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News sentiment indicators and the cross-section of stock returns in the European stock market

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ABSTRACT

This paper investigates whether the Bloomberg investor sentiment index can provide valuable information for investors and fund managers for the purposes of stock picking and portfolio selection. The dataset consists of all the listed companies in the Euro area for the period from 2010 to 2021. By exploiting portfolio sorting strategies, the paper evaluates to what extent and for how long investor sentiment can affect stock returns. Moreover, it considers whether additional factors can affect the relationship between sentiment and returns, casting light on the asymmetric effect related to positive and negative news.

The findings are as follows. First, high (low) sentiment stocks exhibit high (low) returns on average. Second, the predictability of stock returns holds for at least three months. Third, the market is less efficient in relation to small capitalization stocks compared to big ones. Fourth, positive news is factored into the stock price more slowly than negative news. Finally, sentiment is a priced factor in the cross-section of stock returns.

1. Introduction

Investor sentiment can be defined as expectations about future cash flow and investment risks that are not justified by the facts at hand, or as the propensity to speculate, or overall optimism or pessimism about a given asset (Baker and Wurgler, 2006, 2007). Sentiment interrelates with the investors' emotions, whether optimism or pessimism, and can influence financial decisions with implications for asset prices (Benhabib et al., 2016; Piccione & Spiegler, 2014). The role of investor sentiment in explaining stock returns is attracting increasing attention among practitioners and researchers, as sentiment has been shown to explain financial market movements, especially in periods of irrational panic or unjustified optimism (Reis & Pinho, 2020a). In addition, stock return co-movements are found to be mainly driven by investor sentiment, which can explain the level, variance, and covariance of the non-fundamental component of returns (Frijns et al., 2017).

Since investor (or market) sentiment is not a directly measurable variable, this concept has been historically analysed by means of proxy variables and surveys (e.g., Chau et al., 2016), and more recently exploiting news, microblogging sites, and web searches (e.g., Gao et al., 2020). However, there is no consensus in the literature on the construction of sentiment indicators (Chan et al., 2017), and the relationship between sentiment and returns remains far from fully understood, especially outside the context of the U.S. market.

In this study, we aim to conduct an in-depth analysis of the role sentiment indicators in predicting stock returns in the European

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market. The relationship between sentiment indicators and stock prices is still a topic of debate in the literature. While some studies suggest a connection between investor sentiment and market prices (e.g., Baker et al., 2012; Uhl, 2014), others (e.g., González-Sánchez & Morales de Vega, 2021) suggest that there is no significant correlation. Some studies have found that returns and volatility variations actually influence sentiment rather than the other way around (Das et al., 2005). Moreover, there is no consensus in the literature on the term structure of return predictability using sentiment measures, since empirical evidence spans from the next trading day (Seok et al., 2019) to one or more months (Uhl, 2014). Additionally, the impact of positive and negative news on returns is not well-understood. Finally, most studies are focused on the US market.

To fill the existing gap, we aim to investigate the duration of sentiment effects on returns, the role of additional factors like stock size, the existence of potential asymmetries in the impact of positive and negative news, and whether sentiment constitutes a priced risk factor in the cross-section of stock returns. To capture sentiment at the individual stock level, we exploit the Bloomberg Investor Sentiment Index, designed to quantify investor reactions to news related to company-specific events. Unlike the extensively studied Thomson Reuters News Analytics (TRNA), which assigns a score to individual news items, the Bloomberg index aggregates daily news sentiment for a given company (see Bloomberg, 2016, for further details). The analysis covers all listed companies in the Euro area from 2010 to 2021, a period encompassing diverse market conditions, including bullish and bearish phases as well as episodes of market turmoil and stability.

In order to investigate the debated relationship between sentiment and future stock returns, we take the following steps. First, each month, we sort the available stocks by their Bloomberg sentiment index to construct portfolios representing varying sentiment levels. Additionally, we create a long-short portfolio that takes a long position in stocks within the highest sentiment group and a short position in those within the lowest sentiment group. Second, to evaluate how long sentiment impacts stock returns, portfolios are held for different investing periods and their post ranking return is evaluated with respect to Fama and French (1997, 2015) factors. Third, equally- and value-weighted procedure and other sorting techniques are employed to assess whether the role of sentiment is more or less impactful for small capitalizations stocks compared to large capitalization ones. Fourth, we examine the term structure of stock returns for very low and very high sentiment levels and for stocks with different size to detect asymmetry effects related to the impact of positive and negative news on future stock returns. Finally, we evaluate the role of sentiment in explaining the cross-section of stock returns by employing Fama and MacBeth (1973) regressions.

Our results have important implications both for investors and policymakers. First, we find evidence of a positive relationship between sentiment and the cross-section of future stock returns. Stocks characterized by very high sentiment earn higher returns than stocks characterized by very low sentiment. The return gap is both statistically and economically significant, and it is robust to the inclusion of Fama and French (1997) and Fama and French (2015) risk factors. Second, the forecasting horizon of sentiment indicators depends on the portfolio sorting procedure. When adopting an equal-weighted approach, high sentiment stocks outperform low sentiment ones for holding periods of up to three months. On the other hand, when exploiting a value-weighted procedure, profitability declines fast after one month. Third, investment gains for a long-short sentiment portfolio based on big capitalization stocks are limited. However, the profitability of a long-short strategy investing in stocks with small capitalization is high, declining slowly with the investment period length, indicating that the market requires more time to embed all the relevant information in small capitalization stock prices. Fourth, inefficiency is higher (lower) for positive (negative) news, which require up to three months (a few days) to be incorporated into the stock price. Finally, according to the Fama-Macbeth regression, sentiment affects stock returns and matters in asset pricing.

Our study makes several contributions to the literature. First, we add to the understanding of the relationship between sentiment and stock returns by providing new empirical evidence for the European stock market. While most existing studies focus on the U.S. market, cultural differences between the two regions may influence how sentiment impacts returns (see, e.g., Gric et al., 2023). Second, we highlight the usefulness of the Bloomberg sentiment index, which has been explored in only a few studies, either limited to specific markets (Vanstone et al., 2019), sectors (González-Sánchez & Morales de Vega, 2021) or for purposes other than predicting stock returns (Figà-Talamanca & Patacca, 2022). Although numerous papers examine the predictive properties of sentiment derived from Reuters (e.g., Allen et al., 2017, 2019; Du, 2020; Gan et al., 2020; Nooijen & Broda, 2016; Smales, 2015; Uhl, 2014), the relationship between the Bloomberg sentiment index and the cross-section of future stock returns remains underexplored. Third, we offer new insights into the debated term structure of return predictability using sentiment measures, addressing gaps in the literature. Additionally, we shed light on the asymmetric effects of positive and negative news on returns, a topic that is not yet well understood. Finally, our findings have significant practical implications for investors and asset managers, demonstrating that incorporating sentiment factors into asset pricing models can enhance their predictive power and improve investment strategies.

The paper proceeds as follows. Section 2 provides a review of the literature, then Section 3 provides a detailed description of the dataset and the methodology adopted in the analysis, whereas Section 4 investigates the relationship between sentiment indicators and the cross-section of future stock returns. In Section 5, we investigate whether sentiment is a priced factor in the cross-section of stock returns and, finally, Section 6 concludes by examining strategic and policy implications.

2. Literature review

Since investor (or market) sentiment is not a directly measurable variable, there is no consensus in the literature on its measurement. As a result, sentiment has usually been analysed through proxy variables. Among the most frequently used variables, mention should be made of investors' trades, mutual fund flows, trading volume, premia on dividend-paying stocks, closed-end fund discounts, option-implied volatility, first day returns on initial public offerings (IPOs), volume of initial public offerings, new equity issues, and insider dealing (e.g., Bathia & Bredin, 2018; Ben-Rephael et al., 2012). For an in-depth literature review, see, e.g., Sun et al.

(2016). In the following we review investor sentiment measures in Section 2.1, the relationship between sentiment and other factors in Section 2.2 and the relationship between sentiment and future market returns in Section 2.3.

2.1. Investor sentiment measures

It is possible to identify three main approaches for constructing investor sentiment indices. The first one is based on the aggregation of several market variables (Baker & Wurgler, 2007) or by combining a range of economic and financial indicators (Reis & Pinho, 2020a, 2020b). One drawback of this approach is the risk of incorporating information not related to investor sentiment in the final market sentiment index. At the aggregate market level, Reis and Pinho (2020a) create the EURsent investor sentiment index by aggregating several economic and financial variables. Similarly, Reis and Pinho (2020b) aggregate multiple categories of investor sentiment based on market or survey data, as well as technical analysis, risk measures, company fundamentals, and macroeconomic variables, demonstrating the role of a number of investor sentiment measures in predicting stock returns.

The second approach adopted in the literature is the development of investor sentiment indicators based on surveys (Chau et al., 2016; Da et al., 2015), a widely used approach for the US market. Examples are the University of Michigan Consumer Sentiment Index, the American Association of Individual Investor sentiment survey, and the Investor Intelligence and Daily Sentiment Index. For the European markets, the European Commission's monthly consumer confidence indicator, the Economic Sentiment Indicator (ESI), and the ZEW Indicator of Economic Sentiment have been developed. The indicators that belong to the survey-based approach are usually computed by aggregating the replies to selected questions addressed to firms or institutional investors, depending on the indicator. Consequently, sentiment indices based on survey data are characterized by a low observation frequency (monthly or quarterly) and are less reliable when the non-response rate in surveys is high, or the incentive to answer honestly is low (Da et al., 2015). More importantly, these indicators cannot respond quickly to changing market conditions, especially in the event of a volatility spillover or others unexpected shocks in financial markets. Schmeling (2009) finds that consumer confidence (used as a proxy for individual investor sentiment) is a significant predictor of expected returns across countries; however, the predictive power of sentiment changes depending on the time horizon and the country under investigation.

A third and relatively newer approach is the construction of sentiment indices using the information obtained by news, micro-blogging sites, and web searches. The advantages of the third approach compared to the previous ones are numerous. First, it is possible to compute such indices also for a restricted number of stocks, up to the individual firm level. Second, using an individual firm-level sentiment makes it possible to aggregate raw data at different levels, such as the sectoral or geographical ones. By doing this, the indicator can support investors and fund managers when they choose the sectors or stocks that should be over or underweighted. Third, the indicators can be computed at a higher frequency (up to intraday data) and respond quickly to the evolution of the market. Within this approach based on news, we can identify three different forms of application based on the news source. More specifically, news can be obtained from specialized financial media such as Bloomberg, Reuters, the *Financial Times*, the *Wall Street Journal*, or the *New York Times* (see e.g., García, 2013; Tetlock, 2007), internet search engines such as Google, and Yahoo (see e.g., Da et al., 2015; Dimpfl & Jank, 2016), or from social media such as Facebook, Twitter or Live Journal (see e.g., Siganos et al., 2014, 2017). Depending on the source of the news, the results should be interpreted with some degree of caution due to the lack of transparency about how the data were selected and uncertainty about the reason of the search. As a consequence, the trend is to use information directly extracted from specialized media or platforms with high data traffic (Twitter and Google). In line with this approach, we include attention-based sentiment, measuring the impact of investor attention on price reaction to news announcements. While variables such as trading volume (see Loh, 2010) and short-selling volume (Boehmer & Wu, 2013) have historically been used as proxy variables for measuring investor attention, recent studies use measures based on news searches and news reading in relation to specific stocks from different information providers. Ben-Rephael et al. (2017) distinguish between institutional investor attention based on search activity on Bloomberg terminals and a retail investor attention measure obtained using Google search frequency. Empirical evidence suggests that institutional investor attention responds more quickly to major news events, influencing retail behaviour and facilitating permanent price movements. On the other hand, Zhang et al. (2023) examine investor attention and sentiment variables by using the investors' posts from Guba, the largest stock forum in China. They find that both investor attention and sentiment improve stock return predictability. However, sentiment is more informative than attention in predicting returns. Investor attention has been extensively studied in the cryptocurrency market, where various transformations of trading volume time series and the Google Search Volume Index (SVI) have been found to significantly influence Bitcoin returns and volatility (Figà-Talamanca & Patacca, 2019).

Regarding the explanatory capacity of news-based indicators on other market variables, there is no clear evidence in the literature. More specifically, some studies argue that they have greater potential compared to other sentiment indices (Antweiler & Frank, 2004; Tumarkin & Whitelaw, 2001; Zhang et al., 2012), while others argue otherwise as a consequence of the different individual investor linguistic perception, the characteristics of the market the news is from, the asymmetry between negative and positive terms and expressions, or the language in which the news is published and the analysis of words out of context.

2.2. Relationship between sentiment and other factors in the cross-section of stock returns

Recent studies on the cross-section of stock returns focus on the relationship between sentiment and Fama-French factors. As suggested by Sadhwani et al. (2018), small firms are more likely to be impacted by economic downturns than large ones, and investors tend to move to stocks of large firms in the case of bearish market conditions. Additionally, value stocks are viewed as riskier than growth stocks in the case of an economic downturn, leading investors to seek safer investments by moving from value to growth stocks. The existence of a relationship between sentiment and the value premium is supported by Qadan and Jacob (2022), who test different proxies of investor sentiment. The reason for the relationship between the value factor and sentiment may be related to the fact that positive emotional states, reflected in investor sentiment, make investors more likely to purchase riskier assets (Qadan & Jacob, 2022). This hypothesis is supported by Kumar and Lee (2006) and Baker and Wurgler (2007).

From an empirically point of view, results for the relationship between sentiment and Fama-French factors are mixed. Liang (2018) finds a low correlation between the five Fama-French factors and the consumer sentiment risk factor. On the other hand, according to Dhaoui and Bensalah (2017), the relationship between investor sentiment and asset value is highly sensitive to capital investment, profitability, and portfolio size. Similarly, Habibah et al. (2021) find that investor sentiment plays a significant role in driving the premia of the Fama-French factors, particularly the size and profitability premia. Kuo and Huang (2022) test whether Baker–Wurgler's market sentiment affects the performance of several factor investing strategies in the US market, and find that the growth investing strategy based on the profitability factor performs better in high-sentiment cycles than in low-sentiment ones. Additionally, the long-short portfolio utilizing the size factor achieves superior returns during low-interest rate and low-sentiment cycles. Salur and Ekinci (2023) examine whether investor sentiment can explain anomalies such as size and book-to-market in the US stock market and in other portfolios around the world. Their findings suggest that the explanatory power of investor sentiment might be universal, but it changes on the basis of anomalies. Additionally, the impact of sentiment on returns is related to market capitalization. In conclusion, although several studies identify a correlation between sentiment and other factors, this connection may differ depending on the region under examination and the type of sentiment indicators used.

2.3. Investor sentiment and future market returns

An increasing number of studies have examined the relationship between sentiment indicators and market variables (such as returns, volume, or volatility), reporting mixed results about the sign of the relationship (Klemola et al., 2016). In the following, we will focus on studies examining the connection between investor sentiment and equity movements. However, it is important to acknowledge the fact that other studies have explored the impact of investor sentiment on other assets such as bonds (Isakin & Pu, 2023), oil prices (Qadan & Nama, 2018) and other commodities (Omura and Todorova, 2019), realized and expected stock market volatility (Xie et al., 2023).

Nardo et al. (2016), who investigate whether online news affects the financial market by exploiting the frequency of web searches for specific keywords, find mixed evidence. Even if the web can anticipate market fluctuations, the possible gains are limited, and sophisticated models exploited using machine learning do not necessarily produce better results. However, Uhl (2014) finds that Reuters sentiment can explain and predict changes in stock returns better than macroeconomic factors, and negative Reuters sentiment has more predictive power than positive Reuters sentiment. Meanwhile, Guo et al. (2017) use an investor sentiment index based on comments on a social networking site of the Chinese stock market and find that sentiment is not helpful to predict the stock price all the time. In particular, sentiment can only predict the stock price if the concern about the stock market is at a high level and the stock attracts a high-level attention on the part of investors. Gomez-Carrasco and Michelon (2017) assess the influence of social media activism on stock market performance by using information posted on Twitter by consumer associations and trade unions. Their findings suggest that the Twitter activism of key stakeholders has a significant impact on investors' decisions, and they identify a significant and negative effect of tweets posted by trade unions on the stock price and trading volume. Moreover, the market reaction is more significant on bearish trading days compared to bullish market conditions. Zhang et al. (2012) adopt eight widely applied text classifiers, and using stock message board data, examine their ability in predicting future stock returns. They find that sentiment messages can help in explaining same-day returns and predicting subsequent stock returns. Finally, Johnman et al. (2018) analyse the effect of positive and negative sentiment based on business news articles on daily excess returns and volatility in the FTSE 100 index. They find that sentiment does not affect excess returns in the FTSE 100 index, but it influences volatility: negative sentiment increases volatility and positive sentiment reduces it.

To sum up, the financial literature generally agrees on the existence of a relationship between sentiment measures and future returns or other market variables such as volume and volatility. However, the strength, the sign, and the relationship direction are influenced by macroeconomic conditions (Chung et al., 2012) or the stock characteristics, and cross-country cultural or institutional differences (Corredor et al., 2013). Moreover, the relationship is highly dependent on the measures of sentiment adopted and the context analysed (single stocks vs. aggregate market, country, economic period, market phase). An additional issue not sufficiently addressed in the literature is the time predictability or frequency effect of investor sentiment on future returns.

One possible explanation for the heterogeneity of the results is the fact that, while the literature initially focused on low-frequency sentiment measure based on Baker and Wurgler (2006), empirical studies on sentiment predictability have recently moved towards using high-frequency data, such as daily and intraday data (Gao & Liu, 2020; Renault, 2017; Sun et al., 2016). Another possible explanation is based on an extension of the noise trader risk model of De Long et al. (1990) proposed by Ding et al. (2019): they suggest that while the relationship between short-term sentiment and portfolio returns is positive, in the long term, the relationship is negative.

Moreover, there is no consensus on how to build these indices and which variables or information to include (Chan et al., 2017), leaving investors and fund managers without a single sentiment indicator for investment and asset allocation purposes. As a result, some information providers and financial institutions have attempted to fill this gap by producing reports and developing their own investor sentiment indices at the individual stock level (Reuters and Bloomberg have such indices). The idea of computing the sentiment index on an individual stock basis (with respect to an aggregate basis) presents many advantages including the possibility of subsequently aggregating the information at different levels (e.g., sectors, countries or firm characteristics). It is therefore crucial for investors to understand whether these sentiment indices can explain future stock returns. While there exist several studies that investigate the forecasting performance of sentiment based on Reuters (Allen et al., 2017, 2019; Du, 2020; Gan et al., 2020; Nooijen &

Broda, 2016; Smales, 2015; Uhl, 2014), the empirical evidence is scant for the Bloomberg sentiment index.

To the best of our knowledge, the only studies investigating the relationship between the Bloomberg sentiment index and stock returns are those by González-Sánchez and Morales de Vega (2021) and Vanstone et al. (2019).[1] While these studies offer valuable insights, they are limited in both scope and the time span of their analyses. González-Sánchez and Morales de Vega (2021) focus on the financial sector during the 2014–2018 period, a time characterized by a positive market trend and low volatility. Similarly, Vanstone et al. (2019) is restricted to the Australian market over the 2015–2018 period. To fill this gap, the present study investigates the information embedded in the Bloomberg sentiment index using data on all the stocks listed in the Eurozone, spanning across all the market sectors for the period 2010–2021. The sample under investigation is characterized by different market phases (bullish and bearish) and by periods of market turmoil and stability, thus making it possible to assess the behaviour of the Bloomberg sentiment index in different market conditions.

3. Data and methodology

This study is intended to assess the role of the Bloomberg sentiment index in explaining the cross-section of future stock returns in the Eurozone stock market. The Bloomberg sentiment index differs from the Thompson Reuters News Analytics index (TRNA) which attributes a score to each news, as Bloomberg construct a sentiment index in an aggregate way with all the news published daily for a given company (see Bloomberg, 2016, for a detailed description).

More specifically, 10 min before the market opens, Bloomberg compiles news and web content related to each public company in the previous 24 h. In light of the news reporting, Bloomberg assigns a positive, negative or neutral valuation depending on how the reports would affect investors with a long position, that is, if they would react by taking a bullish, bearish or neutral stance. This assessment is then introduced into automatic learning models, resulting in the Bloomberg sentiment index (one based on news and the other on social networks - Twitter/X).

In particular, we prefer the Bloomberg sentiment index based on news rather than the one based on Twitter/X due to its superior reliability and quality of source. In fact, professional news outlets exploit rigorous fact-checking and editorial processes, ensuring a higher degree of accuracy and dependability than the often unverified and potentially misleading content found on social media platforms. In addition, relying on a news-based index mitigates concerns regarding sentiment manipulation, high levels of irrelevant "noise" in the data, and potential biases in data samples that are common with Twitter/X analysis. The volatility of sentiment on social media, often driven by transient events, also renders news a more appropriate resource for longer-term analysis. Finally, user participation on social media platforms can fluctuate over time due to factors such as trending topics, platform policies, or broader societal shifts, further complicating its reliability for extended analyses.

The index based on news is available for European stocks from 2007, though the number of stocks for which the indicator has been computed until 2010 is limited. Therefore, the sample used for the present analysis based on portfolio sorting strategies starts in 2010 and continues until March 2021. The present study considers more than ten years characterized by different market phases (bullish and bearish) and by periods of market turmoil and stability. Moreover, the study considers all the listed companies in the Euro area. In this way, it is able to test the behaviour of sentiment indices in different market conditions and for stocks belonging to different sectors.

3.1. Data preparation

Daily stock returns in the Eurozone and the Bloomberg sentiment index for each stock in the Euro-denominated area are obtained from Bloomberg. The initial input is a matrix of around 4000 daily observations for 3474 stocks. Each day, Bloomberg computes the sentiment index by using news and web content related to each public company in the past 24 h. The sentiment index can be missing on some days, if the stock is not covered by any news or web content. After analysing the initial data, we are able to identify at least one observation of the Bloomberg sentiment index for 2409 stocks out of the original 3474. These 2409 stocks are included in the filtered dataset. We have a total of 395,563 values of the Bloomberg sentiment index, i.e., an average of 164 observations for each stock in the filtered dataset. The number of companies for which the sentiment indicator is available is relatively low at the beginning of the sample but grows fast from 2010 and then remains stable with on average between 100 and 200 stocks covered per day. For this reason, a further filter for the stock dataset will be introduced later in the portfolio sorting section.

Fama-French factor returns for the European market were obtained from Kenneth French's data library.[2] All the returns used in the analysis (Fama-French returns and individual stock returns) included dividends and capital gains. Since factors are provided in dollars, they need to be converted to avoid skewed estimated alphas (Glück et al., 2021). The currency conversion of downloaded factors is thus relevant in drawing reliable conclusions when applying factor models from a non-US-dollar perspective. Following Glück et al. (2021), the currency conversion for long factors such as the market factor is given by:

$$MKT_t^{EUR} = \frac{1}{\left(1 + r_{FX,t}^{USD/EUR}\right)} \left(1 + MKT_t^{USD} + r_{f,t}^{USD}\right) - 1 - r_{f,t}^{EUR} \tag{1}$$

[1] The Bloomberg sentiment index is adopted also by Dunham & Garcia, 2020, who focus on the effect of firm-level investor sentiment on the liquidity of the firm's shares.

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed.

where MKT_t^{USD} is the market factor in dollars obtained from the Kenneth French's data library, $r_{FX,t}^{USD/EUR}$ is the exchange rate return over day t; $r_{f,t}^{USD}$ and $r_{f,t}^{EUR}$ are the risk-free rates in US dollars and Euros, respectively.

On the other hand, long-short factors such as *SMB* or *HML*, require a different formula for their conversion. The returns on these European long-short factors are generally computed as the difference between the returns of a long portfolio of European stocks with certain characteristics (e.g., value stocks) and a respective short position in a portfolio with the opposite characteristics (e.g., growth stocks). Starting from long-short factors in US dollars, the daily return of long-short factors in Euro (LS_t^{EUR}) can be obtained as:

$$LS_t^{EUR} = \frac{1}{\left(1 + r_{FX,t}^{USD/EUR}\right)} \quad LS_t^{USD} \tag{2}$$

where LS_t^{USD} is the return of the long-short factor in US dollars.

3.2. Investor sentiment and the cross-section of stock returns

Recent empirical studies (see e.g., Dong & Gil-Bazo, 2020), provide support for the hypothesis that investor sentiment, as inferred from the activity of individuals interacting on social media platforms or from news, drives stock returns at the individual firm level. The traditional perspective in finance is that investors driven by sentiment are considered "noise traders" and irrational (refer to De Long et al., 1990). As a result, past research has shown that periods of high sentiment led to low stock returns, as any mispricing is eventually corrected. A possible explanation is provided by Seok et al. (2019), who suggest that the low-frequency sentiment measures used in the past are not effective in capturing the mispricing process or estimating the time frame of the mispricing. In a perfectly efficient market, mispricing is corrected immediately, resulting in negative short-term returns due to sentiment. However, in an inefficient or partially efficient market, mispricing caused by investor sentiment and trading pressure lasts longer, resulting in positive short-term returns. Daily sentiment measures can aid in determining whether and how long a mispricing persists, providing valuable insights.

In the empirical analysis in the present study, the daily investor sentiment is measured using the Bloomberg sentiment index. Based on preliminary analyses on the Bloomberg sentiment index,[3] stocks characterized by positive sentiments are expected to exhibit higher average returns than those characterized by negative sentiments. It is also expected that the return predictability of sentiment indicators will reach a maximum at a certain point and then decline with the increase of the time horizon. For this reason, the study will take into account different holding periods. Moreover, the relationship between sentiment and future stock returns could be more prominent for certain categories of stocks, such as small capitalization ones (Seok et al., 2019). For instance, Hao et al. (2018) suggested that behavioural biases are particularly stronger for small firms. These stocks are generally associated with arbitrage limitations and, as a result, demand shocks caused by investor sentiment may not be absorbed by the market (Seok et al., 2019). A significant association between investor sentiment measures and small stock premiums have been identified, among others, in Qadan and Aharon (2019) using daily, weekly and monthly data for the period 1965–2017. Thus, in our study various procedures are adopted to understand whether the return predictability can be affected by individual stock features.

To investigate whether the Bloomberg sentiment index provides useful information about the cross-section of future stock returns, the following strategy was adopted. At the end of each month (observation period), stocks with at least five observations on the Bloomberg sentiment index are selected. The average value of the Bloomberg sentiment index is used as a proxy for stock sentiment. Then, the selected stocks were ranked based on their sentiment index, and five portfolios were created, based on sentiment quintiles, exploiting both an equal-weighted and a value-weighted procedure. The first (fifth) portfolio consists of the stocks with the lowest (highest) value of sentiment. At the end of the sorting procedure, the time series of post-ranking returns for each portfolio over the following month (investment period) is collected, along with the returns of the 5-1 portfolio formed as a long position in stocks with very high sentiment and a short position in stocks with a very low sentiment. In particular, if the Bloomberg sentiment index can provide useful information about future stock returns, the portfolio return is expected to increase in average sentiment, and a positive performance for the long-short portfolio. Following previous analyses on the cross-section of stock returns (e.g., Elyasiani et al., 2020), the procedure is repeated each month by rolling the observation period and the investment period over to the next month, with a monthly portfolio rebalancing.

To assess whether the effects of investor sentiment on future stock returns are robust to the inclusion of Fama and French (1997) risk factors, the three-factor alpha for each of the five portfolios (Q1, Q2, Q3, Q4, Q5) plus the long-short portfolio (Q5-Q1) is calculated by estimating Eq. (3):

$$R_{j,t} = \alpha^j + \beta_{MKT}^j MKT_t + \beta_{SMB}^j SMB_t + \beta_{HML}^j HML_t \tag{3}$$

where $R_{j,t}$ is the portfolio return (post-ranking) in day t, for $j=1, \ldots, 6$, and *MKT*, *SMB*, and *HML* are the factors used to evaluate the robustness of the intercept. The intercept, referred to as the three-factor alpha, represents the amount of portfolio return not explained by Fama and French (1997) risk factors. *MKT* is the excess market return with respect to the risk-free rate. The "small-minus-big"

[3] According to Bloomberg, the optimal number of days to hold the position after the trade based on the Bloomberg sentiment indicator is eight (https://www.bloomberg.com/professional/blog/can-get-edge-trading-news-sentiment-data).

(*SMB*) size factor captures the return compensation for additional risk attached to stocks with low capitalization, which are more exposed to economic and financial uncertainty. The book-to-market factor (or value factor), "high-minus-low" (*HML*), measures the difference in return between stocks with high book-to-market ratios (value stocks) and low book-to-market ratios (growth stocks).

More recently, Fama and French (2015) introduced two additional factors to account for the return spread between the most profitable firms minus the least profitable ones (*RMW*) and the return spread between firms that invest conservatively minus those that invest aggressively (*CMA*). To account for these additional factors, the five-factor alpha for each of the five portfolios (Q1, Q2, Q3, Q4, Q5) plus the long-short portfolio (Q5-Q1) is calculated by estimating Eq. (4):

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{RMW} RMW_t + \beta^j_{CMA} CMA_t \tag{4}$$

4. Empirical findings

This section investigates the relationship between the Bloomberg sentiment index and the cross-section of stock returns by exploiting portfolio sorting strategies. Section 4.1 reports the results for portfolios sorted based on sentiment and held for one month, to provide an initial understanding about the relationship between sentiment and future stock returns. Section 4.2 investigates the forecasting power of the Bloomberg sentiment index on returns for different investment horizons, to assess the term structure of return predictability using sentiment measures. Section 4.3, is intended to cast light on the asymmetric patterns in the relationship between sentiment and future stock returns. Section 4.4 analyses the role of company's size in the relationship between sentiment and returns. Finally, Section 4.5 discusses the empirical results in relation with the underlying economic theory.

4.1. Portfolios sorted based on sentiment and held for one month

A preliminary indication of the relationship between sentiment and returns is provided by the results of the average post-ranking returns, the three-factor alpha, and the five-factor alpha, reported in Table 1 (t-stats in parentheses), Panel A (Panel B), if the value-weighted (equal weighted) method is used. The results indicate a strong and positive relationship between sentiment and future portfolio returns. Although the average returns and the alphas are not monotonically increasing along the five quintiles, the portfolio that takes a long position in stocks with very high sentiment and a short position in stocks with very low sentiment earns a positive and statistically significant return. In terms of magnitude, the return of the long-short portfolio is higher than 1 % monthly, indicating that the strategy based on the Bloomberg sentiment index is highly profitable. The results are also robust to the inclusion of commonly used risk factors, such as market excess return (*MKT*), size (*SMB*), book-to-market (*HML*), risk-weighted asset (*RMW*), and the conservative minus aggressive (*CMA*) factors. Even when considering the five-factor model, the value-weighted return of the long-short sentiment portfolio is equal to 0.58 % monthly. As a result, the excess return of the long-short portfolio based on sentiment not explained by the Fama and French (2015) factors is also significant from an economic point of view since it is equal to 6.14 % on an annual basis. As expected, the average portfolio returns and the alphas increase using the equal-weighted procedure (Panel B) since an equal-weighted portfolio has higher exposure to systematic risk compared to a value-weighted one.

The cumulative return of the five portfolios over the sample period is depicted in Fig. 1: value-weighted (equal-weighted) results are depicted at the top (bottom) of the figure. Several observations can be made. First, the portfolio characterized by very high sentiment achieves an outstanding return over the sample period, close to 300 %. Second, the cumulative portfolio performance increases along the sentiment quintiles, indicating a positive relationship between the Bloomberg sentiment index and future stock returns. Third, while portfolios with very low sentiment reveal a moderately negative cumulative performance, those characterized by positive sentiment show a much more pronounced positive performance during the period. This pattern may suggest the existence of an asymmetrical effect in the relationship between news sentiment indicators and future stock returns, indicating that high sentiment affects returns with a time delay compared to low sentiment.

An asymmetric pattern, even if in the opposite direction, has been detected also by Reis and Pinho (2020a), who observe that optimism and good news have a stronger impact on volatility than pessimism and bad news. A possible explanation for the pattern in the present study is that pessimism in investor sentiment spreads faster than optimism. To elaborate, a negative news causes a sudden fall in the stock price, and its effect is exhausted within the observation period (the month in which the sentiment data are collected), i.e., it runs out before the investment period. On the other hand, if the effect of positive news is incorporated slowly into the stock price, positive returns span over the following month (the month in which the post-ranking returns are collected and evaluated). This hypothesis will be empirically investigated in Section 4.3.

Fig. 2 shows the cumulative performance on portfolios that take a long position in stocks with very high sentiment and a short position in stocks with very low sentiment (both for the equal- and value-weighted methods), along with the performance of the STOXX Europe 600 and EURO STOXX indices.[4] It is possible to observe from the figure a significant overperformance of the long-short sentiment portfolios compared to the performance achieved by the European market index, confirming the important role of sentiment on stock returns. Moreover, the performance is fairly stable throughout the sample period, indicating that the importance of sentiment is not limited to a single period or a specific market condition.

[4] The EURO STOXX Index is a broad yet liquid subset of the STOXX Europe 600 Index. With a variable number of components, the index represents large, mid and small capitalization companies of 11 Eurozone countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

Table 1
Investment results for portfolios sorted based on sentiment and held for one month.

Panel A: Value-weighted ret.	Quintiles: Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	−0.133	0.028	0.112	0.210	0.382	
Avg. Ret.	0.23 %	0.75 %*	0.66 %*	0.93 %***	1.27 %***	**1.04 %*** **
	(0.450)	(1.664)	(1.765)	(2.749)	(3.899)	**(3.007)**
FF3 Alpha	−0.22 %	0.16 %	−0.08 %	0.09 %	0.37 %***	**0.58 %*** **
	(-0.998)	(0.831)	(-0.672)	(0.668)	(2.715)	**(2.647)**
FF5 Alpha	−0.10 %	0.15 %	−0.09 %	0.11 %	0.41 %***	**0.51 %** **
	(-0.491)	(0.760)	(-0.774)	(0.862)	(3.148)	**(2.313)**
Panel B: Equal-weighted ret.	Quintiles: Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	−0.133	0.028	0.112	0.210	0.382	
Avg. Ret.	−0.04 %	0.65 %	0.61 %	1.00 %**	1.28 %***	**1.31 %*** **
	(-0.060)	(1.374)	(1.381)	(2.470)	(3.556)	**(3.364)**
FF3 Alpha	−0.55 %	0.04 %	−0.12 %	0.18 %	0.39 %***	**0.94 %*** **
	(-1.606)	(0.208)	(-0.739)	(1.364)	(2.849)	**(2.695)**
FF5 Alpha	−0.37 %	0.09 %	−0.07 %	0.22 %	0.44 %***	**0.80 %** **
	(-1.148)	(0.435)	(-0.412)	(1.535)	(3.199)	**(2.386)**

Note: This table shows the results for portfolios sorted based on sentiment measured using the Bloomberg sentiment index. Panel A (Panel B) show the results for portfolios obtained using a value- (equal-) weighted method. Quintile 1 (5) collects stocks with the lowest (highest) values of sentiment, Q5-Q1 portfolios are obtained combining a long position in Q5 and a short position in Q1. For each quintile portfolio plus the Q5-Q1 portfolio, the table shows the pre-ranking average sentiment, the post-ranking return (monthly return in percent), and the three- and the five-factor alpha computed with respect to the Fama and French (1997), and Fama and French (2015) risk factors. The three-factor (FF3) and the five-factor (FF5) alphas are computed as the intercepts obtained by estimating the following equations.

$$R_{j,t} = \alpha^j + \beta^j_{MKT}MKT_t + \beta^j_{SMB}SMB_t + \beta^j_{HML}HML_t$$

$$R_{j,t} = \alpha^j + \beta^j_{MKT}MKT_t + \beta^j_{SMB}SMB_t + \beta^j_{HML}HML_t + \beta^j_{RMW}RMW_t + \beta^j_{CMA}CMA_t$$

where $R_{j,t}$ is the monthly portfolio return (post-ranking) in day t, for j = Q1, Q2, Q3, Q4, Q5, Q5-Q1.
MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the daily Fama and French risk factors used in order to evaluate the robustness of the intercept. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

4.2. Forecasting power of the bloomberg sentiment index on returns for different investment horizons

A moot point in the literature is the time predictability of future returns using sentiment proxies. Empirical evidence spans from the next trading day to one or more months. To provide further evidence about the forecast horizon of news sentiment indicators, the sorting exercise is repeated by varying the holding period. In this way, it is possible to ascertain whether sentiment predictability spans over the one-month horizon investigated in Table 1. The following strategy is adopted to examine whether the Bloomberg sentiment index provides valuable information about individual future stock returns also beyond the one-month horizon. At the end of each month, stocks that have at least five observations of the Bloomberg sentiment index are selected, i.e., the observation period is held fixed at one month. As in the previous exercise, the average Bloomberg sentiment index is taken as a proxy for sentiment. Unlike the procedure adopted in Table 1, the five portfolios sorted based on sentiment, plus the 5-1 portfolio, are held for two and three months, and the results are reported in Tables 2 and 3, respectively. Then, the procedure is repeated by rolling the estimation window over to the next two or three months, depending on the length of the investment period under investigation.[5]

The results are shown at the top (bottom) of each table if the value-weighted (equal-weighted) method is used to compute the portfolio returns. Unlike the one-month holding period results (Table 1), the outcomes presented in Tables 2 and 3 change significantly depending on the choice of the method used to compute the portfolio return (value- or equal-weighed). For the two-month investment horizon (Table 2), the value-weighted results point to a marginally significant return for the 5-1 portfolio. Moreover, the average alpha is statistically significant only when accounting for the three Fama and French (1997) factors. On the other hand, it is not statistically different from zero when adding the *RMW* and *CMA* factors (Fama & French, 2015). This result indicates that these additional risk factors explain the long-short portfolio return. Therefore, we find weak evidence of profitability for a strategy that invests (using a value-weighted approach) for two months based on the Bloomberg sentiment index. Still, the results are not robust to the inclusion of commonly used risk factors. The profitability of the value-weighting strategy is completely offset when considering an investment horizon of three months (Table 3, Panel B). In this case, neither the average returns nor the alphas of the long-short portfolio are statistically different from zero.

On the other hand, if the equal-weighted method is adopted, the return and the alphas of the 5-1 portfolios are still statistically significant for the two-month (Table 2, Panel B) and the three-month (Table 3, Panel B) investment horizons. Moreover, the average portfolio returns and alphas are slightly lower than the ones shown in Table 1. This result suggests that the return predictability of

[5] To avoid overlapping results, we wait for the previous investment period to conclude before reinvesting the portfolios.

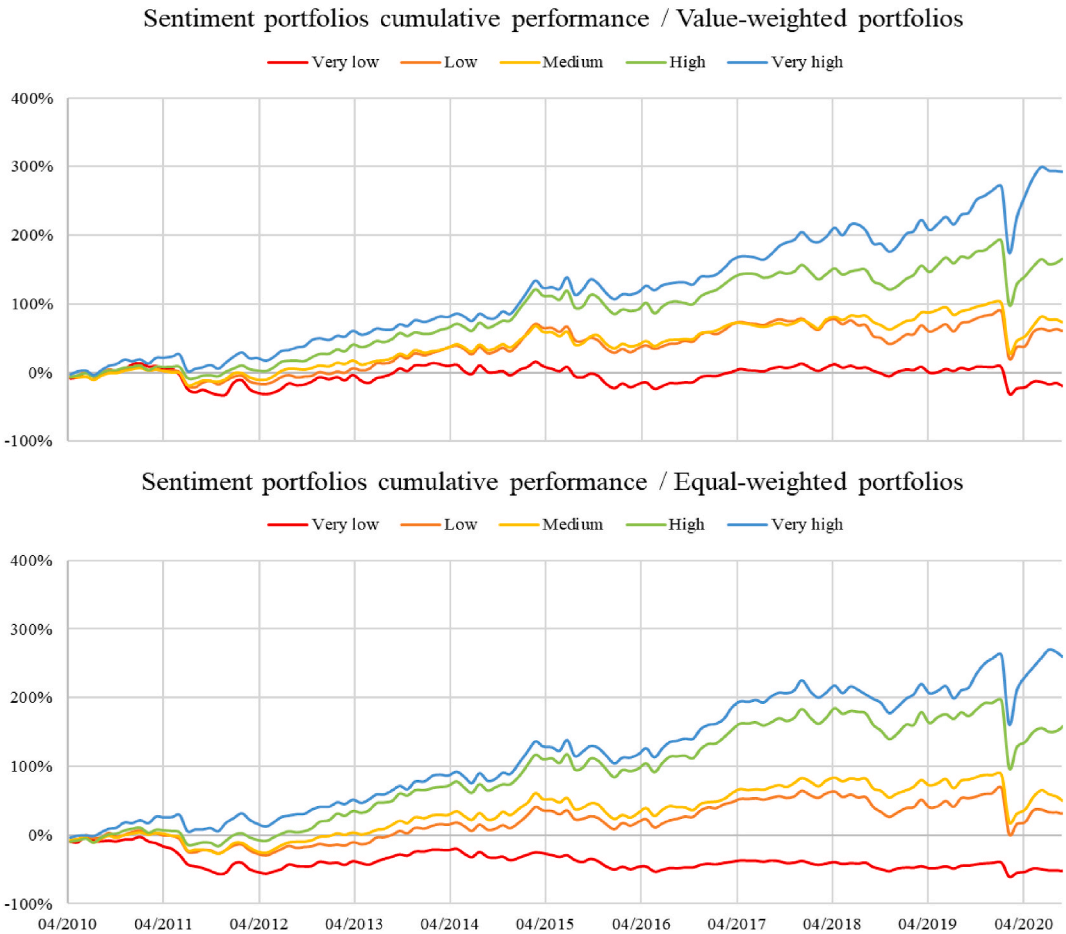

Fig. 1. Cumulative performance on portfolios sorted based on sentiment and held for one month.

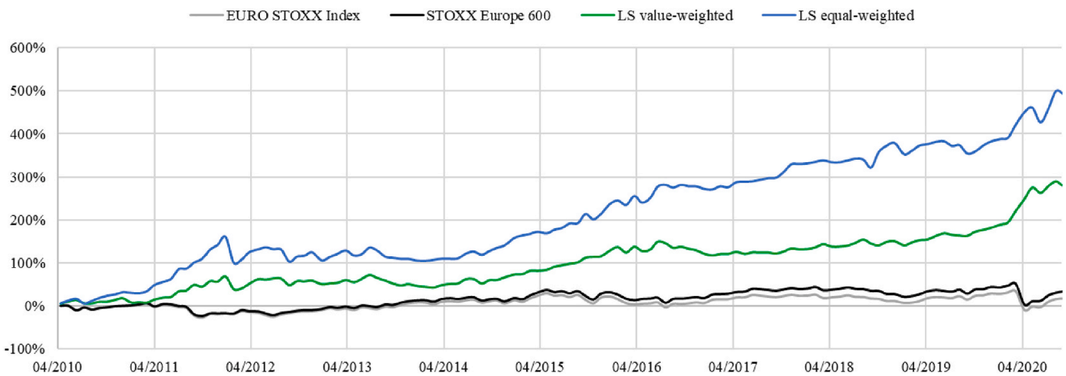

Fig. 2. Cumulative performance on portfolios that take a long position in stocks with very high sentiment and a short position in stocks with very low sentiment.

investor sentiment still holds also for longer time horizons. The noticeable difference in outcomes between the equal and the value-weighted portfolios can be motivated by a different reaction to sentiment for stocks characterized by different market capitalization.

Another pattern that can be observed from Tables 1–3 is that the relationship between sentiment and returns is, in some instances, non-monotonic. Acknowledging that sentiment is but one component in the complex interplay of factors driving asset returns, we note that the association may not be strictly linear. Specifically, the impact of sentiment may exhibit greater sensitivity at the tails of its distribution, where extreme positive or negative sentiment could have a more discernible directional effect compared to more neutral levels. To assess the robustness of our results, we have conducted a thorough sensitivity analysis by employing various portfolio sorting

Table 2
Investment results for portfolios sorted based on sentiment and held for two months.

Panel A:	Quintiles:					
Value-weighed Ret.	Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	*−0.131*	*0.029*	*0.113*	*0.212*	*0.383*	
Avg. Ret.	0.56 %	0.59 %	0.73 %**	0.98***	1.18 %***	**0.62 %***
	(1.104)	(1.401)	(2.535)	(3.236)	(4.925)	**(1.740)**
FF3 Alpha	−0.10 %	−0.05 %	−0.02 %	0.16 %	0.30 %**	**0.41 %****
	(-0.464)	(-0.285)	(-0.163)	(1.023)	(2.112)	**(2.032)**
FF5 Alpha	0.18 %	−0.14 %	−0.03 %	0.17 %	0.36 %**	**0.18 %**
	(0.745)	(-0.827)	(-0.230)	(1.029)	(2.403)	**(0.740)**
Panel B:	Quintiles:					
Equal-weighed Ret.	Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	*−0.131*	*0.029*	*0.113*	*0.212*	*0.383*	
Avg. Ret.	0.14 %	0.67 %	0.71 %*	0.83 %**	1.12 %***	**0.99 %****
	(0.234)	(1.377)	(1.855)	(2.310)	(3.650)	**(2.517)**
FF3 Alpha	−0.57 %*	0.03 %	−0.12 %	0.06 %	0.26 %*	**0.82 %*****
	(-1.853)	(0.162)	(-0.781)	(0.528)	(1.717)	**(2.950)**
FF5 Alpha	−0.25 %	0.04 %	−0.04 %	0.11 %	0.31 %*	**0.56 %****
	(-0.786)	(0.195)	(-0.285)	(0.833)	(1.731)	**(2.007)**

Note: This table shows the results for portfolios sorted based on sentiment held for a period of two months. For a definition of the measures see Table 1. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

Table 3
Investment results for portfolios sorted based on sentiment and held for three months.

Panel A:	Quintiles:					
Value-weighed Ret.	Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	*−0.134*	*0.021*	*0.101*	*0.195*	*0.367*	
Avg. Ret.	0.21 %	0.70 %	0.53 %	0.98 %***	0.87 %***	**0.66 %**
	(0.376)	(1.444)	(1.578)	(3.009)	(2.896)	**(1.513)**
FF3 Alpha	−0.12 %	0.14 %	−0.20 %*	0.20 %*	0.04 %	**0.16 %**
	(-0.743)	(0.789)	(-1.658)	(1.734)	(0.400)	**(0.942)**
FF5 Alpha	−0.06 %	0.11 %	−0.14 %	0.22 %*	0.08 %	**0.15 %**
	(-0.389)	(0.551)	(-1.213)	(1.873)	(0.881)	**(0.971)**
Panel B:	Quintiles:					
Equal-weighed Ret.	Q1	Q2	Q3	Q4	Q5	**Gap: Q5-Q1**
Avg. Sentiment	*−0.134*	*0.021*	*0.101*	*0.195*	*0.367*	
Avg. Ret.	−0.06 %	0.43 %	0.55 %	0.97 %**	1.02 %***	**1.08 %****
	(-0.094)	(0.849)	(1.353)	(2.379)	(2.910)	**(2.559)**
FF3 Alpha	−0.57 %*	−0.14 %	−0.18 %	0.26**	0.26 %***	**0.83 %*****
	(-1.886)	(-0.618)	(-1.235)	(2.182)	(2.618)	**(2.685)**
FF5 Alpha	−0.40 %	−0.05 %	−0.11 %	0.27 %**	0.34 %***	**0.73 %****
	(-1.402)	(-0.216)	(-1.000)	(2.006)	(2.991)	**(2.562)**

Note: This table shows the results for portfolios sorted based on sentiment held for a period of three months. For a definition of the measures see Table 1. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

procedures. This included varying the number of quantiles and, importantly, exploring alternative portfolio construction methods. Notably, we also implemented an innovative sorting scheme that does not rely on pre-defined quantile thresholds. The results from these analyses, reported in Appendix A are consistent with the findings obtained in Sections 4.1 and 4.2, further strengthening the robustness of our conclusions. As an additional robustness check, we also conducted the analysis using sentiment proxies at the aggregate market level, such as the VIX and VSTOXX indices. The results, presented in Appendix B, demonstrate how the Bloomberg Sentiment Index captures a distinctive dimension of market sentiment, that cannot be explained by traditional volatility measures.

4.3. Term structure of stock returns for different sentiment levels

This section aims to provide insight on asymmetric patterns in the relationship between sentiment and future stock returns. To detect asymmetric patterns in the term structure of sentiment predictability, the following steps are taken. First, in line with the sorting procedure adopted in the previous section, stocks were selected with at least five observations for the Bloomberg sentiment index at the end of each month (observation period). The average of the Bloomberg sentiment index was used as a proxy for the stock sentiment. Second, for each stock selected in the observation month, the cumulative return was collected from the first day of the observation month for a period of four months (i.e., considering the observation period plus a three-month investment period). In this way, it is possible to track the performance of each stock from the period in which the news is released to understand whether pessimism in investor sentiment spreads faster than optimism or vice versa. Third, observed sentiment is split into deciles, and the weighted (average) returns for stocks in the sentiment decile is plotted in Fig. 3, at the top (bottom). In this way, it is possible to obtain further insights about the equal-weighted and the value-weighted results presented in Tables 1–3

The figures confirm the hypothesis that pessimism in investor sentiment spreads faster than optimism. This pattern is particularly noticeable in the bottom panel of Fig. 3, depicting the surface of cumulative stock returns (scale on the vertical axis) along sentiment deciles (represented on the depth axis) and trading days after the beginning of the observation period (which refer to the scale on the horizontal axis). In particular, when the news sentiment index is very low, the average cumulative return declines quickly within 30 trading days from the beginning of the observation period. Then, the cumulative return remains almost unchanged for the remainder of the period under investigation.

On the other hand, stocks in the highest deciles of sentiment are characterized by an average return that increases during the entire period under investigation. This indicates that the incorporation of positive news into stock prices is slower than negative news, i.e., positive sentiment requires more time to be reflected in higher stock prices. It may also be observed that the surface in the upper panel (in which returns are weighted based on market capitalization) is flatter than the one in the lower panel (where the returns are computed using an equal-weighted method). Moreover, when the cumulative return is computed using the value-weighted method, the cumulative performance of stocks characterized by high (low) sentiment increases (decreases) faster until the end of the first investment month (observation month), and then is quite flat or characterized by limited variations. On the other hand, the surface computed using the average cumulative return (lower panel) is steeper, and the steepness increases until the end of the period under investigation. This pattern is closely related to the results obtained in Tables 2 and 3 (i.e., to the higher profitability of the strategy based on the equal-weighed method compared to the value-weighted one) and it will be further investigated in the following subsection.

4.4. *Term structure of stock returns for different sentiment levels and for stocks with different size*

In this section, we aim to shed light on the role of company's size in the relationship between sentiment and returns. To assess

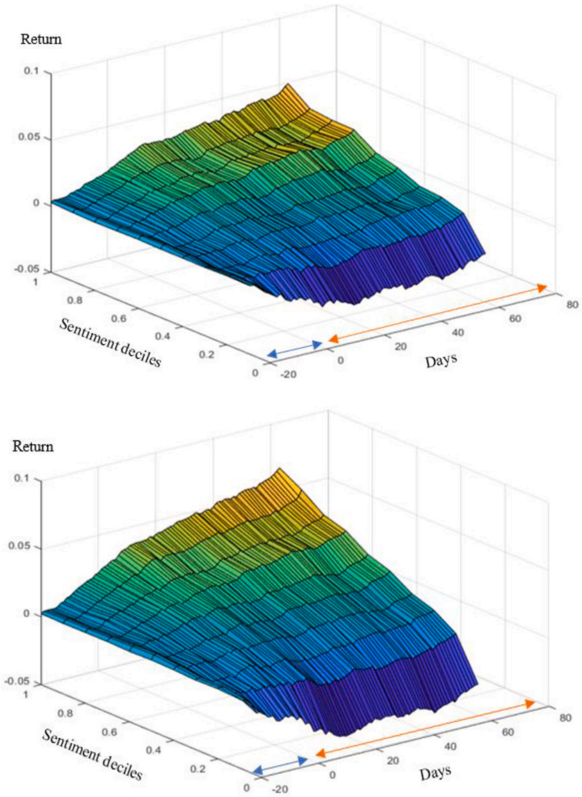

Fig. 3. Term structure of the cumulative return for a strategy that invests in portfolios with different level of sentiment using a value-weighted and an equal-weighted method.
Note: the figure at the top (bottom) graphically represents the term structure of the cumulative return for a strategy that invests in stocks belonging to a sentiment decile using a value-weighted (equal-weighted) method. The magnitude of the cumulative return is depicted on the vertical axis, while the investment horizon (in days) is indicated on the horizontal axis. Sentiment deciles are represented on the depth axis. The blue (orange) arrow indicates the observation (investment) period.

whether stock size plays an important role in the relationship between sentiment and future stock returns, the following procedure is implemented. Starting from the list of stocks selected in the observation period (see Section 3), they are split into three terciles based on their market capitalization at the beginning of the month. Within the first (small capitalization stocks) and the third (big capitalization stocks) group, the cumulative return is collected from the first day of the observation period for a period of four months. Finally, sentiment for stocks characterized by big (low) capitalization is split into deciles, and the average cumulative return for stocks in the sentiment deciles is plotted in Fig. 4, at the top (bottom).[6] The difference between the two surfaces is striking. In particular, the surface for stocks characterized by big capitalization is much flatter than for those characterized by low capitalization, indicating that the possible gains for a long-short strategy based on sentiment investing in stock with high capitalization are limited. On the other hand, the profitability of a long-short strategy that invests in stocks with low capitalization is high, declining slowly with the length of the investment period. Even if the cumulative return for stocks characterized by high sentiment increases faster in the first part of the period (during the observation month and the first investment month), it continues to grow until the end of the third investment month.

Combined with the different profitability of equal-weighted and value-weighted portfolios detected in previous sections, the results suggest that sentiment affects small capitalization stocks more than big ones. The stronger influence of sentiment on small companies can be attributed to two main factors. First, since a higher level of risk generally characterizes small capitalization stocks, positive news can have a stronger impact on their future earnings and expected returns compared to big companies. Second, the market may be characterized by a different level of efficiency between big and small capitalization stocks.[7] To elaborate, positive and negative news about stocks with big capitalization can be already factored into their price, or they may be factored into the stock price more quickly compared to small capitalization stocks. As a result, the effect on the stock return related to the increase (or decrease) in sentiment after the news tends to run out quickly. On the other hand, for small capitalization stocks, the market may be not particularly efficient, and as a consequence, it takes longer time for investors to embed all the recent information into the stock price. Moreover, the inefficiency is greater for the highest sentiment quintiles, for which the positive information requires up to three months to be incorporated in the stock price. However, negative news is likely to be rapidly factored into the stock price also for small capitalization stocks, since the major decline in prices occurs during the observation month. These results are of crucial importance for investors and fund managers since they can exploit news sentiment indicators for stock-picking purposes to improve the performance and outperform the benchmark.

4.5. Discussion of the results

Our results suggest that investors in the European stock market tend to react more quickly and strongly to negative news compared to positive news, highlighting an asymmetric behaviour. It is important to acknowledge that the asymmetric relationship between market sentiment and asset returns, is not unique to the Bloomberg sentiment index. Recent research has also documented such asymmetric effect using other proxies for sentiment. For instance, studies exploring the impact of Economic Policy Uncertainty (EPU, Baker et al., 2016), geopolitical risk (GPR, Caldara & Iacoviello, 2022) or volatility indices (VIX, OVX) have consistently shown that these factors exhibit asymmetric impacts on equity markets (Bossman et al. 2023a, 2023b). We highlight that the latter indices refer to the market as a whole, while in our study the asymmetric relationship is found between the Bloomberg sentiment index of a stock and its return.

This pattern may be also justified based on established behavioural and economic theories. One key concept is loss aversion, which is a central idea in Prospect Theory (Kahneman & Tversky, 1979), suggesting that the psychological pain of experiencing a loss is felt more intensely than the pleasure derived from an equivalent gain. As a result, investors are incentivized to react swiftly and decisively to negative information in an effort to mitigate potential losses. This asymmetry is further supported by Elyasiani et al. (2018), who highlight that investors are more willing to pay to hedge against 'bad volatility' (associated with negative returns) than 'good volatility' (associated with positive returns).

In the European context, this effect may be heightened by a perceived higher level of uncertainty and a greater sensitivity to downside risks. Consequently, adverse news can trigger immediate selling pressure and lead to more dramatic market corrections, while positive developments might be processed more slowly and with less impact. Finally, information asymmetry can intensify this reaction. When negative news is released, it may be interpreted as a signal of deeper, undisclosed problems, prompting investors to exit potentially affected assets more quickly. In addition, the asymmetric effect seems to be more pronounced for small capitalization stocks. This result is consistent with Baker and Wurgler (2006), who suggest that sentiment has a stronger impact on the valuations of smaller, more difficult-to-value stocks. The amplified reaction to negative news in small-cap stocks can be explained by the greater information asymmetry surrounding these firms, as highlighted by Bhushan (1989), making negative news a more potent signal of risk. Furthermore, the lower liquidity characteristic of small-cap stocks, as evidenced by Amihud and Mendelson (1986), means that even moderate selling pressure can result in more significant price declines, as even moderate selling pressure initiated by negative news can translate into significantly larger and more rapid price declines compared to their larger, more liquid counterparts.

The same factors may lead to a longer time to incorporate positive news. First, with fewer analysts actively following and

[6] We adopt a sorting approach based on deciles, as in this step we consider all stocks with high and low sentiment, regardless of the specific time period in which returns are collected. This approach ensures that we do not face the risk of having an insufficient number of stocks in each decile, and by applying deciles instead of quintiles we are able to enhance the graphical representation and readability of the results.

[7] https://www.bloomberg.com/professional/blog/finding-novel-ways-trade-sentiment-data/.

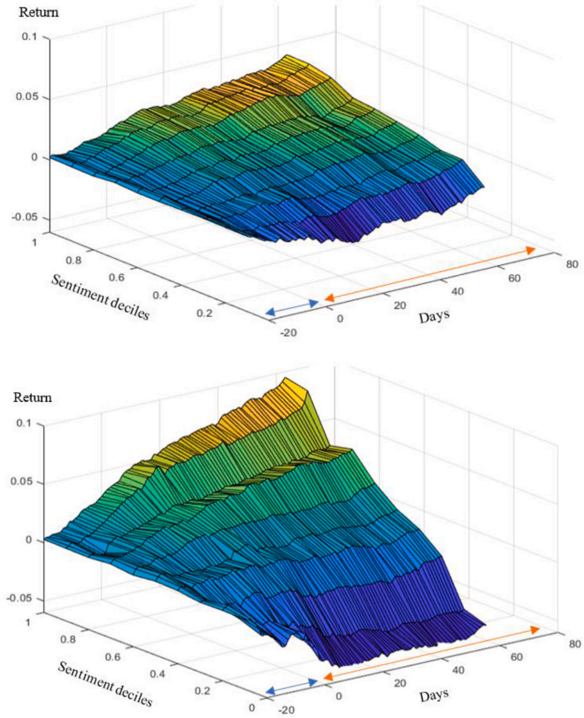

Fig. 4. Term structure of the cumulative return for a strategy that invests in portfolios with different level of sentiment using stocks with high and low market capitalization.
Note: the figure at the top (bottom) graphically represents the term structure of the cumulative return for a strategy that invests in big (small) capitalization stocks belonging to a sentiment decile using an equal-weighted method. The magnitude of the cumulative return is depicted on the vertical axis, while the investment horizon (in days) is indicated on the horizontal axis. Sentiment deciles are represented on the depth axis.

disseminating information about these firms, and lower institutional ownership leading to less immediate scrutiny, positive news may take longer to reach a wider investor base and be fully appreciated. Second, the inherent uncertainty and higher perceived risk associated with smaller firms (see e.g., Fama & French, 1993) can lead investors to adopt a more cautious approach when evaluating positive news, thus investors might require more sustained positive signals or stronger confirmation before adjusting their valuations of small firms upwards. Finally, lower liquidity in these stocks, as highlighted by Amihud and Mendelson (1986) and Pastor and Stambaugh (2003), can slow down price adjustments. Even with positive news, a lack of active trading and readily available buyers can hinder the rapid translation of positive sentiment into significant price increases compared to more liquid and larger companies.

5. The relevance of sentiment for asset pricing

Our objective in this section is to evaluate the importance of investor sentiment, as measured by the Bloomberg sentiment index, in asset pricing. To this end, we create a sentiment factor and assess whether the factor is priced in the cross-section of stock returns. To account for the non-traded nature of sentiment, we begin by creating a mimicking portfolio that reflects an exposure to sentiment. One way to create a sentiment factor is by using a portfolio that includes stocks with high sentiment in a long position and stocks with low sentiment in a short position. The Q5-Q1 portfolio discussed in Section 3.2 is a straightforward example of a sentiment factor. The

Table 4
Correlation between risk factors before and after the two-way sorting procedure.

	MKT	*SMB*	*HML*	*CMA*	*RMW*	$SENT_{5\text{-}1}$	*FSENT*
MKT	1.000	−0.670	0.368	0.006	−0.250	−0.374	−0.086
SMB		1.000	−0.272	−0.067	0.220	0.290	0.062
HML			1.000	0.536	−0.752	−0.667	−0.297
CMA				1.000	−0.463	−0.331	−0.202
RMW					1.000	0.559	0.190
$SENT_{5\text{-}1}$						1.000	0.571
FSENT							1.000

Note: This table reports the correlations among Fama and French (2015) risk factors, the factor constructed as a long-short sentiment portfolio Q5-Q1 ($SENT_{5\text{-}1}$), and the factor obtained through the two-way sorting procedure (*FSENT*).

return on this portfolio reflects the investor's profit or loss from sentiment exposure.

One drawback of the multivariate sorting analysis outlined in Section 3.2 is the difficulty in separating the effect of each risk factor because the stock exposures to the different factors considered can be correlated. Table 4 shows the correlations between the sentiment factor obtained in Section 4.1 as the 5-1 portfolio formed as a long position in stocks with very high sentiment and a short position in stocks with a very low sentiment ($SENT_{5\text{-}1}$) and the Fama and French (1997) and Fama and French (2015) risk factors. $SENT_{5\text{-}1}$ shows a high degree of correlation (−0.667) with *HML* and a moderate correlation with the remaining factors (0.559 with *RMW*, −0.374 with *MKT*, and −0.*331* with CMA). In order to address this issue, we follow the methodology proposed in Chang et al. (2013) and Elyasiani et al. (2020) that suggest a sorting procedure to isolate the pricing effects of the different risk factors. In order to avoid having portfolios with too few stocks, due to the limited number of stocks with a Bloomberg sentiment index value, we implement a two-way sorting procedure and choose to sort with respect to the *HML* factor, since it is the one with the highest correlation with the sentiment portfolio ($SENT_{5\text{-}1}$). The adopted procedure is based on the following steps. First, each month we sort the stocks into two different sub-samples based on their exposure to the *HML* factor. Second, within each sub-sample, we sort again the stocks into three sub-samples: stocks characterized by a low, medium and high value of the Bloomberg sentiment index, respectively. In this way we obtain six groups of stocks and we compute the return of a value-weighted portfolio within each group over the next month. The use of terciles instead of quintiles allow us to prevent the risk of including an insufficient number of stocks in each group and recall the construction methodology of the Fama and French (1997) factors, which are constructed using the 6 value-weight portfolios formed on size and book-to-market.

Finally, in order to have a portfolio exposed to sentiment and well diversified with respect to the *HML* factor, we take a long position on the two portfolios with the highest level of investor sentiment and a short position on the two portfolios with the lowest level of investor sentiment. Diversification over the *HML* risk factors is ensured by the fact that the portfolios obtained collect stocks with both low and high exposure to *HML*. The return of the factor portfolio exposed to sentiment (*FSENT*) is computed as:

$$FSENT = (1/2)(Rsent_H - Rsent_L) \tag{5}$$

where $Rsent_H$ is the value-weighted return of the portfolios characterized by the highest level of sentiment and $Rsent_L$ is the value-weighted return of the portfolios characterized by the lowest level of sentiment. The correlation of *FSENT* with the remaining factors is reported in Table 4, last column. Unlike the sentiment factor constructed using the Q5-Q1 method ($SENT_{5\text{-}1}$), the correlation of the factor obtained through the two-way sorting procedure (*FSENT*) with the remaining factors is low (maximum correlation is −0.297 with *HML*).

The results for the portfolios of the two-way sorting procedure are outlined in Table 5. The reported statistics confirm that the return of the sentiment portfolio (*FSENT*) is positive and significant, and it is robust to the inclusion of Fama and French (1997) and Fama and French (2015) risk factors. Moreover, the interval of the betas reported in the last three rows of Table 5 suggest that the obtained portfolios in the three groups (with low, medium and high sensitivity to sentiment) are well-diversified with respect to the *HML* factor. On the other hand, the portfolios with a low, medium and high value of sentiment, show a beta with respect to the sentiment factor equal to −0.665, −0.098, and 0.336 respectively, thus reflecting an increasing exposure to sentiment. As a result, *FSENT* is a zero-cost portfolio constructed to be highly exposed to sentiment and neutral to the *HML* factor and it represents a tradable asset,[8] as well as the Fama and French factors. The average return of the *FSENT* portfolio represent the investors' reward for exposure to investor sentiment.

In order to evaluate the relevance of sentiment as a priced factor in the cross-section of stock returns, we apply the two-pass regressions of Fama and MacBeth (1973) to the 25 Fama and French portfolios. We select the 25 Fama and French portfolios sorted on size and book-to-market, for their wide adoption (see, e.g., Chang et al., 2013), and their easy accessibility.[9]

First, we estimate the betas on daily returns for a one-month estimation window by running three different model specifications, namely the market model augmented with the sentiment factor (6), the three-factor Fama and French (1997) model augmented with the sentiment factor (7), and the five-factor Fama and French (2015) model augmented with the sentiment factor (8):

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i MKT_t + \beta_{FSENT}^i FSENT_t + \varepsilon_{i,t} \tag{6}$$

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{FSENT}^i FSENT_t + \varepsilon_{i,t} \tag{7}$$

$$\begin{aligned} R_{i,t} - R_{f,t} = {} & \beta_0^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t \\ & + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \beta_{FSENT}^i FSENT_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

The procedure is repeated by rolling the estimation window over to the next month.

Second, in order to compute the price of the risk factors, we use the estimated betas from equations (6)–(8) as regressors in the

[8] An alternative methodology to create a tradable factor is the one proposed in Barillas and Shanken (2017), who suggest replacing factors with traded mimicking portfolios the weights of which are equal to the slope coefficients in the regression of the factor on the available returns (and a constant), normalized to sum to one. However, in this case, the portfolios are not guaranteed to be neutral to other factors.

[9] Daily returns on the 25 Fama and French portfolios sorted by size and book-to-market are obtained from the Kenneth French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed) and are converted in Euro by means of the procedure detailed in Section 3.1.

Table 5
Two-way sorting results: portfolios average return and exposure to the risk factors.

	L	M	H	FSENT (H-L)
Avg. Ret.	0.69 % (1.454)	0.77 % (1.734)	1.20 %*** (2.863)	0.52 %** (2.336)
FF3 alpha	0.05 % (0.285)	0.03 % (0.225)	0.43 %*** (2.963)	0.38 %* (1.830)
FF5 alpha	0.00 % (0.028)	−0.01 % (−0.070)	0.41 %*** (2.940)	0.41 %** (2.028)
Avg. Sent	−0.041	0.145	0.344	
β_{FSENT}	−0.665	−0.098	0.336	
Min. β_{HML}	−2.316	−1.115	−1.072	
Avg. β_{HML}	0.138	0.215	0.185	
Max. β_{HML}	0.824	0.829	0.817	

Note: This table shows the monthly post-ranking returns and average betas for portfolios sorted on low (L), medium (M) and high (H) sentiment obtained in the two-way sorting procedure. For each tercile portfolio plus the H-L portfolio, we report the post-ranking value-weighted return (monthly return in percent) and the four-factor alphas computed with respect to the Fama and French (1997, 2015) factor models. The three-factor alpha (FF3 alpha) and the five-factor alpha (FF5 alpha) are computed as the intercept obtained by estimating the following equations.

FF3 alpha: $R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML + \varepsilon_{j,t}$.

FF5 alpha: $R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{RMW} RMW_t + \beta^j_{CMA} CMA_t + \varepsilon_{j,t}$

where $R_{j,t}$ is the portfolio return (post-ranking) in day t, for $j = L, M, H, H\text{-}L$ and MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the daily factors used in order to evaluate the robustness of the intercept. In line with Chang et al. (2013), we report the monthly alpha computed as the daily alpha multiplied by 21. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). ***, **, * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

models described by equations 9–11, respectively. We estimate equations 9–11 for the next month, where $E[R_i]$ is proxied by the next-month return of each of the considered asset:

$$E[R_i] - R_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{FSENT}\beta^i_{FSENT} \tag{9}$$

$$E[R_i] - R_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{SMB}\beta^i_{SMB} + \lambda_{HML}\beta^i_{HML} + \lambda_{FSENT}\beta^i_{FSENT} \tag{10}$$

$$\begin{aligned} E[R_i] - R_f = {} & \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{SMB}\beta^i_{SMB} + \lambda_{HML}\beta^i_{HML} \\ & + \lambda_{RMW}\beta^i_{RMW} + \lambda_{CMA}\beta^i_{CMA} + \lambda_{FSENT}\beta^i_{FSENT} \end{aligned} \tag{11}$$

Table 6 reports the average of the monthly estimates of the price of risk (lambdas) obtained by using the three different model specifications (*MKT + SENT*, *FF3+SENT*, *FF5+SENT*). If the pricing model includes all the relevant factors, the value of the intercept should be not significant. On the other hand, an intercept statistically different from zero implies that the model does not include all priced risk factors.

The lambda coefficient for the sentiment factor is positive and significant in all model specifications. The results indicate that sentiment is a priced factor in the cross-section of stock returns and is relevant for asset pricing.

6. Conclusions

In recent years, investor sentiment has attracted increasing interest among practitioners and researchers. Various methodologies have been proposed to capture and measure investor sentiment, and an increasing number of studies focus on the role of sentiment in predicting stock returns.

The present study investigated the forecasting power of the Bloomberg sentiment index on the cross-section of European stock returns, during the period 2010–2021, which is characterized by different market phases (bullish and bearish) and by periods of turmoil and stability in the market. A portfolio sorting procedure was adopted based on sentiment to ascertain whether individual stock sentiment can provide useful information to investors for stock picking purposes. Moreover, the study investigated the time predictability of the Bloomberg sentiment index on stock returns and the factors (e.g. stock size) that can affect the relationships between sentiment and stock returns. Finally, we tested whether sentiment is a priced factor in the cross-section of stock returns.

The findings were as follows. First, evidence was found of a positive relationship between sentiment and the cross-section of future stock returns. Stocks that are characterized by very high sentiment earn significantly higher returns than stocks characterized by very low sentiment. Moreover, the performance of the portfolio that takes a long position in stocks with very high sentiment and a short position in stocks with very low sentiment is significant also from an economic point of view. The results are also robust to the inclusion of other risk factors, such as market excess return (*MKT*), size (*SMB*), book-to-market (*HML*), risk-weighted asset (*RMW*), and the conservative minus aggressive factor (*CMA*). Furthermore, they remain consistent across different portfolio construction methodologies and cannot be explained by other aggregated sentiment proxies, such as the VIX and VSTOXX indices.

Second, evidence was found of a significant overperformance (underperformance) of stocks characterized by a high (low) sentiment up to three months from the sentiment observation when an equal-weighted procedure is used in the portfolio construction. However, when value-weighted portfolios are investigated, profitability declines faster after one month, indicating a possible influence of the size factor on the relationship between sentiment and returns. Third, while possible gains for a long-short strategy based on

Table 6
Estimation output of Fama and MacBeth (1973) regressions.

	λ_0	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{FSENT}	*Avg.* R^2
MKT+	0.010**	−0.001					0.008**	36.44 %
SENT	(2.037)	(-0.286)					(2.432)	
FF3+	0.007	0.001	0.001	−0.003			0.004**	65.03 %
SENT	(1.514)	(0.281)	(0.787)	(-1.373)			(2.033)	
FF5+	0.006	0.002	0.001	−0.003	−0.002*	0.002	0.004**	80.84 %
SENT	(1.193)	(0.824)	(0.954)	(-1.472)	(-1.678)	(1.284)	(2.001)	

Note: This table shows the estimated price of risk by applying the two-pass Fama & MacBeth, 1973 regressions to the 25 Fama and French portfolios sorted on size and book-to-market. We test the market model augmented with the sentiment factor (*MKT* + *SENT*), the three-factor Fama and French (1997) model augmented with the sentiment factor (*FF3* + *SENT*), and the five-factor Fama and French (2015) model augmented with the sentiment factor (*FF5* + *SENT*). The lambda (λ) coefficients capture the price of risk for each risk factor. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

sentiment investing in stock with high capitalization are quite limited, the profitability of a long-short strategy investing in stocks with low capitalization is high and declines slowly with the length of the investment period. This result indicates that the market is less efficient in relation to small capitalization stocks compared to big ones since it takes more time to factor all the recent information into the stock price. Fourth, the inefficiency is higher for the highest sentiment quintiles since positive news requires up to three months to be factored into the stock price. On the other hand, negative news is more rapidly factored into the stock price for both large and small capitalization stocks. Finally, the Fama-Macbeth regression results indicate that sentiment is a priced factor in the cross-section of stock returns and matters in asset pricing, suggesting the need for investors and fund managers to incorporate sentiment measures into asset pricing models.

The results of the paper are of interest to investors, fund managers, policymakers, and firms' managers. Investors and fund managers can exploit individual sentiment indicators as an additional tool for stock-picking purposes. Policymakers can exploit the sentiment measures to monitor the level of greed and fear in the market, and promptly act to avoid the formation either of speculative bubbles or of excessive pessimism. Moreover, they can monitor the profitability of sentiment strategy to detect the existence of inefficiencies or frictions in certain sectors of the stock market, such as the small-capitalization segment. Finally, firms' managers should proactively manage crises, addressing negative events (e.g., scandals, earnings misses, regulatory issues) swiftly through transparent communication to minimise stock price and investor confidence impacts, and incorporate sentiment analysis into longer-term strategic planning for investor relations and capital-raising to align with high positive sentiment periods for optimal market impact.

While our findings offer valuable insights, it is important to consider potential limitations related to data quality and unobserved factors, which are inherent in studies of this nature. Moreover, in this study the news coverage is limited to the Bloomberg horizon, which may not fully represent the broader informational landscape. Future research could address this aspect by comparing the impact of Bloomberg news with those obtained from other sources, such as Reuters, and reflected in their respective sentiment indicators, to evaluate potential differences and broaden the scope of the analysis.

Declarations of interest

None.

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Appendix A. Robustness analysis on portfolio formation methodologies

This appendix provides a robustness analysis of the sentiment-sorted portfolio results presented in Sections 4.1 and 4.2. Specifically, we investigate the sensitivity of our findings to the choice of portfolio sorting procedure, comparing the performance of portfolios constructed using terciles, deciles, and the power sorting methodology proposed in Kagkadis et al. (2024).

Power sorting improves upon conventional portfolio methods by offering a more robust analysis of factor-return relationships. Differing from traditional quantile sorting and fixed weights, it directly models portfolio weights as a function of characteristic rank, capturing non-linearities and asymmetries. By parameterizing weight allocation with power exponents, power sorting provides a data-driven and targeted approach, enhancing tail signals while retaining interpretability.

In the following, we recall some key steps of the methodology; for a comprehensive discussion, we refer readers to the original paper (Kagkadis et al., 2024). The process begins by transforming firm characteristics into a standardized rank:

$$s_{t,(n)} = \left[\mathrm{rank}\left(x_{t,(n)}\right) - \frac{N_t + 1}{2}\right] \tag{A1}$$

$$\tilde{s}_{t,(n)} = \begin{cases} -\dfrac{s_{t,(n)}}{s_{t,(1)}} & \text{for} \quad s_{t,(n)} < 0 \\ 0 \quad \text{for} \quad s_{t,(n)} = 0 \\ \dfrac{s_{t,(n)}}{s_{t,(N_t)}} & \text{for} \quad s_{t,(n)} > 0 \end{cases} \tag{A2}$$

where $x_{t,(n)}$ represents the characteristic of stock n at time t (i.e. the Bloomberg sentiment index for stock n on month t), and N_t is the number of stocks; rank $(\cdot)$ is the rank function and $[\cdot]$ is the function rounding to the nearest integer. Portfolio weights are then derived from these standardised ranks according to Equation (A2):

$$w_t^{PS}\left(\tilde{s}_{t,(n)}; p, q\right) = w_{t,(n)}^{PS} \begin{cases} -\dfrac{\left|\tilde{s}_{t,(n)}\right|^q}{\sum\limits_{\tilde{s}_{t,(n)}<0} \left|\tilde{s}_{t,(n)}\right|^q} & \text{for} \quad \tilde{s}_{t,(n)} < 0 \\ 0 \quad \text{for} \quad \tilde{s}_{t,(n)} = 0 \\ \dfrac{\tilde{s}^p_{t,(n)}}{\sum\limits_{\tilde{s}_{t,(n)}>0} \tilde{s}^p_{t,(n)}} & \text{for} \quad \tilde{s}_{t,(n)} > 0 \end{cases} \tag{A3}$$

where p, $q \in [0,1]$ are two parameters which control the concentration of the power sorting portfolio weights, i.e., higher parameter values lead to portfolios that are more concentrated in the extreme ranks.

For value-weighted portfolios, the methodology incorporates market capitalization through an additional parameter $h \in [0,1]$, as described in Equation (A4):

$$w_{t,(n)}^{PS,cap} \begin{cases} -\dfrac{\left|\tilde{s}_{t,(n)}\right|^q \cdot mcap^h_{t,(n)}}{\sum\limits_{\tilde{s}_{t,(n)}<0} \left|\tilde{s}_{t,(n)}\right|^q \cdot mcap^h_{t,(n)}} & \text{for} \quad \tilde{s}_{t,(n)} < 0 \\ 0 \quad \text{for} \quad \tilde{s}_{t,(n)} = 0 \\ \dfrac{\tilde{s}^p_{t,(n)} \cdot mcap^h_{t,(n)}}{\sum\limits_{\tilde{s}_{t,(n)}>0} \tilde{s}^p_{t,(n)} \cdot mcap^h_{t,(n)}} & \text{for} \quad \tilde{s}_{t,(n)} > 0 \end{cases} \tag{A4}$$

The parameter h controls the concentration in high-capitalization stocks, ranging from a pure characteristic-weighted portfolio ($h = 0$) to fully a value-weighted portfolio ($h = 1$). For our application, we set the parameters p and q equal to 0.5, and $h = 0$ ($h = 1$) to obtain the equal- (value-) weighted results. For a comprehensive understanding of the Power Sorting methodology—encompassing parameter estimation, adjustments for time-varying parameters, and other methodological details, we refer to Kagkadis et al. (2024).

In Table A1, we focus on presenting the results for the sentiment long-short factor portfolio. Full results for each of the quantiles are omitted for conciseness and to enhance comparison, but are available on request. Our results demonstrate a strong consistency with the outcome reported in Table 1, both in terms of sign and statistical significance. Specifically, we observe that stocks characterised by high sentiment scores significantly outperform those with the lowest sentiment scores over a one-month investment horizon. This effect is robust to both equal-weighted and value-weighted portfolio construction methodologies, reinforcing the immediate predictive power of sentiment for short-term returns. However, when considering longer investment horizons, our results align with the patterns identified in Tables 2 and 3 We confirm that the significant outperformance of stocks with high sentiment is primarily observed when employing equal-weighted portfolios. In contrast, the significant outperformance using a value-weighted approach tends to diminish over longer horizons, indicating that the sentiment effect, while present, is less potent for large capitalization stocks over longer periods. Finally, the results indicate that portfolios sorted based on deciles achieve higher returns compared to those using alternative sorting methods. This suggests that the sentiment effect on returns is more pronounced for extreme sentiment values.

Table A1
Investment results for portfolios sorted based on sentiment and held for one, two, and three months.

	Value weighted results			Equal weighted results		
	Q3-Q1	Q10-Q1	Power sorting	Q3-Q1	Q10-Q1	Power sorting
Panel A: Investment results for portfolios sorted based on sentiment and held for one month						
Avg. Ret.	0.76 %*** (2.812)	1.20 %*** (3.548)	0.52 %** (2.431)	0.91 %*** (3.140)	1.62 %*** (3.283)	0.77 %*** (2.630)
FF3 Alpha	0.58 %*** (4.117)	0.71 %** (2.501)	0.42 %*** (3.148)	0.61 %** (2.151)	1.24 %*** (2.686)	0.68 %*** (2.989)
FF5 Alpha	0.44 %** (2.324)	0.71 %** (2.470)	0.30 %* (1.672)	0.52 %* (1.880)	1.19 %** (2.504)	0.45 %** (2.539)
Panel B: Investment results for portfolios sorted based on sentiment and held for two months.						
Avg. Ret.	0.48 %* (1.721)	0.92 %** (1.973)	0.58 %*** (2.638)	0.66 %** (2.048)	1.02 %*** (2.936)	0.84 %*** (3.148)
FF3 Alpha	0.32 %* (1.951)	1.00 %*** (2.654)	0.29 % (1.582)	0.56 %** (2.546)	0.89 %*** (3.198)	0.57 %** (2.286)
FF5 Alpha	0.20 % (1.116)	0.46 % (1.235)	0.28 % (1.471)	0.40 %* (1.834)	0.71 %** (2.522)	0.50 % (1.492)
Panel C: Investment results for portfolios sorted based on sentiment and held for two months.						
Avg. Ret.	0.66 %** (2.574)	0.36 % (1.476)	0.40 %* (1.656)	0.87 %*** (2.698)	1.60 %*** (2.908)	1.20 %** (2.087)
FF3 Alpha	0.30 % (1.531)	0.22 % (0.977)	0.24 % (1.386)	0.73 %*** (3.092)	1.73 %*** (3.326)	0.60 %** (2.494)
FF5 Alpha	0.26 % (1.297)	0.03 % (0.148)	0.17 % (0.887)	0.49 %*** (2.653)	1.26 %** (3.364)	0.35 %* (1.800)

Note: This table shows the results for long-short portfolios sorted based on sentiment measured using the Bloomberg sentiment index. The left (right) panel show the results for portfolios obtained using a value- (equal-) weighted method. Q3-Q1 (Q10-Q1) portfolios are obtained combining a long position in Q3 (Q10) and a short position in Q1. The last column in each panel corresponds to the portfolio obtained using the power sorting procedure developed by Kagkadis et al. (2024). Power sorting models portfolio weights as a flexible function of the underlying characteristic rank. For our application, we set the parameters p and q equal to 0.5, and $h = 0$ ($h = 1$) to obtain the equal- (value-) weighted results.
For each long-short portfolio, the table shows the post-ranking return (monthly return in percent), and the three- and the five-factor alpha computed with respect to the Fama and French (1997), and Fama and French (2014) risk factors. The three-factor (FF3) and the five-factor (FF5) alphas are computed as the intercepts obtained by estimating the following equations:

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t$$

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{RMW} RMW_t + \beta^j_{CMA} CMA_t$$

where $R_{j,t}$ is the monthly long-short portfolio return (post-ranking) in day t, MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the daily Fama and French risk factors used in order to evaluate the robustness of the intercept. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

Appendix B. Analysis of the role of VSTOXX and VIX indices as sentiment indicators

The VSTOXX and VIX are widely recognised as measures of market sentiment, albeit with different focuses compared to the Bloomberg sentiment index, which is computed at the individual stock level. In fact, the VSTOXX index measures the implied volatility of options on the EURO STOXX 50 index, thus representing expectations of volatility in the Eurozone stock market. It is considered as a "fear gauge" or indicator of uncertainty among European investors. Similarly, the VIX measures the implied volatility of options on the S&P500 index. Although primarily linked to the US stock market, the VIX is often used as a proxy for global market sentiment, including the European market, due to the influence of the US market on international markets. An increase in the VIX is generally interpreted as an increase in uncertainty and risk aversion among investors.

In this appendix we bring these indices into our analysis, by conducting a supplementary study focusing on the role of VSTOXX and VIX as sentiment indicators in the European context. To utilise these indices, which are aggregate measures of volatility, in the context of individual stocks in our dataset, we adopt the methodology outlined by Ang et al. (2006), Chang et al. (2013), and Elyasiani et al. (2020). Specifically, each month we estimate at the stock level the exposure with respect to the changes in the volatility index under investigation. In other words, we quantified how the return of each stock responds to fluctuations in volatility as measured by these indices, by performing the following regression model:

$$R_{j,t} - R_f = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{VOL} \Delta VOL_t + \varepsilon \tag{B1}$$

where the stock excess return is regressed on the market factor (*MKT*) and changes in the volatility index under investigation (ΔVOL, where VOL_t is proxied alternatively by the *VSTOXX* and *VIX*) to obtain the multivariate beta.

To investigate whether the VSTOXX and VIX volatility indices provide useful information about the cross-section of future stock returns, the selected stocks were ranked based on their β^j_{VOL}, and five portfolios were created, based on beta quintiles, exploiting a value-weighted procedure. The first (fifth) portfolio consists of the stocks with the lowest (highest) value of the beta with respect to changes in volatility. At the end of the sorting procedure, the time series of post-ranking returns for each portfolio over the following month (investment period) is collected, along with the returns of the 5-1 portfolio formed as a long position in stocks with very high beta and a short position in stocks with a very low beta. Following previous analyses on the cross-section of stock returns (e.g., Elyasiani et al., 2020), the procedure is repeated each month by rolling the observation period and the investment period over to the next month, with a monthly portfolio rebalancing.

To assess whether the effects of investor sentiment on future stock returns are robust to the inclusion of Fama and French (1997) risk factors, the three-factor alpha for each of the five portfolios (Q1, Q2, Q3, Q4, Q5) plus the long-short portfolio (Q5-Q1) is calculated by estimating Eq. (3) and Eq. (4).

The results presented in Table B1 suggest that the *VIX* and *VSTOXX* indices do not appear to have predictive power regarding European market returns during the analysed period. This conclusion is primarily drawn from observing the Q5-Q1 gaps, as the small magnitude of the negative coefficient suggests that the return difference between the portfolios with the highest and lowest volatility sensitivity is minimal and not statistically significant. Notably, the results for the *VSTOXX* index are in contrast to findings from previous studies on the European market (e.g., Elyasiani et al., 2020), which has shown a negative and statistically significant coefficient for a volatility-based long-short portfolio in the European region. This discrepancy could be attributed to several factors. Firstly, the investigation period in this study is different from those in earlier research, potentially capturing different market dynamics. Secondly, and perhaps more significantly, the sample of companies utilised here is much broader than in studies like Elyasiani et al. (2020), which focused on the Eurostoxx 600 stocks. This wider sample (all European listed stocks are considered in the analysis) may dilute or alter the relationship observed in more concentrated indices.

Moreover, if we call *FVOL* the volatility factor portfolio (obtained as the long-short portfolio) where *VOL* is proxied by the *VSTOXX* or the *VIX*, it is crucial to evaluate the relationship between this volatility-based long-short portfolio and our sentiment factor portfolio (*FSENT*). The results indicate a very low correlation between the two factors, regardless of whether the long-short portfolio is based on the VSTOXX (−0.031) or the VIX (−0.028). This low correlation is a key finding, as it highlights that what is captured by the Bloomberg Sentiment Index is distinct and cannot be explained by other international sentiment indices such as the *VSTOXX* or the *VIX*. This suggests that the Bloomberg Sentiment Index is capturing a unique dimension of market sentiment that is not reflected in traditional volatility measures, reinforcing its potential value as a complementary sentiment indicator.

Table B1
Investment results for portfolios sorted based on sentiment and held for one month.

Panel A: Betas estimated based on the VSTOXX index						
	Quintiles:					
	Q1	Q2	Q3	Q4	Q5	Gap: Q5-Q1
Avg. Ret.	0.63 %	0.76 %**	0.82 %**	0.73 %**	0.55 %	−0.08 %
	(1.358)	(2.233)	(2.382)	(2.005)	(1.292)	(-0.258)
FF3 Alpha	−0.04 %	0.13 %	0.18 %*	−0.04 %	−0.26 %	−0.22 %
	(-0.215)	(1.106)	(1.794)	(-0.404)	(-1.143)	(-0.724)
FF5 Alpha	0.02 %	0.13 %	0.16 %*	−0.05 %	−0.14 %	−0.15 %
	(0.106)	(1.131)	(1.703)	(-0.415)	(-0.591)	(-0.486)
Panel B: Betas estimated based on the VIX index						
	Quintiles:					
	Q1	Q2	Q3	Q4	Q5	Gap: Q5-Q1
Avg. Ret.	0.67 %	0.72 %*	0.74 %**	0.88 %***	0.57 %	−0.10 %
	(1.426)	(1.915)	(2.181)	(2.600)	(1.304)	(-0.361)
FF3 Alpha	−0.02 %	−0.04 %	0.07 %	0.14 %	−0.15 %	−0.13 %
	(-0.070)	(-0.321)	(0.747)	(1.137)	(-0.825)	(-0.397)
FF5 Alpha	0.04 %	−0.02 %	0.02 %	0.16 %	−0.13 %	−0.17 %
	(0.193)	(-0.169)	(0.227)	(1.256)	(-0.736)	(-0.511)

Note: This table shows the results for portfolios sorted based on their sensitivity to changes in volatility measured using the VSTOXX (Panel A) and the VIX (Panel B) volatility indices. Quintile 1 (5) collects stocks with the lowest (highest) values of estimated beta, Q5-Q1 portfolios are obtained combining a long position in Q5 and a short position in Q1. For each quintile portfolio plus the Q5-Q1 portfolio, the table shows the pre-ranking average sentiment, the post-ranking return (monthly return in percent), and the three- and the five-factor alpha computed with respect to the Fama and French (1997), and Fama and French (2015) risk factors. The three-factor (FF3) and the five-factor (FF5) alphas are computed as the intercepts obtained by estimating the following equations.

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t$$

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{RMW} RMW_t + \beta^j_{CMA} CMA_t$$

where $R_{j,t}$ is the monthly portfolio return (post-ranking) in day t, for j = Q1, Q2, Q3, Q4, Q5, Q5-Q1.
MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the daily Fama and French risk factors used in order to evaluate the robustness of the intercept. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). Significance at the 1 % level is denoted by ***, at the 5 % level by **, and at the 10 % level by *.

References

Allen, D. E., McAleer, M., & Singh, A. K. (2017). An entropy-based analysis of the relationship between the DOW JONES Index and the TRNA Sentiment series. *Applied Economics, 49*, 677–692. https://doi.org/10.1080/00036846.2016.1203067

Allen, D. E., McAleer, M., & Singh, A. K. (2019). Daily market news sentiment and stock prices. *Applied Economics, 51*, 3212–3235. https://doi.org/10.1080/00036846.2018.1564115

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics, 17*(2), 223–249. https://doi.org/10.1016/0304-405X(86)90065-6

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance (New York), 61*(1), 259–299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance (New York), 59*, 1259–1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance (New York), 61*, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *The Journal of Economic Perspectives, 21*, 129–151. https://doi.org/10.1257/jep.21.2.129

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics, 104*, 272–287. https://doi.org/10.1016/j.jfineco.2011.11.002

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Barillas, F., & Shanken, J. (2017). Which alpha? *Review of Financial Studies, 30*(4), 1316–1338. https://doi.org/10.1093/rfs/hhw101

Ben-Rephael, A., Da, Z., & Israelsen, R. D. (2017). It depends on where you search: Institutional investor attention and underreaction to news. *Review of Financial Studies, 30*(9), 3009–3047. https://doi.org/10.1093/rfs/hhx031

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics, 104*(2), 363–382. https://doi.org/10.1016/j.jfineco.2010.08.018

Bathia, D., & Bredin, D. (2018). Investor sentiment: Does it augment the performance of asset pricing models? *International Review of Financial Analysis, 59*, 290–303. https://doi.org/10.1016/j.irfa.2018.03.014

Benhabib, J., Liu, X., & Wang, P. (2016). Sentiments, financial markets, and macroeconomic fluctuations. *Journal of Financial Economics, 120*, 420–443. https://doi.org/10.1016/j.jfineco.2016.01.008

Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics, 11*(2–3), 255–274. https://doi.org/10.1016/0165-4101(89)90008-6

Bloomberg. (2016). *Embedded value in Bloomberg news & social sentiment data*. New York, NY, USA: Bloomberg. Technical Report BloombergTM.

Boehmer, E., & Wu, J. (2013). Short selling and the price discovery process. *The Review of Financial Studies, 26*(2), 287–322. https://doi.org/10.1093/rfs/hhs097

Bossman, A., Gubareva, M., & Teplova, T. (2023a). EU sectoral stocks amid geopolitical risk, market sentiment, and crude oil implied volatility: An asymmetric analysis of the Russia-Ukraine tensions. *Resources Policy, 82*, Article 103515. https://doi.org/10.1016/j.resourpol.2023.103515

Bossman, A., Gubareva, M., & Teplova, T. (2023b). Economic policy uncertainty, geopolitical risk, market sentiment, and regional stocks: Asymmetric analyses of the EU sectors. *Eurasian Economic Review, 13*(3), 321–372.

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *The American Economic Review, 112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

Chan, F., Durand, R. B., Khuu, J., & Smales, L. A. (2017). The validity of investor sentiment proxies. *International Review of Finance, 17*, 473–477. https://doi.org/10.1111/irfi.12102

Chang, B. Y., Christoffersen, P., & Jacobs, K. (2013). Market skewness risk and the cross section of stock returns. *Journal of Financial Economics, 107*(1), 46–68. https://doi.org/10.1016/j.jfineco.2012.07.002

Chau, F., Deesomsak, R., & Koutmos, D. (2016). Does investor sentiment really matter? *International Review of Financial Analysis, 48*, 221–232. https://doi.org/10.1016/j.irfa.2016.10.003

Chung, S.-L., Hung, C.-H., & Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance, 19*, 217–240. https://doi.org/10.1016/j.jempfin.2012.01.002

Corredor, P., Ferrer, E., & Santamaria, R. (2013). Investor sentiment effect in stock markets: Stock characteristics or country-specific factors? *International Review of Economics & Finance, 27*, 572–591. https://doi.org/10.1016/j.iref.2013.02.001

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies, 28*, 1–32. https://doi.org/10.1093/rfs/hhu072

Das, S., Martínez-Jerez, A., & Tufano, P. (2005). eInformation: A clinical study of investor discussion and sentiment. *Financial Management, 34*, 103–137. https://doi.org/10.1111/j.1755-053X.2005.tb00112.x

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98*, 703–738. https://doi.org/10.1086/261703

Dhaoui, A., & Bensalah, N. (2017). Asset valuation impact of investor sentiment: A revised Fama–French five-factor model. *Journal of Asset Management, 18*, 16–28. https://doi.org/10.1057/s41260-016-0027-2

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility?: Search queries and market volatility. *Eur Financial Management, 22*, 171–192. https://doi.org/10.1111/eufm.12058

Ding, W., Mazouz, K., & Wang, Q. (2019). Investor sentiment and the cross-section of stock returns: New theory and evidence. *Review of Quantitative Finance and Accounting, 53*, 493–525. https://doi.org/10.1007/s11156-018-0756-z

Dong, H., & Gil-Bazo, J. (2020). Sentiment stocks. *International Review of Financial Analysis, 72*, Article 101573. https://doi.org/10.1016/j.irfa.2020.101573

Du, W. (2020). News and market efficiency in the Japanese stock market. *The Journal of Behavioral Finance*, 1–14. https://doi.org/10.1080/15427560.2020.1774886

Dunham, L. M., & Garcia, J. (2020). Measuring the effect of investor sentiment on liquidity. *Managerial Finance, 47*(1), 59–85. https://doi.org/10.1108/MF-06-2019-0265

Elyasiani, E., Gambarelli, L., & Muzzioli, S. (2018). The risk-asymmetry index as a new measure of risk. *Multinational Finance Journal, 22*(3/4), 173–210.

Elyasiani, E., Gambarelli, L., & Muzzioli, S. (2020). Moment risk premia and the cross-section of stock returns in the European stock market. *Journal of Banking & Finance, 111*, Article 105732. https://doi.org/10.1016/j.jbankfin.2019.105732

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics, 43*, 153–193. https://doi.org/10.1016/S0304-405X(96)00896-3

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*, 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*, 607–636. https://doi.org/10.1086/260061

Figà-Talamanca, G., & Patacca, M. (2019). Does market attention affect Bitcoin returns and volatility? *Decisions in Economics and Finance, 42*(1), 135–155. https://doi.org/10.1007/s10203-019-00258-7

Figà-Talamanca, G., & Patacca, M. (2022). An explorative analysis of sentiment impact on S&P 500 components returns, volatility and downside risk. *Annals of Operations Research*, 1–23. https://doi.org/10.1007/s10479-022-05129-w

Frijns, B., Verschoor, W. F. C., & Zwinkels, R. C. J. (2017). Excess stock return comovements and the role of investor sentiment. *Journal of International Financial Markets, Institutions and Money, 49*, 74–87. https://doi.org/10.1016/j.intfin.2017.02.005

Gan, B., Alexeev, V., Bird, R., & Yeung, D. (2020). Sensitivity to sentiment: News vs social media. *International Review of Financial Analysis, 67*, Article 101390. https://doi.org/10.1016/j.irfa.2019.101390

Gao, B., & Liu, X. (2020). Intraday sentiment and market returns. *International Review of Economics & Finance, 69*, 48–62. https://doi.org/10.1016/j.iref.2020.03.010

Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis, 55*(2), 549–580. https://doi.org/10.1017/S0022109019000061

García, D. (2013). Sentiment during recessions: Sentiment during recessions. *Journal of Finance (New York), 68*, 1267–1300. https://doi.org/10.1111/jofi.12027

Glück, M., Hübel, B., & Scholz, H. (2021). Currency conversion of Fama–French factors: How and why. *Journal of Portfolio Management, 47*, 157–175. https://doi.org/10.3905/jpm.2020.1.192

Gomez-Carrasco, P., & Michelon, G. (2017). The power of stakeholders' voice: The effects of social media activism on stock markets: The effects of social media activism on stock markets. *Bus. Strat. Env., 26*, 855–872. https://doi.org/10.1002/bse.1973
González-Sánchez, M., & Morales de Vega, M. E. (2021). Influence of bloomberg's investor sentiment index: Evidence from European union financial sector. *Mathematics (Basel), 9*, 297. https://doi.org/10.3390/math9040297
Gric, Z., Bajzík, J., & Badura, O. (2023). Does sentiment affect stock returns? A meta-analysis across survey-based measures. *International Review of Financial Analysis, 89*, Article 102773. https://doi.org/10.1016/j.irfa.2023.102773
Guo, K., Sun, Y., & Qian, X. (2017). Can investor sentiment be used to predict the stock price? Dynamic analysis based on China stock market. *Physica A: Statistical Mechanics and Its Applications, 469*, 390–396. https://doi.org/10.1016/j.physa.2016.11.114
Habibah, U., Bhayo, M. U. R., & Iqbal, M. S. (2021). Investor sentiments and Fama–French five-factor premia. *Sage Open, 11*(2). https://doi.org/10.1177/21582440211027
Hao, Y., Chou, R. K., Ko, K. C., & Yang, N. T. (2018). The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis, 57*, 167–183. https://doi.org/10.1016/j.irfa.2018.01.014
Isakin, M., & Pu, X. (2023). Dispersion in news sentiment and corporate bond returns. *International Review of Financial Analysis, 89*, Article 102761. https://doi.org/10.1016/j.irfa.2023.102761
Johnman, M., Vanstone, B. J., & Gepp, A. (2018). Predicting FTSE 100 returns and volatility using sentiment analysis. *Accounting and Finance, 58*, 253–274. https://doi.org/10.1111/acfi.12373
Kagkadis, A., Lohre, H., Nolte, I., Nolte, S., & Vasilas, N. (2024). Power sorting. https://doi.org/10.2139/ssrn.4552208.
Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–291. https://doi.org/10.2307/1914185
Klemola, A., Nikkinen, J., & Peltomäki, J. (2016). Changes in investors' market attention and near-term stock market returns. *The Journal of Behavioral Finance, 17*, 18–30. https://doi.org/10.1080/15427560.2016.1133620
Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and return comovements. *Journal of Finance (New York), 61*(5), 2451–2486. https://doi.org/10.1111/j.1540-6261.2006.01063.x
Kuo, Y. S., & Huang, J. T. (2022). Factor-based investing in market cycles: Fama–French five-factor model of market interest rate and market sentiment. *Journal of Risk and Financial Management, 15*(10), 460. https://doi.org/10.3390/jrfm15100460
Liang, S. X. (2018). The systematic pricing of market sentiment shock. *The European Journal of Finance, 24*(18), 1835–1860. https://doi.org/10.1080/1351847X.2018.1491875
Loh, R. K. (2010). Investor inattention and the underreaction to stock recommendations. *Financial Management, 39*, 1223–1251. https://doi.org/10.1111/j.1755-053X.2010.01110.x
Nardo, M., Petracco-Giudici, M., & Naltsidis, M. (2016). Walking down Wall Street with A tablet: A survey of stock market predictions using the web. *Journal of Economic Surveys, 30*, 356–369. https://doi.org/10.1111/joes.12102
Nooijen, S. J., & Broda, S. A. (2016). Predicting equity markets with digital online media sentiment: Evidence from markov-switching models. *The Journal of Behavioral Finance, 17*, 321–335. https://doi.org/10.1080/15427560.2016.1238370
Omura, A., & Todorova, N. (2019). The quantile dependence of commodity futures markets on news sentiment. *Journal of Futures Markets, 39*(7), 818–837. https://doi.org/10.1002/fut.22010
Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642–685. https://doi.org/10.1086/374184
Piccione, M., & Spiegler, R. (2014). Manipulating market sentiment. *Economics Letters, 122*, 370–373. https://doi.org/10.1016/j.econlet.2013.12.021
Qadan, M., & Aharon, D. Y. (2019). Can investor sentiment predict the size premium? *International Review of Financial Analysis, 63*, 10–26. https://doi.org/10.1016/j.irfa.2019.02.005
Qadan, M., & Jacob, M. (2022). The value premium and investors' appetite for risk. *International Review of Economics & Finance, 82*, 194–219. https://doi.org/10.1016/j.iref.2022.06.014
Qadan, M., & Nama, H. (2018). Investor sentiment and the price of oil. *Energy Economics, 69*, 42–58. https://doi.org/10.1016/j.eneco.2017.10.035
Reis, P. M. N., & Pinho, C. (2020a). A reappraisal of the causal relationship between sentiment proxies and stock returns. *The Journal of Behavioral Finance*, 1–23. https://doi.org/10.1080/15427560.2020.1792910
Reis, P. M. N., & Pinho, C. (2020b). A new European investor sentiment index (EURsent) and its return and volatility predictability. *Journal of Behavioral and Experimental Finance, 27*, Article 100373. https://doi.org/10.1016/j.jbef.2020.100373
Renault, T. (2017). Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking & Finance, 84*, 25–40. https://doi.org/10.1016/j.jbankfin.2017.07.002
Sadhwani, R., Oad Rajput, S. K., & Habibah, U. (2018). Do sentiment indices impact the premium of prominent pricing factors? *Cogent Economics & Finance, 6*(1), Article 1550898. https://doi.org/10.1080/23322039.2018.1550898
Salur, B. V., & Ekinci, C. (2023). Anomalies and investor sentiment: International evidence and the impact of size factor. *International Journal of Financial Studies, 11*(1), 49. https://doi.org/10.3390/ijfs11010049
Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance, 16*, 394–408. https://doi.org/10.1016/j.jempfin.2009.01.002
Seok, S. I., Cho, H., & Ryu, D. (2019). Firm-specific investor sentiment and daily stock returns. *The North American Journal of Economics and Finance, 50*, Article 100857. https://doi.org/10.1016/j.najef.2018.10.005
Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization, Empirical Behavioral Finance, 107*, 730–743. https://doi.org/10.1016/j.jebo.2014.06.004
Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2017). Divergence of sentiment and stock market trading. *Journal of Banking & Finance, 78*, 130–141. https://doi.org/10.1016/j.jbankfin.2017.02.005
Smales, L. A. (2015). Asymmetric volatility response to news sentiment in gold futures. *Journal of International Financial Markets, Institutions and Money, 34*, 161–172. https://doi.org/10.1016/j.intfin.2014.11.001
Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance, 73*, 147–164. https://doi.org/10.1016/j.jbankfin.2016.09.010
Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance (New York), 62*, 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x
Tumarkin, R., & Whitelaw, R. F. (2001). News or noise? Internet postings and stock prices. *Financial Analysts Journal, 57*, 41–51. https://doi.org/10.2469/faj.v57.n3.2449
Uhl, M. W. (2014). Reuters sentiment and stock returns. *The Journal of Behavioral Finance, 15*, 287–298. https://doi.org/10.1080/15427560.2014.967852
Vanstone, B. J., Gepp, A., & Harris, G. (2019). Do news and sentiment play a role in stock price prediction? *Applied Intelligence, 49*(11), 3815–3820. https://doi.org/10.1007/s10489-019-01458-9
Xie, D., Cui, Y., & Liu, Y. (2023). How does investor sentiment impact stock volatility? New evidence from Shanghai A-shares market. *China Finance Review International, 13*(1), 102–120. https://doi.org/10.1108/CFRI-01-2021-0007
Zhang, X., Li, G., Li, Y., Zou, G., & Wu, J. G. (2023). Which is more important in stock market forecasting: Attention or sentiment? *International Review of Financial Analysis.* , Article 102732. https://doi.org/10.1016/j.irfa.2023.102732
Zhang, Y., Swanson, P. E., & Prombutr, W. (2012). Measuring effects on stock returns of sentiment indexes created from stock message boards. *Journal of Financial Research, 35*, 79–114. https://doi.org/10.1111/j.1475-6803.2011.01310.x