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Investor Sentiment in Asset Pricing Models: A Review

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Abstract: despite the number of works on investor sentiment in asset pricing models the results did not allow to obtain a coherent knowledge about this sentiment. Most of the researchers used different measures and various models to study the impact of sentiment on stocks returns. However, the empirical relationship between investor sentiment and stock market behavior remains unclear. This study focuses on reviewing the methodologies and empirical findings of 71 papers published between 2000 and 2021 that apply different investor sentiment measures for modeling returns. The research confirmed two out of the three research hypotheses that the investor sentiment proxies and higher complexity of the model with the investor sentiment indicator improve the coefficient of determination. The second one was rejected, however, this may be due to too small a sample. For the hypothesis that models with more complex sentiment have better predictive power than those with simpler proxies, the number of studies was insufficient to refer strongly to the hypothesis.

Keywords: Investor sentiment, Asset pricing, Multifactor models, Behavioral finance, Risk factors, stock market behavior

JEL codes: G11, G12, G14, G40

1. Introduction

For many decades economists have applied various variables in the asset pricing models to determine the expected rate of return. The simplest model is the CAPM model (Sharpe, 1964) that assumes relationship between systematic risk (i.e. market risk) and expected rate of return. Based on that Fama and French (1992) enriched the CAPM with specific-risk factors, i.e. the company size and its book-to-market value, creating the three-factor model. That model has a lot of extensions (Jegadeesh and Titman, 1993; Carhart ,1997; Fama and French, 2013; Hou et al., 2015; Fama and French, 2015). All of these models follow the rational paradigm because the classical finance theory does not include any behavioral factors. According to this theory a competition among rational investors, who diversify their portfolios to optimize their statistical properties, leads to an equilibrium in which prices equal the rationally discounted value of expected cash flows (Friedman, 1953; Fama, 1965). Even if some investors are irrational, the theory argues, their demands are offset by arbitrageurs and thus have no significant impact on prices.

However, some market participants do not follow rational paradigm. They are known as “noise traders”. They buy or sell based on not technical or fundamental analysis but hype/rumors called investor sentiment and in fact, can affect prices. The definition of sentiment is imprecise. For the purposes of this study, Baker and Wurgler’s (2007, p. 129) definition of investor sentiment is used: “a belief about future cash flows and investment risks that is not justified by the facts at hand”. The most commonly applied behavioral theory of De Long et al. (1990) predicts that an investor sentiment affects stock returns and may persist in financial markets causing that asset prices do not appropriately reflect fundamental values. This may result in inefficient allocation of capital. For investors, this impacts portfolio allocation decisions, for firms it affects the cost of capital, and it may also influence the decision-making process of central banks and government agencies (Smales, 2017). Thus, understanding what the sentiment is, identifying an appropriate sentiment measure, and quantifying the impact of sentiment on asset prices is an important topic.

The researchers has become more and more interested in including behavioral factors (including sentiment) in asset pricing model due to many discoveries of anomalies. From that time there is a growing tendency to include behavioral factors in asset pricing models (Huang et al. 2016). Jegadeesh and Titman (1993) provided evidence of the momentum effect, DeBondt and Thaler (1985, 1987) found long-term reversal over 3–5 years. Since around that time a lot of empirical studies attempt to measure investor sentiment (Lee et al., 1991; Brown and Cliff, 2004; Fisher and Statman, 2000; Brown and Cliff, 2005). Findings showed that individual investors are easily swayed by sentiment. Sentiment indicators increase the traditional model's explanatory power for stocks returns that are traditionally more difficult to arbitrage and to value, for example, small stocks, value stocks, stocks with low prices, and stocks with low institutional ownerships.

Despite the number of published works on the issue of investor sentiment the results did not allow to obtain a coherent knowledge about sentiment as most of the researchers used different measures and various models to study the impact of sentiment on stocks returns. In particular, the empirical question of a relationship between investor sentiment and stock market behavior remains unclear. There were some review articles that tried to provide a synthesis of the behavioral finance literature. However, they were not focused on sentiment itself (i.e. sentiment was only the part of the analysis for which several articles were analyzed), and now they are also relatively obsolete (among others Subrahmanyam, 2007). Hence, given the important role of investor sentiment in asset pricing and that so much has been written on the subject, this paper aims to provide comprehensive coverage of the current status of this research. Taking a utilitarian viewpoint, I believe that the success of an asset pricing model lies in its explanatory and out-of-sample forecasting power. However, it is impossible, in practice, to perform tests on all asset pricing models on a large number of data sets and over many different periods. This study focuses on reviewing the methodologies and empirical findings of 71 papers that apply different investor sentiment measures for modeling stocks' and indices' returns in the markets around the world. I analyze articles published between 2000 and 2021 with a number of citations equal to or higher than 60 (as indicated on the WoS website per January 2022) in which all of the searchable fields at least one of the following statements is present: 'Sentiment indicator', 'Sentiment proxy' or 'Investor sentiment'.

The contribution of this review is to provide a bird's-eye view of the whole return forecasting literature and to provide some recommendations for the practice and future research. Therefore the study search for an answer for the following main research question (RQ):

What is the impact of investor sentiment on stocks and indices returns in the presence of other market factors?

To answer that question based on the available research results, I formulate three auxillary hypotheses:

RH1. Augmenting models with the investor sentiment proxies improves the coefficient of determination;

RH2. The higher the complexity of the model with the investor sentiment indicator, the higher the coefficient of determination;

RH3. Models with more complex sentiment have better predictive power than those with simpler proxies or those using only individual measures.

Some formulations from the above hypotheses require clarification:

1) By writing the word 'models' (R*H1* and R*H3*), i.e. without specifying exactly which models I mean (e.g. multivariate models in R*H2*), I mean all models that were used in analyzed papers in general, i.e. single-factor, medium complex models (i.e. models that use various factors, but not those present in multifactor models, e.g. macroeconomic variables), multifactor and machine learning models;
2) 'the complexity of the model' (RH2) concerns the number of factors applied in the model. For purposes of this study, I assume that the complexity of the models grows from single-factor through the medium complex to multifactor model. This statement does not consider machine learning algorithms.
3) 'complex sentiment' (RH3) means a sentiment created based on at least two individual sentiment measures or sentiment based on data from social or mass media. Simple measures are single sentiment indicators, e.g. survey results, returns on IPOs, or Google Search Volume.

The remaining sections are organized as follows. Section 2 provides some preliminaries such as the definition and measurement of the investor sentiment and explains the model used in research. Section 3 introduces the methodology and materials used in this study, i.e. method of selection and analysis of articles. Section 4 provides the results of the study. Section 5 summarizes and concludes. Appendix A contains a summary of each of the 71 papers.

2. Some Preliminaries

2.1 Sentiment measures

2.1.1. Sentiment definition

The sentiment does not have an indisputable definition (Zhang, 2008). Existing definitions of sentiment in the literature range from vague statements about investors' mistakes to various psychological biases (Shefrin and Belotti, 2007) e.g. general investor attitudes towards markets (Shleifer and Summers, 1990), investor optimism or pessimism (Antoniou et al., 2013) or beliefs about equity returns (Barberis et al., 1998). Furthermore, the term itself is subject to a wide spectrum of classifications and is used in different ways by academic researchers, financial analysts, and the media (Barberis et al., 1998; Daniel et al., 1998; Welch and Qiu, 2004; Cliff and Brown, 2004; Shefrin and Belotti, 2007; Baker and Wurgler, 2007). Due to the lack of one consistent definition of sentiment, it is also impossible to present one formula that would sufficiently illustrate or optionally (with appropriate data) allow to calculate the value of the sentiment. However, on some level, it is possible (Zhou, 2018). Assuming that sentiment relates only to the over- or under-valuation of assets, the sentiment S_t can be defined as the difference between the price observed in the market P_t and the fundamental price estimated from a rational benchmark asset pricing model P_t^*:

$$S_t = P_t - P_t^* \tag{1}$$

With the above definition, $S_t = 0$ implies that the market price agrees with the fundamental value. In practice, however, S_t is rarely zero. The greater the S_t, the more optimistic investors are about the asset value. S_t can of course be negative, representing pessimism about the asset value. Likewise, the investor sentiment can be also derived based on returns:

$$S_t = r_t - r_t^* \tag{2}$$

where r_t is the observed or expected return and r_t^* is the fundamental return from a rational benchmark asset pricing model. In general, we can define sentiment in terms of any characteristic (CH):

$$S_t = CH_t - CH_t^* \tag{3}$$

Existing sentiment studies largely rely on prices, returns, and expected probabilities; Much work remains to be done on volatility sentiment, tail sentiment, and sentiment of other characteristics of asset returns. Most research focused on developing indicators based on proxies without a well-defined sentiment. The common point is the reliance on information for which there is no fundamental foundation.

2.1.2 Indirect and direct sentiment

While there is no single definition of sentiment, researchers agree on two types of investor sentiment measures. The research distinguishes direct and indirect measures of sentiment. However, this distinction is not clear. For this study, I assume that direct measures come from surveys about opinion on the stock market conditions such as the Michigan Consumer Sentiment Index (MCSI) or Investors' Intelligence (II) (Qiu and Welch, 2004). Whereas indirect ones represent economic variables such as the closed-end fund discount or returns on IPOs that capture an investor's state of mind. The second category also includes data available from sources like Natural Language Processing (NLP) for social media or news, and exogenous non-economic factors e.g. cloud cover (Hirschleifer and Shumway, 2003). Both types of measures have their advantages and disadvantages. For modeling purposes, indirect measures have an advantage over direct ones. They are easy to construct, observed in real-time, and reflect both rises and falls in the market. However, they are difficult to interpret and some of them are based on questionable theoretical fundamentals. Moreover, these indicators are a combination of expectations and sentiment. The process of separating one from the other may be difficult, if not impossible (Beer and Zouaoui, 2013). But this argument refers also to direct ones. Also for this study, it was assumed that the combined measure of sentiment comes from at least two data sources.

2.1.3 Theories of investor sentiment

The concept of market sentiment is not a new idea and was noticed even among the most popular economists, e.g. Keynes (1936) has provided an early analysis of speculative markets and investor sentiment. However, even now, there is no consensus on the theoretical structure of behavioral finance and the investor sentiment research area (Ángeles López-Cabarcos et al., 2020). The most popular in terms of citations is prospect theory created by Kahneman and Tversky (1979). This theory is an alternative to expected utility theory. Its authors showed that the value assigned to gains or losses is assessed asymmetrically. That fact may significantly affect equity prices. Tversky and Kahneman (1974) explained also three other heuristics, i.e. representativeness, availability of instances or scenarios, and adjustment from an anchor. They employed them in making judgments under uncertainty and showed their application in economics. De Bondt and Thaler (1985) analyzed how over-reaction behavior influences stock prices, finding inefficiencies in the weak form market proposed by the efficient markets theory. Shiller et al. (1984) explained sentiment in terms of social dynamics. Shefrin and Statman (1985) dealt with the behavior pattern known as the disposition effect, which causes investors to sell winners too early and hold losers for too long. Winners are those assets that in the previous period had a positive rate of return, while losers are those that brought losses. Daniel et al. (2005) analyzed two psychological biases experienced by an investor, i.e. overconfidence and biased self-attribution on the securities market. They showed that both biases affect volatility, short-run earnings, and future returns. Barberis et al. (1998) proposed a model of investor sentiment. It is based on psychological evidence regarding conservatism, and the representativeness heuristic, producing under- and over-reaction and showing that investor sentiment is related to these behaviors. However, the most influential work regarding investor sentiment was presented by De Long et al. (1990). They presented a model whereby irrational noise traders affect prices. The existence of noise traders was theoretically accepted as a solution to the results achieved by Grossman and Stiglitz (1980) which showed that under most circumstances an investor with superior information cannot get higher profit based on that information. The theory explains some anomalies such as the excess volatility of asset prices or the mean reversion of stock returns and provides evidence that assets exposed to the noise traders are riskier and offer a return premium. As emphasized by Cochrane (2008), the market risk premium has important implications in all areas of finance e.g. it can lead to market bubbles followed by massive devaluations (Brown and Cliff, 2004) or it enables to create profitable trading strategies (Baker and Wurgler, 2006; Fisher and Statman, 2000). Subsequently, several models have been proposed to explain sentiment. Thaler (1993) and Brunnermeier (2001) reviewed some of the first advances. Shefrin (2008) provided a synthesis of behavioral theories in the stochastic discount framework of asset pricing. Baker and Wurgler (2012) reviewed the implications of sentiment models in the context of corporate decision-making. In recent work, Greenwood et al. (2016) used extrapolation learning to explain credit sentiment. Some scholars have proposed psychological and behavioral decision theories to explain many abnormal effects, including overreaction, under-reaction, overconfidence, group behavior, the emergence of speculative bubbles, the excessive volatility of the stock market, and so on (Barberis and Thaler, 2003). Many works challenge the models presented above (see among others Loewenstein and Willard, 2006; Fama, 2021).

The size of theoretical schools makes it difficult to interpret the results, hence causing the research is not consistent with each other and slowing down the creation of consistent knowledge among researchers. However, this situation did not arise without a reason. High investor sentiment can mean investors are bullish about stock markets (Liu, 2015), which can produce noise trading (De Long et al., 1990; Renault, 2017). High investor sentiment could also indicate high overconfidence (Odean, 1998). Additionally, investor sentiment can be related to over-reaction, which increases when investor sentiment is low (Piccoli and Chaudhury, 2018). Notwithstanding undoubtedly, it is due to such differences between theories and empirical results that this field has recently gained a lot of interest.

2.1.4 Measures of sentiment

Starting with the direct measures of investor sentiment. The American Association of Individual Investors (AAII) conducts a monthly allocation survey since 1987 that asks participants whether they have a bullish or bearish attitude towards the market. De Bondt (1993) found that individual investors surveyed by the AAII forecast future stock returns. Solt and Statman (1988) and Clarke and Statman (1998) point out that investor sentiment compiled by the Investors Intelligence survey is not useful as an indicator. The second popular survey measure, i.e. the MCSI Index focuses on five questions related to perceiving future financial situation by respondents. Answers are coded on a scale from 1 (good) to 5 (bad) and averaged (equal-weighted). Lemmon and Portniaguina (2006) find that sentiment index as proxied by consumer confidence can forecast the returns of small stocks and those with low institutional ownership. There is also *Investor Intelligence's*[1] (II) sentiment index that classifies 150 independent market newsletters as bullish, bearish or correction and releases the resulting percentages every Friday.

In terms of direct measures, there is a plenty of them from various sources. The most popular is the BW index created by Baker and Wurgler (2006) as a linear combination of popular indirect measures, i.e. closed-end fund discount, stock turnover ratio, number of Initial Public

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[1]Investors Intelligence (II) is a provider of technical research in the field of investment. Abe Cohen, the editor of II, introduced the sentiment index in 1965.

Offerings (IPOs), average returns on the day per IPO, the share of equity issue in a total issuance of shares and debt (EQTI), and dividend premium. The study showed that measures combining a lot of information about sentiment are better at predicting than single measures. Wider comparison ofall available measures indicated that complex sentiment indices (both those consisting only of indirect measures and those that also contain direct ones) dominated in forecasting returns. Single direct indicators predicted only a size premium and from individual indirect proxies only the ratio of odd purchases to sales predicted portfolios' returns sorted by size, profitability, and tangibility (Beer and Zouaoui, 2013). Now combined proxies are one of the most popular applied for asset pricing purposes. There are several influential studies on the measure of media-based sentiment (Narayan and Bannigidadmath, 2017; Narayan, 2020; Li et al., 2020). For example, Narayan et al. (2017a, 2017b) and Narayan (2019) used financial news to reflect public expectations for stock returns. In addition to the use of news to measure sentiment, indicators derived from social media have been attracted more and more attention, since investors not only read market information, but also share individual investment opinions in social media (Oliveira et al., 2016).

2.1.5 Alternative indicators

Some measures are unusual as weather variables, media-based proxies (based on Twitter, Google, or news data), or even some indicators which have never been used in the study of asset pricing. These could be investor sentiment measures that can be subscribed to serve as a proxy for particular psychological bias, i.e. herd behavior (Cipriani and Guarino, 2014). One of the popular examples of such an indicator is the Economic Policy Uncertainty (EPU) Index, developed by Baker et al. (2016). The index has three basic components. The first is based on a normalized measure of the volume of news articles discussing economic policy uncertainty from 10 newspapers in the U.S. The second component relies on reports by The Congressional Budget Office, which publishes a list of temporary federal tax code provisions. The third component uses the disagreement among economic forecasters as an indicator of uncertainty. The data are published monthly and daily starting from 1985. Some researchers also developed EPU index for other countries like EU countries (Phan et al., 2018) and China (Chen et al., 2017).

2.2 Application of investor sentiment

The applications of investor sentiment do not end with asset pricing models. Some research also supports the predictive effect of sentiment on volatility. At first, Mitchell and Mulherin (1994) found weak correlations between market volatility and news. Later, Antweiler and Frank (2004) investigated the number and the tone of stock market posts on Yahoo! Finance and Raging Bull for large US stocks. The number predicted the volatility of returns and the volume. Guidolin and Pedio (2021) showed that GARCH models augmented to include media coverage and media tone outperformed traditional GARCH models for FTSE 100 returns. However, so for there are no studies that test whether investor sentiment could improve forecasting down-side risk measures such as Value-at-Risk or Expected shortfall.

Some studies use investor sentiment to price commodities (He et al., 2019, Balcilar et al., 2017) and research that tests causality between indirect and direct investor sentiment proxies. Brown and Cliff (2004) analyzed various direct and indirect sentiment indicators. They showed a correlation between them. Many popular indicators are related to survey data and are significant as regressors to predict direct measures. However, some research using different data found no association between direct and indirect measures (Qiu and Welch, 2006)

2.3 Multifactor models

This section describes the multifactor models used in the analyzed studies, to which researchers added a sentiment measure as an exogenous variable.

2.3.1 CAPM

Capital Asset Pricing Model (CAPM) is a model that allows illustrating the relationship between the incurred systematic risk and the expected rate of return on a portfolio of financial assets (Sharpe, 1964). The equation of this model is as follows:

$$R_i - R_f = \alpha_i + \beta_i * (R_m - R_f) \quad (4)$$

where:

R_i – the expected rate of return on the ith portfolio of financial asset;

R_f – risk-free rate;

R_m – return on the market portfolio;

α_i – the intercept;

β_i (the beta) – the sensitivity of the expected excess of the ith asset returns to the expected excess market returns.

2.3.2 FF three-factor model

Fama–French (FF) three-factor model is a model designed by Fama and French in 1992. They added two factors to CAPM to reflect a portfolio's exposure to these two classes:

$$R_i - R_f = \alpha_i + \beta_i * (R_m - R_f) + \beta_{i,s} * SMB + \beta_{i,v} * HML \quad (5)$$

where:
SMB – size premium (Small Minus Big);
HML – value premium (High Minus Low);
$\beta_{i,s}, \beta_{i,v}$ – factor coefficients.

2.3.3 Carhart four-factor model

Carhart wrote a paper in 1997 where he presented the model as a tool for valuating mutual funds. He based his work on Jegadeesh and Titman´s (1993) article which revealed a tendency for good and bad performances of stocks to persist over a couple of months, in other words, a momentum effect. Thus, Carhart added the WML (Winner Minus Lossers, i.e. the return of the momentum factor) factor to the FF three-factor model:

$$R_i - R_f = \alpha_i + \beta_i * (R_m - R_f) + \beta_{i,s} * SMB + \beta_{i,v} * HML + \beta_{i,m} * WML \quad (6)$$

In addition to the models described here, in individual cases there were other models such as the six-factor model that is Carhart four-factor model augmented with factors for short-term and long-term reversal, and models augmented with the MGMT factor that is constructed from a set of six anomaly variables that can be directly influenced by a firm's management (Fang and Taylor, 2021) or the PERF factor constructed from five anomaly variables that represent a firm's performance (Fang and Taylor, 2021).

2.4 Assessment of models

Depending on the hypotheses being verified, researchers are interested in different statistics. Most often, the hypotheses concern the significance (p-value lower than 0.05 or 0.01) of the investor sentiment proxy and the expected sign of the relationship between expected return and the investor sentiment. When the study is to compare multiple countries or statistics, researchers sometimes refer to adjusted R-squared or incremental adjusted R-squared, i.e. how the adjusted R-squared increases after adding a proxy of the investor sentiment.

3. Methods and Materials

3.1 The scope of the study

This study focuses on articles that apply different investor sentiment measures for modeling stocks' and indices' returns in the markets around the world. Articles were searched on the Web of Science (WoS) website. I recognize that the field of behavioral finance is too vast and it is impossible to review every known work. Therefore, some subjective choices in terms of which scholarly articles to mention are inevitable. Thus. I analyze articles published between 2000 and 2021 with a number of citations equal to or higher than 60 (as indicated on the WoS website per January 2022) in which all of the searchable fields at least one of the following statements is present: 'Sentiment indicator', 'Sentiment proxy' or 'Investor sentiment'. This resulted in the initial sample of 232 papers. However, in this review papers with the following characteristics have been excluded: 1)calculate only correlations and/or test causation between investor sentiment and stocks' returns; 2) forecast another characteristic than return (e.g. volatility), 3) apply a non-empirical method of studying, i.e. the authors performed experiments, provided a concept of a model or theoretical background, etc.; 4) are conducted on prices other that stocks, i.e. on currencies (including cryptocurrencies), commodities, options, etc. Finally, the analyzed sample consisted of 71 papers. They are listed in Appendix A.

3.2 Methodology of analyzing articles

The articles were analyzed qualitatively and quantitatively. The first type of analysis consisted in getting to know the research methodology, the way of creating a measure of sentiment, the models used, descriptions and explanations of the obtained results, and its references to similar studies. For quantitative analysis, data were consisted of the coefficient for sentiment and other factors, adjusted R2, as well as t-statistics and standard errors. After that weighted averages and frequencies of occurrence were calculated.

4. Results

I first consider measures of sentiment used, models applied for them, scopes of the studies, years, etc. In general, the evidence in favor of the notion that investor sentiment matters in asset pricing under control of other variables remains quite tenuous at best because most of the research applies the sentiment as the only one factor. At the same time, most of the studies apply only one or two models without actually comparing results between them. There is only one popular investor sentiment measure. However, when a new one is introduced it's not compared with this or any other in any way. Moreover, for each case, other characteristics seem far more relevant in the cross-section of expected returns.

Table 1 presents numbers and percentage shares of articles analyzed in this study divided by various characteristics of papers[2]. First of all, most of study were conducted on the U.S stocks market, which constitutes 54 of the 71 papers analyzed. There were also four studies regarding the Chinese market, one per German, Japanese, and UK markets, and, what is important in terms of generalizing the results, 11 studies concerning multiple countries exchanges. In most of the papers stocks with share prices, less than 5$ or 3$ were excluded, primarily to avoid micro-structure effects i.e. illiquidity or market manipulation. Time intervals on which the research were conducted are evenly diversified. For the ranges of time period in years: (0; 1], (1; 5], (5; 10], (10; 20], (20; 40], (40; 100), the number of articles is between 9 and 15. Additionally, four studies analyzed data divided into subperiods, i.e. a the whole sample period was divided, for example, into the pre-crisis period and the post-crisis period. Data frequency was mostly monthly (30 studies) and daily (33 articles). Besides, four research were conducted on weekly data, and one on quarterly data or comparing results for daily, weekly, and monthly intervals. Two studies were conducted on intraday intervals, i.e. on half-hour and hour data. The investor sentiment measures used in the research differed significantly among studies, but one may notice some similarities. The BW index appeared in 12 articles as the only measure of sentiment in a paper. Only measures based on sentiment from the media, i.e. newspapers, internet forums, reports from companies'

[2] Please note that the sum of the number of articles and percentages shares when divided by models applied and asset used may exceed 71 and 100%, respectively, because most of the studies cover at least two of these assets.

statements, etc., were more frequent than the BW index, namely appeared in 17 research. However, there is no consensus regarding the method used to develop such indicators. The Naïve Bayes classification appeared several times, although in most cases the researchers used various dictionaries or their own created algorithms. Sentiment measures based on data from Google or Twitter occurred with a similar frequency, i.e. five and four, respectively. Important from the point of view of this review is the fact that 14 articles contained at least two measures, often including the BW index and indirect measures. The rest of the analyzed articles, i.e. 19, focused on various measures such as VIX, closed-end fund discount, or survey proxies. In the vast majority of cases, these were single measures of sentiment. The diversity can also be seen in the models used in studies. Most often, because in 27 papers, the researchers used several different multifactor models, i.e. CAPM, FF three-factor model, and the Carhart four-factor model. In such comparison articles, there were also very elaborate models, i.e. five- and six-factor models. Only 13 articles used only one model of the commonly known ones, i.e. CAPM, FF three-factor model, or Carhart four-factor model. In 22 cases, medium complex models were used, i.e. the model that takes into account sentiment and additional control variables that do not appear in known multifactor models, such as a volume, day of the week or macroeconomic variables. 19 studies applied only single-factor models, i.e. the model that takes into account only a sentiment. In recent years also machine learning models (7 papers) have been applied for including investor sentiment in asset pricing. Note that the sum of the articles for the division by models may exceed 71 as the paper sometimes used two or more different types of models. The same holds for assets.

Table 1: The number and percentage share of articles analyzed in this study divided by various features of articles.

Characteristic	Number of articles	Percentage share of articles in this study
	Geographical scope	
U.S.	54	76%
Multiple countries	10	14%
Other single country	7	10%
	Time interval (in years)	
(0; 1]	9	13%
(1; 5]	13	18%
(5; 10]	12	17%
(10; 20]	11	15%
(20; 40]	15	21%
(40; 100)	11	15%
	Data frequency	
Intraday	2	3%
Daily	34	48%
Weekly	4	6%
Monthly	30	42%
Quarterly	1	1%
	Sentiment measure	
Media-based sentiment	17	24%
BW index	12	17%
Multiple measures	11	15%
Google Search Volume	5	7%
Twitter	4	6%
Other measures	14	20%
	Models	
Single-factor	18	25%
Medium complex	20	28%
Multifactor	30	42%
Machine learning	8	11%
	Asset	
NYSE	14	20%

NASDAQ	12	17%
Various countries' indices	11	15%
S&P500	9	13%
All stocks from CRSP	8	11%
IPOs	6	8%
DJIA	5	7%
Other assets	19	27%

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

Due to the extensive scope of the subject and the multiplicity of approaches in the analyzed studies, two analyzes were carried out. The first, qualitative, is based on a condensed description of the results obtained, drawing consistent conclusions from research, presenting unverified gaps, comparing measures, etc. The second, quantitative, relies on an attempt to quantify the overall relationship between the investor sentiment and stocks' returns and the improvement of the accuracy of models (mainly using adjusted R2 and frequencies).

4.1 Qualitative analysis

The analysis presented in this section consists of describing successively each group of models. The basic division is based on their complexity. The first of them are single-factor models. The second one consists of medium-complex models, i.e. those which, apart from sentiment, used various other factors, but not those present in multifactor models, e.g. macroeconomic variables. The third describes multifactor models such as the FF three-factor model or Carhart four-factor model. The fourth presents models of articles that compare at least two sentiment indicators. Note that papers described in this subsection were not described in the previous three, even though this research may apply models which could have been attributed to the various earlier subsections. This is due to the fact that I would like to emphasize whether comparative studies are able to demonstrate the superiority of one measure over another without considering these studies in two chapters. Then machine learning models are introduced and finally models analyzing data from IPOs.

4.1.1 Single-factor models

The single-factor model was popular type willingly chosen by the researchers to study the effect of a sentiment. However, mostly they examined unusual measures. Only one study, i.e. Fisher and Statman (2003) regressed NASDAQ and S&P 500 returns on customer confidence measures of the MSCI index and Conference Board. There were statistically significant relationships between some components (e.g. expectations) of customer confidence and subsequent NASDAQ and small-capitalization stocks returns. But this relationship was not significant for S&P 500 returns.

Very often a linguistic sentiment was studied in single-factor models. Das and Chen (2007) analyzed tech-sector stocks consisting of the Morgan Stanley High-Tech Index. They regressed the value of the index on its first lag and first lag created by them semantic sentiment on Yahoo's message board[3]. The regression showed that tech index and individual stocks were weakly related to the sentiment from the previous day at the 10% significance and not significant at all, respectively. According to researchers, a more detailed empirical paper is required to explore a longer time series to eliminate the autocorrelation. While these results implied that aggregation of individual stock sentiment may be resulting in a reduction of idiosyncratic error in sentiment measurement, giving significant results at the index level. Further studies showed different results. Kim and Kim (2014) studied a sentiment based on the Yahoo! Finance message board using the Naïve Bayes classification and following the Antweiler and Frank (2004) algorithm. They found positive coefficients for all sentiment variables used in any horizon, irrespective of controlling for size and book-to-market ratio. However, the Antweiler and Frank (2004) approach more often gave significant results. Chen et al. (2014) performed an analysis on daily returns for sentiment indicators based on frequencies of words from Dow Jones News Services (DJNS) and Seeking Alpha (SA) articles and comments. The last two were significantly negative at the level of 5% and the first one was insignificant. The predictability held even after controlling for the effect of traditional advice sources, such as financial analysts and news media predictions. The results were different compared to the literature (Tetlock 2007; Tetlock et al., 2008) due to the difference in the return window. DJNS articles are news articles and, as such, can be expected to have more of an immediate impact on prices. SA articles and comments, on the other hand, reflect more of a medium- or long-term view. Some studies tested the relationship between SP500, DJIA, and NASDAQ returns and the investor sentiment from messages posted on the microblogging platform StockTwits on intraday intervals (Renault, 2017). After controlling for past market returns, it was found that the first half-hour change in an investor sentiment positively and significantly predicts the last half-hour S&P 500 index ETF return. This finding provides evidence that the intraday

[3] Accuracy levels are similar to widely used Bayes classifier, but false positives are lower and sentiment accuracy higher.

sentiment effect is distinct from the intraday momentum effect. Garcia (2013) conducted the longest study regarding a sentiment analysis, i.e. over the period 1905-2005 on the DJIA index. As a sentiment indicator, the fraction of positive, negative, and pessimism (i.e. the difference) words in two columns of financial news from the New York Times was used. Only the first lag for negative, positive, and pessimism proxies were significant. For positive and negative news the effect reverses after 5 days, i.e. the sum of betas was statically not different from zero. However, for pessimism this sum was positive.

Sometimes researchers also applied data from social media. Sprenger et al. (2014) analyzed the impact of stocks-related messages from Twitter on S&P100. The regression on returns showed a significant positive relationship with bullishness and agreement among tweets. However, they did not find message volume to be related to stock returns. Whereas Siganos et al. (2014) examined the relationship between sentiment and stock returns within 20 international markets using Facebook's Gross National Happiness Index. Generally, the research showed a significant and positive impact of sentiment to stock returns for small-large, premium, value, growth. However, after including up to 5 lags for return and sentiment a coefficient for a sentiment become less significant, being even insignificant for Europe and marginally (at 10%) significant for America.

Some researchers apply more unconventional sentiment indicators. Edmans et al. (2007) using indices for 39 countries tested the relationship between its returns and international soccer results. They found that: 1) national stock markets earn a statistically significant negative return on the day after a loss by the national soccer team, 2) the loss effect is stronger in small-capitalization indices, and 3) the loss effect is of the same magnitude in value and growth indices. The research did not show any effect of winning. Similar results were achieved after examining a relationship between game results and returns on twenty UK soccer clubs listed on the LSE. Positive relationship for goal difference and win in all cases, i.e. in abnormal results and cumulative abnormal results up to three days, and negative for loss only for cumulative abnormal returns for 3 days ahead were found (Palomino et al., 2009). Even health data can act as a proxy. Liu et al. (2020) tested the effect of daily COVID cases on 21 stock market indices in major affected countries. They found a significant negative confirmed COVID case and that countries in Asia experienced more negative abnormal returns compared to other countries.

To sum up, the single-factor models showed that it is more common to meet and demonstrate significance in unusual measures such as results of soccer game than in direct ones (in that case the MSCI index and Conference Board measure). In some studies, return reversals have also been observed in a short period. The results obtained for sentiment measures used in single-factor models are briefly described in Table 2.

Table 2: Summary of various sentiments, i.e. their characteristics, frequency and the collective results obtained in studies regarding single-factor models.

Sentiment measure	Description	Frequency	Results
Media-based measures	A sentiment measure based on textual analysis (e.g. using Bayes classifier) from various sources, i.e. forums (Yahoo's message board), news services, microblogging platforms or social media.	6	The results were mostly significant (even on intraday intervals) except for the semantic sentiment based on Yahoo's message board and SA comments. Some studies confirmed the reversal effect of sentiment.
Other	Customer confidence measures of the MSCI index and Conference Board, Facebook's Gross National Happiness Index, soccer game results or disease spread.	5	Most research showed a significant coefficient for sentiment except for one for S&P 500 returns. Most often the negative aspect of sentiment was captured, while the positive one (e.g. winning a match) was insignificant.

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

4.1.2 Medium complex models

Starting with the simplest measure, Chen et al. (1993) tested the discount on a value-weighted portfolio of closed-end fund discount on NYSE stock returns for three different periods, i.e. 1965-1975, 1975-1985, and the whole period. For the first and the third, the coefficient was negative and significant, whereas for the second it was insignificant. While Kurov (2010) regressed the BW index on excess returns on stocks from S&P500 in two market conditions, i.e. under the regime with a higher mean and lower variance of returns (bull market) and a regime with a lower mean and higher variance (bear market). In the bear market environment, a sentiment had no statistically significant effect, while in a bull market conditions were significantly negative. The study also analyzed the term spread factor, which was significant in the same way as the sentiment. This finding is consistent with monetary shocks having little effect on stocks in good times. These findings support the conclusion that Fed policy affects stock returns, at least in part, through its effects on investor sentiment and expectations of credit market conditions. Moreover, Antoniou et al. (2016) using NYSE, AMEX and NASDAQ data observed that the BW index sentiment conditions the occurrence of size and momentum effects. The size effect was present only in pessimistic periods, while the momentum effect is present only in optimistic periods. While the value effect is present in both periods.

There were also similar studies measuring the influence of uncertainty on stocks returns. You et al. (2017) analyzed stock prices from the Resset Financial Database China’s industry data before and post subprime crisis using quantile regression. As a sentiment indicator, they use the EPU index from Baker et al. (2014). They found significant negative effects on stock returns for the full sample, before and after the crisis for almost all quantiles. The impact on stocks in pre-crisis was relatively greater than that in the post-crisis at most quantiles. While Chen et al. (2017) analyzed the relationship between all A-share stocks listed in Shanghai and Shenzhen stock exchanges and China’s EPU. For regression without any controls and including economic and market uncertainty variables authors found EPU significant and negative relationship. An out-of-sample predictions study showed that the MSFE-t and MSFE-F statistics were both statistically significant at 10% level at least.

In two studies researchers used direct proxies for a sentiment. Kurov (2008) examined AAII and II’s sentiment index on the S&P 500 and Nasdaq-100. He regressed returns for the bull and the bear market using the beta factor for the market, the default spread factor, the term spread factor, and sector dummies. He found that both measures were significantly negative for a bear market. Schmeling (2009) examined the relationship between consumer confidence (as a proxy for investor sentiment) and 18 developed countries’ stock returns. The sentiment negatively forecasts aggregated stock market returns on average across countries (for 9 countries on a 5% level of significance and 11 countries on a 10%-level only). The higher the sentiment, the lower the future stock returns and vice versa. This relation held for value, growth, and small stocks for different forecasting horizons. However, there were insignificant results for large stocks in all horizons and size premium for 12M and 24M horizons.

A couple of studies examined the Google SVI index. Da et al. (2011) researched Russell 3000 stocks and found a positive, significant coefficient on the SVI for the first and the second weeks after controlling for alternative measures of investor attention. The relationship was not present for 3rd, 4th or between 5th and 52nd weeks ahead. Also for the first two weeks, studies showed negative interaction between equity market capitalization and positive with retail trading volume measure for the first week. However, none of these relationships were present for 3rd, 4th or between 5th and 52nd weeks ahead. The authors additionally examined long-run returns. Following Barber and Odean (2008), they skip the first month and look at the returns from weeks 5 to 52 and found a negative coefficient on SVI, similar to the magnitude of total initial price pressure in the first two weeks, suggesting that the initial price pressure was almost entirely reversed in 1 year. However, the negative coefficient is marginally insignificant. The same researchers in 2015 performed regressions on S&P500 return every six months also on Google SVI, but this time creating a Financial and Economic Attitudes Revealed by Search (FEARS) index. Such a measure was negatively and significantly related to returns when both were observed at the same time. However, FEARS occurred to be significant and positive for returns in t+1, t+2, and from t+1 to t+2 periods. That supports the reversal nature of the sentiment, while the cumulative impact of an increase in FEARS predicts a cumulative increase of returns over days 1 and 2. This was significant after controlling the EPU, VIX, and changes in the Aruoba-Diebold-Scotti business conditions index. Although, the model does not predict returns for times t+3, t+4, and t+5. Bijl et al. (2016) examined the effect of Google SVI on the S&P 500 in two periods. One included the subprime crisis (2008-2013), whereas the letter covered the only period after the crisis (2010-2013). For the first period, the authors found a significant negative coefficient for search volume for its first and the third lags, and also a significant positive coefficient for the second lag. While the second-period coefficient was significantly negative only for the first and fourth lag. Then the reversal of prices was observed only in the full sample period.

In medium complex models also the media-based indicator was used. Klibanoff et al. (1998) on a sample of country funds consisting of the 39 single-country publicly traded funds applied major news events using the column width of front-page articles in the New York Times. The regression was conducted on the fund's returns one day ahead. They found that a news variable was never significant (in any proposed model), while its interaction with returns was significant, but not with lags of returns.

Finally, four studies referred to unconventional proxies for a sentiment. Goetzmann et al. (2015) examined the impact of the sky cloud cover variables on stocks from CRSP in subsamples based on arbitrage costs. Using survey and disaggregated trade data the study showed that more cloudy days increased perceived overpricing in individual stocks and DJIA Index as well as increased selling propensities of institutions. Based on that the authors introduced stock-level measures of investor mood. The investor optimism positively impacted stock returns among stocks with higher arbitrage costs. These findings complement existing studies on how weather impacts stock index returns and identify another channel through which it can manifest. Similarly, Chang et al. (2008) examined on NYSE stocks whether the weather in New York City, i.e. wind speed, snowiness, raininess, and temperature. In general, weather control variables are not significantly related to returns. Kaplanski and Levy (2010) examined the effect of aviation disasters on NYSE stock prices. When regressed on the lagged rate of returns and other controls disasters event coefficient on the first day was significantly negative significant, while on the second day was insignificant. The effect was greater in small and riskier stocks and firms belonging to less stable industries. Białkowski et al. (2012) analyzed the impact of Ramadan in 14 predominantly Muslim countries. The positive and significant effect of Ramadan materialized only when the society chooses to participate in this religious experience collectively, i.e. at least 50% of citizens were Muslims. Authors found these results consistent with a theory that Ramadan positively affects investor psychology, because it promotes feelings of solidarity and social identity among Muslims, leading to optimistic beliefs that extend to investment decisions. Ichev and Marinč (2018) examined whether the geographic proximity of information disseminated by Ebola outbreak events with intense media coverage affected stock prices of NYSE and NASDAQ indices. The negative event effect was the strongest for the stocks with exposure of their operations to the African countries and the U.S. Moreover, the events located in these regions were also the strongest. This result suggests that the information about Ebola outbreak events is more relevant due to geographical distance to both the place of the Ebola event and the financial markets. The effect was greater for small and more volatile stocks, stocks of a specific industry, and stocks exposed to intense media coverage.

To summarize, medium complex models applied similar measures to those used in single-factor models. Also, the reversal effect was here observed as well as the bearish and bullish market conditions moderated the results. However, here all the results were significant, even for the same measures (as customer confidence). The results obtained for sentiment measures used in medium complex models are briefly described in Table 3.

Table 3: Summary of various sentiments, i.e. their characteristics, frequency and the collective results obtained in studies regarding single-factor models.

Sentiment measure	Description	Frequency	Results
BW index	The first principal component of the following six sentiment proxies suggested by prior research: the closed-end fund discount, market turnover, number of IPOs, average first day return on IPOs, equity share of new issuances, and the log difference in book-to-market ratios between dividend payers and dividend non-payers.	2	The BW index sentiment conditioned the occurrence of size and momentum effects. The sentiment had no statistically significant effect in the bear market environment, while it had negative impact in the bullish market.
EPU	The Economic policy uncertainty (EPU) is a risk in which policies and regulatory frameworks are uncertain for the near future.	2	The EPU had a significant negative effect on stock returns in both studies. One also showed that sentiment was significant for the full sample, before and after the crisis for almost all quantiles.
Direct measures	AAII's survey shows the percentage of investors who are bearish, bullish, or neutral on stocks. The Consumer Confidence reflects consumer attitudes, buying intentions, and consumer expectations for stock prices, inflation, and interest rates.	2	The first study found that both measures were significantly negative for a bear market. The second showed negative relationship for value, growth, and small stocks for different forecasting horizons. There were insignificant results for large stocks in all horizons and size premium for 12M and 24M horizons.
Google SVI / FEARS	Google SVI shows how often a specific term is searched in relation to the total search volume globally, within a defined date range. The Financial and Economic Attitudes Revealed by Search (FEARS) index	4	Studies revealed a significant coefficient on the SVI for the first and the second weeks. The relationship was not present for further weeks ahead. One study showed that returns from weeks 5 to 52 were negatively related to SVI. Another included the subprime crisis the period

	aggregates daily search volume for keywords related to household economic and financial situation.		after the crisis. The reversal effect was only present in the first period. FEARS was negatively significant when SVI was also present in the regression.
Other	One media-based index, two measures related to weather, one per aviation disaster, Ramadan, and the spread of disease.	5	For 39 countries a news variable was insignificant, while its interaction with returns was significant, but after including lags of returns. In one of two studies using weather variables indicator was significant. Ramadan and the spread of disease were significant.

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

4.1.3 Multifactor models

Some research used the CAPM model or CAPM model with one or a couple of additional dependent variables. Phan et al. (2018) using data from 16 countries tested whether the EPU measures (i.e. country-specific and a global one) can predict stocks' returns. They found predictability of excess returns for 5 countries, where both the country and the global EPU models outperformed the constant model. No predictability was found for 10 countries for the local EPU and global EPU. Lee et al. (1991) tested the effect of the monthly CEFD on NYSE divided in deciles by equity value. The largest firms, did significantly poorer when discounts narrowed, while for the other nine portfolios, stocks did significantly better when discounts shrank. When an equal-weighted market index was used, however, the five portfolios of the largest firms all showed negative movement with the value-weighted discount, while the five smaller portfolios all had positive coefficients.

One of the most popular models applied in research was the FF three-factor model. Tetlock (2007) analyzed the effect of the pessimism media factor from the Wall Street Journal column on DJIA using that model. It occurred that the first and the fourth lags of the pessimism factor were negative and significant. Stambaugh et al. (2015) applied the lagged BW index on the FF three-factor model for portfolios (NYSE, AMEX, and NASDAQ stocks) containing stocks with either the highest (top 20%) or the lowest (bottom 20%) idiosyncratic volatility[4]. They found significant negative loadings for the BW index for the highest three quintiles in the highest minus the lowest

[4] An idiosyncratic volatility measures the part of the variation in returns that cannot be explained by the particular asset-pricing model used.

quintiles and the lowest quintile and all stocks. Chung et al. (2012) regressed the BW index on the same portfolio's returns as a single-factor model and with the FF three factors. For both regressions, the study showed similar results, i.e. positive loading for the long-short portfolios based on size, Book to Market value, age, earnings, dividend premium, and negative for volatility, R&D expense, sales growth, and external finance. Corredor et al. (2013) referred all stock listed in four of the key European markets, i.e. France, Germany, Spain, and the UK to the BW index and EU sentiment measures. The second was constructed from the first principal component of the first factors obtained for each country and then the principal component analysis was used to create an aggregate index. Regressions of long-short portfolios for a 6, 12, and 24-month time horizon were constructed for book-to-market ratio, size, volatility, and dividend premium. The BW was significant and had the expected size for most of the portfolio, whereas European sentiment mostly was insignificant. Hribar and McInnis (2012) used the BW index as a dummy variable equal to 1 if the beginning of the year sentiment index was positive, and 0 in other cases. Findings showed that such an indicator is significant in predicting young minus old, volatile minus smooth, nonpayers minus payers stock returns. After including the FF three-factor in the regression proxy became insignificant. Han et al. (2013) verified the BW index on NYSE and AMEX stocks' returns. The findings showed that the coefficient for the sentiment index in the FF three-factor model was insignificant. Takeda and Wakao (2014) tested the impact of Google SVI on the Nikkei 225 index by augmenting the FF three-factor model with the SVI. They found that the coefficient on the search intensity was significantly positive. Jacobs (2015) found that the BW index is a powerful predictor for most anomaly returns (out of 100), in particular on the short side of the portfolios. Ni et al. (2015) used an opening accounts number and a turnover rate to constitute the investor sentiment. They employed the quantile regression model to verify the effect of investor sentiment on monthly stock returns in the Chinese stock market. The findings showed that the influence of investor sentiment was significant from 1 month to 24 months. The effect was asymmetric and have a reversal nature, i.e. it was positive and large for stocks with high returns in the short term and negative and small in the long term. This reversal effect testified to the existence of an overreaction in the Chinese stocks' returns. Drakos (2010) explored whether terrorism events have a significant negative impact on daily stock market returns in a sample of 22 countries by augmenting with them the FF three-factor model. The terrorist activity had a negative impact and reduced significantly daily returns even after controlling for global financial crises.

Even more often than the FF three-factor model researchers employed the Carhart four-factor model. Baker and Wurgler (2006) studied how their newly created investor sentiment index affects the cross-section of stock returns. They created long-short portfolios based on low, medium and high firm characteristics, where low is defined as a firm in the bottom three NYSE deciles, high in the top three NYSE deciles, while medium in the middle four NYSE deciles. The study showed that when sentiment at the start of the period is low, subsequent returns are relatively high for stocks with low market capitalization, low age, high volatility (i.e. the annual standard deviation in monthly returns for the last 12 months), unprofitable (i.e. with net income lower than zero), and dividend-free. For the growth and distress variables (i.e. external finance over assets and sales growth) the results did not show simple monotonic relationships with sentiment. For both low and high sales growth and external finance over asset returns are low relative to returns on medium of these characteristics. Whereas, when sentiment is high, these stocks earn low. They found that the size effect of Banz (1981) appears only in low sentiment periods. The sentiment was negative for size and volatility long-short strategies and positive for age long-short strategies. Fong and Toh (2014) examined the BW index on NYSE, AMEX, and NASDAQ returns. They regressed excess returns of the long-short MAX (see Bali et al., 2011) portfolio against the lagged BW sentiment index for each institutional ownership (IO) quintiles controlling Carhart's four factors plus liquidity risk factor. Returns on the portfolios were negatively related to the sentiment proxy for most IO quintiles except for the third and the fifth quantiles. Mian and Sankaraguruswamy (2012) used the BW index on CRSP stock returns. They performed regression on sentiment and Carhart's four factors. The sentiment was negatively related to the difference in returns between the high and low news stocks. However, Moskowitz et al. (2012) using quarterly data for nine equity indexes from developed markets showed on the Carhart model that the BW index of sentiment and its extreme values (top 20% / bottom 20%) were insignificant in regression of time series momentum returns on the market. Bartov et al. (2018) investigated the relationship between the aggregate opinion in individual tweets and Russell 3000 index using the same model. They found a significant and positive relationship between Twitter opinion and returns around earnings announcements with various controls. After controlling the Carhart factor the effect persisted only for volatility and age-based portfolios. Joseph et al. (2011) examined the ability of online ticker searches in the Google search index to forecast S&P 500 abnormal stock returns using the Carhart four-factor model on volatility sorted portfolio deciles. The betas associated with the sentiment indicator generally increased as the volatility grew, starting from a negative value at the first decile and finishing at the positive value for the tenth decile. The letter was greater in absolute value as compared to this from the first decile. Xiong and Bharadwaj (2013) obtained the firms' monthly frequencies of news data from Lydia/TextMap (Lloyd et al., 2005). They regressed those frequencies on abnormal returns got from the Carhart four-factor model. They observed that positive and negative news had significant effects on returns. The interaction between positive news and advertising was positive, while for negative news this interaction was insignificant. Yu et al. (2013) used a web crawler to download blogs, forums, and news web pages and applied the Naïve Bayes algorithm to conduct sentiment analysis. They got abnormal returns from the Carhart four-factor model and run fixed effect regression on volumes with interactions. Findings suggested that generally social media had a stronger relationship with stock returns than conventional media. Whereas social and conventional media had a strong interaction effect on stock performance. Moreover, the impact of different types of social media varied significantly. Banerjee et al. (2007) wanted to find whether the VIX predicts returns on stock market indices (NYSE, AMEX, and NASDAQ). They examined portfolios sorted on book-to-market equity, size, and beta with controlling of the four Carhart four factors. The coefficients were positive and significant except for portfolios based on the low beta, the low book-to-market value, and large size. Kumar and Lee (2006) using the buy-sell imbalance of more than 1.85 million retail investor transactions over 1991–1996 showed that systematic retail trading can explain return comovements for stocks with high retail concentration (i.e. small capitalization, value, lower institutional ownership, and lower-priced stocks), especially if these stocks are also costly to arbitrage.

There was research comparing different multifactor models, as well. Fang and Peress (2009) examined the relationship between the number of newspaper articles about a stock (coming from the LexisNexis database) with NYSE and NASDAQ stocks. The difference between the no- and high-coverage groups is statistically significant and economically meaningful. In the regressions on long no-media stocks and short high-media stocks CAPM, FF 3-factor, Carhart 4-factor all factors were significant. Hillert et al. (2014) tested whether stocks traded on NYSE, AMEX or NASDAQ can be related to firm-specific articles from newspapers from the LexisNexis database. They calculated media coverage as a frequency, tone came from a textual analysis following the dictionary approach developed by Loughran and McDonald (2011). They computed different risk-adjusted (i.e. CAPM, 3F, 4F, 6F) momentum returns for stock portfolios sorted by residual media coverage based on a holding period of six months. They showed that firms covered by the media exhibited stronger momentum depending on the tone. That effect reversed in the long run and was more pronounced for stocks with high uncertainty characteristics. These results collectively lent credibility to an overreaction-based explanation for the momentum. However, media coverage did not change loser and mid returns, but only for the winner. Stambaugh and Yuan (2017) regressed for and five-factor alternative models on NYSE, AMEX, and NASDAQ excess returns on either the long, short, long-short leg for following factors: market, SMB, MGMT and PERF, and the BW index. For MGMT[5] and PERF[6], the coefficients on short legs are uniformly negative and positive for long-short. The slopes for market and SMB were insignificant.

For almost every multifactor model, investor sentiment turned out to be important, which emphasizes its importance and indicates that its impact cannot be explained by fundamental factors. The models described in this subsection specifically indicate that augmenting models with the investor sentiment proxies improves the accuracy of models. Thus, they support the first hypothesis. The results obtained for sentiment measures used in medium multifactor models are briefly described in Table 4.

Table 4: Summary of various sentiments, i.e. their characteristics, frequency and the collective results obtained in studies regarding single-factor models.

Sentiment measure	Description	Frequency	Results
BW index	Explained in Table 3.	10	The BW index explained portfolios' returns based on book-to-market ratio, size, dividend premium, volatility, R&D expense, sales growth, MAX factor (see Bali et al., 2011), profitability, and external finance. The indicator was also important in explaining most of the anomalies, in particular on the short side of the portfolios. One study showed that using the Carhart model the index was insignificant in regression on momentum returns.

[5] The MGMT factor is constructed from a set of six anomaly variables that can be directly influenced by a firm's management (Fang and Taylor, 2021).
[6] The PERF factor is similarly constructed from five anomaly variables that represent a firm's performance (Fang and Taylor, 2021).

Media-based measures	Explained in Table 2.	6	All measures (both based on tone and frequencies) applied were significant explaining excess returns and momentum returns. One study showed that media coverage was insignificant in regression on losers and mid returns, but only for the winners.
Other	The CEFD, the opening accounts number and a turnover rate, terrorism events, the VIX, the buy-sell imbalance, the EPU, and Google SVI.	7	The CEFD was significant in regression on returns divided in deciles by equity value. The opening accounts number and turnover rate were significant in the quantile regression conducted on the Chinese stock market. Terrorism events had a significant impact on stock market returns in 22 countries. The VIX was significant in regression on portfolios sorted on book-to-market equity, size, and beta. The buy-sell imbalance explained returns for stocks with high retail concentration. The Google SVI was significant in regression on volatility sorted portfolio deciles. Some studies confirmed the reversal effect for the sentiment.

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

4.1.4 Multiple indicators

Some research considered comparing individual proxies performance in asset pricing models. Neal and Whitley (1998) using extensive data from 1933 to 1993 for NYSE-AMEX analyzed the impact of the closed-end fund discount, the ratio of odd-lot sales to purchases, and the net mutual fund redemption on stocks returns. They found that fund the first one and the last predicted the size premium, but the odd-lot ratio did not. Brown and Cliff (2005) investigated the impact of the II survey results and closed-end fund discount, the ratio of NYSE odd-lot sales, the net mutual fund flows, the ARMS index (a popular measure of sentiment among technical analysts), the number and returns on IPOs on DJIA stock returns. Coefficients are almost universally significant and negative and tend to be most negative for the larger and growth firms. For these firms, sentiment is a significant predictor of future returns at the 1-, 2-, and 3-year horizons. When including all variables together, the survey indicator of sentiment remained significant. There was no evidence that the closed-end fund discount is related to subsequent stock returns. Simon and Wiggins (2001) analyzed the S&P 500 futures contract with the indicators including the VIX, the put-call ratio, and the trading index. All of the proxies were positive and significant. Lemmon and Portniaguina (2006) explored the time-series relationship between investor sentiment and the small-stock premium using the MSCI index and the Conference Board survey of consumer confidence as a measure of investor optimism. In the period before 1977, the measures were insignificant, however, after 1977 for 3,6,12 months periods there were significant and negative coefficients. The estimate for the interaction between the customer confidence measure and the return on the market index was negative and statistically significant.

Other research compared more complex sentiment indicators such as the BW index. Ben-Rephael et al. (2012) tested the lagged MSCI index, the lagged BW index, the lagged aggregate net exchanges of equity funds on a value-weighted index composed of NYSE, AMEX, and NASDAQ stocks. The results showed that MCSI and VIX were statistically significant and positive, while the BW index was insignificant. Stambaugh et al. (2012) explored the role of the BW and the MCSI indices on NYSE, AMEX, and NASDAQ in a broad set of anomalies in cross-section stock returns. Both measures were significant in most of the anomalies, however, the BW index was more often significant and had a greater value of a t-statistic. Huang et al. (2015) proposed a new investor sentiment proxy created using the Partial Least Squares (PLS) procedure sentiment index from the six individual proxies used to create the BW index and compared it with the BW index, the Naive investor sentiment index, and individual proxies. Regression on returns using only sentiment measures revealed that the BW index was insignificant, the naïve one was marginally statistical significance at the 10% level, while the PLS sentiment was significant and negative at the 1% level. Also return on IPOs and EQTI displayed high power in forecasting the excess market returns. Overall, the PLS index beat all the individual proxies and remained statistically significant when augmenting the model by other economic predictors. Moreover, it exhibited stronger predictive power than other measures. Jiang et al. (2019) examined regressions on stock returns on various portfolios sorted on proxies for limits to arbitrage or speculation. Authors used the following proxies for investor sentiment: the BW index, the PLS investor sentiment index, the MCSI index, the Conference Board Consumer Confidence Index, the FEARS indicator, and the manager sentiment index, which was based on the aggregated textual tone of corporate financial disclosures. All of the indicators were significant. But only Huang investor sentiment remained significant, when in regression also the manager sentiment index was present.

Comparing the measures of sentiment often ended with all measures being significant. Although sometimes direct measures turned out to be more significant while single indirect measures did not. In most cases, only studies examining out-of-sample accuracy showed some differences. It turns out that the commonly used BW index is not the best indicator, because even combining the same component variables differently can give more accurate results. Such a fact support the second hypothesis that more complex sentiment have better predictive power than simpler ones.

4.1.5 Machine learning

Through the last decade, researchers started to employ machine learning techniques to include investor sentiment in asset pricing models. Bollen et al. (2011) used two methods to create a sentiment based on Twitter data for DJIA stock returns. The first was OpinionFinder, which measures positive versus negative mood from text content, and the second was GPOMS which measures 6 different mood dimensions from text content. For the first, no effect on prediction accuracy was found compared to using only historical values. While the second “Calm” created the highest prediction, “Sure” and “Vital” reduced prediction accuracy significantly, while “Happy” significantly decreased average MAPE. Ranco et al. (2015) also used the Twitter data to calculate sentiment for 30 stocks from the DJIA index. However, they used Support Vector Machine to compute the proxy. The values of cumulative abnormal returns were significantly positive for ten days after the positive sentiment events. The same holds for negative sentiment events, but the cumulative abnormal returns were twice as large in absolute terms. Oliveira et al. (2017) examined more indices, i.e. the S&P 500, the Russell 2000, the DJIA, the NASDAQ 100, and constructed couple of variables based on microblogging data from Twitter – bullish ratio, bearish ratio, bullishness index, variation of ratios and agreement. Then applied different machine learning models. The study found that Twitter sentiment and posting volume were relevant for the forecasting of returns of the S&P 500 index, portfolios of lower market capitalization, and some industries. Mostly the best predictive results were provided by Support Vector Machine. These results confirm the usefulness of microblogging data for financial expert systems, allowing them to predict stock market behavior and providing a valuable alternative for existing survey measures with advantages (e.g., fast and cheap creation, daily frequency). Other researchers used various data for the models. Li et al. (2014) constructed lexical sentiment for the CSI 100 list and applied it into the predictive eMAQT model that captures the hidden connections between the input (textual information, public mood, and current stock prices) and the output (future stock prices). The researchers concluded that: 1) representing news articles with proper nouns could achieve a good directional prediction but attain a poor RMSE; 2) the pessimistic public mood had a significant contribution in predicting stock movements; 3) news articles related to restructuring issues are the most predictable. Weng et al. (2018) employed various machine learning models based on Wikipedia hits, financial news, Google trends, and technical indicators for 20 U.S.-based stocks. MAPE was lower for the simulations with no PCA than with PCA. The boosted regression tree and random forest regression methodologies were the most predictive, while the support vector regression ensemble had the lowest performance. Ding et al. (2015) proposed a deep learning method for event-driven stock market prediction. Results show that our model can achieve nearly 6% improvements on S&P 500 index prediction and individual stock prediction, respectively, compared to state-of-the-art baseline methods. Nguyen et al. (2015) employed historical prices for the 18 stocks and created sentiment measures for them based on various methods. The aspect-based method occurred to have the best performance. Li et al. (2014) based on the stocks listed in Hong Kong Stock Exchange implemented a generic stock price prediction framework and plugged in six different models. They conducted the textual news articles are then quantitatively measured and projected onto the sentiment space and evaluated the models' prediction accuracy and empirically compare their performance at different market classification levels. Results showed that at all levels, i.e. at an individual stock, sector, and index, the models with sentiment analysis outperform the bag-of-words model in both validation set and independent testing set.

The above-described results proved that machine learning algorithms can be applied to increase the predictive power of the asset pricing model, however they have a major shortcoming. They are difficult to interpret and what we should not forget they also can fail as the traditional models.

4.1.6 IPOs

Some researchers also applied an investor sentiment on returns of IPOs. Cook et al. (2006) got all IPOs from the Securities Data Company's New Issues database. They applied the number of news articles that had mentioned the firm's name in the headline(s) and found a strongly significant positive relationship. Cornelli et al. (2006) used prices from the grey market (the when-issued market that precedes European IPOs) to proxy for small investors' valuations for 486 companies that went public in 12 European countries High grey market prices (indicating overoptimism) were a good predictor of first-day prices, while low grey market prices (pessimism) were not. Moreover, the authors found that long-run price reversal only follows high grey market prices. This asymmetry occurred because institutional investors could choose between keeping or reselling them when small investors are overoptimistic. Dorn (2009) investigated IPOs of the Frankfurt Stock Exchange. They applied two investor sentiment measures, i.e. the logarithm of gross When-Issued purchases, the logarithm of the gross day plus 1 purchase. In the study the regression of excess returns over Dax 100, Nemax 500, Industry, Size, book to market ratio, internet dummy, and High-tech dummy. Both of the indicators were negative and significant. Da et al. (2011) regressed IPO first-day returns on pre-IPO week abnormal search volume with and without IPO characteristics. In both cases the sentiment proxy was significant.

The research proved that investor sentiment could be applied to explain returns on IPOs. However, in the studies, authors used mostly unconventional indicators. Thus, we cannot be sure whether these measures reflect the same phenomenon as the popular measures.

4.1.7 Summary

Summarizing, the results obtained in the qualitative analysis showed that sentiment is almost always an important factor in asset pricing models. However, there were also studies showing that the sentiment was completely insignificant. Moreover, the sentiment often exhibited a reversal effect, i.e. the phenomenon in which the effects of the influence of sentiment are at least partially reversed in subsequent periods. This often resulted in a significance of the first and fourth or fifth lags, and no significance in the second and third lags. Moreover, the research divided into sub-periods often turned out to be insignificant for the earlier period, which may indicate that investor sentiment is becoming an increasingly important factor. The results described in this section are difficult to generalize, because the results on many issues were not consistent, such as the significance of the sentiment in split by deciles of other variables or in various time horizons. Nevertheless, due to its significance, its coefficient, and the influence on R2, it can be concluded that the obtained results confirm the first research hypothesis (RH1) that augmenting models with the investor sentiment proxies improves the coefficient of determination.

4.2 Quantitative analysis

The Table 5 presents the number of studies in which positive and negative sentiment measure occurred with its coefficients for three groups of models, i.e. single-factor, medium complex, and multifactor models. Note that the number of studies for medium complex and multifactor models is lower by one in comparison to this presented in Table 1 due to the fact that two studies were only comparing the difference between stocks with high and low media coverage and therefore sentiment was not a factor in regression there.

Generally, the negative sentiment measures were used more often than positive ones, However the difference was not so huge. Only for single-factor models the number of studies with sentiment measures with positive coefficient was higher than those with negative. Such a phenomenon indicates a very different perception of sentiment through researchers, i.e. as negative and positive, and the fact that researchers are mostly interested in investing the reasons for bearishness in the market. This may also be due to the fact that the most commonly used indicator (i.e. the BW index) is a positive proxy, so researchers are looking for an measure that can capture a different phenomenon that this identified by the BW index. However, none of the studies used several measures that could capture both the positive and negative effects of sentiment. Additionally, in the table average value of coefficients were calculated. However, these numbers should be treated with caution as they contain both slopes for returns expressed in basis points and raw returns. Indicated that even though the single-factor models had higher number of studies with positive sentiment measure, the average was on negative. Maybe because of the fact that applied indicators for negative sentiment were more economically significant. At the same time, I would like to point out that no statistical analysis (due to small number of studies) has been performed here, so the presented conclusions are only an idea to explain the results.

Table 5: The number of articles with positive and negative sentiment coefficients divided by the type of model.

Models	**No. of studies with positive sentiment measures**	**No. of studies with negative sentiment measures**	**Avg. of coefficients**
Single-factor	11	7	-3.02
Medium complex	6	13	-0.52
Multifactor	12	18	-0,27
All	29	38	-1,10

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

The first hypothesis (RH1) concerning the improvement of the coefficient of determination cannot be directly verified quantitatively due to the lack of appropriate data (e.g. incremental R-squared).

A deeper look at the collected data allowed more accurate verification of the second hypothesis (RH2). To support the qualitative analysis, a comparison of the means for adjusted R-squared for three types of models (i.e. single-factor, medium factor, and multifactor divided into FF three-factor model and Carhart four-factor model) was made. Table 6 presents the results of such an analysis. Note that the number of studies analyzed in the table is lower than those in the qualitative analysis sections due to the fact that not all of the research published R-squared for their model. The differences between single-factor and medium complex seem negligible, however, the average of R-squared only seems to be higher for multifactor. To compare the R-squared means between single-factor and multifactor models and between medium complex and multifactor models, t-tests were performed. Both tests gave a p-value above 10%, i.e. insignificant difference. However, the results could be insignificant due to the small sample of papers. Therefore, one should be careful with interpreting those results.

Table 6: Means of adjusted R-squared for single-factor, medium complex and multifactor models (divided into the FF three-factor model and the Carhart four-factor model).

Models	**No. of studies**	**Avg. R-squared**	**Std Dev of R-squared**	**Avg. / Std Dev**
Single-factor	11	0.23	0.29	0.78
Medium complex	14	0.20	0.23	0.85
Multifactor	13	0.32	0.26	1.20
FF three-factor	*4*	*0.35*	*0.20*	*1.76*
Carhart four-factor	*9*	*0.30*	*0.30*	*1,01*
All	38	0.24	0.29	0.81

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

Ultimately, to test the third hypothesis (RH3) that the models using more complex measures of sentiment have better predictive power, the number of research supporting this statement was analyzed. Unfortunately, only nine studies were comparing the measures of sentiment, while for the analysis remained eight, because one study analyzed only simple indicators. Of the remaining ones, five showed the superiority of composite indices, while three were not. This is a difference in favor of complex measures of sentiment, but it is not an unequivocal result. Therefore, this hypothesis cannot be verified.

5. Conclusions

The study managed to answer the research question about the impact of investor sentiment on stocks and indices returns in the presence of other market factors. The impact of sentiment was significant regardless of what variables were controlled in the research. These could be macroeconomic or noneconomic variables, previous returns, and factors such as SMB, HML, or WML. The study demonstrated the stability of the results over time, i.e. the results were significant regardless of the date of the study, the range of the sample period, the frequency of the data, and the division of the study period into sub-periods. Moreover, the research confirmed that sentiment conditioned some commonly known phenomena, such as the size premium or momentum effect. The study also showed the prevalence of the reversal effect of the sentiment, which means that the impact of sentiment on returns usually was reversed with the same magnitude after 4 or 5 days. However, the exact influence of sentiment varied greatly due to the measures used. The average impact is difficult to estimate as its direction was positive as often as negative.

The research failed to reject (both quantitatively and qualitatively) one out of the three hypotheses (RH1) presented in the article. The second hypothesis (RH2) was rejected, although this matter requires a more extensive study, as the sample in this study was small. For the third hypothesis (RH3), the number of studies were insufficient to conduct a broader analysis to confirm or reject hypothesis. The collected data made it possible to condense the current knowledge from the most popular articles and to identify gaps requiring wider research, i.e. comparison of sentiment in various models (including multifactor models), a broad comparison between various measures of sentiment, and finding a universal measure for asset pricing models that will be competitive with the BW index and its variants. Further verification of the hypotheses verified in the study should take into account a wider range of models and sentiment drivers.

Finally, the review revealed a few possible directions for the development of further research, i.e. a small number of studies comparing the use of the same measure of sentiment in various multifactor models or the lack of studies comparing many popular measures of sentiment. However, the study also had some limitations such as a small number of comparative studies in the sample, which made the vast majority of quantitative analysis impossible. A way to resolve this issue would be to conduct an extensive metanalysis based on data obtained by other researchers, but this would require extensive and long cooperation between researchers.

References

Ángeles López-Cabarcos, M., M Pérez-Pico, A., & López Perez, M. L. (2020). Investor sentiment in the theoretical field of behavioural finance. *Economic research-Ekonomska istraživanja*, 33(1), 0-0.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, 48(1), 245-275.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. *Management Science*, 62(2), 347-367.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of finance*, 59(3), 1259-1294.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The journal of Finance, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of economic perspectives, 21(2), 129-152.

Baker, M., & Wurgler, J. (2013). Behavioral corporate finance: An updated survey. In *Handbook of the Economics of Finance* (Vol. 2, pp. 357-424). Elsevier.

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2017). The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. *Resources Policy*, *51*, 77-84.

Banerjee, P. S., Doran, J. S., & Peterson, D. R. (2007). Implied volatility and future portfolio returns. *Journal of Banking & Finance*, *31*(10), 3183-3199.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of financial economics, 49(3), 307-343.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, *1*, 1053-1128.

Bartov, E., Faurel, L., & Mohanram, P. S. (2018). Can Twitter help predict firm-level earnings and stock returns?. *The Accounting Review*, *93*(3), 25-57.

Beer, F., & Zouaoui, M. (2013). Measuring stock market investor sentiment. *Journal of Applied Business Research (JABR)*, *29*(1), 51-68.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of financial Economics*, *104*(2), 363-382.

Białkowski, J., Etebari, A., & Wisniewski, T. P. (2012). Fast profits: Investor sentiment and stock returns during Ramadan. *Journal of Banking & Finance*, *36*(3), 835-845.

Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis*, *45*, 150-156.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of computational science*, *2*(1), 1-8.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of empirical finance, 11(1), 1-27.

Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *The Journal of Business*, *78*(2), 405-440.

Brunnermeier MK. 2001. Asset Pricing Under Asymmetric Information: Bubbles, Crashes, Technical Analysis and Herding. Oxford, UK: Oxford Univ. Press

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57-82.

Chang, S. C., Chen, S. S., Chou, R. K., & Lin, Y. H. (2008). Weather and intraday patterns in stock returns and trading activity. *Journal of Banking & Finance*, *32*(9), 1754-1766.

Chen, H., De, P., Hu, Y. J., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, *27*(5), 1367-1403.

Chen, J., Jiang, F., & Tong, G. (2017). Economic policy uncertainty in China and stock market expected returns. *Accounting & Finance*, *57*(5), 1265-1286.

Chen, N. F., Kan, R., & Miller, M. H. (1993). Are the discounts on closed-end funds a sentiment index?. *The Journal of Finance*, *48*(2), 795-800.

Chung, S. L., Hung, C. H., & Yeh, C. Y. (2012). When does investor sentiment predict stock returns?. *Journal of Empirical Finance*, *19*(2), 217-240.

Cipriani, M., & Guarino, A. (2014). Estimating a structural model of herd behavior in financial markets. *American Economic Review*, *104*(1), 224-51.

Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *The Review of Financial Studies*, *21*(4), 1533-1575.

Cook, D. O., Kieschnick, R., & Van Ness, R. A. (2006). On the marketing of IPOs. *Journal of Financial Economics*, *82*(1), 35-61.

Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006). Investor sentiment and pre‐IPO markets. *The Journal of Finance*, *61*(3), 1187-1216.

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.

Clarke, R. G., & Statman, M. (1998). Bullish or bearish?. *Financial Analysts Journal*, *54*(3), 63-72.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The journal of finance*, *66*(5), 1461-1499.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, *28*(1), 1-32.

Daniel, H. Subrahmanyam, Daniel, K., Hirschleifer, D., & Subrahmanyam, A.,(1998, December). Investor psychology and security market under-and overreactions. The Journal of Finance, 53(6), 1839-1885.

Daniel, K. D., Hirshleifer, D. A., & Subrahmanyam, A. (2005). Investor psychology and tests of factor pricing models. *Available at SSRN 854024*.

Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management science*, *53*(9), 1375-1388.

De Bondt, W. P. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of forecasting*, *9*(3), 355-371.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of finance*, *40*(3), 793-805.

De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of finance*, *42*(3), 557-581.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy*, *98*(4), 703-738.

Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015, June). Deep learning for event-driven stock prediction. In *Twenty-fourth international joint conference on artificial intelligence*.

Dorn, D. (2009). Does sentiment drive the retail demand for IPOs?. *Journal of Financial and Quantitative Analysis*, *44*(1), 85-108.

Drakos, K. (2010). Terrorism activity, investor sentiment, and stock returns. *Review of financial economics*, *19*(3), 128-135.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of finance*, *62*(4), 1967-1998.

Fama, E. F. (1965). The behavior of stock-market prices. The journal of Business, 38(1), 34-105.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427-465.

Fama, E. F., & French, K. R. (2013). A four-factor model for the size, value, and profitability patterns in stock returns. *Fama-Miller Working Paper, University of Chicago*.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116*(1), 1-22.

Fama, E. F. (2021). *Market efficiency, long-term returns, and behavioral finance* (pp. 174-200). University of Chicago Press.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, *64*(5), 2023-2052.

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal*, *56*(2), 16-23.

Fisher, K. L., & Statman, M. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management*, *30*(1), 115-127.

Fong, W. M., & Toh, B. (2014). Investor sentiment and the MAX effect. *Journal of Banking & Finance*, *46*, 190-201.

Friedman, M. (1953). The case for flexible exchange rates. Essays in positive economics, 157(203), 33.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance*, *68*(3), 1267-1300.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *The Review of Financial Studies*, *28*(1), 73-111.

Greenwood, R. M., Hanson, S. G., & Jin, L. J. (2016). A model of credit market sentiment. *Harvard Business School working paper series 17-015*.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. The American economic review, 70(3), 393-408.

Guidolin, M., & Pedio, M. (2021). Media attention vs. sentiment as drivers of conditional volatility predictions: An application to Brexit. *Finance Research Letters*, *42*, 101943.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, *48*(5), 1433-1461.

He, Z., Zhou, F., Xia, X., Wen, F., & Huang, Y. (2019). Interaction between oil price and investor sentiment: nonlinear causality, time-varying influence, and asymmetric effect. *Emerging Markets Finance and Trade*, *55*(12), 2756-2773.

Hillert, A., Jacobs, H., & Müller, S. (2014). Media makes momentum. *The Review of Financial Studies*, *27*(12), 3467-3501.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The journal of Finance*, *58*(3), 1009-1032.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3), 650-705.

Hribar, P., & McInnis, J. (2012). Investor sentiment and analysts' earnings forecast errors. *Management Science*, *58*(2), 293-307.

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, *28*(3), 791-837.

Huang, J. Y., Shieh, J. C., & Kao, Y. C. (2016). Starting points for a new researcher in behavioral finance. International Journal of Managerial Finance.

Ichev, R., & Marinč, M. (2018). Stock prices and geographic proximity of information: Evidence from the Ebola outbreak. *International Review of Financial Analysis*, *56*, 153-166.

Jacobs, H. (2015). What explains the dynamics of 100 anomalies?. *Journal of Banking & Finance*, *57*, 65-85.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65-91.

Jiang, F., Lee, J., Martin, X., & Zhou, G. (2019). Manager sentiment and stock returns. *Journal of Financial Economics*, *132*(1), 126-149.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, *27*(4), 1116-1127.

Kahneman D., Tversky A. (1979), Prospect Theory: An Analysis of Decision under Risk, „Econometrica", XLVII (1979), s. 263–291.

Kaplanski, G., & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, *95*(2), 174-201.

Keynes J. 1936. The General Theory of Employment, Interest and Money. London: Macmillan

Kim, S. H., & Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior & Organization*, *107*, 708-729.

Klibanoff, P., Lamont, O., & Wizman, T. A. (1998). Investor reaction to salient news in closed-end country funds. *The Journal of Finance*, *53*(2), 673-699.

Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and return comovements. *The Journal of Finance*, *61*(5), 2451-2486.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review*, *43*(1), 107-127.

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking & Finance*, *34*(1), 139-149.

Lee, C. M., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The journal of finance*, *46*(1), 75-109.

Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies*, *19*(4), 1499-1529.

Li, Q., Wang, T., Li, P., Liu, L., Gong, Q., & Chen, Y. (2014). The effect of news and public mood on stock movements. *Information Sciences*, *278*, 826-840.

Li, X., Xie, H., Chen, L., Wang, J., & Deng, X. (2014). News impact on stock price return via sentiment analysis. *Knowledge-Based Systems*, *69*, 14-23.

Li, C. C., Xu, H. C., & Zhou, W. X. (2020). News coverage and portfolio returns: Evidence from China. *Pacific-Basin Finance Journal*, *60*, 101293.

Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance*, *16*(1), 51-67.

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health*, *17*(8), 2800.

Loewenstein, M., & Willard, G. A. (2006). The limits of investor behavior. *The Journal of Finance*, *61*(1), 231-258.

Mian, G. M., & Sankaraguruswamy, S. (2012). Investor sentiment and stock market response to earnings news. *The Accounting Review*, *87*(4), 1357-1384.

Mitchell, M. L., & Mulherin, J. H. (1994). The impact of public information on the stock market. *The Journal of Finance*, *49*(3), 923-950.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of financial economics*, *104*(2), 228-250.

Narayan, P. K. (2019). Can stale oil price news predict stock returns?. *Energy Economics*, *83*, 430-444.

Narayan, P. K. (2020). Oil price news and COVID-19—Is there any connection?. *Energy Research Letters*, *1*(1), 13176.

Narayan, P. K., & Bannigidadmath, D. (2017). Does financial news predict stock returns? New evidence from Islamic and non-Islamic stocks. *Pacific-Basin Finance Journal*, *42*, 24-45.

Narayan, P. K., D. H. B. B. Phan, and D. Bannigidadmath. 2017b. Is there a financial news risk premium in Islamic stocks? Pacific Basin Finance Journal 42:158–70.

Narayan, P. K., K. Ranjeeni, and D. Bannigidadmath. 2017a. New evidence of psychological barrier from the oil market. Journal of Behavioral Finance 18 (4):457–69.

Neal, R., & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns?. *Journal of Financial and Quantitative Analysis*, *33*(4), 523-547.

Nguyen, T. H., Shirai, K., & Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, *42*(24), 9603-9611.

Ni, Z. X., Wang, D. Z., & Xue, W. J. (2015). Investor sentiment and its nonlinear effect on stock returns—New evidence from the Chinese stock market based on panel quantile regression model. *Economic Modelling*, *50*, 266-274.

Oliveira, N., Cortez, P., & Areal, N. (2016). Stock market sentiment lexicon acquisition using microblogging data and statistical measures. *Decision Support Systems*, *85*, 62-73.

Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with applications*, *73*, 125-144.

Palomino, F., Renneboog, L., & Zhang, C. (2009). Information salience, investor sentiment, and stock returns: The case of British soccer betting. *Journal of Corporate finance*, *15*(3), 368-387.

Piccoli, P., & Chaudhury, M. (2018). Overreaction to extreme market events and investor sentiment. *Applied Economics Letters*, *25*(2), 115-118.

Phan, D. H. B., Sharma, S. S., & Tran, V. T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Markets, Institutions and Money*, *55*, 134-150.

Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. (2015). The effects of Twitter sentiment on stock price returns. *PloS one*, *10*(9), e0138441.

Qiu, L., & Welch, I. (2004). Investor sentiment measures. *NBER Working Paper 10794.*

Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking & Finance*, *84*, 25-40.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance*, *16*(3), 394-408.

Shiller, R. J., Fischer, S., & Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings papers on economic activity*, *1984*(2), 457-510.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442.

Shefrin H. 2008. A Behavioral Approach to Asset Pricing. New York: Elsevier. 2nd ed

Shefrin, H., & Belotti, M. L. (2008). Risk and return in behavioral SDF-based asset pricing models. *Journal of Investment Management*, *6*(3), 1-18.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, *40*(3), 777-790.

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. Journal of Economic perspectives, 4(2), 19-33.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization*, *107*, 730-743.

Simon, D. P., & Wiggins III, R. A. (2001). S&P futures returns and contrary sentiment indicators. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *21*(5), 447-462.

Smales, L. A. (2017). The importance of fear: investor sentiment and stock market returns. *Applied Economics*, *49*(34), 3395-3421.

Solt, M. E., & Statman, M. (1988). How useful is the sentiment index?. *Financial Analysts Journal*, *44*(5), 45-55.

Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management*, *20*(5), 926-957.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288-302.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, *70*(5), 1903-1948.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, *30*(4), 1270-1315.

Subrahmanyam, A. (2008). Behavioural finance: A review and synthesis. *European Financial Management*, *14*(1), 12-29.

Takeda, F., & Wakao, T. (2014). Google search intensity and its relationship with returns and trading volume of Japanese stocks. *Pacific-Basin Finance Journal*, *27*, 1-18.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, *62*(3), 1139-1168.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The journal of finance*, *63*(3), 1437-1467.

Thaler R. 1993. Advances in Behavioral Finance. New York: Russell Sage Found.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124-1131.

Weng, B., Lu, L., Wang, X., Megahed, F. M., & Martinez, W. (2018). Predicting short-term stock prices using ensemble methods and online data sources. *Expert Systems with Applications*, *112*, 258-273.

Xiong, G., & Bharadwaj, S. (2013). Asymmetric roles of advertising and marketing capability in financial returns to news: Turning bad into good and good into great. *Journal of Marketing Research*, *50*(6), 706-724.

You, W., Guo, Y., Zhu, H., & Tang, Y. (2017). Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression. *Energy Economics*, *68*, 1-18.

Yu, Y., Duan, W., & Cao, Q. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision support systems*, *55*(4), 919-926.

Zhang, C. (2008). Defining, modeling, and measuring investor sentiment. University of California, Berkeley, Department of Economics.

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, *10*, 239-259.

Appendix A

Table 8. All (71) papers analyzed in the study with its characteristic sorted by the year of publication.

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
1	Lee, C. M., Shleifer, A., & Thaler, R. H. (1991)	American - NYSE	July, 1956 and December, 1985 (inclusive)	Monthly	CEFD	Multifactor
2	Chen, NF; Kan, R; Miller, MH (1993).	American - NYSE	July 1965 to December 1985	Monthly	CEFD	Medium complex /
3	Neal & Whitley (1998)	American - NYSE and AMEX	1933-1993	Monthly	Multiple	Single-factor
4	Klibanoff, P., Lamont, O., & Wizman, T. A. (1998).	Various countries	January 1986 to March 1994	Weekly	Based on media	Medium complex
5	Simon, DP; Wiggins, RA (2001).	American - S&P 500	January 1989 to June 1999	Daily	Multiple	Multifactor
6	Fisher, K. L., & Statman, M. (2003).	American - S&P 500 and NASDAQ	January 1989 to July 2002	Monthly	Multiple	Single-factor
7	Brown, G., & Cliff, M. (2005)	American - DJIA	January 1963 to December 2000	Monthly	Multiple	Single-factor / Multifactor
8	Baker, M. & Wurgler, J. (2006)	American - CRSP with share codes 10 and 11	07.1962-06.2001	Monthly	BW	Multifactor
9	Kumar & Lee (2006)	American - major US brokerage houses	January 1991 to November 1996	Monthly	Sell-buy inbalance	Multifactor
10	Lemmon, M., & Portniaguina, E. (2006)	American - all CRSP	1956 - 2002	Monthly	Multiple	Medium complex / Multifactor

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
11	Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006)	Various countries - IPO	November 1995 to December 2002	Daily	Grey market indicators	Single-factor
12	Cook, D. O., Kieschnick, R., & Van Ness, R. A. (2006).	American - IPOs	January 1993 to December 2000	Daily	Based on media	Medium complex
13	Tetlock (2007)	Amercian - DJIA	January 1984 to September 1999	Daily	Based on media	Multifactor
14	Das, S. R., & Chen, M. Y. (2007)	American - Morgan Standley High-Tech Index	July to August 2001	Daily	Based on media	Single-factor
15	Edmans, A., Garcia, D., & Norli, Ø. (2007).	Various countries	January 1973 to December 2004	Daily	Sport game results	Single-factor
16	Banerjee, P. S., Doran, J. S., & Peterson, D. R. (2007)	American - NYSE, AMEX and NASDAQ	June 1986 to June 2005	Daily	VIX	Multifactor
17	Kurov, A. (2008).	American - S&P 500 and Nasdaq-10	2002–2004	Daily	BW	Medium complex
18	Chang, S. C., Chen, S. S., Chou, R. K., & Lin, Y. H. (2008).	American - NYSE	1994-2004	Intraday – hourly intervals	The sky cloud cover variables	Multifactor
19	Fang, L., & Peress, J. (2009).	American - NYSE and NASDAQ	January 1, 1993 and|December 31, 2002	Monthly	Based on media	Multifactor
20	Schmeling (2009)	Various countries	Different for different countries	Monthly	Consumer confidence	Medium complex
21	Palomino, F., Renneboog, L., & Zhang, C. (2009).	UK - soccers cllubs listed on the LSE	1999-2002	Daily	Multiple	Single-factor

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
22	Dorn, D. (2009).	Germany - IPOs	August 1999 to May 2000	Daily	When issued purchases	Medium complex
23	Kaplanski, G., & Levy, H. (2010).	American - NYSE	January 1950 to December 2007	Daily	Aviation disasters	Medium complex
24	Kurov, A. (2010).	Amercian - S&P 500	January 1990 to November 2004	Daily	Multiple	Medium complex
25	Drakos, K. (2010).	Various countries	January 1994 to December 2004	Daily	Terrrorist activity	Multifactor
26	Da, Z., Engelberg, J., & Gao, P. (2011)	American - Russel 3000	January 2004 to June 2008	Weekly	Google	Single-factor / Medium complex
27	Joseph, K., Wintoki, M. B., & Zhang, Z. (2011).	Amercian - S&P 500	2005–2008 excl. 2004	Weekly	Google	Multifactor
28	Bollen, J., Mao, H., & Zeng, X. (2011).	American - DJIA	February 2008 to December 2008	Daily	Twitter	Machine learning
29	Stambaugh, R. F., Yu, J., & Yuan, Y. (2012)	American - NYSE, AMEX and NASDAQ	from July 1965 to December 2007	Monthly	Multiple	Multifactor
30	Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012)	Various countries	January 1965 to December 2009	Quarterly	BW	Multifactor
31	Ben-Rephael, A., Kandel, S., & Wohl, A. (2012).	American - NYSE, AMEX and NASDAQ	January 1984 to December 2008	Monthly	Multiple	Single-factor
32	Mian, G. M., & Sankaraguruswamy, S. (2012).	American - all CRSP	1972-2007	Daily	BW	Multifactor
33	Hribar, P., & McInnis, J. (2012).	American - all CRSP	August 1982 to December 2005	Monthly	BW	Multifactor

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
34	Białkowski, J., Etebari, A., & Wisniewski, T. P. (2012).	Various countries	1989–2007	Daily	Ramadan	Medium complex
35	Chung, S. L., Hung, C. H., & Yeh, C. Y. (2012).	American NYSE, AMEX and NASDAQ	January 1966 to December 2007	Monthly	BW	Multifactor
36	Garcia, D. (2013).	Amercian - DJIA	1905-2005	Daily	Based on media	Single-factor
37	Han, Y., Yang, K., & Zhou, G. (2013)	American - NYSE and AMEX	July 1965 to December 2007	Daily	BW	Multifactor
38	Corredor, P., Ferrer, E., & Santamaria, R. (2013).	Various countries	1990-2007	Monthly	BW	Multifactor
39	Xiong, G., & Bharadwaj, S. (2013).	American - all CRSP, Ken French's website and Compustat	November 2004 to February 2010	Monthly	Based on media	Multifactor
40	Yu, Y; Duan, WJ; Cao, Q (2013).	American - CRSP and compustat	July 2011 to September 2011	Daily	Based on media	Multifactor
41	Chen, H., De, P., Hu, Y. J., & Hwang, B. H. (2014).	American - all CRSP	2005 - 2012	Daily	Based on media	Single-factor
42	Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014).	American - S&P 100	January 2010 to June 2010	Daily	Twitter	Single-factor
43	Li, Q., Wang, T., Li, P., Liu, L., Gong, Q., & Chen, Y. (2014).	Chinese - CSI 100	2011	Daily	Based on media	machine learning

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
44	Kim, S. H., & Kim, D. (2014).	American - 91 firms posted on theYahoo! Finance message board	January 2005 to December 2010	Monthly, weekly, daily	Based on media	Single-factor
45	Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014).	Various countries	September 2007 to March 2012	Daily	Facebook's Gross National Happiness Index	Single-factor
46	Hillert, A., Jacobs, H., & Müller, S. (2014).	American - NYSE, AMEX and NASDAQ	January 1989 to December 2010	Monthly	Based on media	Multifactor
47	Takeda, F., & Wakao, T. (2014).	Japanese - Nikkei 225	January 2008 to December 2011	Weekly	Google	Multifactor
48	Fong, W. M., & Toh, B. (2014).	American - NYSE, AMEX and NASDAQ	July 1965 to December 2007	Monthly	Multiple	Multifactor
49	Li, XD; Xie, HR; Chen, L; Wang, JP; Deng, XT (2014).	Chinese - Hong Kong stock exchange	January 2003 to March 2008	Daily	Based on media	Machine learning
50	Da, Z., Engelberg, J., & Gao, P. (2015).	Amercian - SP500, NASDAQ, Russel 1000	January 2004 to December 2011	Daily	Google	Medium complex
51	Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015).	Amercian - S&P 500	July 1965 to December 2010	Monthly	Multiple	Single-factor

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
52	Stambaugh, R. F., Yu, J., & Yuan, Y. (2015)	American - NYSE, AMEX and NASDAQ	August 1965 to January 2011	Monthly	BW	Multifactor
53	Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015).	American - all CRSP	January 1999 to December 2010	Monthly	The sky cloud cover variables	Medium complex
54	Jacobs, H. (2015).	American - CRSP and compustat	Different periods	Monthly	BW	Multifactor
55	Ni, Z. X., Wang, D. Z., & Xue, W. J. (2015).	Chinese - Shanghai Stock Exchange (SSE) Large & Mid & Small Cap Index	January 2005 to September 2013	Monthly	Opening accounts number and turnover rate	Multifactor
56	Ding, X; Zhang, Y; Liu, T; Duan, JW (2015).	American - S&P 500	October 2006 to November 2013	Daily	Based on media	Machine learning
57	Nguyen, TH; Shirai, K; Velcin, J (2015).	American	July 2012 to July 2013	Daily	Based on media	Machine learning
58	Ranco, G; Aleksovski, D; Caldarelli, G; Grcar, M; Mozetic, I (2015).	American - DJIA	May 2013 to September 2014	Daily	Twitter	Machine learning
59	Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016).	American - S&P 500	January 2007 to December 2013	Monthly	Google	Medium complex
60	Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016).	American - NYSE, AMEX and NASDAQ	1966-2010	Monthly	BW	Medium complex

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
61	Stambaugh , R. F., & Yuan, Y. (2017).	American - NYSE, AMEX and NASDAQ	January 1967 to December 2013	Monthly	BW	Multifactor
62	Oliveira, N., Cortez, P., & Areal, N. (2017).	American - S&P 500, RUSELL 2000, DJIA, NASDAQ 100	January 2014 to June 2014	Daily	Multiple	Machine learning
63	You, W., Guo, Y., Zhu, H., & Tang, Y. (2017).	American - all CRSP	January 1995 to March 2016	Monthly	EPU	Medium complex
64	Chen, J., Jiang, F., & Tong, G. (2017).	Chinese - All A-share stocks listed in Shanghai and Shenzhen stock exchanges	January 1996 to December 2013	Monthly	Based on media	Medium complex
65	Renault, T. (2017).	American - S&P 500, DJIA and NASDAQ	January 2012 to December 2016	Intraday at half-hour intervals	Based on media	Single-factor
66	Ichev, R., & Marinč, M. (2018).	American NYSE and NASDAQ	January 2014 to June 2016	Daily	Ebola outbreak events	Medium complex
67	Bartov, E., Faurel, L., & Mohanram, P. S. (2018).	American - Russel 3000	January 2009 to December 2012	Daily	Twitter	Multifactor
68	Phan, D. H. B., Sharma, S. S., & Tran, V. T. (2018).	Various countries	Different periods for	Monthly	EPU	Multifactor

#	Author(s)	Asset(s)	Data period	Data frequency	Investor sentiment measure(s)	Model(s)
			different countries			
69	Weng, B; Lu, L; Wang, X; Megahed, FM; Martinez, W (2018).	American	2013 - 2016	Daily	Multiple	Machine learning
70	Jiang, F., Lee, J., Martin, X., & Zhou, G. (2019).	American - all CRSP, Ken French's website and Compustat	January 2003 to December 2014	Monthly	Multiple	Single-factor / Medium complex
71	Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020).	Various countries	January 2020 to March 2020	Daily	COVID-19 cases	Single-factor

Source: The data in the table has been prepared on the basis of articles specified in detail in the bibliography.

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