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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 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. The average return of the portfolio that takes a long position in the stocks with very high sentiment and a short position in stocks with very low sentiment is statistically and economically significant and is robust to the inclusion of commonly used risk factors. Second, the predictability of stock returns using the sentiment indicator declines fast after one month. Third, evidence is found of the profitability of a long-short strategy that invests in stocks with low capitalization: profitability declines with the duration of the investment period. Finally, it is found that positive news is factored into the stock price more slowly than negative news, especially for stocks with low market capitalization.

Keywords: Investor sentiment, Cross section, Portfolio strategies, Future returns, Stock size

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; Baker and Wurgler, 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 and Spiegler, 2014). The role of investor sentiment in explaining market returns is attracting increasing attention among practitioners and researchers. Recently, Campisi and Muzzioli (2020) outlined a sentiment index to model the trading decisions of financial investors, enabling the model to generate more complex price dynamics. From an empirical point of view, sentiment has been shown to explain financial market movements, especially in periods of irrational panic or unjustified optimism (Reis and 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). The relevance of investor sentiment for risk assessment is also shown by its inclusion among the European Securities and Markets Authority (ESMA) indicators measuring and monitoring systemic risk (Semi-annual ESMA Trends, Risks and Vulnerabilities Report (TRV) and Quarterly ESMA Risk Dashboard (RD)).

Since investor (or market) sentiment is not a directly measurable variable, this concept has been historically analysed by means of proxy variables (such as investor trades, mutual fund flows, trading volume, option-implied volatility) and surveys. Recently, research on this topic has moved toward sentiment measures and indicators extracted from news, microblogging sites, and web searches. Within this strand of research, a well-known example is the EPU index (Economic Policy Uncertainty Index) proposed by Baker et al. (2016), which aims to capture uncertainty about economic policy decisions and the economic effects of policy actions (or inaction) by exploiting newspaper coverage frequency. The main drawback of this index is that it is unable to distinguish between good and bad news, and as a result, it does not appear to be particularly useful for ascertaining the level of fear or greed in the market.

Further developments in sentiment indices have focused on the distinction between good and bad news (see e.g., Gao et al. (2020). In particular, text mining has been exploited to extract the relevant information and to carry out a "polarity classification" to check the positive and negative comments (bullish or bearish) on the main topics under examination (see, e.g., Loughran and McDonald Sentiment Word Lists, Loughran and McDonald, 2011).

However, there is no consensus in the literature about the construction of sentiment indicators (Chan et al., 2017), leaving investors and fund managers without a single measure of sentiment to support their investment and asset allocation decisions. Consequently, some information providers and financial institutions have taken steps to fill this gap by producing reports and developing their own investor sentiment indices up to the individual stock level. Thomson Reuters generates sentiment indicators based on comprehensive finance-specific sentiment data obtained from news and social media content. Similarly, Bloomberg has constructed an Investor Sentiment Index to measure the reaction of investors to the news published about events concerning companies. In particular, the sentiment index was constructed by taking into account the news and tweets considered relevant to a given company and assigning a numerical valuation of investor sentiment (see Bloomberg, 2016, for a detailed description). More specifically, Bloomberg assigns a positive, negative or neutral valuation depending on how the published information 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. As a result, the Bloomberg sentiment index is based on an aggregate of all the news published and posted daily about a company. While many papers investigate the forecasting properties of sentiment based on Reuters (Uhl, 2014; Smales, 2015; Nooijen and Broda, 2016; Allen et al., 2017, 2019; Araujo et al., 2018; Du, 2020; Gan et al., 2020), there is no clear evidence about the relationship between the Bloomberg sentiment index and the cross-section of future stock returns. More generally, there is no consensus in the literature about the relationship between sentiment indicators and stock prices. Some studies find evidence of a relationship between investor sentiment and market prices (see e.g., Uhl, 2014), whereas others (see e.g., González-Sánchez and Morales de Vega, 2021) conclude that there is no significant relationship between investor sentiment and market returns. In addition, there are studies showing that the explanatory power is in the opposite direction (Das et al., 2005), in the sense that returns and volatility variations affect sentiment, rather than the other way around.

The relationship between the Bloomberg sentiment index on the one hand, and abnormal returns and volume shocks on the other, is investigated in González-Sánchez and Morales de Vega (2021) for the major European financial companies. Their study shows that the effects of the Bloomberg sentiment index on abnormal returns and volume shocks are low. Moreover, the effects are more closely related to a sectoral aspect (banking, real estate, finance, or insurance) than to the individual characteristics of each firm. Therefore, the authors suggest that the Bloomberg sentiment index reflects a sectoral sentiment effect more than an individual one. However, their results are based on a limited sample period (2014–2018), characterized by a positive market trend and a fairly low level of volatility. As a consequence, investor sentiment, limited to the financial sector on a short-term horizon, could reflect expectations regarding monetary policy decisions and thus affects the entire financial sector in a uniform manner. There is no evidence as to whether the Bloomberg sentiment index can provide useful information on individual stocks in order to help investors and fund managers in stock picking and asset allocation decisions.

To fill this gap, this paper examines the information embedded in the Bloomberg sentiment index in the period 2010-2021, which is characterized by market conditions of both turmoil and stability. Unlike González-Sánchez and Morales de Vega (2021), the present study takes into account all the listed companies in the euro area. The choice of the dataset makes it possible to assess the behaviour of sentiment indices in different market conditions and across different economic sectors. The aim of the paper is manifold. First, to understand whether individual sentiment indicators provide useful information about the cross-section of future stock return and assess whether they can support investors for stock pricking purposes. Second, to evaluate how long positive or negative sentiment affects the cross-section of stock return, which is highly debated in the literature. Third, to assess whether additional factors, such as stock size, could explain the relationship between sentiment and future returns. Fourth, to cast light on the existence of asymmetric effects on returns related to positive and negative news.

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 profitability of the portfolio that takes a long position in the stocks with very high sentiment and a short position in stocks declines fast after one month. Third, investment gains for a long-short sentiment portfolio based on high capitalization stocks are limited. However, the profitability of a long-short strategy investing in stocks with low 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 stock prices. Finally, inefficiency is higher (lower) for positive (negative) news, which require up to three months (a few days) to be incorporated into the stock price.

The paper proceeds as follows. Section 2 provides a review of the existing 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. Finally, Section 5 concludes and examines the 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. For an in-depth literature review, see, e.g., Sun et al. (2016).

2.1 Investor sentiment measures

According to González-Sánchez and Morales de Vega (2021), 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 and Wurgler, 2007) or by combining a range of economic and financial indicators (Reis and 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 (González-Sánchez and Morales de Vega, 2021). At the aggregate market level, Reis and Pinho (2020a) create the EURsent investor sentiment index by aggregating several economic and financial variables. They find EURsent to be a reliable predictor of market returns in Europe through in-sample and out-of-sample analyses over several horizons and in periods of recession or growth. In particular, when sentiment is low, future stock returns are expected to be higher and positive. More specifically, when sentiment is bearish, investors purchase fewer risky assets, leading to a decline in price and increasing expected returns. A low level of sentiment makes institutional and retail investors more selective, cautious, and rational. As a result, they invest in stocks prudently, reflecting higher levels of risk in the discount rate used for valuation, which will increase future expected returns. On the other hand, bullish sentiment periods give rise to excess demand, pushing up prices, and decreasing expected future returns.

Reis and Pinho (2020a) also observe an asymmetric influence of the sentiment index on market variance since optimism and good news have a stronger impact on volatility than pessimism and bad news do. Moreover, during the financial crisis, the market reaction to sentiment was quicker than during periods of optimism, and peaks or troughs in sentiment are strongly related to the most significant financial, economic, and political events. 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 (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 a more detailed description of the indices, see González-Sánchez and Morales de Vega, 2021). 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 provided by the media. 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, González-Sánchez and Morales de Vega (2021) 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., Tetlock, 2007; García, 2013), internet search engines such as Google, and Yahoo (see e.g., Da et al., 2015; Dimpfl and Jank, 2016), or from social media such as Facebook, Twitter or Live Journal (see e.g., Siganos and Vagenas-Nanos, 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 (González-Sánchez and Morales de Vega, 2021). As a consequence, the trend is to use information directly extracted from specialized media or platforms with high data traffic (Twitter and Google).

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 and Frank, 2004; Tumarkin and 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 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 particular, 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-Carsrasco 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. Finally, 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.

To sum up, the financial literature generally agrees on the existence of a relationship between sentiment measures and future market 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 market 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 (Renault, 2017; Sun et al., 2016; Gao and Liu, 2020). 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 (Uhl, 2014; Smales, 2015; Nooijen and Broda, 2016; Allen et al., 2017, 2019; Araujo et al., 2018; Du, 2020; Gan et al., 2020), the empirical evidence is scant for the Bloomberg sentiment index.

To the best of our knowledge, the only study that investigates the relationship between the Bloomberg sentiment index and stock market returns is González-Sánchez and Morales de Vega (2021).[1] However, their study focuses on the financial sector during the period 2014–2018, characterized by a positive market trend and a limited level of volatility. 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.

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

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 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. Unlike previous studies (e.g., González-Sánchez and Morales de Vega, 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 takes into account 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. The study includes at least one observation of the Bloomberg sentiment index for 2409 stocks: these stocks will compose the filtered dataset. The study consists of a total 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.

The next step was to download the Fama-French factor returns for the European market from Kenneth French’s data library. All the returns used in the analysis (Fama-French returns and individual stock returns) include 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:

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

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:

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

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

3.2 Investor sentiment and the cross-section of stock returns

A theoretical framework for the relationship between sentiment and the cross-section of stock returns has recently been outlined by Ding et al. (2019). They extend the De Long et al. (1990) model by introducing multiple risky assets that differ in their exposure to market-wide sentiment. In their model, Ding et al. (2019) consider both long- and the short-run investor sentiment components. While the long-run sentiment accounts for the average bullishness (i.e., optimism) of noise traders, the short-run sentiment represents the transitory deviations from the long-run sentiment. Unlike previous models, Ding et al. (2019) suggest that both components have cross-sectional implications. In particular, as the short-run component increases, irrational investors become more bullish and drive up the relative returns of more sentiment-prone stocks. Hence, the model predicts a positive correlation between contemporaneous changes in the short-run sentiment and the returns of sentiment-prone stocks. However, a higher long-run sentiment exerts more upward pressure on the prices of more sentiment-prone stocks and reduces their expected future returns, thus making the long-run component a contrarian predictor of subsequent cross-sectional returns.

In the empirical analysis in the present study, the Bloomberg sentiment index is expected to be a proxy for short-run investor sentiment. In particular, 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, various procedures will be 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 is adopted. At the end of each month (observation period), stocks are selected with at least five observations on the Bloomberg sentiment index. The average value of the Bloomberg sentiment index is used as the proxy for the stock sentiment. Then, the selected stocks are ranked based on their sentiment index, and five portfolios are created, based on sentiment quintiles, exploiting 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):

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

where $R_{j,t}$ is the portfolio return (post-ranking) in day t, for $j=1,\dots,6$, 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” (*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):

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

4. Empirical results: Bloomberg sentiment index and the cross-section of stock returns

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. Section 4.2 investigates the forecasting power of the Bloomberg sentiment index on returns for different investment horizons. Section 4.3, is intended to cast light on the term structure of stock returns for different sentiment levels, and finally, Section 4.4 analyses the role of stock market capitalization in the relationship between sentiment and returns.

4.1 Portfolios sorted based on sentiment and held for one month

The results of the average post-ranking returns, the three-factor alpha and the five-factor alpha are reported in Table 1 (t-stats in parentheses); the value-weighted method is used for the computation of the post-ranking returns. 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.

The cumulative return of the five portfolios over the sample period is depicted in Figure 1. 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 market 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 market 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 4.2.

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.[2] 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 are selected that have at least five observations of the Bloomberg sentiment index, 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 Table 2 and Table 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.

The results for the two-month investment horizon (Table 2) 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 and French, 2015). This result

[2] 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).

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 strategy is completely offset when considering an investment horizon of three months (Table 3). In this case, neither the average returns nor the alphas of the long-short portfolio are statistically different from zero.

4.3 Term structure of stock returns for different sentiment levels

This subsection aims to provide further insight into the term structure of the relationship between sentiment and future stock returns. To evaluate 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 value-weighted returns for stocks in the sentiment decile is plotted in Figure 2. In this way, it is possible to obtain further insights about the results presented in Tables 1-3.

Figure 2, 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), confirm the hypothesis that pessimism in investor sentiment spreads faster than optimism. 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.

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

To assess whether stock size plays an important role in the relationship between sentiment and future market 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 cap) and the third (big cap) 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 high (low) capitalization is split into deciles, and the average cumulative return for stocks in the sentiment deciles is plotted in Figure 3, at the top (bottom). The difference between the two surfaces is striking. In particular, the surface for stocks characterized by high 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 sample (during the observation period and the first investment month), it continues to grow until the end of the third investment month.

The results suggest that sentiment affects small 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 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 stocks.[3] To elaborate, positive and negative news about stocks with high capitalization can be already factored into their price, or they may be factored into the stock price more quickly compared to small 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-cap 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 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.

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

5. 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 market returns.

Interesting extensions of the investor sentiment concept and indicators include the use of indicators extracted from news, microblogging sites, and web searches. However, given that sentiment is not a directly measurable variable, there is no consensus on how to build these indices. Some information providers and financial institutions (mainly Reuters and Bloomberg) have taken steps to fill this gap by developing their own investor sentiment indices. While there are several studies that investigate the forecasting performance of sentiment based on Reuters (Uhl, 2014; Smales, 2015; Nooijen and Broda, 2016; Allen et al., 2017, 2019; Araujo et al., 2018; Du, 2020; Gan et al., 2020), the only study that investigates the relationship of the Bloomberg sentiment index and the stock market is González-Sánchez and Morales de Vega (2021). However, their study is limited both in terms of the short time period analysed and the number of stocks considered (EU financial sector), leaving some important points to be clarified. First, the relationship between sentiment and future returns is a moot point in the literature. Second, there is no consensus on the time predictability of future returns using sentiment proxies since empirical evidence spans from the next trading day over one or more months. Third, most studies investigate the US market, and there is limited evidence on European stocks and on the characteristics of stocks that can affect the relationship between sentiment and future returns.

To fill this gap, 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.

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).

Second, the profitability of the portfolio that takes a long position in the stocks with very high sentiment and a short position in stocks declines fast after one month. Third, while possible gains for a long-short strategy based on 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 stocks compared to big ones since it takes more time to factor all the recent information into the stock price. Finally, 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 stocks.

The results of the paper are of interest to investors, fund managers, and policymakers. 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.

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

	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%***
						(3.007)
FF3 Alpha	-0.22%	0.16%	-0.08%	0.09%	0.37%	0.58%***
						(2.647)
FF5 Alpha	-0.10%	0.15%	-0.09%	0.11%	0.41%	0.51%**
						(2.313)

Note: This table shows the results for portfolios sorted based on sentiment measured using the Bloomberg sentiment index. 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 (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 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 *.

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

	Quintiles:					
	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%*
						(1.740)
FF3 Alpha	-0.10%	-0.05%	-0.02%	0.16%	0.30%	0.41%**
						(2.032)
FF5 Alpha	0.18%	-0.14%	-0.03%	0.17%	0.36%	0.18%
						(0.740)

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

	Quintiles:					
	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%
						(1.513)
FF3 Alpha	-0.12%	0.14%	-0.20%	0.20%	0.04%	0.16%
						(0.942)
FF5 Alpha	-0.06%	0.11%	-0.14%	0.22%	0.08%	0.15%
						(0.971)

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 *.

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

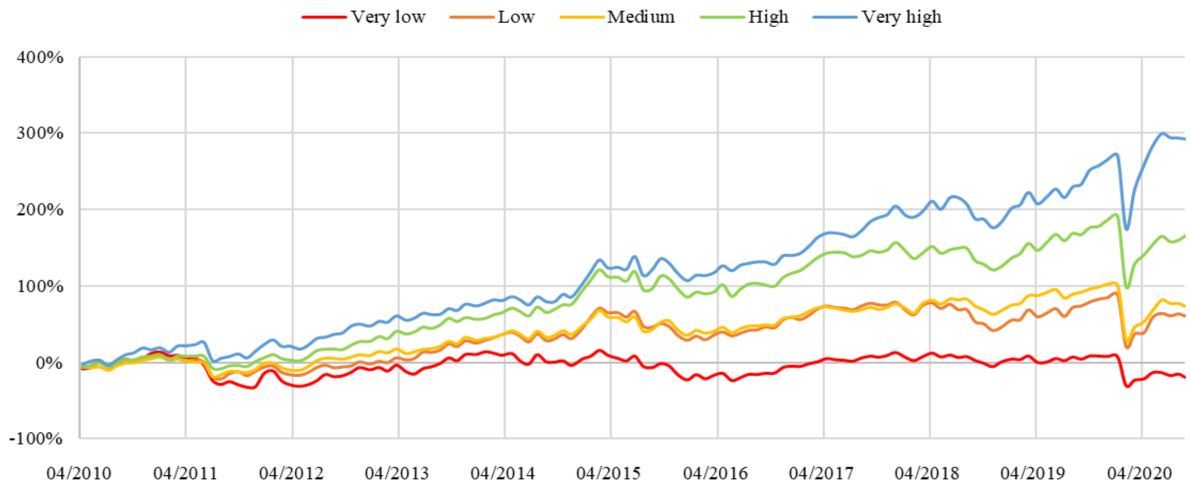
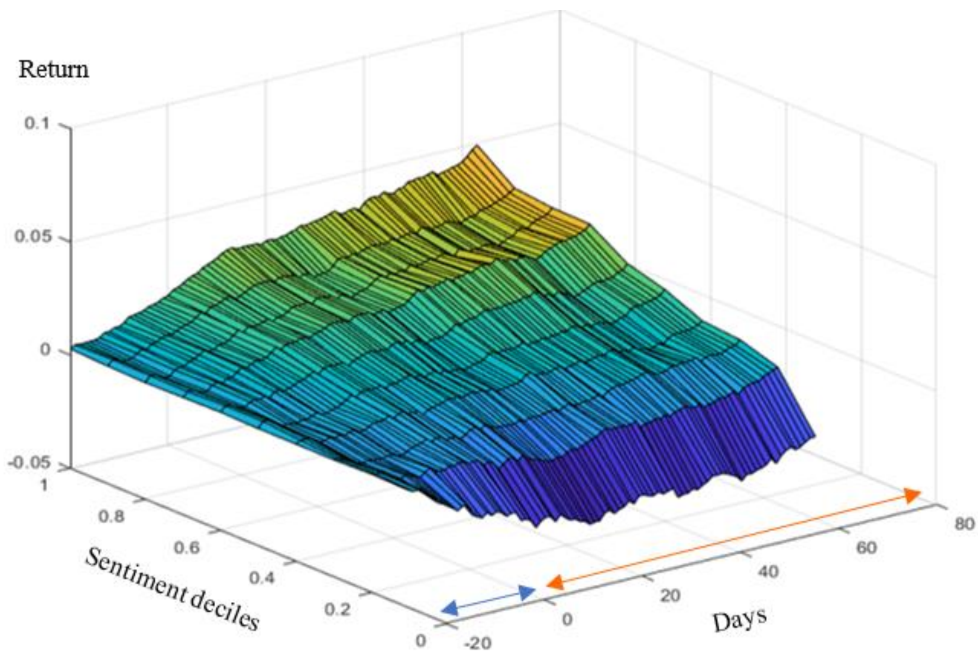
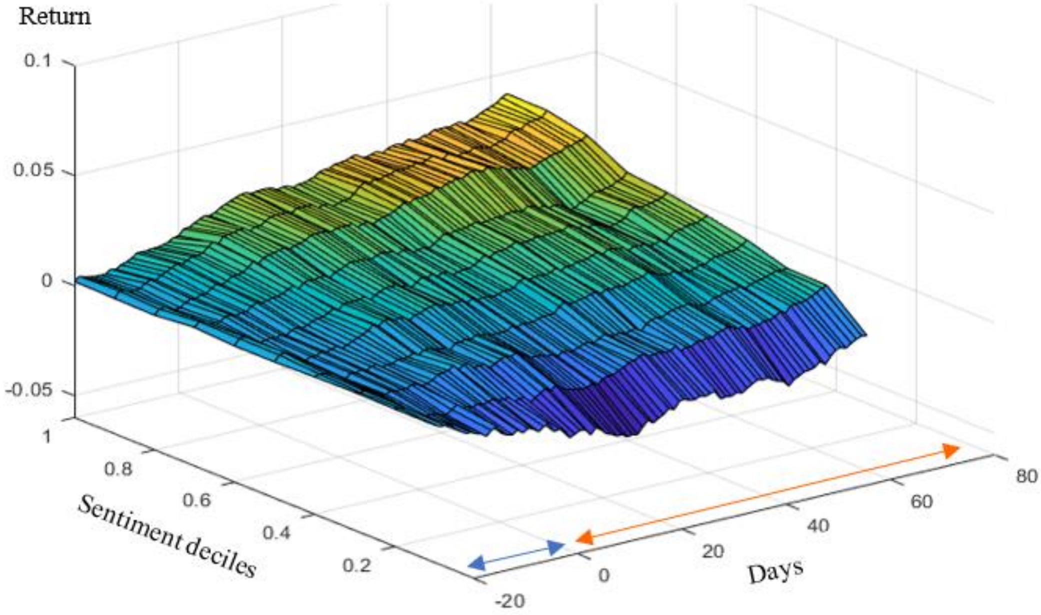


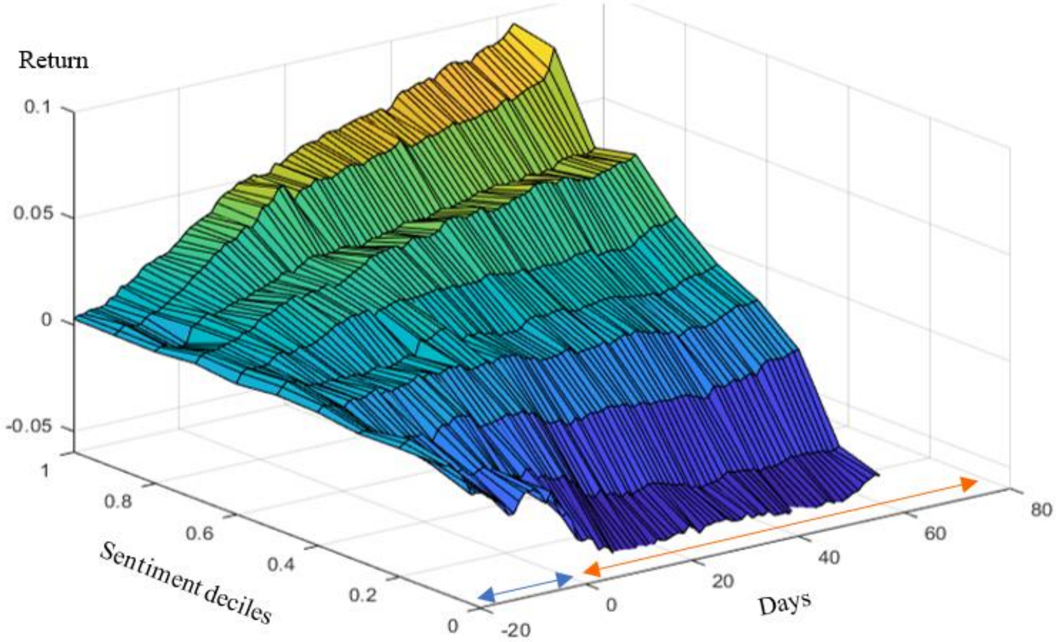
Figure 2. Term structure of the cumulative return for a strategy that invests in portfolios with different level of sentiment.



Note: the figure 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 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.

Figure 3. 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) 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.