading as trading on noise rather than on news. He argues that noise trading inserts noise into stock prices and that the price level is determined by investors' expectations. De Long et al. (1990) present evidence of this and conclude that noise trading can create a large discrepancy between market prices and fundamental values. Traditionally, any mispricing of this kind was said to disappear quickly thanks to the work of arbitrageurs (Fama, 1970). However, a vast amount of studies contradict this view. As Malkiel (1977) puts it, "The pricing of shares of closed-end investment companies appears to provide a startling counter-example to the general rule", the pricing of shares' deviation from net asset value being a consequence of investors' thinking and the general rule being that markets are highly efficient.

Efforts have been taken to study this causal relationship between psychology and the stock market a step further. Barberis et al. (1998) create a model of investors' *sentiment* based on psychological evidence and investigate how sentiment affects forecasts about stock prices. They conclude that stock prices overreact to consistently good or bad news and underreact to earnings announcements. Neal and Wheatley (1998) examine three generally accepted measures of sentiment and their respective forecasting power. They find that two out of three, namely fund discounts and net redemptions, do predict the size premium of firms. Baker and Wurgler (2006) form a composite index of six proxies for sentiment and evaluate the index's predictive power of the U.S. market. They find that sentiment can cause firm characteristics that previously did not have any predictive power of stock returns to have some. Hribar and Mcinnis (2009) show that high sentiment in previous period results in more than average optimistic earnings forecasts. They argue that the earnings forecasts biases are at least partially the reason for the association between sentiment and stock returns.

The outlay above reveals that psychology/sentiment indeed affects stock returns. The task at hand is now to figure out how to measure this abstract property with its shifting state of mind, and to find out where it has the greatest impact.

2.1. What is sentiment?

There is no consensus on the term sentiment. Different authors use different definitions. Barberis and Thaler (2003) summarize surveys conducted by multiple other economists, and by psychologists. They end up dividing sentiment into *beliefs* and *preferences*, which are said to origin from a number of underlying characteristics and/or psychological errors with people's thinking. Belief is said to derive from overconfidence, optimism, representativeness, conservatism, belief perseverance, anchoring and the availability bias. Preferences appear to relate to the prospect theory and ambiguity aversion. Baker and Wurgler (2006) also mention *the propensity to speculate* as a possible definition of sentiment. This is explained in more detail in their subsequent study as not only biases in terms of overconfidence, representativeness, etc. but also as differences in opinion, in general but likewise when sitting on the same information (Baker and Wurgler, 2007). Cliff and Brown (2004) also incorporate the belief about future cash flows in their definition of sentiment: "Intuitively, sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever "average" may be."

2.2. How to measure sentiment

Sentiment is unpredictable and thus impossible to forecast. However, looking back, you can make use of historical data. There are mainly two approaches that have been used in previous studies: the top-down and the bottom-up approach. These approaches are common when analyzing data.[1] An investor employing the bottom-up approach investigates the fundamentals of a stock and then makes the decision whether to believe that the stock will (continue to) perform well or not, regardless the market conditions. Contrarywise, an investor employing the top-down approach investigates diverse factors that affect the market as a whole. In the context of stock returns and sentiment, then, one can say that the bottom-up approach simply reveals whether stocks are affected by sentiment or not, while the top-down approach reveals what kind of stocks are affected the most (Baker and Wurgler, 2007). The top-down approach is thus broad and general, incorporating cycles in stock returns and macro variables, while the bottom-up approach is narrow, with a focus on a few general biases in human psychology.

Many different indicators have been proposed as investor sentiment. They can be divided into two large categories: direct and indirect measures (Cliff and Brown, 2004). Direct measures of sentiment are obtained through surveys conducted to consumers, investors or other agents, who reveal their sentiment towards some specific question. Typical examples are the Consumer Confidence Index[2] (CCI) and the Economic Sentiment Indicator[3] (ESI) (for Europe). For instance, Horta and Lobão (2018) study sentiment and stock returns in no less than seven European markets (the U.K., France, Germany, Belgium, the Netherlands, Greece and Portugal), using ESI as an indicator for sentiment.

[1] https://www.investopedia.com/articles/investing/030116/topdown-vs-bottomup.asp and

[2] https://data.oecd.org/leadind/consumer-confidence-index-cci.htm

[3] https://data.europa.eu/euodp/sv/data/dataset/c04BuUz6WXIQGJkHPwLug

The benefit of a direct measure of this kind, such as a survey, is that you can specify a quite narrow question to which you seek an answer. A disadvantage of using a survey, is that you may not be able to address a proper sample of those who influence the stock market. Cliff and Brown (2004) find that there are two types of speculative investors, individuals and institutions, and that the latter has the strongest relation to large stocks. If surveys are aimed at individual investors, a large piece of input to the sentiment measure is thus lost.

Indirect measures, on the other hand, are economic variables or indices that are used as proxies for sentiment. The benefit of an indirect measure is thus, that you can observe the true actions by people and not fall victim to false answers.

To provide a comprehensive analysis, I choose to apply a top-down approach using indirect measures of sentiment. I therefore choose to follow the methodology put forth by Baker and Wurgler, from here on referred to as BW, in their paper from 2006 about investor sentiment and the cross-section of stock returns. BW (2006) apply the top-down approach using an indirect measure of sentiment, namely, a composite index.

2.2.1. Baker and Wurgler's composite sentiment index

BW (2006) construct a composite index that is based on the common variation in six underlying proxies for sentiment, all known to be indicators of sentiment across earlier studies. These are the closed-end fund discount, the share turnover, the number and first-day returns of IPOs, the equity share in new issues and the dividend premium. An advantage of this strategy of using multiple proxies is that the shortcomings of one proxy might be compensated for by one of the other proxies.

Table 1.
Baker and Wurgler's proxies for sentiment

The first column in table 1 depict the acronym of each proxy. The second column provides the full name/description. The third column states each proxy's correlation with sentiment in general and thus also its correlation with Baker and Wurgler's sentiment index.

Acronym	Description	Correlation with sentiment
CEFD	Closed-end fund discount	Negative
TURN	Share turnover	Positive
NIPO	Number of IPOs	Positive
RIPO	First-day returns of IPOs	Positive
S	Equity share in new issues	Positive
P^{D-ND}	Dividend premium	Negative

CEFD is the closed-end fund discount. A closed-end fund is a portfolio created to raise capital through an initial public offering (IPO).[4] It then trades its shares like any other stock on an exchange market. The difference from an open-end fund is that the parent company doesn't issue any additional shares or perform any buybacks after the IPO. The closed-end fund's trading price fluctuates according to supply and demand and often deviate from its net asset value (NAV). The discount refers to when the price is less than the NAV. The CEFD is calculated as the average difference between shares' NAV and price.

TURN is the NYSE share turnover. As other turnover ratios, it is a measure of liquidity, as it indicates whether the shares are easy or hard to sell.[5] The measure is calculated as the ratio of share volume to average shares listed.

The NIPO and RIPO measures both stem from the IPO market. They are measures of the annual number and annual average first-day returns of IPOs, respectively.

S stands for equity share in new issues and is calculated as gross annual equity issuance over gross annual equity and long-term debt issuance.

[4] https://www.investopedia.com/terms/c/closed-endinvestment.asp
[5] https://www.investopedia.com/terms/s/shareturnover.asp

P^{D-ND} denotes the dividend premium. The measure is the result of taking the difference of dividend payers and non-dividend payers' market-to-book ratios. This proxy is one of two (the other being CEFD) that exhibits a negative correlation with sentiment.

The BW index is based on broad, general and comprehensive measures. The result is an index that correlates nicely with anecdotal accounts of swings in sentiment. In other words, the index is positive when the stock market is generally viewed as experiencing a boom. The proxies used in the index are all indirect measures. As Burghardt (2011) puts it, indirect measures require a theory that connects them to sentiment. For this sake, I will dig a little deeper into what each proxy stands for in terms of sentiment and provide an intuitive reasoning behind the inclusion of it into the sentiment index.

2.2.2. Reasoning behind the proxies

In the first part of section 2, I report that investors' psychology matters. It influences the stock market through its effect on investors' decision-making and behavior. The outcome is often seen as a deviation of price from fundamental value. One can therefore find it intuitive that three out of six proxies in BW's index are measures of price deviations (namely, CEFD, RIPO and P^{D-ND}). These three should then capture a fair deal of the variation in stock prices caused by sentiment.

Lee et al. (1991) explain that the CEFD has puzzled academics for years. They mention that the discount has been as large as 10 to 20 percent during recent time. In their paper, they evaluate previous research stating that the discount represents investors' expectations and/or noise trading. They come to the explicit conclusion that the discount is, in fact, a measure of investor sentiment, with discounts being high when investors are pessimistic. The correlation between this measure, CEFD, and sentiment should therefore be negative in any report. However, there are only a few closed-end funds in the Swedish market. Most of them was initiated as late as 2017. Therefore, there is not sufficient data for this proxy and it is therefore excluded from my analysis and any further discussion regarding the proxies from here on.[6]

Rajan and Servaes (1997) include the concepts of irrational behavior and investors' optimism into their analysis regarding why phenomenon such as *underpricing* and *hot issue market* exist. They find that analysts are overly optimistic about the long-run performance of firms going public and, subsequently, the share price tend to increase after the initial price is set. Investors who rely on these analysts are inclined to purchase these overvalued shares. The result is high first-day returns of IPOs. The correlation between this measure, RIPO, and sentiment would thus be positive in any report.

BW (2004) study the dividend premium exclusively, suggesting that the measure represents investors' demand for dividends. In their paper about *the catering theory*, they insinuate that managers maximize share price by paying dividends at times when the demand for dividends is especially high. They also investigate the source of the dividend demand and find that sentiment is the main driver. It probably fluctuates with the desire for "safer" investments, since paying out dividends is a sign of a mature company. Shefrin and Statman (1984) also draw this conclusion and relates it to the prospect theory; pessimism about growth opportunities in general cause the demand for dividend payers to increase. The correlation between this measure, P^{D-ND}, and sentiment would thus be negative in any report.

The above measures are deviations of price from the fundamental value. Price is typically viewed as being determined by demand and supply. If one think of the sentiment proxies in terms of demand and supply, one notices that the three previously described measures end up in the sentiment-based *demand* category, as does TURN.

Shleifer and Vishny (1992) find that the number of transactions increases when the market is high, as investors are more willing to part with their assets and sell them at good times. The

[6] BW (2012) also choose not to include the CEFD proxy in their analysis from 2012 covering the countries Canada, France, Germany, Japan and the U.K.

opposite is true in periods of low markets. They also draw associations between this behavior and investors' beliefs and argue that it plays a key role here. The correlation between the turnover ratio, TURN, and sentiment would thus be positive in any report. That being said, the meaning of the turnover ratio might have lost its significance during recent years. On the New York University website, Jeffrey Wurgler mentions that TURN is nowadays dropped as a proxy in their sentiment index.[7] The reason for this is the increase of institutional high-frequency trading and the relocation of trading to a variety of places. Since my data ranges from 2000 up until today, I have chosen to include TURN nonetheless, to be able to explain as much as possible during all years, early as recent. However, I keep this in mind when interpreting results.

Previous discussion regarded sentiment-based demand measures. S and NIPO, on the other hand, end up in the sentiment-based *supply* category. Hendersen, Jegadeesh and Weisbach (2006) find that firms time the market by issuing equity or debt based on how inefficient the market is at the moment. If equity is overvalued relative to firms' fundamentals, new equity will be issued to benefit old shareholders at the expense of new ones (Kim and Weisbach, 2008). The opposite applies when equity is undervalued. BW (2000) find that a high equity share in new issues also predicts future returns: the subsequent period yields lower return. A large equity issue is thus a signal that the market is overvalued, a sign of overoptimistic investors. The correlation between this measure, S, and sentiment would thus be positive in any report.

As for NIPO, similar conclusions can be drawn. Kim and Weisbach (2008) name three reasons for a firm to go public. These are (1) the financing of investments, (2) the transferring of wealth between new and old shareholders and (3) to increase liquidity. The reasons remind us of the argument for issuing equity. Lowry (2002) investigates the cause of the time-series variation in the number of IPOs and find that investor sentiment partly regulates the level of new IPOs. That

[7] http://people.stern.nyu.edu/jwurgler/

is, when sentiment is high, investors overvalue companies and the number of IPOs is high. NIPO is also strongly correlated with RIPO. Lowry and Schwert (2002) show a reiterating pattern in the IPO market: high and increasing returns are followed by high IPO volume. It seems that market conditions are the foremost reasons for an IPO and the firm-specific motivations a secondary issue. The correlation between this measure, NIPO, and sentiment would thus be positive in any report.

2.3. The impact of sentiment

So far, I have discussed what sentiment is and how to measure it. An even more intriguing question is, where does sentiment have the greatest impact? Shiller and Pound (1989) find that the contagion effect is not equally large across securities. They say that "only certain stocks are 'interesting'". A question that naturally arises is then, what stocks are interesting? Thaler and Ziemba (1988) draw similarities between the stock market and horse race betting. The so-called *favorite-longshot bias* constitute the tendency to favor lottery-like bets with a high outcome, in spite of a low probability to achieve said outcome. This issue brings us back to the beginning of this section (and, in doing so, completes the circle), namely, the discussion of how psychology influences our decision-making and thus the stock market. The prospect theory partly explains the behavior of favoring longshots by describing how individuals place greater weight than what's legitimate on small probabilities of high outcomes (Kahneman and Tversky, 1979). BW (2006) incorporates this aspect into their study. They suggest that speculative stocks are of particular interest for investors and, as such, are more prone to be affected by sentiment. They define speculative stocks as those that are hard to evaluate and hard to arbitrage. To know if a specified type of security is hard to evaluate, one should look for certain characteristics within the firm that issued the security. These are size, age, volatility, profitability, dividend policy, asset tangibility, and finally growth opportunities and/or distress.

Table 2.
Characteristics of speculative-prone stocks

Table 2 reveals what characteristic is considered being that of a sentiment-prone firm. These characteristics are later used for creating various portfolios. The first column states the kind of characteristic, while the second column defines it more explicitly by a chosen key figure. The third column displays the acronym of the key figure. All acronyms are pretty much self-explanatory. Regardless, BE stands for book equity and A stands for total assets.

Characteristic	Key figure	Acronym
Size	Market Equity	ME
Age	Years since first appearance	Age
Volatility	Sigma	Sigma
Profitability	Return on Equtiy	ROE
Dividend Policy	Dividends	D/BE
Asset Tangibility	Property, Plant & Equipment	PPE / A
	Research & Development	RD / A
Growth Opportunities and / or Distress	Book-to-Market	BE/ME
	External Financing	EF/A
	Sales Growth	GS
	Sales Growth Decile	GS/10

Size is considered equal to a firm's market equity (ME). Age is the number of years since the firm's first appearance on the database from which the data is retrieved. Volatility is the standard deviation of returns (Sigma). Profitability is the return on equity (ROE). The dividend policy is calculated as the amount of dividends scaled by book equity (D/BE). Asset tangibility is reflected by the magnitude of firms' property, plant and equipment values and their expenses on research and development, both scaled by assets (PPE/A and RD/A, respectively). Growth opportunities and/or distress is measured in terms of book-to-market values, external financing scaled by assets and sales growth (BE/ME, EF/A and GS).

The result of BW's analysis is coherent with their hypothesis. Their conditional analysis reveals patterns that are concealed in an unconditional analysis. In particular, they find that the size effect appears only when sentiment is negative. They also find that young stocks are more popular when sentiment is positive, whereas old stocks are more popular when sentiment is negative. The same goes for volatile stocks, being more popular in good times than in bad times.

In terms of profitability and dividend policy, positive sentiment has the effect of boosting returns for profitable and dividend-paying firms in subsequent year, whilst negative sentiment has the opposite effect. Regarding growth and distress characteristics, BW find a u-shaped pattern across deciles, since firms with extreme values of one characteristic can be viewed as either in distress or so-called high-flyers. Stable firms are thus found in the middle deciles, hence, a u-shaped pattern. Conclusively, BW find that when sentiment is low, returns for the following period are relatively high for all speculative-prone securities. This means that, securities that possess speculative characteristics are less popular in times when sentiment is low. The opposite is then true, when sentiment is high.

2.4. Adding to existing literature

BW's result is fascinating, to say the least, and motivates me to extend their analysis a bit further by applying it on a different market, specifically, Sweden. This market is, to my knowledge, uninvestigated when it comes to using the BW index as a sentiment measure. Indeed, there is a large body of literature that make use of BW's index and employ it on other markets. BW themselves, for instance, extend their analysis of the U.S. onto five other major markets, namely, Canada, France, Germany, Japan and the U.K. (BW, 2012). My study differs from this in terms of stock market. Weissofner and Wessels (2020) recently published an article in which they investigate twenty countries, Sweden included, using overnight returns as a proxy for sentiment. My study differs from this in terms of methodology.

My study would thus be the first to look into the Swedish market with a composite index as an indirect proxy for sentiment. As such, it constitutes an addition to existing literature. What's more, an analysis of this kind is essential for Swedish investors, as it can assist in taking the right action when detecting anomalies in these proxies for sentiment. Observing deviations in these proxies can help you understand the behavior of the market and, more specifically, when and where sentiment will influence the most.

3. Data

The data gathering for my analysis is twofold, namely, stock panel data (market and fundamental) and proxies data. The stocks that represent the Swedish market in my analysis are those listed on Nasdaq Stockholm Main Market. Financial and utilities stocks are excluded, due to their divergent structure. Since data on some of the proxies date back only as far as 20 years, my sample of the Swedish market is also bounded to these years. My analysis thus corresponds to data on 295 stocks during the years 2000 to 2019.

Unlike the stock data, the data for the sentiment proxies (in particular, NIPO and RIPO) could not be limited to Nasdaq Stockholm Main Market. The reason for this is that several firms were listed on First North GM Sweden, before conducting an IPO on the main market. As such, the actual date for the IPO, and the date that would have an effect on the first-day return, is the date of the listing on First North. Measures of NIPO and RIPO would then be skewed, had I not been taking this other market into account.

3.1. Stock returns

I retrieve information regarding company name and international securities identification number (ISIN) from Nasdaq's website.[8] Market data and fundamental data are downloaded from Thomson Reuters Eikon. Market data is the monthly return, from which momentum is calculated as the cumulative return for the 11-month period between 12 and 2 months. Fundamental data consists of characteristics of speculative-prone stocks. These are size, age, volatility, profitability, dividend policy, asset tangibility and, ultimately, growth opportunities and/or distress. Each characteristic is defined in a similar way as in BW (2006). *Size* is the log of the product of price per share and the number of shares outstanding, i.e. the market equity (ME). A*ge* is the number

[8] http://www.nasdaqomxnordic.com/

of years since the firm's first presence on Thomson Reuters Eikon.[9] *Volatility* is calculated as the standard deviation of the monthly raw returns and is denoted sigma. *Profitability* is represented by the return on equity (ROE). This is calculated as net income before extraordinary items for the fiscal period divided by average total equity, where average total equity is the average of total equity at the beginning and at the end of the year. The *dividend policy* is obtained by dividing gross dividends by book equity. A dummy variable is created for both the profitability and dividend policy characteristics. The dummy for profitability is taking on a value of one whenever ROE is positive and a value of zero otherwise. The dummy for the dividend policy is taking on a value of one whenever there is a dividend payout and a value of zero otherwise. *Asset tangibility* is split into two measures: property, plant and equipment as well as retained earnings, both scaled by total assets. *Growth opportunities and/or distress* is also measured in several ways. First out is book-to-market ratio, calculated as the log of the ratio of book equity to market equity. External financing is calculated as the change in total assets minus the change in retained earnings, divided by total assets. I use net income less dividends whenever the change in retained earnings is not available whereas a measure of net income less dividends is. Lastly, sales growth is the change in net sales divided by prior year's net sales. GS/10 is the decile of the firm's sales growth.

I winsorize the data on the 0.5 and 99.5 percentiles to mitigate the effect of outliers. The fundamental data is then matched to the stock market data in the following way: accounting data for fiscal year-ends in calendar year t-1 is matched to the monthly returns from July in year t to June in year t+1.[10] I then calculate descriptive statistics, namely the mean, the minimum and maximum value, the standard deviation and the number of observations for all variables above. Table A1 in the appendix summarizes all data.

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[9] Due to the software's own restraints, this can be a maximum of 60 years since the record on Thomson Reuters Eikon stretch only as far back as to 1960.

[10] The methodology is the same as the one applied in BW (2006).

3.2. Sentiment

Constructing a composite index of sentiment consists of two parts. The first part is data gathering of each of the five proxies. The second part is the composition of the actual index, where I make use of the proxies I have assembled and create a final variable that, for each point in time, represents a value of the general sentiment at that time.

3.2.1. Sentiment proxies

The index consists of five indicators, all measured annually. These are the turnover ratio (TURN), the number of IPOs (NIPO), the average first-day returns of IPOs (RIPO), the equity share in new issues (S) and the dividend premium ($P^{D\text{-}ND}$). Each proxy is generally defined in a similar way as in BW (2006; see also 2000, 2004).

TURN is the natural log of the turnover ratio of the main market. Data on TURN is retrieved from the statistics site at Nasdaq OMX.[11]

NIPO is measured as the yearly sum of IPOs and RIPO is measured as the average first-day returns on IPOs. Both NIPO and RIPO are annualized to smooth noise. The data for the proxies are retrieved manually from the statistics and listings sites at Nasdaq OMX, in combination with Nyemissioner[12] and Thomson Reuters Eikon. This choice of multiple sources for conducting the measures stem from the goal to achieve as close as survivorship-bias free proxies as possible. IPOs of ETFs are then excluded, as is any name changes classified as an IPO. In addition, many firms conduct an IPO on First North before meeting the criteria to enter the main market. Due to this duplicity issue of IPOs, data on NIPO and RIPO come from not only the main market but from First North as well.

[11] http://www.nasdaqomxnordic.com/news/statistics
[12] https://www.nyemissioner.se/foretag/planerad-noteringar/sok

The equity share in new issues, S, is calculated as gross annual equity issuance (both common and preferred) over gross annual equity and long-term debt issuance. The data is downloaded from Thomson Reuters Eikon.

The dividend premium, P^{D-ND}, is the result of taking the log of the difference between dividend payers and non-dividend payers' average, year-end market-to-book ratios. The data is from Thomson Reuters Eikon. The market-to-book ratio is calculated as book assets minus book equity plus market equity, divided by book assets. Market equity is defined as stock price times the number of shares outstanding. The market-to-book ratio is equal-weighted and averaged, separately for payers and non-payers in each year. A firm is regarded a payer whenever the firm pays a positive dividend a given year. Then the difference is calculated of the logs of the averages. This is the dividend premium.

3.2.2. Sentiment index

To separate the common component, I use principal component analysis (PCA), a technique for exploratory data analysis that is very useful when the data is wide and to uncover patterns in complex datasets.[13] All proxies are first standardized to zero mean and unit variance, in order to make the variables comparable. The PCA reveals that the first principal component explains 47.3% of all the variance, which means that the first factor captures almost half of the common variation. Figure 1 below plots the PCA, grouping the points together in assemblages of three years' time. A major ellipse indicate little clustering, whilst a small ellipse reveal observations that are similar to each other. Each proxy, with its lag, is represented by an arrow. An arrow is a loading. The further away from the origin, the more does the variable explain the data. If two arrows are close to each other, they exhibit a strong correlation.

[13] https://www.datacamp.com/community/tutorials/pca-analysis-r#intro

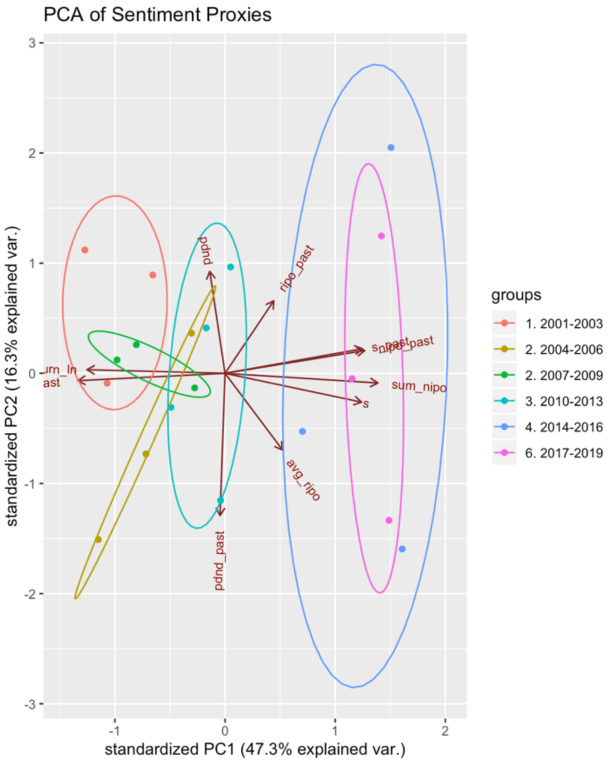

Figure 1.
PCA of sentiment index proxies
The figure above plots the PCA, grouping the points together according to the passage of time. Early years (2001-2009) are very much explained by the turnover ratio (TURN). Middle years (2010-2013) are explained by the dividend premium (P^{D-ND}). The most recent years (2014-2019) varies a lot with new equity on the market, both in terms of equity issues (S) and IPOs (NIPO and RIPO).

In figure 1, the data is depicted as practically a time-series, with its start to the far left and its end to the far right.[14] The points representing years 2001-2009 are quite tightly grouped. These observations are very much explained by TURN. Then something happened that turned this around. Interestingly, this corresponds nicely with the hypothesis that TURN has lost its strength in explaining recent years' sentiment, however, one cannot exclude it since it adds value to older observations. Subsequent years are consequently not explained by this proxy. Instead, years 2010-2013 vary a lot with P^{D-ND}. An intuitive explanation for this might be that the period is characterized by uncertainty, following the big drop in the financial markets in 2007/2008. Perhaps people sought to invest in safer firms rather than in new and exciting companies. Since dividend-paying

[14] Creating lagged values of the proxies involves creating NAs in the first row of the dataset. Since the PCA procedure requires a full set of observations across proxies, without missing values, I had to drop the first row of the dataset (year 2000) since it contains missing values.

firms are often viewed as mature and stable companies, this line of thinking should have boosted the demand for dividend-payers. Therefore it seems only natural that the dividend-premium has strong explaining power here.

Interestingly, the most recent years are explained a lot by not one but three proxies (NIPO, RIPO and S). This indicates that new equity (new entries on the market as well as new issues) has gotten a great deal of attention lately and is very significant in explaining investors' sentiment. As the arrows of NIPO and S are longer than the arrows of RIPO, the former two proxies should exhibit a higher correlation with sentiment than the latter (a correlation analysis is carried out below to support this conclusion).

Using the result of the PCA, a first-stage index is created from the first principal component. The first-stage index includes all five proxies and their lags, resulting in an index with ten components.

$$\begin{aligned} Sentiment_t = {} & -0.3872TURN_t + 0.4287NIPO_t + 0.1613RIPO_t + 0.3831S_t \\ & - 0.043P_t^{D-ND} - 0.4130TURN_{t-1} + 0.3920NIPO_{t-1} + 0.1367RIPO_{t-1} \\ & + 0.3855S_{t-1} - 0.0138P_{t-1}^{D-ND} \end{aligned}$$

A correlation analysis is performed in order to determine what timing of each proxy, lead or lag, that correlates the strongest with the first-stage index. Those with the highest correlations are kept and a second-stage, composite index is created with these remaining five components. The second-stage index is then rescaled to unit variance. The result is the following index:

$$\begin{aligned} Sentiment_t = {} & -0.4130TURN_{t-1} + 0.4287NIPO_t + 0.1613RIPO_t + 0.3855S_{t-1} \\ & - 0.043P_t^{D-ND} \end{aligned}$$

Unlike BW (2006), I do not find that the lagged value of P^{D-ND} exhibits the highest correlation, hence I keep the lead value. The opposite is true for S, for which I use the lagged value in the index, whilst BW (2006) use the lead. However, dropping five components and keeping only the five that exhibits the highest correlations is not causing any major implications, seeing as the correlation between the two indices is 0.96. Table 3 below displays the descriptive statistics of each proxy used in the final index as well as the correlation matrix.

Table 3.
Descriptive statistics of sentiment proxies and index
The data in this table refer to years 2001-2019. The left hand side of table 3 depicts the number of observations, mean and standard deviation as well as the minimum and maximum value of each of the sentiment proxies. TURN is the Nasdaq main market turnover. The index uses the natural log of the value. NIPO is the annual number of IPOs. RIPO is the average annual first-day returns of IPOs. S is the gross annual equity issuance over gross annual equity and debt issuance. P^{D-ND} is the dividend premium, calculated as year-end log ratio of average market-to-book ratios of payers and non-payers. The right hand side of table 3 depicts the correlation of each sentiment proxy with the sentiment index as well as with the other proxies. Sentiment is the sentiment index, calculated as the first principal component of the proxies.

					Correlation					
	Mean	SD	Min	Max	$Sentiment_t$	$TURN_{t-1}$	$NIPO_t$	$RIPO_t$	S_{t-1}	P^{D-ND}_t
$TURN_{t-1}$	4.59	0.32	4.14	5.02	-0.77	1				
$NIPO_t$	36.05	26.82	5	94.00	0.96	-0.79	1			
$RIPO_t$	-0.37	2.88	-10.93	2.90	0.24	-0.27	0.23	1		
S_{t-1}	4.13	1.39	2.13	7.28	0.85	-0.62	0.80	0.23	1	
P^{D-ND}_t	15.62	27.10	-50.26	54.64	-0.22	-0.13	-0.14	-0.14	-0.10	1

NIPO and S are the two proxies that exhibit the strongest correlation to the sentiment index (0.96 and 0.85, respectively). They are, together with RIPO, the three proxies that are positively correlated with sentiment whilst the relationship between sentiment and P^{D-ND} is inversed, as hypothesized. TURN is unexpectedly negatively correlated with sentiment, however, a look at the graphical representation in figure A1 (in the appendix), panel A, reveals that TURN used to be positively correlated with sentiment but the relationship is nowadays reversed.

Figure A1 portrays all proxies as well as the sentiment index in separate graphs. Panels B, D and F clearly shows the similarity and co-movement of NIPO and S with the sentiment index. This supports the above discussion regarding the significance of these proxies in explaining investor sentiment today. It seems like it's all about new equity on the market, these days. This stands in contrast to the findings by BW (2006). In their analysis, P^{D-ND} exhibits the highest correlation with sentiment. NIPO comes in third and S actually correlates the least with the index. The conclusion to be drawn here is, thus, that the importance of sentiment proxies varies a lot across time and market. BW (2006) investigate the U.S. market during 1963-2001, whereas I investigate the Swedish market between 2001-2019. It would be interesting to find out whether this seemingly high importance of new equity in Sweden today is true for the U.S. market as well these days. If so, this would indicate that time drives this measure's relationship with sentiment the most, whilst the opposite would reveal that market instead is the major determinant factor.

Panel F also shows that the sentiment index turns negative following the bursting of anecdotal bubbles. Those are the Dot-com bubble in 2000/2001, with a subsequent drop in the financial markets in 2003, and the housing market bubble in 2007/2008, with a subsequent drop in 2008/2009. A closer look at the graph reveals that the sentiment index is negative pretty much all the time of the early 2000's, however, the graph depicts the *scaled* index. The actual level of the sentiment index (not displayed here) lies somewhat higher across times, than the scaled sentiment index does. The index is scaled to retain unit variance and zero mean.

4. Methodology

Following the methodology by BW (2006), I sort the returns into equal-weighted portfolios, conditioning on deciles of characteristics. Decile one contains the value that is smallest in magnitude, whereas decile ten contains the value that is largest in magnitude. Within each portfolio, I split the returns into subgroups, depending on whether sentiment was positive or negative in the previous year-end. The average return of each subgroup is then calculated. This represents the cross-section of returns. The aim is to reveal patterns (if any) in the average returns as well as in the difference of average returns. BW call this a "conditional characteristics model" and the structure of the model is as following:

$$E_{t-1}\left[R_{i,t}\right] = \beta_0 + \delta_1 Sent_{t-1} + \beta_1 Char_{i,t-1} + \beta_2 Sent_{t-1} * Char_{i,t-1} \qquad (1)$$

where *t* stands for time, *i* represents the firm index, *Sent* is a proxy for sentiment and *Char* is a vector of characteristics. The characteristic is the first sort and sentiment the second. The coefficient δ_1 picks up the generic effect of sentiment, and the vector β_1 the generic effect of characteristics. β_2 is the coefficient of interest. The hypotheses are the following:

$$H_0: \beta_2 = 0$$

$$H_1: \beta_2 \neq 0$$

The result of the sorts is found in table 4 in section 5 below. I then proceed to create long-short portfolios of the sorts. Most of the portfolios are created as *high minus low,* where high consists of the top three deciles and low consists of the bottom three deciles. Size is an exception, since the portfolio is created as *small minus big* (SMB). Age is another exception, since the portfolio goes long the *top half* deciles (6-10) and short the *bottom half* deciles (1-5). I then investigate whether sentiment has any predictive power over these portfolios, first in a univariate regression but later controlling for the Fama French factors, according to the following regressions:

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \beta_0 + \delta_1 Sent_{t-1} + \varepsilon_{it} \qquad (2)$$

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \beta_0 + \delta_1 Sent_{t-1} + \beta_1 RMKT_t + \beta_2 SMB_t + \qquad (3)$$

$$+ \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{it}$$

In equation 2, the dependent variable is the long-short portfolio and the explanatory variable is the sentiment index, as of previous year-end. In equation 3, the same applies but the Fama French factors have been added as explanatory variables. RMKT is the excess market return, SMB is the small minus big factor, HML is the high minus low factor and MOM is the momentum factor. When SMB and HML are the portfolios to be regressed, I exclude these factors from the right side of equation 3. The Fama French factors are downloaded from the Swedish House of Finance's datacenter and cover the Swedish market.[15] From here on, they are referred to as the FF factors. The results of the regressions are found in table 6.

Finally, as a last step, I run regressions of the FF factors against sentiment. The first regression make use of the FF factors that cover Sweden but subsequent regressions make use of FF factors that cover other geographic and demographic areas of which Sweden is a part. These are the European market and developed markets, and the FF factors are downloaded from Ken French's website.[16] The regressions are carried out according to the following equation:

$$FF_t = \beta_0 + \delta_1 Sent_{t-1} + \varepsilon_t \qquad (4)$$

where FF is one of the three Fama French factors (SMB, HML or MOM). Results are found in table 7.

These regressions are just another means of determining if characteristics have conditional effects that differ from already uncovered unconditional effects. They thus add robustness to the test.

[15] https://data.houseoffinance.se/

[16] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

5. Results

The result of my analysis is summarized in subsequent tables. Table 4 depicts the result from the sorts, i.e. the forecasts of the various portfolios. Table 5 displays the correlation matrix and table 6 presents the results when regressing the long-short portfolios against sentiment. Finally, table 7 presents the results from the regression of FF factors against sentiment.

5.1. Conditional portfolio sorts

Each section in table 4 below first describes the characteristic exclusive for that portfolio and then the average return of each decile of that characteristic, conditioning on sentiment of previous year-end being positive or negative. The result is a set of average returns for each decile. Below them, there is a row demonstrating the difference between these averages. Across almost all cross-sections, the return following a period of negative sentiment is higher than the return following a period of positive sentiment. This shows up as a negative difference in the difference row. This means that, when times are bad, investors are generally less willing to invest in stocks that exhibit one or more of these characteristics, than they would if times are good. As such, sentiment indeed has a large effect on stocks with these speculative features. This is the most consisting pattern that I find across the conditional portfolio sorts and it is coherent with BW's findings on the U.S. market.

The first three rows of table 4 show that smaller firms earn on average higher returns than do larger firms. Decile one depicts relatively high returns (1.47% when sentiment is positive and 2.95% when sentiment is negative) whilst decile ten depicts relatively low returns (0.63% and 1.09%, respectively). This indicates that the small-firm effect exists in periods of both positive and negative sentiment, which stands in contrast to BW's findings of a small-firm effect in periods of positive sentiment only. That being said, the effect I find is more pronounced in periods of negative sentiment. The difference between the bottom and top decile is as large as 1.86% when sentiment is negative, whereas it is only 0.84% when sentiment is positive. The effect is also more pronounced in the bottom decile, which is coherent with the small-firm effect established by Banz (1981). This shows as a jump in return from decile two to decile one. Finally, sentiment has the largest impact in the bottom decile, since the difference between averages is largest here (1.48%).

I find no consisting pattern across the deciles of age when sentiment is positive, however, I find a large difference between the absolute top and bottom deciles. It seems to me that the effect of positive sentiment on age is concentrated to the very youngest, which is in line with BW's findings. Young firms deliver a return that is 0.76% less than older firms do. On the contrary, when sentiment is negative, I find that older firms generate smaller returns than younger firms. The difference between the top decile and bottom decile is 0.10% which is perhaps not a lot, but zooming out reveals a greater difference: if looking at the top three deciles versus the bottom three deciles, the difference is 1.39% (on average 0.46%). This can be interpreted as investors seeming to prefer older firms when sentiment is low, which is coherent with the idea that investors seek to invest in stable and mature companies in times of uncertainty. BW (2006) state these findings as evidence that age in fact has an effect on stock returns, only that the effect is the opposite in periods of positive and negative sentiment, therefore cancelling out in an unconditional analysis. This means that a characteristic that previously was thought to not have any explanatory power over stock returns now shows signs to have some. Interestingly, these are the results that BW find most exceptional and remarkable in their analysis on the U.S. market. It is therefore exciting that the same results seem to be valid for the Swedish market as well.

Table 4.
Forecasts of equal-weighted portfolios subdivided by sentiment

This table present the equal-weighted average return in percent of each decile portfolio. Size is measured as market equity (ME). Age is measured in years since the firm first appeared in Thomson Reuter's database. Volatility is measured as the standard deviation of returns (Sigma). Profitability is calculated as return on equity (ROE) and the dividend policy is calculated as dividends divided by book equity (D/BE). Asset tangibility is measured in terms of property, plant and equipment (PPE/A) and research and development (RD/A). The measures are scaled by assets. Growth opportunities/distress are measured as book equity divided by market equity (BE/ME), scaled retained earnings (EF/A) and sales growth (GS). Portfolio 1 contains the lowest values and portfolio 10 the highest values of each characteristic. The portfolios are then divided into two subgroups, depending on whether the sentiment was positive or negative during previous year-end. A third row displays the difference between the subgroups, to reveal any patterns that might be concealed in an unconditional analysis.

		Decile									
	Sentiment$_{t-1}$	1	2	3	4	5	6	7	8	9	10
ME	Positive	1.47	0.8	1.08	0.72	0.32	0.8	0.55	0.39	0.61	0.63
	Negative	2.95	1.94	1.64	1.46	1.54	1.61	1.73	1.79	1.53	1.09
	Difference	-1.48	-1.14	-0.56	-0.74	-1.22	-0.81	-1.18	-1.4	-0.92	-0.46
Age	Positive	0.91	0.94	-0.7	-0.19	0.08	1.24	1.22	0.04	0.4	1.67
	Negative	1.68	2.06	2.31	1.71	1.59	1.63	2.19	1.57	1.51	1.58
	Difference	-0.77	-1.12	-3.01	-1.9	-1.51	-0.39	-0.97	-1.53	-1.11	0.09
Sigma	Positive	0.67	0.85	0.77	1,00	0.47	0.78	0.24	0.37	-1.04	3.88
	Negative	1.27	1.27	1.34	1.11	1.13	1.3	1.57	1.69	1.89	5.21
	Difference	-0.6	-0.42	-0.57	-0.11	-0.66	-0.52	-1.33	-1.32	-2.93	-1.33
ROE	Positive	1.33	0.51	0.79	0.86	0.96	1.13	0.55	0.94	0.25	-0.07
	Negative	1.89	1.7	1.9	1.79	1.48	1.71	1.75	1.77	1.68	2.11
	Difference	-0.56	-1.19	-1.11	-0.93	-0.52	-0.58	-1.2	-0.83	-1.43	-2.18
D+/BE	Positive	0.76	0.87	1.08	0.35	1.05	0.92	0.38	0.1	0.76	0.32
	Negative	1.65	1.47	1.66	2.04	1.87	2.23	1.86	1.67	1.77	1.59
	Difference	-0.89	-0.6	-0.58	-1.69	-0.82	-1.31	-1.48	-1.57	-1.01	-1.27
PPE/A	Positive	0.79	0.37	0.94	1.03	0.8	0.29	-0.05	0.15	0.06	1.01
	Negative	1.81	1.8	1.41	2.17	2.17	1.43	1.97	1.79	1.65	1.47
	Difference	-1.02	-1.43	-0.47	-1.14	-1.37	-1.14	-2.02	-1.64	-1.59	-0.46
RD/A	Positive	0.73	0.46	0.33	0.71	-0.21	0.71	1.83	1.84	0.28	1,00
	Negative	2.59	2.71	2.17	1.82	2.1	1.87	1.2	1.06	1.75	1.62
	Difference	-1.86	-2.25	-1.84	-1.11	-2.31	-1.16	0.63	0.78	-1.47	-0.62
BE/ME	Positive	0.38	1.25	0.89	0.49	0.83	0.3	-0.01	1.26	0.72	0.86
	Negative	1.52	1.37	1.21	1.56	2.1	1.95	2.13	1.67	1.67	2.32
	Difference	-1.14	-0.12	-0.32	-1.07	-1.27	-1.65	-2.14	-0.41	-0.95	-1.46
EF/A	Positive	0.31	0.87	0.83	1.33	1.04	0.62	0.7	0.96	-0.1	0.47
	Negative	2.05	1.6	1.37	1.72	1.66	1.8	1.72	1.5	1.71	2.24
	Difference	-1.74	-0.73	-0.54	-0.39	-0.62	-1.18	-1.02	-0.54	-1.81	-1.77
GS	Positive	1.39	1.1	1.05	0.31	1.01	1.02	0.55	0.58	0.84	0.25
	Negative	2.21	1.71	1.78	1.9	2.02	1.82	1.58	1.28	1.49	0.96
	Difference	-0.82	-0.61	-0.73	-1.59	-1.01	-0.8	-1.03	-0.7	-0.65	-0.71

The stocks that are the most volatile deliver an extremely high return in periods of negative sentiment (5.21%). This return decreases when one moves towards the lower deciles of volatility. This pattern can be an indication that investors demand less volatile stocks in periods of uncertainty. The opposite is true across most of the deciles, when sentiment is positive. Finally, the impact of sentiment is greatest in the top deciles.

In terms of profitability, the most obvious result is that returns following periods of negative sentiment are higher than returns following periods of positive sentiment. The effect varies little across deciles. Regarding dividend payers, I find that middle deciles seem less popular in periods of negative sentiment.

I find no consisting patterns across the deciles of PPE/A when sentiment is negative, however, I find that the lower deciles deliver smaller returns than the top deciles in periods of positive sentiment (with the exception of decile ten). This goes hand in hand with the hypothesis that firms with less tangible assets, and thus more intangible assets, are more popular in positive periods. The hypothesis builds on the belief that firms with a lot of intangible assets are harder to value and thus more prone to be affected by sentiment.

Unlike BW, I find reasonably strong patterns in the RD/A section and evidence of strong conditional effects. When sentiment is positive, firms in the higher deciles earn higher returns whereas when sentiment is negative, firms in lower deciles earn higher returns. These findings, however, stand in contrast to the hypothesis that investors seek to invest in firms with high RD/A in times of positive sentiment, not in times of negative sentiment.

Another pattern can be found in the BE/ME section. When sentiment is negative, firms with higher BE/ME earn higher returns. This means that investors demand firms with lower BE/ME ratios. This is in line with the idea that high BE/ME is a sign of a distressed firm and would thus be unpopular in uncertain times. Unlike BW, I don’t find a u-shaped pattern here. It seems that investors explicitly demand firms with low BE/ME ratios in periods when sentiment is negative.

An obvious u-shaped pattern is, however, found in the next section of table 4, regarding EF/A. This is shown graphically by the dotted line in panel I of figure A2 in the appendix. In times of positive sentiment, investors seek out stocks that are in the bottom and top deciles of the EF/A-sorted firms. The returns are thus low in extreme cases, whilst the returns are higher for middle deciles. The opposite is true, when sentiment is negative. This results in a u-shaped conditional difference effect. The bottom and top deciles are very much affected by sentiment, whilst the middle deciles are less so. BW (2006) explains this outcome with the multidimensional nature of these characteristics. More specifically, the extreme values in either direction are signs of unstable firms, while the middle deciles are signs of mature companies. As such, it is intuitive that they are less affected by sentiment.

Finally, investors seem to refrain from investing in stocks with low GS values, when sentiment is negative. Low growth in sales can be viewed as a sign of a company in distress, which could be the explanation of this behavior. Investors seem more interested in investing in companies with high growth in sales and particularly so in periods of positive sentiment.

Despite the findings discussed above, my results are not as clear as those achieved by BW (2006). This is easiest shown in figure A2 in the appendix, panels A through J. Whilst BW portrays relatively smooth lines, my graphs depict a lot of fluctuations and more or less cycles, specifically in the difference between averages (shown as the solid line). This entails me to draw the conclusion that my results are unfortunately not statistically significant in this difference. To test this, I perform a robustness check in the form of regressions of long-short portfolios on sentiment (equation 2 and equation 3).

5.2. Regression results

The regressions are made in two steps. First, I regress the constructed long-short portfolios against sentiment, in a univariate as well as a multivariate regression, the latter controlling for the FF factors. Second, I perform a regression of various geographic and demographic FF factors, of which Sweden is a part, against sentiment.

5.2.1. Long-short portfolios

The correlation analysis is displayed in table 5 below and the results from the regressions are found in table 6. Coherent with BW (2006), I find that portfolios created by size, age, profitability and asset tangibility are more correlated with each other than with other portfolios. Also, there is a higher correlation revealed when incorporating the multidimensional aspect of certain characteristics by creating high minus medium and medium minus low portfolios. For instance, the EF/A portfolio is only slightly correlated with the ME portfolio, when created as high minus low (ρ = 0.13). However, when created as high minus medium, the correlation coefficient amongst the portfolios more than triples (ρ = 0.58).

As I pinpointed before, the large swings in the difference between averages of returns indicate little significance, which is also the case when conducting a univariate regression (equation 2). However, when controlling for the FF factors, more significant results are achieved as well as results in the hypothesized direction. For instance, the univariate regression on age delivered a coefficient that neither deviated a lot from zero nor proved statistically significant. Once controlling for the FF factors, the coefficient jumped from 0.03 to 0.41, significant at the 10% level. This can be viewed in the second row of panel A in table 6.

The first row in table 6 adheres to size. A one-unit increase in sentiment results in a -64% lower monthly return when controlling for the FF factors, with a p-value of 0.11. The next row regards age. The sentiment coefficient is 0.41 with a p-value of 0.10. The third row concerns sigma, with a coefficient of -0.58 but a p-value of 0.28, and the fourth row depicts profitability, with a coefficient of 0.62 with a p-value of 0.10. The conclusions that can be drawn here

Table 5.

Correlation analysis of long-short portfolios

This table present the correlation between various long-short portfolios. The results refer to a sample between years 2001-2019. Size is measured as market equity (ME). Age is measured in years since the firm first appeared in Thomson Reuter's database. Volatility is measured as the standard deviation of returns (Sigma). Profitability is calculated as return on equity (ROE) and the dividend policy is calculated as dividends divided by book equity (D/BE). Asset tangibility is measured in terms of property, plant and equipment (PPE/A) and research and development (RD/A). The measures are scaled by assets. Growth opportunities/distress are measured as book equity divided by market equity (BE/ME), scaled retained earnings (EF/A) and sales growth (GS). The portfolios are typically created as high minus low, where high is referring to the top three deciles and low is referring to the bottom three deciles. Size is an exception, since it is created as small minus big (SMB). Age is another exception, since the portfolio goes long the top half deciles of age (6-10) and short the bottom half deciles (1-5). Finally, the last two rows concerning EF/A incorporates the multidimensional aspect of this property. The portfolios are created as high minus medium and medium minus low.

		Correlations															
		ME	Age	Sigma	ROE	D+/BE	PPE/A	RD/A	BE/ME	EF/A	GS	BE/ME	BE/ME	EF/A	EF/A	GS	GS
ME	SMB	1															
Age	High-Low	-0.52	1														
Sigma	High-Low	0.41	-0.28	1													
ROE	High-Low	-0.60	0.39	-0.30	1												
D+/BE	High-Low	-0.16	0.13	-0.68	0.29	1											
PPE/A	High-Low	-0.46	0.45	-0.45	0.48	0.12	1										
RD/A	High-Low	0.47	0.39	0.42	-0.54	-0.02	-0.57	1									
BE/ME	HML	0.03	0.25	-0.07	-0.03	-0.15	0.42	-0.40	1								
EF/A	High-Low	0.13	-0.25	-0.03	-0.02	-0.04	-0.02	-0.03	0.03	1							
GS	High-Low	-0.07	-0.10	0.02	0.27	0.03	-0.04	0.07	-0.33	0.25	1						
BE/ME	High-Medium	0.27	0.12	0.05	-0.24	-0.20	0.13	-0.13	0.64	-0.10	-0.36	1					
BE/ME	Medium-Low	-0.23	0.20	-0.14	0.20	0.00	0.40	-0.39	0.65	0.13	0.06	-0.17	1				
EF/A	High-Medium	0.58	-0.49	0.48	-0.47	-0.18	-0.42	0.40	-0.10	0.56	0.20	-0.01	-0.11	1			
EF/A	Medium-Low	-0.45	0.22	-0.52	0.47	0.14	0.41	-0.44	0.13	0.53	0.07	-0.09	0.26	-0.40	1		
GS	High-Medium	0.42	-0.41	0.36	-0.33	-0.08	-0.41	0.44	-0.23	0.22	0.55	-0.10	-0.20	0.55	-0.33	1	
GS	Medium-Low	-0.50	0.29	-0.39	0.63	0.12	0.36	-0.36	-0.13	0.06	0.56	-0.30	0.13	-0.33	0.41	-0.38	1

Table 6.

Regressions on long-short portfolios

The table presents the regression results from equations 2 and 3 (regressions use White standard errors). P-values are in brackets. The first regression is a univariate regression of sentiment on a long-short portfolio. The second regression controls for the Fama French factors (SMB, HML and MOM). SMB and HML are excluded as control variables when they are the dependent variable. Size is measured as market equity (ME). Age is measured in years since the firm first appeared in Thomson Reuter's database. Volatility is measured as the standard deviation of returns (Sigma). Profitability is calculated as return on equity (ROE) and the dividend policy is calculated as dividends divided by book equity (D/BE). Asset tangibility is measured in terms of property, plant and equipment (PPE/A) and research and development (RD/A). The measures are scaled by assets. Growth opportunities/distress is measured as book equity divided by market equity (BE/ME), scaled retained earnings (EF/A) and sales growth (GS). The portfolios are typically created as high minus low, where high is referring to the top three deciles and low is referring to the bottom three deciles. Size is an exception, since it is created as small minus big (SMB). Age is another exception, since the portfolio goes long the top half deciles of age (6-10) and short the bottom half deciles (1-5). Finally, the last two rows concerning EF/A incorporates the multidimensional aspect of this property. The portfolios are created as high minus medium and medium minus low.

		Sentiment$_{t-1}$		Sentiment$_{t-1}$ Controlling for SMB, HML and MOM	
		δ	$p(\delta)$	δ	$p(\delta)$
		Panel A			
ME	SMB	0.10	[0.78]	-0.64	[0.11]
Age	High-Low	0.03	[0.86]	0.41*	[0.10]
Sigma	High-Low	-0.21	[0.61]	-0.58	[0.28]
ROE	High-Low	-0.08	[0.79]	0.62*	[0.10]
D/BE	High-Low	0.01	[0.96]	-0.04	[0.87]
PPE/A	High-Low	-0.09	[0.69]	0.36	[0.22]
RD/A	High-Low	0.66*	[0.08]	0.25	[0.67]
BE/ME	HML	0.04	[0.90]	0.05	[0.89]
EF/A	High-Low	0.22	[0.35]	0.35	[0.25]
GS	High-Low	0.03	[0.91]	0.07	[0.84]
		Panel B			
BE/ME	High-Medium	0.54*	[0.07]	0.45**	[0.05]
BE/ME	Medium-Low	-0.50***	[0.01]	-0.34	[0.21]
EF/A	High-Medium	0.13	[0.51]	-0.05	[0.86]
EF/A	Medium-Low	0.08	[0.20]	0.41*	[0.09]
GS	High-Medium	0.42*	[0.06]	0.30	[0.37]
GS	Medium-Low	-0.39*	[0.09]	-0.23	[0.37]

*** 0.01   ** 0.05   * 0.10

are that size, age, volatility and profitability have a pronounced, but only partly significant, effect on stock returns. When sentiment increases, firms that are small, new, volatile and profitable earn lower returns in the coming period. This matches with my findings from the portfolio sorts.

The rest of the characteristics provide results in a lesser extent both in terms of magnitude and significance. However, when taking the multidimensional natures of BE/ME, EF/A and GS into account, results are improved further. For instance, the BE/ME high minus low portfolio shows no significant relationship with sentiment, regardless if controlling for FF factors or not. The high minus medium and medium minus low portfolios, however, do. Though not consistent with the u-shaped pattern found by BW (2006), the regression results support my findings from the portfolio sorts. The highly significant negative relationship between medium minus low and sentiment (-0.50 at 1% level) confirm the conclusion that investors explicitly demand firms with lower BE/ME when sentiment is negative.

The portfolio sort reveals a u-shaped pattern in the EF/A portfolio. This shows up as a (slightly) negative relationship between sentiment and the high minus medium portfolio, and a significant positive relationship between sentiment and the medium minus low portfolio, equivalent with the findings by BW (2006).

The GS portfolios prove significant if not controlling for the FF factors, but they do this in the opposite direction of those in BW's analysis.

5.2.2. Fama French factors

My final regression investigates the relationship between the sentiment index and FF factors exclusively (equation 4). Results are displayed in table 7 below. The results are neither large in magnitude nor significant when regressing against the Swedish FF factors.[17] However, the results

[17] The Fama French factors for Sweden are downloaded from Swedish House of Finance's datacenter. At the time of writing, they are improving the factors since the current ones exhibit some errors.

from regressions on the European market and the developed market segment comply with earlier results with statistical significance. More specifically, a one unit increase in sentiment is associated with a drop of -16% in the European SMB factor, significant at the 10% level, and a drop of -20% in the developed markets SMB factor, significant at the 5% level. In terms of HML, a one unit increase in sentiment is associated with a drop of -25% in the European HML factor, significant at the 10% level, and a drop of -26% in the developed markets HML factor, significant at the 5% level. This point to the conclusion that the size and value effects are influenced by swings in investors' sentiment. When sentiment decreases, the returns on SMB and HML factors increases. The size and value effects are thus enlarged when times are bad and investors' become pessimistic.

Table 7.

Regressions on Fama French factors

Table 7 presents the regression results from equation 4 (regressions use White standard errors). P-values are in brackets. The regressions are univariate, with the Fama French factor as the dependent variable and the sentiment index as the explanatory variable. SMB stands for small minus big, HML stands for high minus low and MOM stands for momentum. The parentheses (involving ew and vw) stands for equal-weighted and value-weighted portfolios, respectively. The Fama French factors cover different geographic and demographic areas of which Sweden is a part, such as Sweden, Europe and developed markets.

		Sentiment$_{t-1}$	
		δ	$p(\delta)$
Sweden	SMB (ew)	-0.00	[0.84]
	SMB (vw)	-0.00	[0.76]
	HML (ew)	-0.00	[0.52]
	HML (vw)	-0.00	[0.97]
	MOM (ew)	-0.00	[0.37]
	MOM (vw)	-0.00	[0.80]
Europe	SMB	-0.16*	[0.10]
	HML	-0.25*	[0.07]
	MOM	-0.05	[0.80]
Developed	SMB	-0.20**	[0.04]
	HML	-0.26**	[0.04]
	MOM	-0.06	[0.74]

*** 0.01 ** 0.05 * 0.10

6. Conclusion

Existing research within behavioral finance conclude that investors' behavior has implications for the stock market. By composing an index as a proxy for sentiment, and by employing it in a bivariate portfolio sorts, I reveal that this is true even for the Swedish market. Inspired by the work of Baker and Wurgler (2006), I compose the sentiment index based on underlying proxies for sentiment using principal component analysis. The index follows ups and downs anecdotally thought of as bubbles, and bursts of bubbles, in the financial stock market. I then turn to a sample of stocks that represent the Swedish market. The stocks are sorted according to certain characteristics that are viewed as more speculative than others. The characteristics are features of firms that one would normally associate with being hard to value and hard to arbitrage, such as small, young and volatile firms, profitable firms, dividend-paying firms, firms with low values of tangible assets and firms with extreme growth opportunities and/or in distress. Stocks of these firms are hypothesized to be affected by sentiment swings to a greater extent than other stocks.

Portfolios are split into deciles, conditional on sentiment being positive or negative during the previous year-end. A pattern emerges when viewing the difference between the average return within each decile portfolio. My results clearly shows that the returns following periods of negative sentiment are higher than the returns following periods of positive sentiment, across nearly all cross-sections of returns. This means that, when times are bad, investors are less willing to invest in stocks that exhibit one or more of speculative-prone characteristics, than they would if times are good. As such, sentiment indeed has a large effect on stocks with these features. This is the most consisting pattern that I find across the conditional portfolio sorts.

Employing the sentiment index in various regressions, including both long-short portfolios and the Fama French factors of different geographic and demographic areas of which Sweden is a part, reveal that the results are (at least partially) significant. Specifically, when regressing SMB and HML factors against sentiment, results indicate that these exhibit a significant negative relationship with sentiment. The size and value effects are thus enlarged when times are bad and investors' become pessimistic.

The findings of this study is essential for Swedish investors, as it can assist in taking the right action when detecting anomalies in the proxies for sentiment. Observing deviations in these proxies can thus help an investor to better understand the behavior of the market and, more specifically, when and where sentiment will influence the most.

Limitations of my study mostly comprise certain facets that I could not include, whilst Baker and Wurgler (2006) could. For instance, I could not integrate a CEFD proxy in my sentiment index. Had this measure been available for the Swedish stock market, my composite index perhaps would have done an even better job in representing investors' sentiment. Neither could I carry out the same numerous amount of sorts, beyond the necessary ones, that Baker and Wurgler did in their analysis, due to the scope of my analysis. However, I do include some regressions that Baker and Wurgler do not. Lastly, I did not have the benefit to make use of pre-calculated proxies but rather had to construct them myself, which was time-consuming but more importantly leaves room for errors.

Suggestions for further research are, firstly, the inclusion of another explanatory proxy for sentiment into the composite index, perhaps something that resembles the way that closed-end fund discounts vary with investor sentiment. Secondly, one might want to look into other characteristics for conditional effects. Barber and Odean (2008) find evidence on their hypothesis that investors select stocks according to the amount of attention that the stock has gotten. They measure attention in terms of news announcements, abnormal trading volume and extreme one-day returns. Incorporating a variable resembling news announcements into the sorts would therefore be an interesting approach to extend the investigation of speculative characteristics.

7. References

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8. Appendix

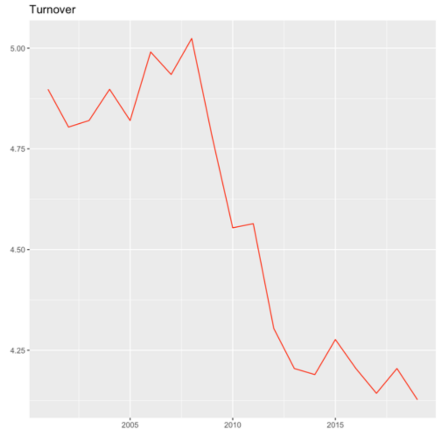
Table A1.

Descriptive statistics of returns and characteristics

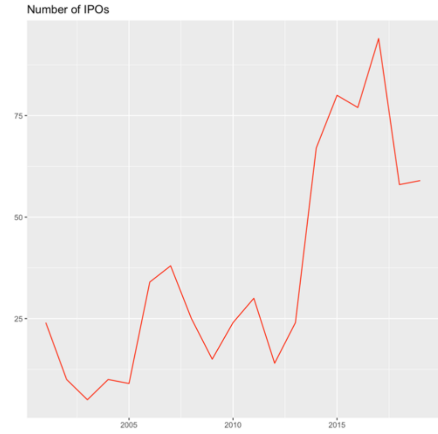
The table depicts the number of observations, the mean and the standard deviation as well as the minimum and maximum value of the monthly returns, the momentum variable and the characteristics of the firms. Parentheses next to each characteristic reveal what unit they are measured in (an exception being for log calculations).

	N	Mean	SD	Min	Max
R_t (%)	47632	1.13	12.53	-36.71	62.96
MOM_{t-1} (%)	47632	13.51	46.63	-133.39	208.04
ME_{t-1}	47632	21.44	2.25	16.29	26.94
Age_t (years)	47632	11.42	7.85	0.00	30.00
$Sigma_{t-1}$ (%)	47632	11.39	7.18	2.93	48.16
$+ROE_{t-1}$ (%)	47632	13.80	15.06	0.00	102.19
E > 0	47632	0.75	0.44	0.00	1.00
$D+/BE_{t-1}$	47632	6.23	8.61	0.00	61.76
D > 0	47632	1.00	0.05	0.00	1.00
PPE/A_{t-1} (%)	47632	38.41	35.11	0.05	156.74
RD/A_{t-1} (%)	47632	11.04	18.49	0.00	145.15
BE/ME_{t-1}	47632	0.97	0.04	0.82	1.11
EF/A_{t-1} (%)	47632	-2.45	92.34	-937.96	179.39
GS_{t-1}	47632	22.13	87.80	-81.80	896.02

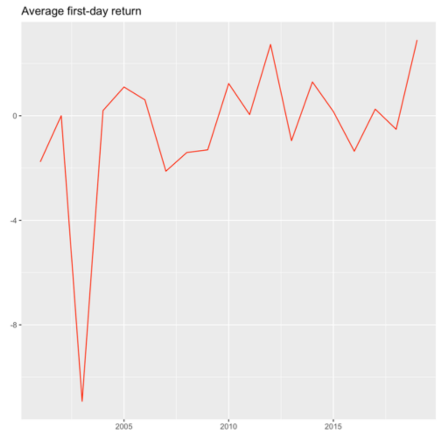
Panel A. TURN



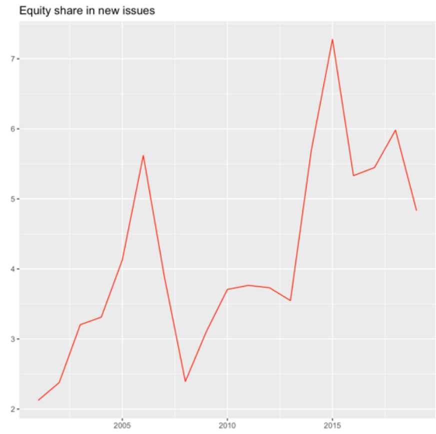
Panel B. NIPO



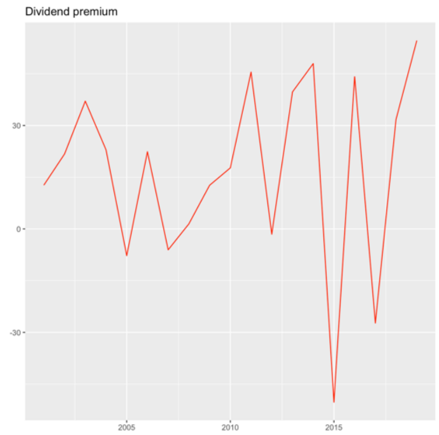
Panel C. RIPO



Panel D. S



Panel E. P^{D-ND}



Panel F. Sentiment

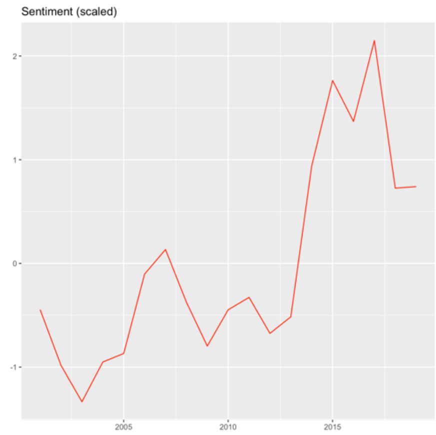


Figure A1.

Sentiment proxies and index

Graphs correspond to data for years 2001-2019. Panel A illustrates the turnover ratio, TURN. Panel B illustrates the number of IPOs, NIPO. Panel C illustrates the first-day return of IPOs, RIPO. Panel D illustrates the equity share in new issues, S. Panel E illustrates the dividend premium, P^{D-ND}. Panel F illustrates the composite sentiment index, Sentiment, scaled for zero mean and unit variance.

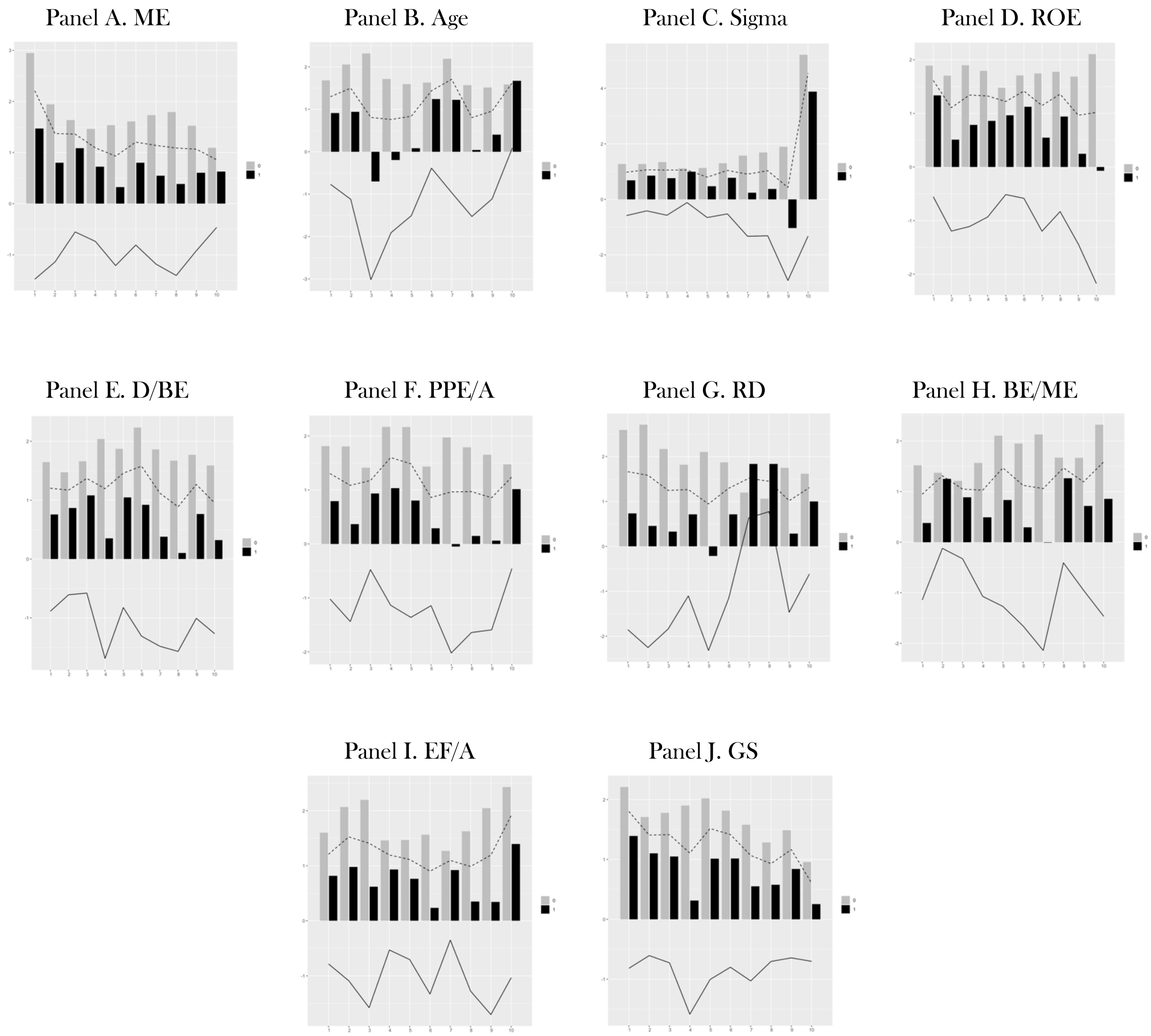


Figure A2.

Bivariate portfolio sorts

Graphs correspond to data for years 2001-2019 and display average returns of equal-weighted portfolios, conditional on deciles of characteristics and whether sentiment was positive (1) or negative (0) in the previous year-end. Decile 10 contains the value that is largest in magnitude, whereas decile 1 contains the value that is smallest in magnitude. Panel A illustrates the deciles of size (market equity, ME). Panel B illustrates the deciles of age. Panel C illustrates the deciles of volatility (sigma). Panel D illustrates the deciles of profitability (return on equity, ROE). Panel E illustrates the deciles of dividend policy (dividends through book equity, D/BE). Panels F-G illustrate asset tangibility (property, plant and equipment scaled, PPE/A, and research and development scaled, RD/A). Panels H-J illustrate growth opportunities and/or distress (book equity through market equity, BE/ME, retained earnings scaled, EF/A, and sales growth, GS). The dotted line represents the mean of each decile whilst the solid line represent the difference between the average means in the same decile when conditioning on sentiment.