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Can investor sentiment predict the European size premium?

An empirical investigation of regional size premium predictability

by

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Abstract

Research on the determinants of the size premium, i.e. that small stocks on average outperform large stocks, has traditionally focused on financial and macroeconomic factors. However, recent academic studies shed light on the influence of behavioral factors on the size premium, specifically investor sentiment. In line with this research, our study analyzes the influence of investor sentiment measures on the next periods' European size premium. To comprehensively capture the variation of the utilized sentiment measures, we further conduct a principal component analysis. Coinciding with behavioral models, we identify that the size premium rises following optimism and declines following pessimism among investors. Our analysis reveals that market-based sentiment measures such as the VSTOXX exhibit highest efficacy in predicting the European size premium, while survey-based measures exhibit low predicting power. The most effective results in predicting the size premium, we obtain through the implementation of a market-based principal component.

Keywords: Size Premium, Investor Sentiment, Return Predictability, Behavioral Finance

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1 Introduction

The efficient market hypothesis (EMH) posits that financial markets reflect all available information and future prices cannot be predicted from historical returns. However, empirical evidence in the form of market anomalies contradicts this theory. It suggests that there is some level of predictability of abnormal returns. Lee, Shleifer and Thaler (1991) discovered that the EMH could be partly rejected as closed-end funds, containing a certain non-changing basket of stocks, traded at a discount of 20% or more compared to the stocks individually. Several studies relate the closed-end fund discount to agency costs, tax liabilities, and illiquidity of assets (Lee et al., 1991). However, it did not even account for most of the fund discount. Eventually, Lee et al. (1991) showed that investor sentiment by noise traders, i.e. irrational investors, accounts for the largest part of closed-end fund discounts. They also assume that individual investor sentiment affects all stocks mostly held by individual investors, i.e., small stocks. Thus, next to their researched closed-end fund discount they had the conjecture that especially small stocks are influenced by investor sentiment. We aim to address their conjecture by examining whether the size premium is not only due to rational economic factors but also due to investor sentiment.

The size premium is one of the stock market's most popular and extensively scrutinized market anomalies. Fama and French (1992) illustrate that on average small cap stocks outperform large cap stocks. In academia, this effect is mostly attributed to financial fundamentals and macroeconomic factors, as investors who purchase small stocks are compensated for a range of risks, including systematic, idiosyncratic, liquidity, and default risk. But are there factors that explain the strong variation of the size premium over time? In classical financial theory, a potential predictor for the magnitude of the size premium has been ignored for a long time: Investor Psychology. Research suggests that retail investors hold a disproportionate share of small cap stocks (Nagel, 2005) and that these investors are more likely than institutional investors to change their portfolio allocation when their sentiment changes (Lee et al., 1991). Cliff and Brown (2004) mentioned that that mostly institutional sentiment drive returns in large cap stocks. With our study, we combine the two notions and examine the predictability of the size premium by investor sentiment.

The notion behind our research is that sentiment has an influence on the return of assets (Baker & Wurgler, 2006; Brown & Cliff, 2004). In our research, we specifically investigate if there is an effect that investors buy riskier stocks when their sentiment is positive, i.e. optimistic, and buy secure stocks when their sentiment is negative, i.e. pessimistic. The supposed structure behind this coincides with behavioral models which explain that a rise in sentiment leads to more risk tolerance, which in turn leads to investments in small stocks and vice versa (Nofsinger, 2005). If sentiment indeed has explanatory power for the size premium, combining significant sentiment measures with traditional economic models not only improves the models overall but also provides us with a more holistic view of how investor sentiment is related to stock market returns and which factors drive the size premium.

Qadan and Aharon (2019) were the first that demonstrate the explanatory power of investor sentiment in relation to the size premium for the US market. We extend their work and aim to explore whether a similar relationship exists in the European stock market. In our research, we use the size premium, combined with investor sentiment measures for Europe. However, a further advancement of our research is the investigation of the predictive power of cross-regional sentiment measures for the European size premium. Further, we classify the collected sentiment measures into two main categories: Market-based measures that rely on observable market data, such as the VSTOXX, and text-based measures, including surveys or newspaper-based indicators, such as the Consumer Confidence Index (CCI). Based on this categorization, we construct three principal components as potential predictors for the size premium. The first principal component is derived from the four market-based measures and the second principal component is based on the four text-based measures. Lastly, the third principal component incorporates all sentiment measures.

To validate our findings, we gradually introduce macro-financial variables, such as market returns or the consumer price index (CPI) as further independent variables in our regression analysis. This allows us to examine the stability of our results and the impact of these additional factors. Furthermore, for robustness purposes, we calculate the size premium based on the returns of country specific small and large indices for four different European countries and assess the predictability of their size premiums using the sentiment measures. The four countries are Germany, the UK, Sweden, and Switzerland.

Indeed, our study provides results that demonstrate the explanatory power of sentiment measures for the size premium in the European stock market. Especially the market-based measures seem to be strong predictors. By incorporating these measures into traditional financial models, we can enhance the size premiums' predictability and deepen our understanding of investor sentiment's impact on market behavior and stock returns. These findings have important implications for both, financial research, and practitioners, offering valuable insights for improving investment strategies to achieve higher returns in the European stock market.

We proceed as follows: The theoretical background section provides an overview of efficient markets, asset pricing, and anomalies. The literature review explores existing research on the size premium, behavioral finance, and investor sentiment. The methodology section explains our chosen measures and techniques. The results chapter presents the empirical results, including principal components and robustness tests. The conclusion summarizes our key findings on size premium predictability.

2 Theoretical Background

This chapter provides a background of financial theories in the context of this paper. We begin by exploring the basic financial theories, namely the efficient market hypothesis (EMH). Subsequently, we analyze the theory of anomalies, which builds the basis for the understanding of the size premium.

2.1 Efficient markets

Investors' rationality is assumed in many of the modern portfolio theories within finance. According to the theory, rational investors exploit arbitrage opportunities resulting from irrational trades that make prices deviate from a companies' fundamental value. The EMH assumes that all investors are rational and that stock prices reflect all publicly available information. This hypothesis was initially introduced by Fama (1970) and is considered one of the central theories in finance. According to the efficient market hypothesis, it is impossible to beat the market or make arbitrage returns on the long run. Since asset prices reflect all the available information, it is not possible to buy assets under or over their fair market value. Even if there arise misvaluations, arbitrageurs will exploit them immediately.

The market efficiency is categorized into three distinct forms, each predicated on the level of information available to investors. The first, known as weak-form efficiency, suggests that stock prices solely reflect historical prices, making technical analysis ineffective. The second form, semi-strong efficiency, contends that the market captures all publicly available information, whereby changes in prices reflect the new information, and makes fundamental analysis of little value. Finally, the third form, strong-form efficiency, posits that the market captures not only publicly available information but also private, insider information. The strong-form market efficiency implies that insider trading based on private information is not profitable as all available information is incorporated in the price. The academic consensus is that there exists either the weak or semi-strong form market efficiency as it is possible – though not legal – to make a profit based on insider trading (Finnerty, 1976). In the context of this paper, Fama's EMH implies that investors make investment decisions purely objectively and are not influenced by psychological factors. Any mispricing is quickly resolved by rational investors, as the market reflects the fair value of assets.

2.2 Asset Pricing Anomalies

Asset pricing anomalies appear to contradict the EMH. These anomalies suggest that there is some level of return predictability or patterns present in the stock market. They either indicate that the markets are inefficient or that the underlying asset-pricing model is incorrect (Schwert, 2002). Some of the most well-known and researched anomalies that challenge the EMH include the size premium (SMB), value premium (HML), and momentum (MOM).

Criticism of research on asset pricing anomalies, especially those that have already been uncovered, has been raised within the academic community. Schwert (2002) criticized that researchers are "data snooping". They either try to extend present academic research regarding anomalies by either using a larger historical data set or trying to identify international evidence. Sometimes it goes as far as when sufficient time after discovery has elapsed, the analysis of subsequent data gives a possibility of further – though mostly meaningless – academic research. It is argued by Lo and McKinlay (1990b) that by doing this kind of research, no additional and even misleading evidence is created.

While it could be shown that mispricing in combination with limits to arbitrage is the main reason why anomalies exist (McLean & Pontiff, 2013), there also have been claims that there might exist unmeasured risk. There has been developed a wide range of extensions of the CAPM to capture such risk. The most widely accepted models are the previously discussed FF3, FFC4, and FF5 factor models, whereby the FF3 model serves as the theoretical basis for our following research.

Asset pricing anomalies can be broadly categorized into two groups. The first and much larger group are cross-sectional anomalies. Cross-sectional anomalies propose that stocks with certain characteristics tend to outperform other stocks that lack those characteristics. Further categorization of cross-sectional anomalies can be achieved by dividing them into subgroups, including momentum and value anomalies. An example of a value anomaly is the size premium. Momentum anomalies on the other hand describe the phenomenon in which stocks that moved in a certain direction in the past tend to have a certain performance in the future. An example would be the momentum effect which is incorporated in the previously described Carhart-Four-Factor Model. It states that stocks that performed well in the previous twelve months will continue to do so in the following months. The second group, despite being significantly smaller, includes anomalies related to time series. Time series anomalies contend that stocks experience higher or lower returns on specific days or during certain periods of the year in contrast to the average of the year. The January effect, which is also explored in our paper, is an example of a time series anomaly, in which stocks tend to perform exceptionally well in January relative to other times throughout the year.

3 Literature Review

In this section, we analyze the literature of the size premium, which we aim to predict and approach its characteristics. After that, we introduce the variable with which we aim to predict size premium, namely investor sentiment.

3.1 Size Premium

The size premium, captured by Banz (1981) and Reinganum (1981), is one of the anomalies in the financial markets we discussed in 2.3. It suggests that a firm's market value can be a factor explaining stock returns. Banz's findings reveal that during the years 1936-75, smaller firms on the New York Stock Exchange (NYSE) had higher risk-adjusted returns than large firms. After the size premium was found, for a long time it was not clear why the size premium exists and even if the reason for higher risk-adjusted returns for small firms is attributable to size or if the real reason just correlates with size. After conducting additional studies on the size premium and its underlying causes, Amihud and Mendelson (1986) demonstrate that the size premium arises from a range of risks. Research reveals that smaller firms exhibit significantly higher levels of liquidity risk, financial distress risk, and business risk. Liquidity risk is particularly pronounced in smaller stocks due to their limited number of tradable shares, resulting in a lower trading volume. Consequently, during periods of high volatility, small stock investors face an increased risk of being unable to transact stocks at fair prices.

However, the size premium is not void of criticism. Keim (1983) found that the size premium mostly exists due to the returns in January. Next, to the finding that it is mostly present in January, it is weak, and almost insignificant historically (Asness, Frazzini, Israel, Moskowitz & Pedersen, 2018). In addition, despite the discovery of Chan et al. (1991) that the size premium exists beyond the US, it exhibits a weak presence internationally. Another commonly raised criticism is that the size premium is not observed in non-price-based metrics of size, such as total assets or the number of employees. Moreover, the size premium is frequently observed in micro stocks, displaying significant variability over time and exhibiting higher levels during economic recessions (Asness et al., 2018). However, our research does not revolve around proving or disproving the size premium, thus avoiding the criticism of "data snooping" for anomalies. Instead, we focus on examining potential drivers that could forecast the extent of the size premium in Europe.

Though research could prove that the size premium exists and that it is attributable to different risks associated with size, there is no consensus among researchers due to which factors the size premium differs substantially over time. Our hypothesis is that certain psychological aspects of investors drive or at least predict the variation of the size premium over time.

3.2 Psychological Aspects of Investing

The application of psychological aspects to financial decision-making is called behavioral finance. It emerged in the 1980s and focuses on the cognitive biases of individuals and their influence on market prices. In contrast to the assumptions of classical finance theories, which posit the validity of efficient markets, behavioral finance examines the psychological factors and biases that influence market participants' decisions and the resulting market prices. According to Barberis and Thaler (2002) the psychological aspect of finance attempts to identify deviations from rational investment behavior. Research has shown that individual biases can interfere with mispricing elimination and even drive mispricing. While rational investors aim to correct mispricing by trading stocks back to their fundamental price, irrational investors try to make an arbitrage by trading assets *to* mispricing (Coval & Shumway, 2005).

Literature in both, psychology and economics, highlights the fundamental importance of emotions in shaping attitudes toward risk and influencing financial decision-making. Certain emotional states can affect an individual's expectations about risk, which in turn can influence returns. Research shows that optimism about future outcomes can lead to an underestimation of the downsides associated with one's choices. Forgas (1995) and the affect infusion model (AIM) detect that the more optimistic an agent is about the market, the more likely he evaluates risky scenarios optimistically, leading to a greater willingness to take risks. The model illustrates how affect impacts an individual's ability to process information from a psychological perspective. In addition to emotions and biases in investment decisions can also arise from heuristics, self-deception, and social influence. In the subsequent sections, we will present an overview of prevalent psychological biases that can shape, enhance, or even amplify the mood of investors among individuals but also groups.

Overconfidence: Moore and Healy (2008) emphasize various aspects of the overconfidence bias. Firstly, individuals tend to overestimate their actual performance, ability, level of control, and chances of success. Secondly, people may place excessive confidence in their performance relative to others. Thirdly, there is a tendency for overprecision in one's beliefs. For example, when study participants were asked about the length of the Nile River and their level of confidence, those who expressed more than 90% confidence were correct less than 50% of the time. Additionally, Kruger and Dunning (1999) found that not only do people make poor decisions, but more importantly, they are often unaware of their own incompetence. The overconfidence bias has a stronger impact on male investment behavior, as observed by Barber and Odean (2001). The study reveals that overconfidence reduces the return for men by an average of 2.65%, compared to 1.72% for women. Our assumption is that when people are overconfident about their choices or notions about the economic and stock market development, this is consolidated in investors sentiment.

Loss aversion: Loss aversion, discovered by Kahneman and Tversky (1979), means that individuals prioritize avoiding potential losses over pursuing potential gains. Some investors may prefer stability, where their investments remain at a consistent value, over risking their capital and foregoing the possibility of profit (Godoi, Marcon, & daSilva, 2005). Shefrin and Statman (1985) found that investors sell their strong going stocks too early while they sell their bad going stocks too late.

Herding behavior: Bikhchandani, Hirshleifer, and Welch (1992) investigate the phenomenon of herding behavior and find that people tend to adopt the same opinions or behaviors without necessarily intending to punish those who disagree. Instead of making decisions based on their own reasoning, individuals tend to follow a larger group. Devenow and Welch (1996) related herding behavior to the stock market and found that there are broadly three reasons for herding behavior. First, there are payoff externalities such as bank runs. Payoff externalities are actions that can impact other investors' payoffs even though they do not directly participate in that action. Regarding bank runs, investors know when this happens, their payoff might be negatively influenced. Therefore, they will act according to the motto "Save yourself if you can". Second, principal-agent problems that show by means of investment decisions, first researched by Scharfstein and Stein (1990). When a few (investment) managers make a certain decision, not necessarily well-informed decision, other managers do not want to be uncovered to be of deficient competence and thus, follow their peers. The third explaining factor for herding behavior might be informational externalities researched by Bikhchandani et al. (1992). The notion is that investors gain information by investment decisions of other market participants which can lead to ignorance and thus, to trading against their own private information. The trading of other market participants can therefore lead to a purchase of stock even though the own information contradicts this decision. Therefore, we assume that herding behavior influences investor sentiment.

Availability: Also, first presented by Tversky and Kahnemann (1973) is the psychological concept of availability bias. The availability bias means that more recent and salient events distort the own perception about the probability of this event (Barberis & Thaler, 2002). Regarding the stock market, investors tend to overvalue the chances of events that recently happened and are more recallable such as a financial crisis, an economic upswing or financial fraud. Therefore, we assume that the availability bias can have an impact on investors' decisions and thus, returns.

Especially the biases mentioned, but also other biases (Lord, Ross and Lepper, 1979; Ariely. Loewenstein & Prelec, 2003) raise the question if rational investors and therefore efficient markets exist. While traditional finance theory assumes that rational investors follow an approach based solely on fundamentals, behavioral finance assumes that even the most rational investor is influenced by emotions and biases in his investment decisions. In our study we therefore assume that the EMH, at least in the form initially suggested, does not hold. Rather we believe that the mood of investors has an extensive influence on the stock market. Our hypothesis is that certain aggregated psychological effects among investors predict the size premium. The presented research on an individual's psychological influences on investment laid the basis for further research which resulted in a more top-down and aggregated approach towards investor psychology. The term for this is "investor sentiment" which we explain in the following section.

3.3 Investor Sentiment

Investor sentiment is a term that is used to refer to the overall attitude or feeling of investors regarding an asset, the market, or an investment strategy. However, according to classical financial theory, there is no "investor sentiment" as markets reflect solely fundamental values. While there is no doubt that individual sentiment, i.e., individual bullish and bearish investors exist, there is uncertainty about the influence of aggregated sentiment on stock prices. Kumar and Lee (2006) identify that there are two main arguments against the systematic role of sentiment in stock markets. First, detractors argue that individual investor sentiment does not collectively aggregate across individuals, i.e., there is no systematic directional investment behavior across large groups of individuals. However, Kumar and Lee (2006) find that stocks preferred by retail investors indeed show similar movement patterns refuting the assertion that there is no aggregating sentiment in the stock market.

Second, critiques say that even if such sentiment in the market exists, it is offset by rational investors. Those rational investors, i.e., arbitrageurs, immediately trade the stocks back to their fundamental value, leaving prices unaffected by sentiment and even driving irrational investors, i.e., noise traders, out of the market due to their inflicted losses. Regarding this critique, research could prove that there exists noise trader risk which limits rational investors from making arbitrage (DeLong et al., 1990; Shleifer and Vishny, 1997). They find that irrational investors sometimes move stocks even further away from their fundamental value, which makes it ineffective and even highly risky for arbitrageurs to exploit this opportunity. It can go as far as that the arbitrageurs are forced to liquidate their positions. The risk that arbitrageurs could inflict a loss, make them more cautious from the beginning, further exacerbating mispricing due to sentiment (Barberis & Thaler, 2002). Therefore, the arguments against the existence and influence of investor sentiment in the stock market could be rejected.

Baker and Wurgler (2006) suggest that there are two different approaches to capture investor sentiment. The first approach is the so-called “bottom-up” approach. In this approach the sentiment is formed by previously discussed psychology and biases such as overconfidence or availability to explain the magnitude of how investors over- or underreact to previous returns or changes in fundamentals. However, a common criticism is that bottom-up approaches are never uniquely true. The argument is that real investors and the actual market is more complicated than solely relying on a few psychological theories (Burghardt, 2010). Though these theories provide a solid understanding of *why* individual investors may act a certain way, they provide no aggregated explanation for stock market behavior, i.e., they fail to evaluate *how much* markets are influenced by these factors.

The other way, a more common way, to capture sentiment is called top-down. Top-down approaches rely on macroeconomic or other aggregated data. Even though they are also seen as imperfect, they are aggregated and therefore, preferred proxies. Examples of those measures are surveys, retail investor trades, mutual fund flows, volatility indices, trading volume, IPO first day returns, and IPO volumes. However, surveys assume that investors indeed trade based on their sentiment. Therefore, due to the potential gap between sentiment and actual trading decisions, economists are often sceptical regarding investor surveys and rather rely on other, more market related data as sentiment proxies (Baker & Wurgler, 2006). To evaluate if the scepticism is justified, we include an appropriate balance of market-based and survey-based sentiment measures in our study.

To connect investor sentiment with the size premium, Lee et al. (1991) were the first that found evidence that sentiment influences the return of small stocks. They show that when investors become optimistic, small stocks do particularly well. Furthermore, they show that when investors become pessimistic, small stocks do particularly badly. According to (Baker & Wurgler, 2002), the subjectivity of valuations could be the reason why small stocks held by individual investors are more vulnerable to shifts in investor sentiment. Small companies are barely covered by analysts which most retail investors usually rely on when evaluating a potential investment. It gives a certain range of possible true values for a company. Moreover, still unprofitable and young companies, which are mostly small companies lack an earnings history. The lack of historical earnings, profitability, and unlimited growth opportunities results in a wide spectrum of possible valuations. This in turn leads to arguing for extremely high or low valuations. When for example investor sentiment turns positive, the allegedly extremely underrated firms constitute an ideal opportunity for overconfident hunger for returns.

Our study picks up these findings and relates investor sentiment towards the return differences between small and large stocks, i.e., the size premium. More specifically, our hypothesis is that investors take higher risks when they are optimistic and less risk when they are pessimistic. In 3.1 we explained that the size premium is related to higher risks for smaller stocks compared to large stocks. Therefore, coinciding with the results of Lee et al. (1991), our notion is that small stocks are more sought after when the overall emotional state of investors is positive and less sought after when the emotional state is negative. We assume that large stocks constitute an appropriate solution for pessimistic investors because they contain less overall risk compared to small stocks. Therefore, we would have a two way effect: When investors turn from optimistic to pessimistic, not only small stocks would be devalued, but also large, though also probably devalued, are seen as a save-haven and more sought after by investors. Aggregating our hypotheses, the size premium, i.e., the return of small stocks over large stocks increases with positive sentiment and decreases with negative sentiment.

4 Empirical Methodology

In this chapter, we first present the data for the size premium and then the variables we have adopted to capture investor sentiment. We provide a detailed description of the data sources, the construction of the variables, and the econometric models used to test our hypotheses.

4.1 Data

In this section we present the data used in our analysis. We begin with the size premium and its construction for Europe, incorporating the countries employed for validation. Subsequently, we outline the market-based and text-based sentiment measures that we consider. Lastly, we introduce the macro-financial variables that we incorporate as independent variables in our regression for validation purposes. Table 7 in Appendix A shows a list of all the variables, their sources, and the periods.

I. Size premium

Initially identified by Benz (1981), the size premium was subsequently incorporated into Fama and French's three factor model. To construct the size premium, Fama and French utilized a methodology involving the subtraction of returns from small-cap stocks from the returns of large-cap stocks. Each year at the end of June, they select the smallest 10% of stocks and the largest 10% of stocks based on market capitalization. The size premium is then derived by subtracting the returns of the largest 10% of stocks from the returns of the smallest 10% of stocks. In addition to the size premium, Fama and French also integrate the value premium (high minus low) into their model, resulting in the calculation of six portfolios categorized by size and book-to-market value. Considering the six portfolios in their notation, the construction of the size premium is as follows:

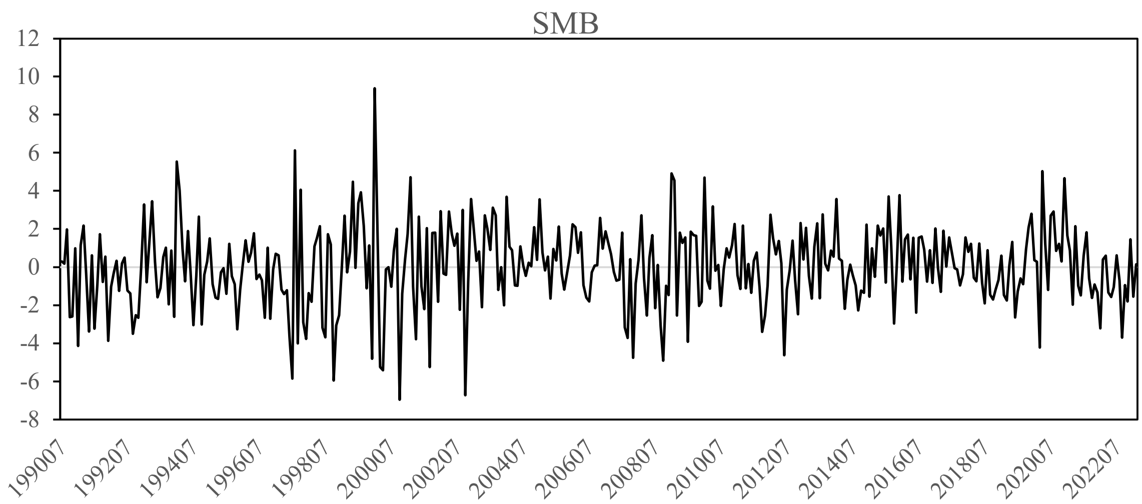
$$SMB = \frac{1}{3}(Small\,Value + Small\,Neutral + Small\,Growth)$$

$$-\frac{1}{3}(Big\,Value + Big\,Neutral + Big\,Growth)$$

When observing the Fama-French European size premium in Figure 1, several notable trends emerge. Between 2000 and 2001, the size premium exhibits predominantly negative values, reflecting the impact of the dotcom bubble burst. A similar pattern can be observed during the period from 2007 to 2008, coinciding with the financial crisis, as well as in 2022, reflecting the influence of the Russian war. Conversely, during the years following the dotcom bubble burst (2003-2006), we predominantly observe small yet positive size premia. Similarly, after the stock market decline caused by the onset of the Covid pandemic in March 2020, the subsequent year primarily displays positive size premia, indicating the stock market's recovery. In terms of volatility, distinct patterns become apparent. The periods including the dotcom bubble and its burst, the financial crisis and its subsequent recovery, as well as the stock market decline and rally following Covid, exhibit higher volatility in the size premium compared to other time periods.

Figure 1: Time Series of the European Size Premium

This figure shows the monthly European size premium (SMB) provided by Fama-French over time from July 1990 to February 2023. The numbers on the vertical axis are percentages.



To validate our analysis regarding the prediction of the size premium, we also construct our own European size premium. We construct the size premium by using the return of the MSCI European Small Cap Index which includes 984 stocks from 15 countries from the returns of the MSCI European Large Cap Index with 199 constituents (MSCI, 2023a; MSCI, 2023b).

For additional validation, we employ the size premium for four European countries, specifically Germany, the UK, Sweden, and Switzerland, based on the data of MSCI indices. Our objective is to investigate the extent to which investor sentiment is reflected in investment decisions in national stock markets. In other words, we aim to determine whether investors trade based on their sentiment or not. Our selection of these four countries is primarily driven by several factors, including a well-established regulatory environment, data availability, strong and stable economic conditions, and a diverse range of financial markets. In addition to these reasons, we choose Germany due to its status as the largest economy and most populous country within the European Union. The UK, which departed from the European Union in 2019, is the second most populous country in Europe and has a distinct industry focus. While Germany's industry focus lies in manufacturing and automotive sectors, the UK, with its financial hub in London, places greater emphasis on banking and insurance industries.

Subsequently, we opted for two smaller countries to have a balance between larger and smaller economies. Considering these contrasting sizes in our analysis is expected to enhance the robustness of our findings. In addition to the before mentioned reasons, we specifically select Sweden and Switzerland due to their notable emphasis on technology and innovation, diverse industry landscapes, and significant GDP figures of $61,000 and $92,000, respectively (World Bank, 2023). Notably, Switzerland's unique position outside the European Union adds an intriguing dimension to our analysis, further motivating our investigation into the disparities observed. We explain the construction of the size premia in detail in chapter 4.2. For all size premia that we collect, we use monthly data due to conformity with the data availability for the investor sentiment measures and macro financial variables.

II. Investor Sentiment Measures

Our interest lies in predicting the size premium using sentiment measures, encompassing both European and US investor sentiment indicators. The inclusion of US sentiment measures is of particular importance due to the nation's status as the world's largest economy and its active investment culture, which distinguishes it from many European countries. Furthermore, the presence of major international funds, including Fidelity or Blackrock with their headquarters located in the US, further reinforces the relevance of incorporating US sentiment data into our analysis. According to the World Investment Report of 2021, foreign direct investments (FDIs) in Europe constitute about 45% of total investments. The US share of FDIs in Europe is 32%, indicating a total share of 14,4% of the FDIs from the US. Consequently, relying solely on European sentiment measures may result in an imprecise prediction of the size premium. Hence, we also incorporate US sentiment measures to ensure a more comprehensive analysis. By including US sentiment measures, we anticipate achieving more accurate and robust outcomes for our analysis. As mentioned in 3.3, investor sentiment can be measured using different kinds of measures. This is why we include volatility indices, a yield-spread- and interest-based measure, IPO- and closed-end fund-based measures, a newspaper-based measure and survey-based measures. We broadly divide the sentiment measures into two categories. Market-based measures that rely on observable market data and text-based measures covering survey- and news-based measures. We select those measures due to their popularity among research as proxies for investor sentiment and due to data availability. For each of the following measures we obtained monthly data from the end of the month. In the following we provide an overview of the selected sentiment measures utilized in our analysis:

VSTOXX: The European volatility index measure is calculated based on real-time options prices of the Euro Stoxx 50, which is an index that includes the 50 largest companies in the Euro area in terms of market capitalization. Like the CBOE Volatility Index (VIX), the VSTOXX is computed by taking the square root of the implied variance across all options with a given time to expiration.

VIX: The CBOE volatility index (VIX), is the volatility index for the American stock market and the most popular volatility index worldwide. Like the VSTOXX, the VIX is based on option prices of the most important US stock index, the S&P500. The value of the VIX is reflecting the implied volatility of the option prices and indicates the following 30-day volatility.

Baker and Wurgler 1, 2: The Baker and Wurgler investors' sentiment is derived from five different metrics, which they use to construct the first principal component. These metrics include the value-weighted dividend premium, IPO first day returns, IPO volume, the closed-end fund discount, and share of equity issues of total issues (Ibbotson et al., 1994). Furthermore, only BW2 is orthogonal to six factors, such as the consumer price index, the recession indicator, and employment growth. Therefore they tend to differ slightly in value from BW1, although the two are highly correlated. Baker and Wurgler strongly advise against using changes in sentiment levels from one period to the next using their measures, suggesting only to take the absolute levels when making analysis. The reason is the way of construction which allows for no economic interpretation when taking the changes. Therefore, we follow their suggestion using the absolute values of sentiment for BW1 and BW2.

St. Louis Financial Stress Indicator: The St. Louis Financial Stress Indicator (STLFSI), is constructed using 18 different weekly data series provided by the Federal Reserve Bank of St. Louis. The data includes seven series of interest rates, six series of yield spreads and five others that captures financial stress in the market. Similar to the VIX and the Baker and Wurgler indices (BW1, BW2), this metric is reflecting the US market. Hence, we must be cautious when interpreting its implications. Additionally, since this metric can assume both positive and negative values, we need to consider absolute changes instead of percentage changes as seen in other measures that exclusively yield positive values.[1]

Economic Policy Uncertainty: The economic policy uncertainty index (EPU) was introduced by American professors' Baker, Bloom and Davis (2016). It is based on newspaper coverage frequency of a combination of words which include “uncertain” or “uncertainty” and “economic” or “economy”. The index covers all articles of ten of the leading newspapers in Europe. The newspapers reside in Germany, France, Spain, Italy and the UK.

Consumer Confidence Index: The Consumer Confidence Index (CCI) is a measure of people's expectations about current and future economic conditions based on a survey conducted by the OECD. The survey consists of five questions, two related to present economic conditions and three related to future economic conditions, such as expectations regarding total family income in six months. The CCI is gathered for various countries and regions, including the US and Europe. In our analysis, we specifically utilize the CCI data series for Europe.

Economic Sentiment Indicator: The Economic Sentiment Indicator (ESI) is like the CCI a survey-based sentiment measure that is specifically created and published for Europe. It is published monthly by the European Commission and includes confidence indicators of five different sectors with different weights (Eurostat, 2023). The sectors include Industrials (40%), Construction (5%), Services (30%), Consumers (20%), and Retail Trade (5%). The specific weights are because the indicator should represent the European economy.

ZEW Indicator of Economic Sentiment for Germany: The ZEW (Center for European Economic Research) economic sentiment indicator (ZEW) is derived from a monthly survey of 300 German experts from banks, insurance companies, and finance departments of selected companies. These experts evaluate and predict significant international financial market data. The ZEW indicator is widely regarded as one of the leading indicators for the German economy. We have chosen to incorporate this measure due to Germany's status as the most populous country in Europe and its position as the largest economy, making it a potential proxy

[1] We illustrate the reason with a simple example: Let us assume the STLFSI increases from 2 to 3 one period to the next. The calculation percentage wise would be: (3/2) -1 = 0.5. Coinciding with the notion that STLFSI rises when the sentiment is negative, we have a 50% increase in negative sentiment. Now, let us assume the sentiment changes from -2 to -3 one period to the next. The calculation percentage wise would be (-3/-2) -1 = 0.5. It is visible that we get the same result, even though the sentiment one time worsened and the other time improved. Therefore, we do not take the percentage changes for this measure but the absolute changes in value. To prohibit loss of information and changes in the values due to a change in the value range, we prefer taking the absolute changes over other methods such as min-max normalization.

for overall European sentiment. Similarly, to the STLFSI, this variable can assume both positive and negative values, which is why we consider absolute changes in its value rather than percentages.[1]

Principal Components: Expanding on the previously mentioned sentiment measures, we construct three principal components (PCs) that serve as additional sentiment measures in our analysis. The first principal component, "PC All," encompasses all available sentiment measures, except for BW2, due to its high correlation with BW1. The second principal component, "PC Market" incorporates the market-based sentiment measures VSTOXX, VIX, BW1 and STLFSI. Finally, the third principal component, "PC Textual," incorporates the text-based sentiment measures the Economic Policy Uncertainty Index (EPU), Economic Sentiment Indicator (ESI), Consumer Confidence Index (CCI), and the ZEW Indicator of Economic Sentiment for Germany (ZEW). For a more comprehensive understanding of the construction process of each principal component, please refer to Section 4.2.

III. Macro financial variables

We incorporate macro financial variables into our analysis considering previous research indicating their significant influence on the size premium. This approach aims to identify additional factors that might explain the size premium and potentially diminish the explanatory power of investor sentiment. The selected macro financial variables we use in our analysis are the value premium (HML) represented by the difference between high and low values, the momentum factor (MOM), the yield spread between Moody's Aaa and Baa-rated corporate bonds (DEF), the returns of the European market provided by Fama-French (MKT), and the Consumer Price Index (CPI) for Europe. By gradually introducing these variables into our model, we aim to gain robustness of our analysis and conduct further checks on the validity of our results.

4.2 Method

In this chapter, we present the construction process of the three principal components: PC All, PC Market, and PC Textual. Subsequently, we present the methodology employed for our analysis. Finally, we show the validation of our results through a series of robustness tests.

I. Principal Component

To enhance our study, we employ a principal component analysis (PCA). The PCA is used to reduce the dimensions of large data sets. It entails converting the original variables into an updated collection of principle components, which are uncorrelated variables where a large part of the contained variables' information is still available. When constructing a principal component, a small part of accuracy is traded for simplicity. By doing this, the number of variables can be significantly reduced. Currently, PCA is gaining a lot of attraction through machine learning. However, finance and economics are two of the many disciplines where PCA has been applied for decades.

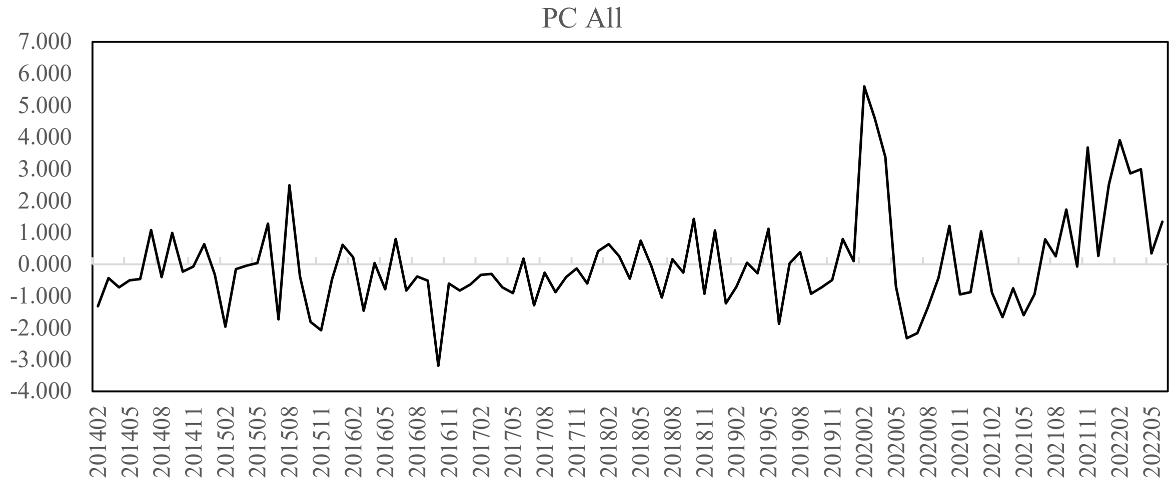
In our analysis, we have access to multiple sentiment measures that capture different aspects of market sentiment. Since these measures cover distinct dimensions of sentiment, it might be advantageous to consolidate this information into a single variable. To achieve this, we construct three principal components (PCs). The first principal component, labelled *PC All* incorporates all available sentiment measures except for BW2. We exclude BW2 due to its high correlation with BW1 and high similarity in terms of construction and information covered. The data set for the variables are standardized before constructing the principal component. The reason is that the variables are on different scales with vastly varying variances. Standardizing makes the changes in sentiment comparable. Thereby, we avoid that the principal component is not mainly influenced by the measure with the highest variance. The individual component weights for this sentiment measure and the time series of the absolute value for PC All can be found below.

$$PC\ All_t = 0.194\ \Delta EPU_t - 0.515\ \Delta CCI_t - 0.316\ \Delta ESI_t - 0.263\ \Delta ZEW_t$$

$$+ 0.450\ \Delta VSTOXX_t + 0.426\ \Delta VIX_t + 0.246\ BW1_t + 0.290\ \Delta STLFSI_t$$

Figure 2: Time Series of PC All

This figure shows the time series of the constructed first principal component based on the following sentiment measures: Economic Policy Uncertainty Index (EPU), Economic Sentiment Indicator (ESI), Consumer Confidence Index (CCI) and the ZEW Indicator of Economic Sentiment for Germany (ZEW), the VSTOXX, VIX, Baker & Wurgler 1 (BW1) and the St. Louis Financial Stress Indicator (STLFSI). The variables have been standardized before the construction due to varying scales. The PC Textual contains for the time span from February 2014 to June 2022, covering 101 months and covers 26.2% of the variance of the four measures. Values above zero suggest a negative sentiment and vice versa.



To gain further insights into which kind of measures perform well in predicting the size premium, we construct two additional principal components based on the categorization of market-based and text-based measures. The second PC, named *PC Market*, focuses exclusively on market-based sentiment measures while BW2 is again excluded. The measures used are VSTOXX, VIX, BW1, and STLFSI. Even though the BW1 and the St. Louis Financial Stress indicator themselves already contain several different data sets, they do not overlap. Therefore, each included measure in PC Market captures distinct aspects of investor sentiment. For the third principal component, namely *PC Textual*, we construct a principal component comprising survey-based and newspaper-based measures, which broadly represent text-based sentiment. The measures included are EPU, ESI, CCI, and ZEW. As before, standardization is applied. The time series of PC Market and PC Textual can be found from the figures 4 and 5 in the appendix. After constructing the PC Market and PC Textual, we obtain the following component weights:

$$PC\ Market_t = 0.673\ \Delta VSTOXX_t + 0.661\ \Delta VIX_t + 0.119\ BW1_t + 0.310\ \Delta STLFSI_t$$

$$PC\ Textual_t = 0.404\ \Delta EPU_t - 0.658\ \Delta CCI_t - 0.545\ \Delta ESI_t - 0.328\ \Delta ZEW_t$$

By constructing these three PCs, we aim to capture the most relevant information present in our sentiment measures, allowing for a comprehensive analysis of their impact on the size premium. Furthermore, we try to identify which kind of principal component performs best in predicting the size premium. Is it by containing all possible relevant information as in PC All, or does a principal component based on market- or text-based measures perform better. Further, we aim to evaluate their performance compared to the individual sentiment measures.

II. Size Premium

Besides the size premium directly provided by Fama-French, we construct our own size premium for Europe, Germany, the UK, Sweden and Switzerland to validate our results. To calculate these size premia, we utilize the European and country specific small and large cap MSCI indices available in Bloomberg Terminal. We opt for these indices because they incorporate the reinvestment of paid dividends into the index and do not account for taxes or other charges related to those dividends. Even though real-life returns might slightly differ due to those feed, these indices provide us with the clear theoretical index return not affected by any implementation costs. The correlation results of the size premia utilized in our analysis can be found in table 1 below. We obtain the returns for both the small cap and large cap index before we subtract the returns of the large cap index from the returns of the small cap index:

$$Return_{small,t} = \frac{Price_{small,t} - Price_{small,t-1}}{Price_{small,t-1}}$$

$$SMB_t = Return_{small,t} - Return_{big,t}$$

Table 1: Correlation of the size premia

This table shows the correlation of the size premia that we use in our study. The size premia we use are the Fama-French European size premium (FF SMB), the own-constructed European size premium (EU SMB), the German size premium (SMB GER), the UK size premium (SMB UK), the Swedish size premium (SMB SWE) and the Swiss size premium (SMB CH). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% significance level, respectively.

	FF SMB	SMB Europe	SMB GER	SMB UK	SMB SWE	SMB CH
FF SMB	1					
SMB Europe	0.619***	1				
SMB GER	0.513***	0.793***	1			
SMB UK	0.648***	0.587***	0.279***	1		
SMB SWE	0.316***	0.634***	0.493***	0.180***	1	
SMB CH	0.447***	0.769***	0.611***	0.398***	0.429***	1

III. Regression Analysis

In our analysis, we employ multiple regression to examine the relationship between sentiment and the size premium. The size premium is treated as dependent variable, while we include three independent variables: changes in investor sentiment from previous months, a January dummy variable, and the lagged value of the size premium. The complete regression model is presented as follows:

$$SMB_t = \alpha + \beta_1 Jan_t + \beta_2 \Delta S_{t-1} + \beta_3 SMB_{t-1} + u_t$$

S is the proxy for one individual investor sentiment measure, e.g. the VSTOXX, which means that we conduct this regression for every utilized sentiment measure. We calculate the changes in investor sentiment as follows:

$$\Delta S_{t-1} = \frac{S_{t-1} - S_{t-2}}{S_{t-2}}$$

As explained in chapter 4.1[1], due to their scale, for the STLFSI and ZEW we use the absolute changes which we calculate as follows:

$$\Delta S_{t-1} = S_{t-1} - S_{t-2}$$

Next, we add a dummy variable to capture the research findings that the size premium is mostly present in January. By doing this, we avoid that our results are distorted due, e.g., we obtain significant results that are mainly due to the January effect.

$$Jan_t = 1, if\ January$$
$$= 0, otherwise$$

To enhance the clarity of the effect of sentiment on the size premium, we account for potential autocorrelation in the size premium, as highlighted by Lo and MacKinlay (1990a; 1990c). Consequently, we introduce the lagged size premium as an additional independent variable in our analysis. By including this variable, we aim to control for any autocorrelation that may exist in the size premium.

After obtaining the results for the basic model, we incorporate additional macro-financial variables as independent variables to ensure the validity of our results. These variables are introduced to mitigate the possibility of specification errors resulting from omitted variables. By including these variables, we can observe the distinct impact of the sentiment measure on the size premium. To incorporate these variables into our model, we introduce a matrix notation (*X'*) that represents the additional variables. In terms of their order, we first add the value premium (HML), followed by the momentum factor (MOM), the Moody's yield spread (DEF), market returns (MKT), and changes in the consumer price index (CPI). The order is selected due to the data availability. Macro-financial variables for which we have longer time span of available data are thus added in the beginning. Table 8 in the appendix shows regression results of the robustness for each model when we add macro-financial variables. Subsequently, the regression equation takes the following form:

$$SMB_t = \alpha + \beta_1 \, Jan_t + \beta_2 \, \Delta S_{t-1} + \beta_3 \, SMB_{t-1} + \sum_{i=1}^{5} \beta_{4,i} \, X'_{t-1} + u_t$$

5 Results

In this chapter, we present our results classified in two sections. Firstly, we examine our empirical findings from the regression analysis. Subsequently, we show the validation results for the gradually added macro-financial variables and the country specific size premia.

5.1 Empirical Findings

Table 1 presents the descriptive statistics for the variables for the size premia, the macro-financial variables and measures of investor sentiment. Notably, the sentiment measures exhibit substantial variation in terms of their deviations and scales. For instance, the two Baker and Wurgler indices (BW1, BW2) are standardized to have a mean of zero and a standard deviation of one, whereas the EPU index shows a mean of 140.4 and a standard deviation of 75.6. To maintain the integrity of the sentiment measures, we have chosen not to apply min-max scaling or winsorization techniques to avoid introducing any potential bias.

Furthermore, the table highlights the disparities in data availability. While the CCI data covers a period of 111 months with 111 data points, the BW1 and BW2 indices have data for 684 months. This discrepancy in data availability is worth considering for the subsequent analysis.

Table 2: Descriptive Statistics

This table provides the mean, median, maximum value, minimum value, standard deviation, skewness, kurtosis and the number of observations for the different size premia (Fama-French (FF), Europe, Germany, UK, Sweden and Switzerland), for the macro-financial variables which are the market return (MKT), the Consumer Price Index (CPI), the Momentum factor (MOM), the spread between Moody's Aaa and Baa rated bonds (DEF) and for the sentiment measures VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW) and the Principal Component (PC)

Variable	Mean	Median	Max	Min	S.D.	Skew	Kurt	n
Mkt-Rf	0.490	0.760	16.620	-22.020	5.012	-0.504	1.466	392
SMB FF	0.048	0.140	8.830	-7.330	2.100	-0.034	1.036	392
SMB EU	0.212	0.226	10.856	-16.193	3.774	-0.215	0.731	338
SMB GER	-0.066	-0.027	17.307	-17.886	4.907	-0.176	1.347	338
SMB UK	0.259	0.168	10.384	-14.399	3.636	-0.547	1.671	338
SMB SWE	0.234	0.191	16.891	-15.278	5.517	0.085	0.397	338
SMB CH	0.342	0.566	17.882	-17.385	4.785	-0.088	0.829	338
HML	0.275	0.300	12.090	-11.300	2.625	0.376	3.655	392
CPI	91.170	91.935	121.240	70.400	12.567	0.062	-0.898	326
MOM	0.854	1.085	13.650	-26.090	3.930	-1.344	7.842	392
DEF	0.952	0.880	3.380	0.550	0.390	3.148	13.938	359
VSTOXX	23.861	22.250	61.340	11.986	8.623	1.441	2.663	292
VIX	19.710	17.915	59.890	9.510	7.734	1.657	4.094	376
BW1	0.000	-0.104	3.042	-2.361	1.000	0.419	0.602	684
BW2	0.000	-0.005	3.214	-2.487	1.000	0.158	0.888	684
ESI	99.604	100.400	117.700	58.700	10.047	-0.939	1.314	457
EPU	140.422	115.925	433.278	33.791	75.582	1.253	1.583	433
CCI	100.066	100.893	102.683	93.651	2.217	-1.389	1.123	111
STLFSI	-0.002	-0.214	7.408	-1.167	0.976	3.670	19.762	351
ZEW	21.339	19.600	89.600	-63.900	37.978	-0.243	-0.770	377
PC All	0.000	-0.306	5.605	-3.191	1.448	1.330	2.818	101
PC Market	0.000	-0.217	10.032	-3.301	1.395	2.181	11.283	281
PC Textual	0.000	-0.093	6.254	-3.687	1.358	1.867	8.329	108

Table 3 presents the correlation matrix for the sentiment variables. The results reveal significant correlations among most of the variables, indicating their ability to capture similar sentiment patterns. We can observe positive and negative correlations between the sentiment measures. These findings align with the notion that some sentiment measures tend to increase during periods of negative investor sentiment, while others tend to decrease.

Specifically, VSTOXX, VIX, BW1, BW2, STLFSI, and EPU are classified as contrarian indicators, as they typically increase during negative sentiment periods and decrease during positive sentiment periods. Conversely, the ESI, CCI, and ZEW are considered conformist sentiment measures, as they tend to decrease during negative sentiment periods and increase during positive sentiment periods. This pattern can be observed in figure 3 in the appendix, particularly during notable events such as the dotcom bubble, the financial crisis, the Ukrainian-Russian war, and subsequent inflation. While there are significant correlations, it does not provide any information regarding the predictive power for the size premiun.

From the correlation values, we can further see that all three principal components are positively correlated with those measures that increase during negative sentiment and vice versa. Therefore, our notion is that the principal components are also contrarian indicators, meaning that they rise when sentiment is low and vice versa. Coinciding with their inputs, PC All is significantly correlated with almost all other measures and PC market is almost exclusively significantly correlated with market-based measures. For the PC Textual, however, we see no clear relationship regarding correlation.

Table 3: Correlation of Investor Sentiment Measures

This table shows the correlation of the sentiment measures VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW) and the three prrincipal components (PC All, PC Market and PC Textual). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% siginificance level, respectively.

	VSTOX.	VIX	BW1	BW2	STLFSI	ESI	EPU	CCI	ZEW	PC All	PC Mkt	PC Text
VSTOX.	1											
VIX	0.89***	1										
BW1	-0.03	0.04	1									
BW2	-0.07	0.00	0.98***	1								
STLFSI	0.72***	0.79***	-0.09	-0.10*	1							
ESI	-0.47***	-0.18***	0.15***	0.13***	-0.43***	1						
EPU	0.14**	0.18***	-0.07	-0.10*	0.09*	-0.12**	1					
CCI	-0.48***	-0.55***	-0.35***	-0.43***	-0.20**	0.61***	-0.53***	1				
ZEW	-0.11	-0.12**	0.06	0.01	-0.34***	0.21***	-0.33***	0.20**	1			
PC All	0.58***	0.61***	0.36***	0.43***	0.41***	0.06	0.25	-0.24**	-0.20**	1		
PC Mkt	0.24***	0.26***	0.17***	0.17***	0.08	-0.01	-0.01	0.03	-0.02	0.63***	1	
PC Text	0.38***	0.34***	0.16	0.27***	0.48***	0.01	0.38***	-0.10	-0.41***	0.68***	0.04	1

Table 4 presents the results of our regression model, where we examined the relationship between the European size premium provided by Fama-French and several key variables. Specifically, we regressed the size premium on the previous month changes in investor sentiment, the January dummy variable, and the lagged value of the size premium. By this, we aim to assess the impact of these variables on the European size premium and gain insights into the factors influencing its variations. The coefficients and statistical significance of these variables provide valuable information on their individual contributions to the size premium and their predictive power in explaining its movements.

Table 4a-b: Regression Results monthly Data Fama-French European Size Premium

This tables shows the regression results where each sentiment measure is regressed individually on the size premium provided by Fama-French using the following formula: $SMB = \beta_0 + \beta_1 Jan_t + \beta_2 S_{t-1} + \beta_3 SMB_{t-1}$, where S_t denotes the sentiment measure, respectively: The applied sentiment measures are the VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% siginificance level, respectively. The standard errors of the in brackets below its respective factor loadings. Furthermore, we present the R^2 and the number of observations for every regression, respectively.

	ΔVSTOX.	**ΔVIX**	BW1	BW2	**ΔSTLFSI**	**ΔESI**	**ΔEPU**	**ΔCCI**	**ΔZEW**
Intercept	0.050	-0.091	-0.079	-0.066	-0.090	-0.142	-0.101	0.099	-0.117
	(0.124)	(0.113)	(0.114)	(0.117)	(0.118)	(0.112)	(0.113)	(0.173)	0.111)
Jan_t	1.725***	1.764***	1.625***	1.631***	1.521***	1.547	1.427***	-0.375	1.642***
	(0.428)	(0.390)	(0.388)	(0.389)	(0.409)	(3.657)	(0.387)	(0.619)	0.388)
$\mathbf{S_{t-1}}$	-2.045***	-1.459***	-0.368**	-0.334*	-0.423*	4.216	-0.770**	31.104	0.032***
	(0.548)	(0.489)	(0.162)	(0.170)	(0.216)	(0.384)	(0.358)	(38.233)	0.008)
SMB_{t-1}	0.015	0.029	-0.003	-0.001	0.006	0.004	0.003	0.040	-0.045
	(0.057)	(0.051)	(0.050)	(0.050)	(0.052)	(0.050)	(0.050)	(0.101)	0.052)
R^2	0.097	0.076	0.057	0.054	0.051	0.044	0.052	0.010	0.090
n	288	371	384	384	349	391	391	108	373

Table 4b: PC All, PC Market and PC Textual
This table shows the regression results where the three principal components are regressed individually on the size premium provided by Fama-French using the following formula: $SMB = \beta_0 + \beta_1 Jan_t + \beta_2 S_{t-1} + \beta_3 SMB_{t-1}$, where S_t denotes the sentiment measure, respectively. In the second table, the regression results for the three principal components (PC All, PC Market, PC Textual) are shown. "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% siginificance level, respectively. The standard errors of the in brackets below its respective factor loadings. Furthermore, we present the R2 and the number of observations for every regression, respectively.

	PC All	PC Market	PC Textual
Intercept	0.147	0.038	0.089
	(0.175)	(0.125)	(0.173)
Jan_t	-0.195	0.007***	-0.379
	(0.639)	(0.434)	(0.622)
S_{t-1}	-0.201*	-0.343***	-0.081
	(0.116)	(0.086)	(0.123)
SMB_{t-1}	0.023	1.828	0.038
	(0.103)	(0.057)	(0.101)
R^2	0.032	0.111	0.008
n	101	281	108

Firstly, our analysis reveals the presence of the January effect, which is consistently positive and statistically significant for all sentiment measures, except for the ESI and CCI. However, it should be noted that the CCI covers a relatively shorter time span, suggesting that the January effect may have already dissipated within this timeframe. Additionally, our results indicate the absence of significant correlations for the lagged value of the size premium, implying no autocorrelation. The absence of significant autocorrelation suggests that the size premium is not influenced by its own past performance and can be considered as an independent variable in our analysis.

Our analysis reveals that the VSTOXX, VIX, and ZEW index demonstrate the most significant results at a 1% significance level in predicting the size premium for the subsequent month. Moreover, the BW1 and EPU exhibit significance at a 5% level, while the STLSI and BW2 exhibit significance at a 10% level. Interestingly, same with the January effect, the CCI and ESI do not exhibit statistical significance in predicting the size premium. This is an initial indicator that neither ESI nor CCI are appropriate measures in predicting the size premium. Furthermore, by looking at which kind of measures are significant, we see that the market-based measures display stronger predictive power, as all of them show significance at a 10% level. Conversely, among the text-based measures, only two out of the four variables exhibit significance at a 10% level. Regarding our upcoming analysis of the principal components, this indicates a relatively weaker performance of PC Textual compared to PC Market.

Examining the results of the principal components, we uncover further significant findings. PC All demonstrates significance at a 10% level. Moreover, our assumption regarding the strength of market-based measures in forecasting the size premium is confirmed by the significant results of PC Market at a 1% level. Also coinciding with previous indications, PC Textual does not exhibit statistical significance. Notably, PC Market stands out with the highest R-squared value (0.111) among all the sentiment measures utilized in our study. This suggests that the models incorporating market-based sentiment measures explain a greater portion of the variation in the size premium. These findings reinforce our initial belief that combining different aspects of market-based sentiment measures leads to a robust predictor for the size premium.

Analyzing the factor loadings of the sentiment measures reveals noteworthy patterns. The contrarian indicators consistently exhibit negative loadings, while the conformist measures exert a positive influence on the size premium. This result aligns with our hypothesis that positive sentiment stimulates increased risk-taking in the form of small stocks, subsequently driving up the size premium, and vice versa. Among the significant measures, it is notable that the VSTOXX holds the highest impact on the size premium for the forthcoming months. Specifically, a one percent increase in the VSTOXX corresponds to a 2.045 percentage point decrease in the size premium. Our findings reveal that the European volatility index, VSTOXX, exhibits a slightly stronger predictive ability for the European size premium compared to its US counterpart, the VIX. This indicates that the VSTOXX effectively captures the unique dynamics and sentiment prevailing within the European market, offering valuable insights into the behavior of the European size premium. The outperformance of the VSTOXX emphasizes the significance of considering region-specific factors when conducting market analysis and forecasting. By recognizing the distinct characteristics of different markets, we can gain a more comprehensive understanding of their specific dynamics and enhance our ability to predict and interpret the size premium in Europe. However, even though the VSTOXX outperforms the VIX, the VIX still delivers good results in cross-regional predictions of the European Size premium.

Furthermore, when considering the geographic coverage of the sentiment measures, we observe that also the other US sentiment measures, including BW1, BW2, and STLFSI, exhibit significance in forecasting the European size premium. This reinforces our hypothesis that foreign market-based measures, such as those from the US, possess predictive power for the European size premium. Overall, these results support our notion that the size increases in periods of positive investor sentiment and declines in negative sentiment periods.

5.2 Robustness Tests

In this subsection, we test the robustness of our regression model in three steps. First, we include macro financial variables to account for broader economic factors. Next, we construct our own European size premium and provide results for its predictability. Lastly, we perform regressions using the size premia of different countries to assess consistency.

I. Macro Financial Variables

To evaluate the robustness of significance of the respective investor sentiment measures in explaining the size premium, we introduce multiple macro financial variables as additional independent variables in the regression. Following a thorough analysis of the influence of each added variable, our focus remains specifically on monitoring the evolving significance of the sentiment measures throughout the process. The results of these robustness tests can be found in Appendix E.

We observe that the HML factor from the previous month does not exert a significant influence on the subsequent size premium. Subsequently, we introduce the momentum factor into the regression analysis. Interestingly, we observe that this variable demonstrates significance in explaining the size premium for most of the sentiment measures and principal components and has negative factor loadings. However, it is important to note that the significance of the momentum factor diminishes when additional variables are included in the analysis.

In model 4, we incorporate the yield spread DEF into the regression analysis. Our findings reveal that DEF exhibits a predominantly positive, yet insignificant, influence on the size premium. Moving on to model 5, we introduce the market factor (MKT) into the regression. Interestingly, in both model 5 and model 6, the market return demonstrates a highly significant influence on the size premium across all sentiment measures. This aligns with prior research, confirming that market returns have a significant positive impact on the size premium. In model 6, we further include the consumer price index (CPI) as an independent variable. Notably, for most sentiment measures, the consumer price index displays a significant negative influence on the subsequent months' size premium.

Regarding the evolvement of the sentiment measures, we observe notable variations in the significance of the sentiment measures as different macro financial variables are incorporated into the regression. Table 5 provides insights into these changes. In the initial model (model 1), we find that nine out of the twelve sentiment measures exhibit at least a 10% significance level. This significance level remains relatively stable until the inclusion of the market variable in model 5. Here, we observe a considerable decrease in the number of significant sentiment measures, with only three measures retaining significance at the 10% level or below.

The STLFSI is the only measure that is significant in model 6, where all selected variables have been added to the regression. It suggests that this measure is relatively stable in explaining following months' size premium. The VSTOXX, ZEW and the PC Market are the measures with the highest explaining power, i.e., significant at a 1% level, until model 4. Because after the MKT variable is added to the regression, they turn insignificant. Like the variables previously mentioned, BW1 and BW2 are significant oat a 5% level in the first four models until the MKT variable is added to the regression. The EPU and PC All measures lose significance after the second model. The CCI has no significant explaining power throughout the models. It once again indicates that the CCI is not a useful sentiment measure in explaining the size premium.

Coinciding with the work from Qadan & Aharon (2019), including all macro-financial variables, especially the market return, we see an overall insignificant effect on the size premium. However, this does not necessarily reject our hypothesis that investor sentiment predicts the size premium. An explanation might be multicollinearity between the macro-financial variables that are added which can lead to a distorted effect of the independent variables on the dependent variable as seen in table 5.

Table 5: Correlation of Macro Financial Variables

This table shows the correlation between the macro-financial variables added to regression as further independent variables. Namely, we add the value premium (HML), the momentum factor (MOM), the spread between Moody's Aaa and Baa rated bonds (DEF), the market return (MKT) and the consumer price index (CPI). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% significance level, respectively.

	HML	MOM	DEF	MKT	CPI
HML	1				
MOM	-0.335***	1			
DEF	-0.077	-0.098*	1		
MKT	0.190***	-0.371***	-0.069	1	
CPI	-0.107*	-0.045	0.145***	-0.034	1

The robustness results reveal the predictive value not only of European sentiment measures but also of US sentiment measures and country-specific measures in forecasting the European size premium. Interestingly, among the European sentiment measures, ESI, EPU, and CCI exhibit the weakest overall performance, while the US measures STLFSI, VIX, BW1, and BW2 demonstrate relatively consistent predictive power for the European size premium. Notably, the European volatility index, VSTOXX, outperforms its US counterpart, suggesting that potential European counterparts for the STLFSI or BW sentiment measures could yield even stronger results.

In contrast, survey-based measures like ESI and CCI, as well as sentiment derived from specific newspapers (EPU), yield poor results. This once more suggests that market-based measures generally serve as better predictors for the size premium and investment behavior. An explanation might be the potential discrepancy between individuals' survey responses and their actual behavior. By acknowledging these complexities, we gain an improved understanding of the limitations of survey-based measures and their implications for predicting the size premium. However, not all survey-based measures yield poor results. Despite being an investor sentiment measure specific to Germany, the ZEW index demonstrates itself as a promising predictor for the European size premium.

Overall, our results underscore the importance of considering the types and regional source of sentiment measures in predicting the European size premium. Market-based measures, with their ability to capture sentiment dynamics, appear to offer overall more reliable insights into investment behavior compared to survey-based or news-derived measures.

II. Personally derived size premium

We validate the results by comparing a personally derived European size premium, calculated by subtracting the monthly returns of the MSCI European large cap fund from the returns of the MSCI European small cap fund. The strong correlation of 0.xx, significant at a level of xx, indicates a close relationship between the personally derived size premium and the Fama-French size premium (Table . While the coefficients of each sentiment variable are similar in direction (positive or negative), there are slight variations in their significance levels. Notably, measures such as the VIX and ZEW, which were significant at a 1% level with the Fama-French size premium, now demonstrate significance at a 10% level. Overall, though, these findings support the results obtained from the Fama-French size premium analysis.

Additionally, our study reinforces the notion that market-based sentiment measures play a crucial role in predicting the size premium. This is evident through the significant outcome of the market-based principal component (PC), which retains its 1% level of significance. These findings underscore the suitability of market-based measures in effectively predicting the size premium.

Table 6: Regression results of our European Size premium

This table shows the regression results where each sentiment measure is regressed individually on the European size premium that we constructed for validity provided using the following formula: $SMB = \beta_0 + \beta_1 Jan_t + \beta_2 S_{t-1} + \beta_3 SMB_{t-1}$, where St denotes the sentiment measure, respectively: The applied sentiment measures are the VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW) and the three principal component (PC All, PC Market and PC Textual). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% siginificance level, respectively. The standard errors of the in brackets under its respective factor loadings.

	ΔVSTOX.	ΔVIX	BW1	BW2	ΔSTLFSI	ΔESI	ΔEPU	ΔCCI	ΔZEW
Intercept	0.399*	0.203	0.232	0.259	0.182	0.166	0.216	0.032	0.186
	(0.234)	(0.216)	(0.219)	(0.222)	(0.202)	(0.216)	(0.218)	(0.350)	(0.214)
Jan_t	1.016	0.433	0.352	0.363	0.144	0.410	0.248	-0.479	0.258
	(0.810)	(0.746)	(0.757)	(0.758)	(0.704)	(0.749)	(0.755)	(1.237)	(0.746)
S_{t-1}	-2.846***	-1.713*	-0.570*	-0.559*	-2.461***	7.811	-1.225	119.287	0.038**
	(1.040)	(0.913)	(0.296)	(0.313)	(0.365)	(7.034)	(0.784)	(79.078)	(0.016)
SMB_{t-1}	0.077	0.091	0.091*	0.093*	0.109**	0.094*	0.097*	0.025	0.080
	(0.059)	(0.055)	(0.055)	(0.055)	(0.051)	(0.057)	(0.055)	(0.100)	(0.056)
R^2	0.043	0.024	0.023	0.021	0.133	0.017	0.021	0.025	0.031
n	288	336	329	329	336	335	336	108	336

	PC All	PC Market	PC Textual
Intercept	-0.005	0.376	-0.002
	(0.357)	(0.232)	(0.350)
Jan_t	-0.655	0.945	-0.525
	(1.291)	(0.814)	(1.243)
S_{t-1}	-0.258	-0.629***	-0.332
	(0.243)	(0.162)	(0.256)
SMB_{t-1}	-0.001	0.050	0.025
	(0.105)	(0.060)	(0.102)
R^2	0.015	0.066	0.019
n	101	281	108

III. Country specific Size premium

We exhibit the regression results using a country specific size premium for Germany, the UK, Sweden and Switzerland in table 9 (Appendix F). Overall, these results confirm our existing results that especially the market-based sentiment measures are good predictors for the size premium. Besides from Sweden, where only two sentiment measures are significant, in the other three countries the market-based sentiment measures produce stable and significant results. The measure STLFSI especially gives strong results regardless of the country, further suggesting that this measure is especially appropriate in predicting the size premium. For the text-based measures we get inconsistent results. While for some countries those measures are weakly significant, for others they are not at all. When comparing the PC Market and PC Textual we again observe those mentioned differences. While the PC Market is significant at a 1% significance level for all countries besides Germany, we see no significant influence of PC Textual or PC All on the size premium.

A possible explanation why for Sweden we do not get significant results might be that the utilized measures do not capture enough country specific sentiment. As Sweden makes up only 2.3% of the population of the European Union, European or US sentiment measures might not effectively capture the country specific sentiment. This country specific sentiment, however, due to a large domestic base of shareholders drives investing behavior the most. Therefore, although sentiment is assumed to correlate country wise, especially in closely related countries within the same region, the specific country sentiment might be hard to measure. A reason might be that country specific sentiment is influenced by local policy changes, local voting results, and many other. This in turn would mean that we cannot predict the country specific size premium unless we use country specific sentiment measures. Speaking of those country specific measures, we get significant results for the ZEW indicator for predicting the German size premium. This further supports our assumption that country specific sentiment predicts the country specific size premium.

6 Conclusion

The existing finance literature predominantly attributes the size premium to rational, macroeconomic factors, while mostly overlooking the potential influence of behavioral factors that drive investment decisions. Our study finds that the EMH does not account for the significant impact of behavioral factors on the size premium. Our initial hypothesis was that a rise in sentiment leads to higher risk taking in the form of small stocks and vice versa. Our findings mainly confirm this hypothesis and demonstrate that during optimistic periods, investors undervalue the risk associated with an investment and are more inclined to select smaller, riskier stocks, whereas during pessimistic periods, they tend to favor larger, safer stocks.

When considering which kind of measures are good predictors of this investor behavior, our findings highlight the superior performance of market-based measures. Especially, the previous months' changes in the VSTOXX, VIX and the St. Louis Financial Stress Indicator (STLFSI) are good predictors for the next months' European size premium. These results partly hold true using next to the Fama-French European, an own-constructed European size premium. Furthermore, our results remain the same introducing country specific size premia and partially hold true adding macro-financial variables as further explanatory variables. Notably, we identify that market-based measures are overall strong in predicting the next months' size premium while text-based measures such as the Consumer Confidence Index (CCI) or Economic Sentiment Indicator yield poor predicting power.

Regarding the principal component analysis, we observe that the PC Market, which is the first principal component of the VSTOXX, VIX, Baker and Wurgler 1 and the St. Louis Financial Stress indicator, is extremely capable in explaining the next months' size premium. This reflects our results on an individual sentiment measure level, where market-based sentiment measures outperformed text-based measures. The PC Market not only yields overall strongly significant results but also captures the highest portion of the variation in terms of R-squared observed in the following months' size premium compared to all other utilized measures. This makes it an invaluable tool for understanding the relationship between investor sentiment and the European size premium. However, PC Textual and PC All which also incorporate the poorly performing text-based measures yield insignificant results. Based on these compelling outcomes, we strongly recommend considering the PC Market as a primary measure in future research endeavors regarding the European size premium. The reasons are its robust predictive abilities and its exceptional explanatory power.

In summary, our study provides evidence that investor sentiment can effectively predict the European size premium. These findings have important implications for investors seeking to optimize their portfolios. Investors should go long small stocks and go short large stocks when the market-based investor sentiment is positive and vice versa if it is negative. Thus, practitioners can enhance their investment strategies and diversify their portfolios based on stock sizes. This approach holds the potential to generate higher returns by leveraging the insights derived from investor sentiment. Incorporating sentiment measures into portfolio construction and allocation can help capitalize on the predictive capabilities of sentiment measures regarding size related returns. Therefore, we recommend that investors and practitioners consider the measures of investor sentiment before making investment decisions.

However, it is important to acknowledge the limitations of our study. Firstly, we observe significant and consistent evidence of size premium predictability in the overall European market, but this predictability does extend to the most, though not to all individual countries e.g., Sweden. This discrepancy could be attributed to the construction of the size premium, or the selection of sentiment measures used in our analysis. Secondly, although our significant findings hold up in certain robustness tests, they do not fully pass all of them.

Our study unveils several intriguing avenues for further research. One important area is to identify the specific factors that drive investor sentiment. In addition to the discussed emotions of fear and greed, it is crucial to analyze the potential impact of other emotional states, including happiness, sadness, anger, or surprise. Another aspect worth exploring is the contribution of various factors to changes in sentiment. Analyzing the share of sentiment changes attributed to news articles, election results, policy changes, inflation rates, or stock price movements can provide a comprehensive understanding of the drivers of sentiment fluctuations.

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Appendix

Appendix A

Table 7: Data Collection

This table shows the sources and the covered period of the macro financial variables and the sentiment measures The macro-financial variables are the market return (MKT), the Consumer Price Index (CPI), the Momentum factor (MOM), the spread between Moody's Aaa and Baa rated bonds (DEF). The sentiment measures are the VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW).

Variable	Source	Period
MKT	Kenneth French Website	1990:07-2022:12
SMB	Bloomberg, Kenneth French Website	1990:07-2022:12
HML	Kenneth French Website	1990:07-2022:12
MOM	Kenneth French Website	1990:07-2022:12
CPI	https://fred.stlouisfed.org/series/EA19CPALTT01IXOBM	1990:01-2022:12
DEF	Bloomberg Terminal	1993:04-2023:02
VSTOXX	https://www.stoxx.com/data-index details?symbol=V2TX	2000:01-2022:12
VIX	Bloomberg Terminal	1992:02-2023:04
BW1, BW2	https://pages.stern.nyu.edu/~jwurgler/	1965:07-2022:06
EPU	https://www.policyuncertainty.com/europe_monthly.html	1987:01-2022:12
ESI	https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Economic_sentiment_indicator_(ESI)	1985:01-2022:12
STLFSI	https://fred.stlouisfed.org/series/STLFSI4	1994:12-2023:02
CCI	https://data.oecd.org/leadind/consumer-confidence-index-cci.htm	2014:01-2022:12
ZEW	https://www.zew.de/en/publications/zew-expertises-research-reports/research-reports/business-cycle/zew-financial-market-survey	1991:12-2023:04

Appendix B

Figure 3a-h: Investor Sentiment Time Series

This figure shows the time series of the absolute values of the following sentiment measures: VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Economic Sentiment Indicator (ESI), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW). The time horizons and the absolute values of the sentiment measures vary broadly.

Figure 4a: VSTOXX

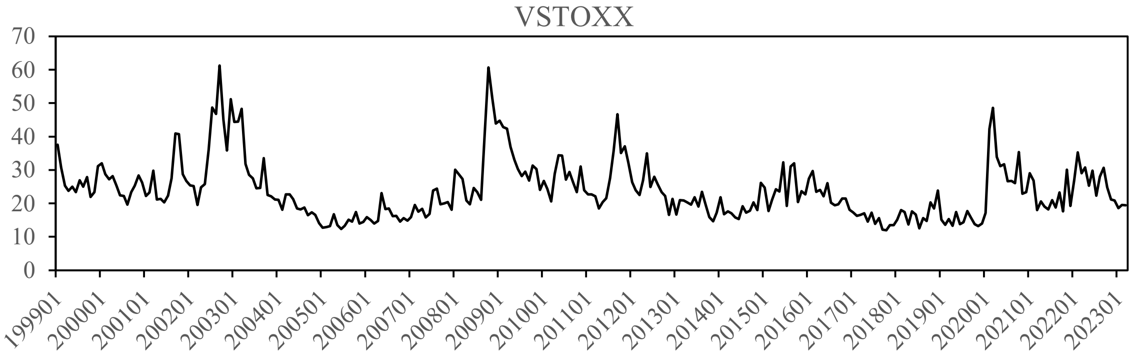


Figure 5b: VIX

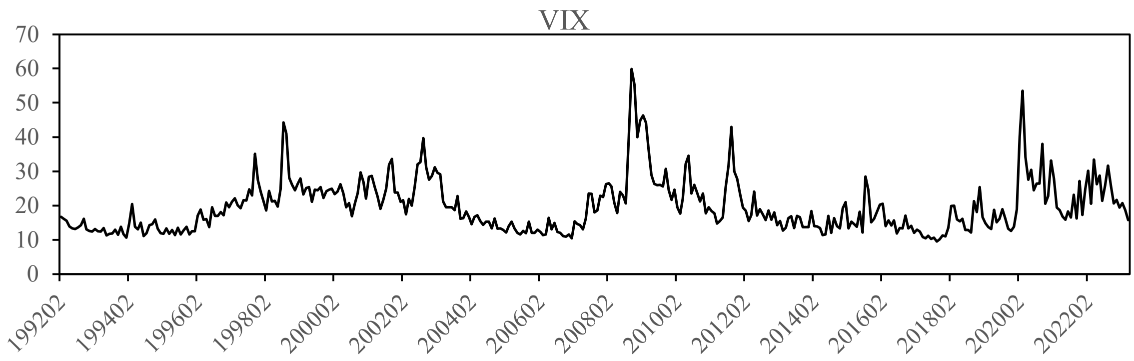


Figure 6c: BW1 & BW2

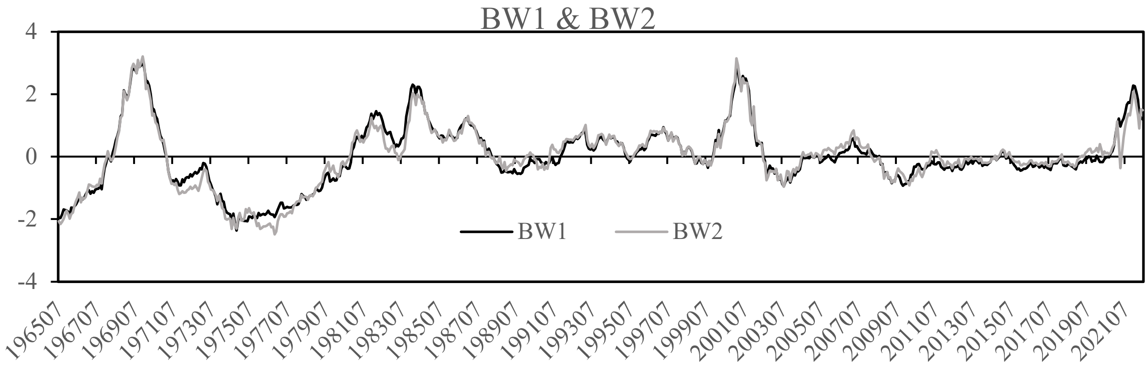


Figure 7d: EPU

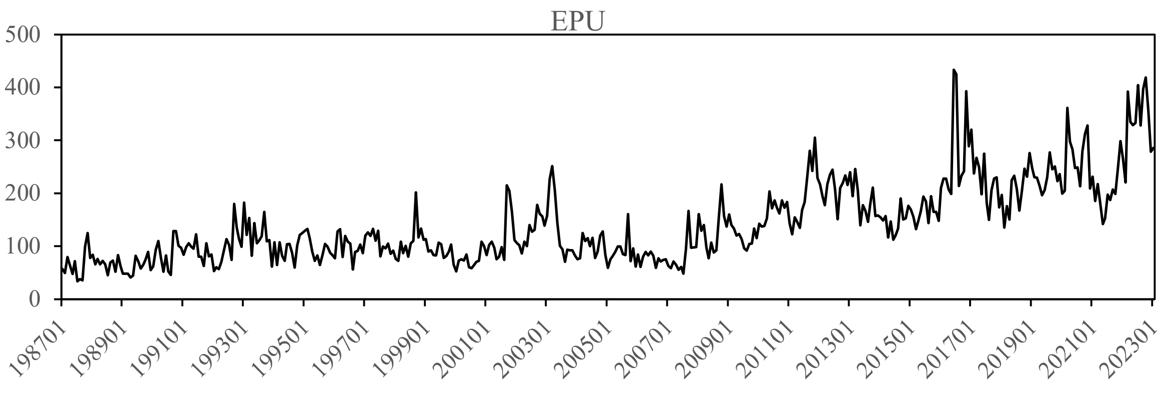


Figure 8e: ESI

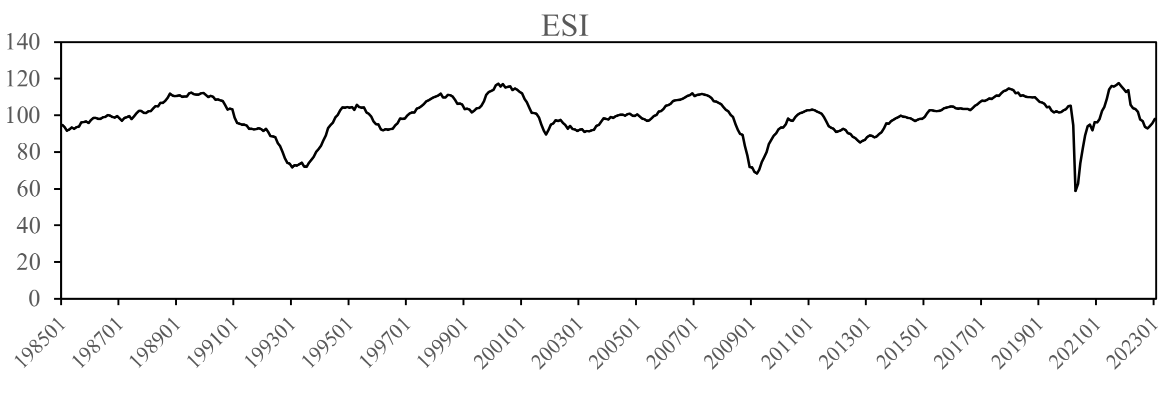


Figure 9f: CCI

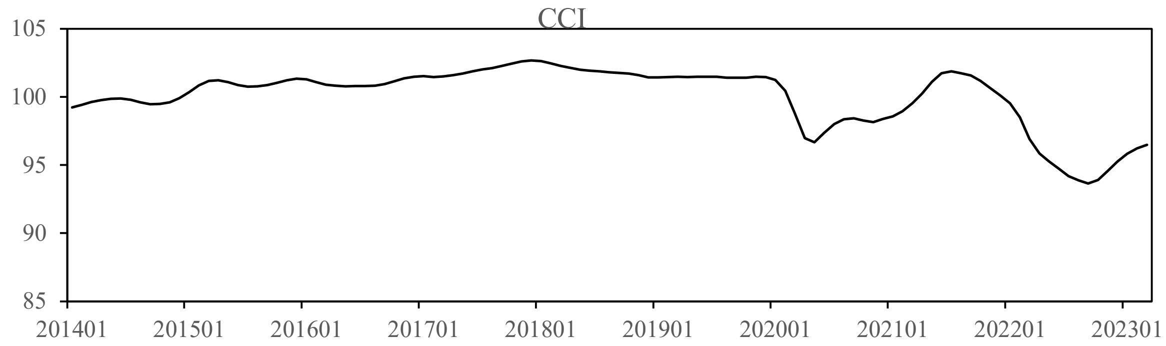


Figure 10g: STLFSI

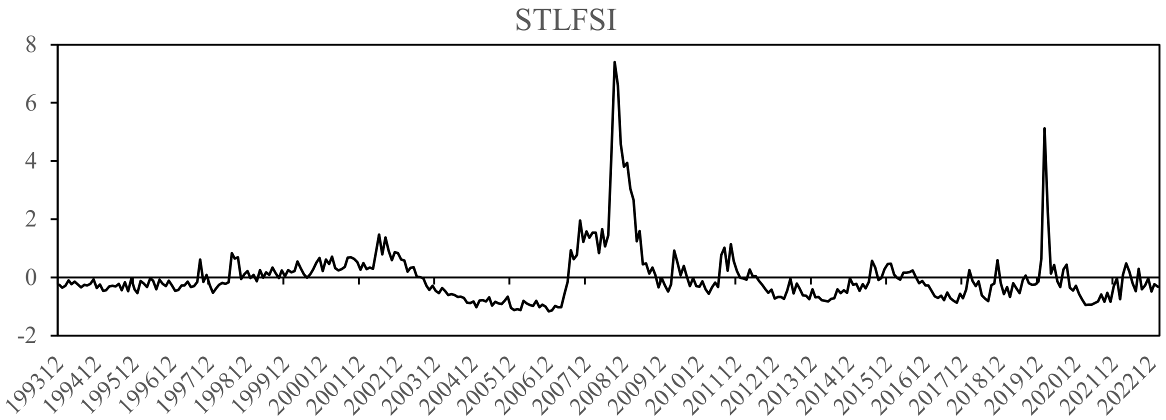
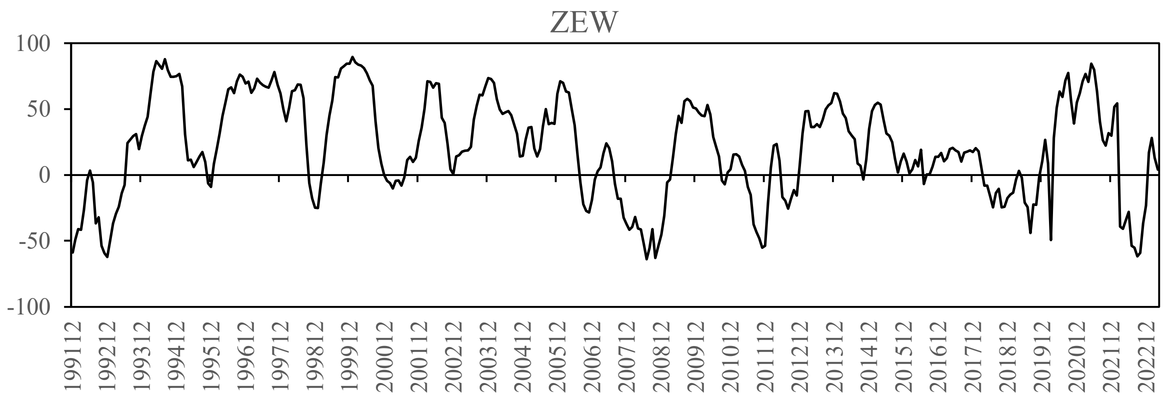


Figure 11h: ZEW



Appendix C

Figure 4: Time Series of PC Market

This figure shows the time series of the constructed first principal component based on the market sentiment measures VSTOXX, VIX, Baker & Wurgler 1 (BW1) and the St. Louis Financial Stress Indicator (STLFSI). The generation of the PC market results in the following formula: $PC\ Market_t = 0.673\ \Delta VSTOXX_1 + 0.661\ \Delta VIX_t + 0.119\ BW1_t + 0.310\ \Delta STLFSI_t$. The variables have been standardized before the construction due to varying scales. The PC Market contains for the time span from February 1999 to June 2022, covering 281 months and covers 48.7% of the variance of the four measures. Values above zero suggest a negative sentiment and vice versa.

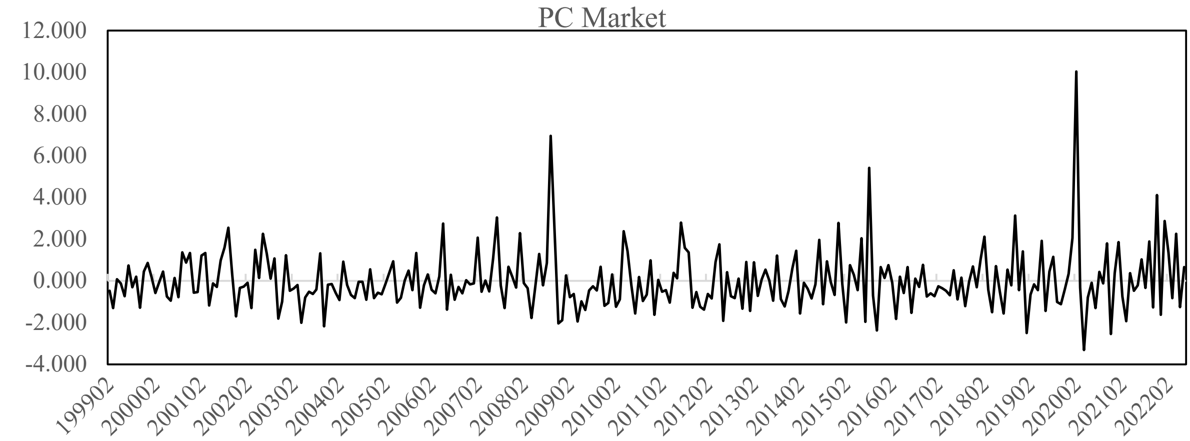
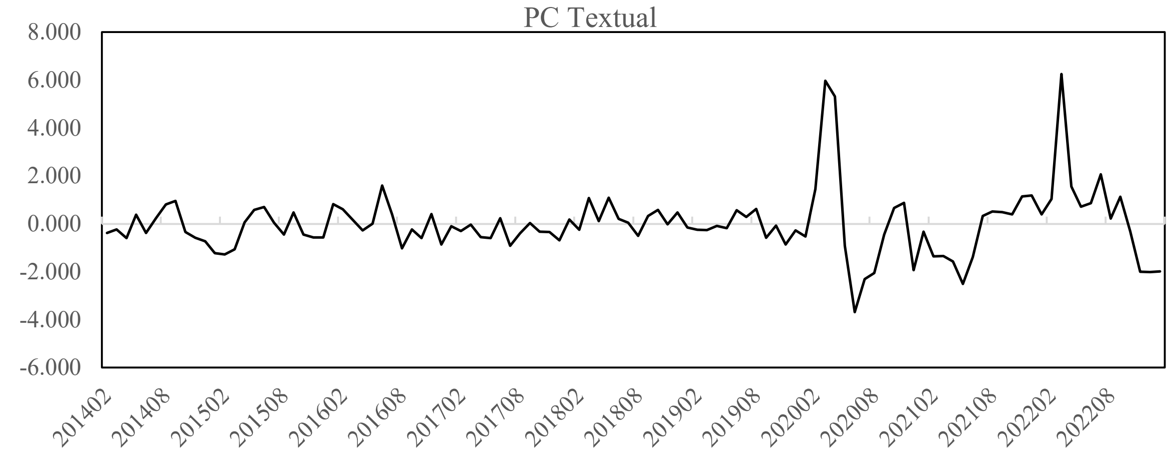


Figure 5: Time Series of PC Textual

This figure shows the time series of the constructed first principal component based on the following textual sentiment measures: Economic Policy Uncertainty Index (EPU), Economic Sentiment Indicator (ESI), Consumer Confidence Index (CCI) and the ZEW Indicator of Economic Sentiment for Germany (ZEW). The generation of the PC market results in the following formula: $PC\ Textual_t = 0.404\ \Delta EPU_t - 0.658\ \Delta ESI_t - 0.545\ \Delta CCI_t - 0.328\ \Delta ZEW_t$. The variables have been standardized before the construction due to varying scales. The PC Textual contains for the time span from February 2014 to January 2023, covering 108 months and covers 46.1% of the variance of the four measures. Values above zero suggest a negative sentiment and vice versa.



Appendix D

Table 8a-l: Predicting the Fama-French European Size premium adding macro-financial variables

This table shows the regression results of the robustness where for each model 2-6, one further independent macro-financial variable is added to regression. Model 1 is the basic regression: $SMB = \alpha + \beta_1\ Jan_t + \beta_2\ S_{t-1} + \beta_3\ SMB_{t-1}$. In model 2-6 one macro-financial variable is added as independent variable, respectively. In model 2, the variable high minus low (HML) is added, in model 3 the momentum factor (MOM), in model 4 the spread between Moody's Aaa and Baa rated bonds (DEF), in model 5 the return of the market (MKT) and in model six the change in the consumer price index (CPI). This robustness test is done for every sentiment measure respectively. We present the robustness tests for the sentiment measures in the following order: VSTOXX, VIX, Baker and Wurgler 1 (BW1), Baker and Wurgler 2 (BW2), Economic Policy Uncertainty index (EPU), Economic Sentiment Indicator (ESI), Consumer Confidence Index (CCI), St. Louis Financial Stress Indicator (STLFSI), ZEW Indicator of Economic Sentiment for Germany (ZEW). In the second table we provide the regression results for the principal components, respectively. The principal components are constructed in the following way: $PC\ All_t = 0.194\ \Delta EPU_t - 0.515\ \Delta CCI_t - 0.316\ \Delta ESI_t - 0.263\ \Delta ZEW_{t.} + 0.450\ \Delta VSTOXX_t + 0.426\ \Delta VIX_t + 0.246\ BW1_t + 0.290\ \Delta STLFSI_t$ $PC\ Market_t = 0.673\ \Delta VSTOXX_{t-1} + 0.661\ \Delta VIX_{t-1} + 0.119\ BW1_{t-1} + 0.310\ \Delta STLFSI_{t-1}$. $PC\ Textual_t = 0.404\ \Delta EPU_{t-1} - 0.658\ \Delta ESI_{t-1} - 0.545\ \Delta CCI_{t-1} - 0.328\ \Delta ZEW_{t-1}$. "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% significance level, respectively. The standard errors of the in brackets under its respective factor loadings. Furthermore, we present the R-squared and the number of observations (n) for every regression, respectively.

Table 8a: VSTOXX

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VSTOXX						
Intercept	0.050	0.043	0.085	-0.147	-0.383	-0.181
	(0.124)	(0.125)	(0.126)	(0.331)	(0.334)	(0.337)
Jan_t	1.725***	1.718***	1.796***	1.778***	1.512***	1.603***
	(0.428)	(0.429)	(0.428)	(0.429)	(0.430)	(0.425)
$\Delta VSTOXX_{t-1}$	-2.045***	-2.025***	-1.703***	-1.696***	-0.346	-0.373
	(0.548)	(0.550)	(0.570)	(0.570)	(0.697)	(0.687)
SMB_{t-1}	0.015	0.018	0.031	0.031	0.011	-0.006
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)
HML_{t-1}		0.022	-0.008	-0.004	-0.007	-0.005
		(0.041)	(0.043)	(0.044)	(0.043)	(0.042)
MOM_{t-1}			-0.061**	-0.058*	-0.022	-0.017
			(0.030)	(0.031)	(0.032)	(0.032)
DEF_{t-1}				0.224	0.373	0.291
				(0.297)	(0.296)	(0.293)
Mkt_{t-1}					0.100***	0.100***
					(0.031)	(0.030)
CPI_{t-1}						-0.738***
						(0.253)
Adj. R^2	0.087	0.085	0.095	0.094	0.124	0.147
n	288	288	288	288	288	288

Table 8b: VIX

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VIX						
Intercept	-0.091	-0.109	-0.066	-0.499*	-0.847***	-0.648*
	(0.113)	(0.114)	(0.116)	(0.299)	(0.302)	(0.333)
Jan_t	1.764***	1.750***	1.815***	1.706***	1.396***	1.366***
	(0.390)	(0.390)	(0.390)	(0.398)	(0.394)	(0.636)
ΔVIX_{t-1}	-1.459***	-1.433***	-1.286***	-1.214**	0.380	0.378
	(0.489)	(0.488)	(0.494)	(0.497)	(0.602)	(0.423)
SMB_{t-1}	0.029	0.037	0.041	0.026	0.024	0.003
	(0.051)	(0.051)	(0.051	(0.051)	(0.050)	(0.053)
HML_{t-1}		0.062	0.037	0.042	0.027	0.017
		(0.040)	(0.043)	(0.043)	(0.042)	(0.044)
MOM_{t-1}			-0.052*	-0.045	-0.001	0.001
			(0.029)	(0.030)	(0.031)	(0.032)
DEF_{t-1}				0.470	0.686**	0.603**
				(0.285)	(0.282)	(0.297)
Mkt_{t-1}					0.130***	0.124***
					(0.029)	(0.031)
CPI_{t-1}						-0.632**
						(0.265)
Adj. R^2	0.068	0.072	0.077	0.076	0.123	0.121
n	371	371	371	358	358	324

Table 8c: BW1

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
BW1						
Intercept	-0.079	-0.092	-0.050	-0.339	-0.672*	-0.500
	(0.114)	(0.113)	(0.116)	(0.318)	(0.317)	(0.343)
Jan_t	1.625***	1.612***	1.649***	1.809***	1.497***	1.487***
	(0.388)	(0.385)	(0.386)	(0.405)	(0.399)	(0.429)
$BW1_{t-1}$	-0.368**	-0.496***	-0.458***	-0.406**	-0.243	-0.208
	(0.162)	(0.166)	(0.169)	(0.180)	(0.179)	(0.185)
SMB_{t-1}	-0.003	0.007	0.011	0.003	0.021	0.002
	(0.050)	(0.050)	(0.050)	(0.052)	(0.050)	(0.054)
HML_{t-1}		0.121***	0.095**	0.086*	0.058	0.044
		(0.043)	(0.046)	(0.046)	(0.046)	(0.047)
MOM_{t-1}			-0.042	-0.039	0.004	0.005
			(0.030)	(0.030)	(0.031)	(0.032)
DEF_{t-1}				0.327	0.565*	0.496
				(0.302)	(0.298)	(0.311)
MKT_{t-1}					0.112***	0.108***
					(0.024)	(0.025)
CPI_{t-1}						-0.594**
						(0.276)
Adj. R^2	0.049	0.067	0.069	0.079	0.130	0.125
n	384	384	380	351	351	317

Table 8d: BW2

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
BW2						
Intercept	-0.066	-0.071	-0.028	-0.352	-0.707*	-0.521
	(0.117)	(0.116)	(0.118)	(0.323)	(0.323)	(0.348)
Jan_t	1.631***	1.620***	1.655***	1.818***	1.498***	1.491***
	(0.389)	(0.385)	(0.386)	(0.405)	(0.400)	(0.430)
$BW2_{t-1}$	-0.334*	-0.462***	-0.432**	-0.368*	-0.182	-0.160
	(0.170)	(0.175)	(0.178)	(0.191)	(0.190)	(0.196)
SMB_{t-1}	-0.001	0.008	0.012	0.004	0.023	0.004
	(0.050)	(0.050)	(0.050)	(0.052)	(0.051)	(0.054)
HML_{t-1}		0.116***	0.091**	0.082*	0.053	0.040
		(0.043)	(0.046)	(0.047)	(0.046)	(0.047)
MOM_{t-1}			-0.042	-0.040	0.004	0.005
			(0.030)	(0.030)	(0.031)	(0.032)
DEF_{t-1}				0.357	0.604**	0.526*
				(0.303)	(0.299)	(0.312)
MKT_{t-1}					0.114***	0.110***
					(0.024)	(0.025)
CPI_{t-1}						-0.615**
						(0.275)
Adj. R^2	0.046	0.062	0.066	0.075	0.128	0.124
n	384	384	380	351	351	317

Table 8e: ESI

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ESI						
Intercept	-0.142	-0.159	-0.097	-0.602**	-0.818***	-0.596*
	(0.112)	(0.112)	(0.115)	(0.305)	(0.299)	(0.329)
Jan_t	1.547***	1.537***	1.602***	1.737***	1.416***	1.390***
	(0.384)	(0.383)	(0.383)	(0.401)	(0.393)	(0.421)
ΔESI_{t-1}	4.216	3.598	3.262	3.734	0.822	-0.622
	(3.657)	(3.666)	(3.655)	(3.769)	(3.694)	(3.841)
SMB_{t-1}	0.004	0.012	0.018	0.009	0.026	0.006
	(0.050)	(0.050)	(0.050)	(0.052)	(0.050)	(0.053)
HML_{t-1}		0.069*	0.038	0.037	0.029	0.020
		(0.041)	(0.043)	(0.044)	(0.042)	(0.044)
MOM_{t-1}			-0.063*	-0.056*	-0.002	0.000
			(0.029)	(0.030)	(0.031)	(0.032)
DEF_{t-1}				0.552*	0.672**	0.568*
				(0.292)	(0.283)	(0.298)
Mkt_{t-1}					0.118***	0.114***
					(0.024)	(0.025)
CPI_{t-1}						-0.649**
						(0.266)
Adj. R^2	0.036	0.041	0.050	0.062	0.122	0.120
n	391	391	387	358	358	324

Table 8f: EPU

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
EPU						
Intercept	-0.101	-0.120	-0.076	-0.526	-0.797	-0.603
	(0.113)	(0.113)	(0.116)	(0.300)	(0.296)	(0.326)
Jan_t	1.427***	1.421***	1.513***	1.636***	1.389***	1.388***
	(0.387)	(0.386)	(0.388)	(0.407)	(0.398)	(0.426)
ΔEPU_{t-1}	-0.770**	-0.739**	-0.524	-0.585	-0.179	-0.015
	(0.358)	(0.357)	(0.383)	(0.413)	(0.408)	(0.452)
SMB_{t-1}	0.003	0.011	0.016	0.005	0.024	0.005
	(0.050)	(0.050)	(0.050)	(0.052)	(0.050)	(0.053)
HML_{t-1}		0.069	0.042	0.040	0.029	0.019
		(0.041)	(0.043)	(0.044)	(0.042)	(0.044)
MOM_{t-1}			-0.056*	-0.049	0.000	0.000
			(0.029)	(0.030)	(0.031)	(0.032)
DEF_{t-1}				0.500*	0.659**	0.576
				(0.286)	(0.279)	(0.294)
MKT_{t-1}					0.117***	0.113***
					(0.024)	(0.025)
CPI_{t-1}						-0.644**
						(0.266)
Adj. R^2	0.044	0.049	0.052	0.065	0.122	0.120
n	391	391	387	358	358	324

Table 8g: CCI

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CCI						
Intercept	0.099	0.088	0.133	-1.086	-1.075	-0.851
	(0.173)	(0.173)	(0.172)	(0.680)	(0.679)	(0.687)
Jan_t	-0.375	-0.323	-0.159	-0.216	-0.221	-0.192
	(0.619)	(0.622)	(0.616)	(0.610)	(0.609)	(0.604)
ΔCCI_{t-1}	31.104	35.900	27.555	37.531	21.732	-1.258
	(38.233)	(38.548)	(38.125)	(38.063)	(40.442)	(42.452)
SMB_{t-1}	0.040	0.022	0.021	0.002	-0.029	-0.048
	(0.101)	(0.103)	(0.101)	(0.101)	(0.104)	(0.104)
HML_{t-1}		-0.056	-0.130*	-0.106	-0.097	-0.079
		(0.057)	(0.066)	(0.066)	(0.067)	(0.067)
MOM_{t-1}			-0.126**	-0.122**	-0.080	-0.065
			(0.060)	(0.059)	(0.070)	(0.070)
DEF_{t-1}				1.340*	1.272*	1.108
				(0.724)	(0.725)	(0.726)
MKT_{t-1}					0.050	0.058
					(0.044)	(0.044)
CPI_{t-1}						-0.500
						(0.303)
Adj. R^2	-0.019	-0.019	0.014	0.037	0.040	0.056
n	108	108	108	108	108	108

Table 8h: STLFSI

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
STLFSI						
Intercept	-0.090	-0.107	-0.053	-0.445	-0.693**	-0.474
	(0.118)	(0.118)	(0.120)	(0.308)	(0.302)	(0.328)
Jan_t	1.521***	1.500***	1.580***	1.554***	1.247***	1.350***
	(0.409)	(0.408)	(0.408)	(0.408)	(0.400)	(0.419)
$\Delta STLFSI_{t-1}$	-0.423*	-0.461**	-0.436**	-0.378*	-0.391*	-0.455**
	(0.216)	(0.217)	(0.216)	(0.220)	(0.213)	(0.216)
SMB_{t-1}	0.006	0.015	0.023	0.021	0.035	0.005
	(0.052)	(0.052)	(0.052)	(0.052)	(0.050)	(0.053)
HML_{t-1}		0.067	0.036	0.042	0.033	0.028
		(0.042)	(0.044)	(0.044)	(0.043)	(0.044)
MOM_{t-1}			-0.062**	-0.057*	-0.003	0.002
			(0.029)	(0.030)	(0.031)	(0.031)
DEF_{t-1}				0.405	0.558*	0.450
				(0.293)	(0.286)	(0.298)
MKT_{t-1}					0.116***	0.114***
					(0.024)	(0.024)
CPI_{t-1}						-0.692***
						(0.264)
Adj. R^2	0.043	0.048	0.057	0.059	0.119	0.132
n	349	349	349	349	349	324

Table 8i: ZEW

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ZEW						
Intercept	-0.117	-0.130	-0.079	-0.420	-0.691**	-0.524
	(0.111)	(0.112)	(0.114)	(0.300)	(0.297)	(0.327)
Jan_t	1.642***	1.638***	1.712***	1.613***	1.342***	1.330***
	(0.388)	(0.388)	(0.388)	(0.398)	(0.391)	(0.421)
ZEW $_{t-1}$	0.032***	0.031***	0.030***	0.027***	0.021**	0.015
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
SMB_{t-1}	-0.045	-0.037	-0.028	-0.037	-0.012	-0.022
	(0.052)	(0.052)	(0.052)	(0.053)	(0.052)	(0.055)
HML_{t-1}		0.045	0.017	0.024	0.018	0.012
		(0.040)	(0.043)	(0.043)	(0.042)	(0.044)
MOM_{t-1}			-0.058**	-0.052*	-0.002	0.000
			(0.029)	(0.029)	(0.030)	(0.032)
DEF_{t-1}				0.376	0.555**	0.499*
				(0.286)	(0.281)	(0.297)
MKT_{t-1}					0.110***	0.106***
					(0.024)	(0.025)
CPI_{t-1}						-0.587**
						(0.266)
Adj. R^2	0.083	0.084	0.091	0.085	0.136	0.127
n	373	373	373	358	358	324

Table 8j: PC All

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PC All						
Intercept	0.147	0.138	0.175	-1.354*	-1.409**	-1.260*
	(0.175)	(0.176)	(0.178)	(0.689)	(0.692)	(0.700)
Jan_t	-0.195	-0.167	-0.090	-0.105	-0.130	-0.102
	(0.639)	(0.643)	(0.643)	(0.630)	(0.631)	(0.629)
PC All $_{t-1}$	-0.201*	-0.212*	-0.190	-0.180	-0.098	-0.048
	(0.116)	(0.117)	(0.118)	(0.116)	(0.147)	(0.152)
SMB_{t-1}	0.023	0.012	0.010	-0.024	-0.058	-0.072
	(0.103)	(0.105)	(0.105)	(0.103)	(0.110)	(0.110)
HML_{t-1}		-0.038	-0.101	-0.062	-0.059	-0.048
		(0.058)	(0.077)	(0.077)	(0.077)	(0.077)
MOM_{t-1}			-0.091	-0.085	-0.057	-0.047
			(0.072)	(0.070)	(0.077)	(0.077)
DEF_{t-1}				1.705**	1.734**	1.633**
				(0.743)	(0.745)	(0.747)
MKT_{t-1}					0.049	0.060
					(0.055)	(0.055)
CPI_{t-1}						-0.393
						(0.310)
Adj. R^2	0.002	-0.004	0.002	0.045	0.043	0.049
n	101	101	101	101	101	101

Table 8k: PC Market

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PC Market						
Intercept	0.038	0.025	0.069	-0.114	-0.352	-0.135
	(0.125)	(0.125)	(0.127)	(0.331)	(0.337)	(0.341)
Jan_t	1.828***	1.819***	1.885***	1.872***	1.620***	1.745***
	(0.434)	(0.434)	(0.434)	(0.436)	(0.438)	(0.434)
PC Market $_{t-1}$	-0.343***	-0.341***	-0.303***	-0.298***	-0.108	-0.125
	(0.086)	(0.086)	(0.088)	(0.088)	(0.109)	(0.107)
SMB_{t-1}	0.007	0.014	0.026	0.026	0.011	-0.003
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)
HML_{t-1}		0.042	0.012	0.016	0.006	0.006
		(0.041)	(0.044)	(0.045)	(0.044)	(0.044)
MOM_{t-1}			-0.054*	-0.052*	-0.019	-0.015
			(0.031)	(0.031)	(0.033)	(0.032)
DEF_{t-1}				0.178	0.363	0.265
				(0.297)	(0.300)	(0.298)
MKT_{t-1}					0.092***	0.090***
					(0.031)	(0.031)
CPI_{t-1}						-0.758***
						(0.261)
Adj. R^2	0.101	0.101	0.108	0.106	0.130	0.153
n	281	281	281	281	281	281

Table 8l: PC Textual

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PC Textual						
Intercept	0.089	0.077	0.125	-1.070	-1.065	-0.839
	(0.173)	(0.173)	(0.172)	(0.680)	(0.678)	(0.686)
Jan	-0.379	-0.331	-0.165	-0.221	-0.223	-0.185
	(0.622)	(0.623)	(0.618)	(0.612)	(0.610)	(0.605)
PC Textual $_{t-1}$	-0.081	-0.107	-0.084	-0.109	-0.059	0.019
	(0.123)	(0.126)	(0.124)	(0.123)	(0.130)	(0.137)
SMB_{t-1}	0.038	0.016	0.017	-0.003	-0.033	-0.047
	(0.101)	(0.104)	(0.102)	(0.101)	(0.104)	(0.103)
HML_{t-1}		-0.059	-0.133**	-0.110	-0.099	-0.078
		(0.058)	(0.066)	(0.067)	(0.067)	(0.068)
MOM_{t-1}			-0.127**	-0.124**	-0.079	-0.064
			(0.060)	(0.059)	(0.070)	(0.070)
DEF_{t-1}				1.310*	1.252*	1.096
				(0.722)	(0.722)	(0.721)
MKT_{t-1}					0.052	0.060*
					(0.044)	(0.043)
CPI_{t-1}						-0.511
						(0.305)
Adj. R^2	-0.021	-0.020	0.013	0.035	0.039	0.056
n	108	108	108	108	108	108

Appendix E

Table 9a-d: Regression Results for the Size Premium on a Country Level

These tables show the regression results using the size premia of four different countries that we constructed based on MSCI indices. We subtracted the monthly return of the respective large cap index from the return of the small cap index to obtain the size premium. Same as using the FF size premium, using the country specific size premium, the regression looks as follows: $SMB = \alpha + \beta_1 Jan_t + \beta_2 S_{t-1} + \beta_3 SMB_{t}$-1. Then, we provide the regression results for the three constructed principal components. PC All is based on all measures besides BW2. PC Market is based on the VSTOXX, VIX, Baker & Wurgler 1 (BW1) and the St. Louis Financial Stress indicator. PC Textual is based on the following four measures: Economic Sentiment Indicator (ESI), Economic Policy Uncertainty Index (EPU), Consumer Confidence Index (CCI) and the ZEW Indicator of Economic Sentiment for Germany (ZEW). "***", "**", and "*" denote statistical significance on the 1%, 5% and 10% significance level, respectively. The standard errors of the in brackets under its respective factor loadings. Furthermore, we present the R-squared and the number of observations (n) for every regression, respectively.

Table 9a: Germany

	ΔVSTOX.	ΔVIX	BW1	BW2	ΔSTLFSI	ΔESI	ΔEPU	ΔCCI	ΔZEW
GER									
Intercept	0.066	-0.186	-0.078	-0.021	-0.168	-0.179	-0.118	0.229	-0.155
	(0.289)	(0.282)	(0.285)	(0.289)	(0.275)	(0.281)	(0.283)	(0.403)	(0.278)
Jan_t	2.646***	1.572	1.461	1.481	1.385	1.558	1.351	0.610	1.339
	(1.001)	(0.973)	(0.986)	(0.985)	(0.956)	(0.974)	(0.982)	(1.412)	(0.970)
SMB_{t-1}	0.060	0.052	0.030	0.028	0.036	0.050	0.051	0.086	0.040
	(0.059)	(0.055)	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)	(0.099)	(0.054)
$\mathbf{S_{t-1}}$	-0.130	0.135	-0.832**	-0.932**	-1.806***	3.933	-1.428	51.584	0.047**
	(1.274)	(1.179)	(0.387)	(0.409)	(0.498)	(8.904)	(1.009)	(89.008)	(0.020)
R^2	0.029	0.011	0.023	0.025	0.049	0.012	0.017	0.015	0.027
n	288	336	329	329	336	335	336	108	336

	PC All	PC Market	PC Textual
GER			
Intercept	0.289	0.093	0.221
	(0.412)	(0.292)	(0.400)
Jan_t	0.311	2.568**	0.534
	(1.477)	(1.022)	(1.415)
$\mathbf{S_{t-1}}$	0.096	-0.200	-0.242
	(0.273)	(0.202)	(0.285)
SMB_{t-1}	0.056	0.046	0.082
	(0.102)	(0.060)	(0.099)
R^2	0.005	0.030	0.018
n	101	281	108

Table 9b: UK

	ΔVSTOX.	ΔVIX	BW1	BW2	ΔSTLFSI	ΔESI	ΔEPU	ΔCCI	ΔZEW
UK									
Intercept	0.461**	0.253	0.304	0.327	0.202	0.195	0.240	0.209	0.219
	(0.224)	(0.208)	(0.212)	(0.216)	(0.202)	(0.209)	(0.212)	(0.364)	(0.208)
Jan_t	1.123	0.878	0.763	0.778	0.693	0.871	0.738	-1.239	0.714
	(0.769)	(0.713)	(0.729)	(0.731)	(0.698)	(0.722)	(0.730)	(1.261)	(0.721)
$\mathbf{S_{t-1}}$	-3.912***	-2.444***	-0.684**	-0.617**	-1.791***	6.700	-1.022	183.602**	0.035**
	(0.990)	(0.871)	(0.287)	(0.304)	(0.363)	(6.842)	(0.778)	(82.685)	(0.015)
SMB_{t-1}	-0.043	0.003	0.007	0.010	0.033	0.007	0.003	-0.141	-0.013
	(0.058)	(0.055)	(0.056)	(0.056)	(0.053)	(0.057)	(0.057)	(0.098)	(0.057)
R^2	0.059	0.028	0.021	0.017	0.073	0.008	0.010	0.060	0.020
n	288	336	329	329	336	335	336	108	336

	PC All	PC Market	PC Textual
UK			
Intercept	0.246	0.444**	0.148
	(0.372)	(0.224)	(0.368)
Jan_t	-1.585	0.956	-1.226
	(1.329)	(0.777)	(1.286)
$\mathbf{S_{t-1}}$	-0.588**	-0.725***	-0.353
	(0.255)	(0.154)	(0.270)
SMB_{t-1}	-0.144	-0.045	-0.122
	(0.102)	(0.058)	(0.100)
R^2	0.075	0.079	0.031
n	101	281	108

Table 9c: Sweden

	ΔVSTOX.	ΔVIX	BW1	BW2	ΔSTLFSI	ΔESI	ΔEPU	ΔCCI	ΔZEW
SWE									
Intercept	0.613*	0.406	0.417	0.402	0.383	0.361	0.403	0.343	0.382
	(0.351)	(0.316)	(0.322)	(0.327)	(0.306)	(0.316)	(0.319)	(0.487)	(0.315)
Jan_t	-1.626	-1.747	-1.879*	-1.876*	-2.061*	-1.768	-1.904*	-3.095*	-1.933*
	(1.221)	(1.098)	(1.122)	(1.122)	(1.072)	(1.101)	(1.114)	(1.721)	(1.103)
$\mathbf{S_{t-1}}$	-3.754**	-1.856	-0.139	0.004	-2.461***	12.353	-0.936	108.458	0.034
	(0.059)	(1.329)	(0.434)	(0.459)	(0.554)	(10.109)	(1.138)	(108.135)	(0.022)
SMB_{t-1}	0.047	0.063	0.067	0.067	0.083	0.060	0.073	-0.041	0.071
	(0.059)	(0.055)	(0.056)	(0.056)	(0.053)	(0.056)	(0.055)	(0.098)	(0.055)
R^2	0.028	0.017	0.012	0.012	0.067	0.016	0.013	0.041	0.018
n	288	336	329	329	336	335	336	108	336

	PC All	PC Market	PC Textual
SWE			
Intercept	0.433	0.606*	0.312
	(0.497)	(0.353)	(0.486)
Jan_t	-3.486*	-1.784	-3.135*
	(1.807)	(1.243)	(1.729)
$\mathbf{S_{t-1}}$	-0.111	-0.698***	-0.291
	(0.337)	(0.243)	(0.347)
SMB_{t-1}	-0.066	0.034	-0.040
	(0.103)	(0.060)	(0.099)
R^2	0.048	0.037	0.039
n	101	281	108

Table 9d: Switzerland

	ΔVSTOX.	ΔVIX	BW1	BW2	ΔSTLFSI	ΔESI	ΔEPU	ΔCCI	ΔZEW
CH									
Intercept	0.581**	0.342	0.341	0.391	0.297	0.276	0.349	0.142	0.314
	(0.292)	(0.274)	(0.279)	(0.283)	(0.263)	(0.274)	(0.278)	(0.388)	(0.272)
Jan_t	1.311	0.613	0.531	0.550	0.272	0.589	0.360	2.347	0.350
	(1.015)	(0.951)	(0.970)	(0.970)	(0.921)	(0.956)	(0.966)	(1.353)	(0.950)
$\mathbf{S_{t-1}}$	-3.441***	-2.646**	-0.767**	-0.845**	-2.585***	15.554*	-1.604	166.671*	0.057***
	(1.287)	(1.157)	(0.378)	(0.400)	(0.475)	(8.872)	(0.993)	(88.359)	(0.020)
SMB_{t-1}	0.026	0.020	0.021	0.020	0.052	0.017	0.031	0.042	0.012
	(0.059)	(0.055)	(0.056)	(0.056)	(0.053)	(0.057)	(0.055)	(0.098)	(0.055)
R^2	0.033	0.019	0.015	0.016	0.085	0.012	0.011	0.075	0.028
n	288	336	329	329	336	335	336	108	336

	PC All	PC Market	PC Textual
CH			
Intercept	-0.007	0.514*	0.093
	(0.398)	(0.291)	(0.388)
Jan_t	2.579*	1.254	2.273*
	(1.424)	(1.026)	(1.363)
$\mathbf{S_{t-1}}$	-0.345	-0.731***	-0.457
	(0.271)	(0.202)	(0.285)
SMB_{t-1}	0.030	0.005	0.048
	(0.103)	(0.060)	(0.099)
R^2	0.053	0.052	0.067
n	101	281	108