Received: 13 October 2021 | Revised: 3 February 2023 | Accepted: 8 May 2023

DOI: 10.1002/ijfe.2836

RESEARCH ARTICLE

WILEY

Does investor sentiment create value for asset pricing? An empirical investigation of the KOSPI-listed firms

Ahmed Bouteska[1] | **Taimur Sharif**[2] | **Mohammad Zoynul Abedin**[3]

[1]Faculty of Economics and Management of Tunis, University of Tunis El Manar, Tunis, Tunisia

[2]School of Management and Economics, University of Kurdistan Hewlêr, Erbil, Kurdistan, Iraq

[3]School of Management, Swansea University, Swansea, UK

Correspondence
Mohammad Zoynul Abedin, School of Management, Swansea University, Swansea, SA1 8EN, UK.
Email: m.z.abedin@swansea.ac.uk, m.abedin@tees.ac.uk

Abstract

This paper proposes the development of an improved investor sentiment index (ISI) to apply on the Korea Composite Stock Price Index (KOSPI) and assess the vitality of sentiment-based factor for explaining critical equity market anomalies in asset pricing in Korea. We follow the methodology of Huang et al. (2015), the align sentiment index, and employ the partial least squares method to overcome the drawbacks of the pioneering BM index of Baker and Wurgler (2006, 2007). Based on the daily trading and price data for individual companies from 2006 to 2021, we construct a novel ISI, which has robust predicting ability for the aggregate stock market return, in comparison to other popular measures of sentiment in the contemporary finance literature. Furthermore, the sentiment-based factor in this paper captures the small firm effect that the asset pricing modelling, containing the more topical Fama–French five factor modelling (5F-FF), has struggled to illuminate completely. Given that our results have shown Korean stock market as fairly well-organised in terms of the availability of the market intelligence, we speculate our results to have important managerial implications for financial regulators in Korea and countries holding similar economic features.

KEYWORDS

asset pricing anomalies, asset pricing modelling, behavioural finance, factor model, investor sentiment, Korean stock market

1 | INTRODUCTION

Much of the late 20th and early 21st century literature has shown a heavy reliance on the classical finance theories, ranging from Markowitz's asset portfolio theory Markowitz (1952) to Ross' arbitrage pricing theory (Ross, 2013), to investigate the universally mentioned stylised evidence of the equity markets. These models were based on the assumption that stock price would always reflect all accessible market intelligence and investors would exhibit rational trading behaviour accordingly. However, since the 1980s, these theories started reflecting signs of weakness in explicating unconventional market movements "such as a momentum effect, an under-reaction anomaly, a small-cap stock over-reaction anomaly, and closed fund discounts behaviour" (Chen & Haga, 2021, p. 3). This backdrop steered ultimately to flourishing of a novel era of finance, namely behavioural finance that has eased explaining the impacts of stakeholders' failure to share

Ahmed Bouteska and Taimur Sharif equally contributed as a first author.

logical expectations on markets (Kim & Lee, 2022). Following the emergence of behavioural finance, researchers commenced focusing on investigating the nexus of investor sentiment with stock yields (Baker & Wurgler, 2006, 2007; Berger & Turtle, 2012; Greenwood & Shleifer, 2014; Kim & Lee, 2022), often explaining the stock market anomalies such as impact of investors' irrational optimism (Byun et al., 2022), the value premium, the momentum impact, analyst prediction flaws and so on by investor sentiment (Sun et al., 2021; Wu et al., 2021). However, early empirical evidence consistently linked investor sentiment with speculative bubbles (Smidt, 1968), subjective anticipations (Zweig, 1973), and noise (Black, 1986; De Long et al., 1990). Contemporary researchers used examples of "black swan" events (popularised as a concept by Taleb, 2008), for example, volatility in technology stocks in the US in the late 1990s, the global COVID-19 pandemic, and so forth, and pointed out nexus between global stock bubbles or crashes and high sentiment (optimism) or low sentiment (pessimism) (Sun et al., 2021). Given that investor sentiment had been related with different attributes, literature failed to develop a universally accepted conceptual framework of this topic. Moreover, given that extant literature uses four categories of methodological approaches based on surveys, social issues, market and texts (Zhou, 2018), majority of the studies have lacked commonality in their findings due to their reliance on a particular approach to construct the sentiment index in respective countries. This backdrop pinpoints the need of constructing an improved investor sentiment index (ISI) for the stock markets that share similar features and investor behaviour.

A considerable amount of empirical literature has focused on explaining the ways sentiment forecasts future stock market returns (e.g., Baker et al., 2012; Ferreira & Santa-Clara, 2011; Kothari & Shanken, 1997; Neal & Wheatley, 1998) and estimating the impact of sentiment on small-stock premiums (Brown & Cliff, 2004; Lee et al., 1991; Neal & Wheatley, 1998; Swaminathan, 1996). Much of the literature on investor sentiment emphasised that sentiment waves mainly influence retail investors in the developed world including the US, who then drive stock prices away from their primary rates (Kumar & Lee, 2006). It implies that the institutional investors rely relatively more on information and hence display superior rational behaviour in their trading activities in comparison to their retail counterparts. In the US, institutional investors hold possession of more than 93% of the market value, indicating a weaker influence of the individual investors' sentiment on the market. On the contrary, a flipped scenario can be seen in the world's largest developing country, that is, China, where at least 90% of the market value and frequency of trading is captured by the individual investors, implying a stronger influence of the individual investors' sentiments on the stock market (Gui et al., 2022; Kling & Gao, 2008; Sun et al., 2021). China's East Asian neighbour, the Republic of (South) Korea, which has managed a remarkable transition from a developing to a developed country, emerging as the world's 10th largest economy and Asia's 4th largest economy by Nominal GDP (World Bank, 2022), has witnessed dominance of individual investors in the stock markets (e.g., 87% of the trading volume) (Byun et al., 2022), smaller size and lower age of business establishments, and amplifying market liquidity (Kim & Lee, 2022). As an increasingly developed market, the Republic has reflected resemblance in some of its stock market characteristics to those of the five major economies of the world, that is, the US, the UK, Germany, France and Japan (Ryu et al., 2017b). Given Korea's emergence as a developed country with similar microstructure market settings and, at the same time, its composition of an investor population like a strong developing economy (e.g., China), and also that only a few attempts have been made to investigate the link between investor sentiment and stock returns (Kim & Lee, 2022), it is timely and vital to explore the link/nexus in a unique context like Korea. We are aware that a number of research attempts failed to find any impact of investor sentiment changes on short-run index returns (Brown & Cliff, 2004, 2005; Wang et al., 2006) and impact of substantial forecasting ability of sentiment on future stock returns (Finter et al., 2012) due to probable emergence of managerial issues or suspensions of stock trading activities, lack of relevant data and/or the high volatility in book values (Kim & Lee, 2022). Moreover, it is evident in literature that the influences of investor sentiment on stock market returns and/or volatility is an extensively researched topic (Cevik et al., 2022) and researchers tend to agree on the possible links between them. Nonetheless, quantifying investor sentiment and its likely influence on stocks has always remained a challenge (Chen & Haga, 2021; Gui et al., 2022). We aim to cover all these gaps in behavioural finance literature.

In light of the above backdrop, this study attempts to address two queries, whether: (a) investor sentiment as an unobservable behaviour and hence a long-standing issue (Chen & Haga, 2021; Gui et al., 2022) actually plays any role in the Korean stock exchange; and (b) sentiment can be assessed through an almost precise measuring rod. Six methodological steps are followed to accomplish these objectives. First, we focus on the composition of an improved investor sentiment index (ISI), and in view of the extant literature (see Qiu & Welch, 2006); we follow Baker and Wurgler (2006, 2007) and Huang et al. (2015), and construct the aligned ISI for Korea. Second, we assess the ability of our index to forecast aggregate stock returns. In order to validate our methodology (Huang et al., 2015) including the ISI, we check the stationarity for the variables used in our analyses. Fourth, we evaluate the existence of anomalies (size, value, price momentum) in the Korean asset pricing and explore whether they can be described by any other asset pricing model. Fifth, we investigate whether asset pricing outcomes display partition sensitivity, that is, whether they diverge subject to various options of portfolio formations (5, 10, or 20). Finally, we assess the value created of investor sentiment factor in stock returns.

This research contributes to literature in multiple ways. First, using the Huang et al. (2015) methodology, this study innovates a new firm-level ISI and extends that of Yang et al. (2017). Moreover, the presence of asset pricing anomalies is checked employing Capital Asset Pricing Model (CAPM) and Fama and French (1993). The more recent Fama and French (2015) is also used to check its power to describe cross section of asset returns. There is, however, an important methodological difference. Moreover, given that corporate profitability dimension used by Fama and French (2015) is credited to Walkshäusl (2013), we adjust the factor model by applying an alternative assessment tool of firm quality, that is, cash flow variability, as proposed by Walkshäusl (2013). Besides, alternative volume of portfolios (5, 10, or 20) are created from the dataset to examine robustness of the asset pricing anomalies in connection with partition sensitivity. This allows the ISI factor to be added well for multifactor models to verify whether it creates additional value or makes any contribution to asset pricing. Finally, in order to develop greater understanding of our ISI factor, we select portfolios based on returns that are not illuminated by the risk models and perform an analysis of their post holding return trajectories.

This paper further progresses in the following order: Section 2 conducts a review of empirical literature on investor sentiment. Section 3 outlines the methodology applied in the construction of an ISI, using partial least square (PLS) method, and its suitability in forecasting stock returns, as well as the data used in the empirical examination. Section 4 offers the findings of research, and makes a comprehensive discussion of the contribution of systematic risk factors and sentiment factor in structuring the dynamics of asset pricing. Section 5 ends with concluding remarks, implications of this research and recommendation of future research.

2 | LITERATURE REVIEW

Extant literature in behavioural finance relates investor sentiment (e.g., emotions and anxiety) to the mood sensitivity hypothesis (Cevik et al., 2022) and uses three broad categories of measures (i.e., direct, indirect and meta) to cover two diverse facets of investor sentiment: investor optimism (Stambaugh et al., 2012; Baker & Wurgler, 2006) and macroeconomic environments (Byun et al., 2022; McLean & Zhao, 2014; Chung et al., 2012). Since investor sentiments are not visible directly, a problem of accuracy arises in connection with observing authentic implications of the above measures. Researchers have therefore considered a variety of proxies in measuring investor sentiments which are now used as important references in behavioural finance research (Cevik, 2022; DeVault et al., 2019; Gui et al., 2022). However, given that extant sentiment measures are currently in vogue in finance literature, as part of the accomplishment of the core aims of this research (of developing an improved ISI with robust predicting power for the total stock market returns in Korea), we review the literature related to measuring investor sentiment below.

2.1 | Survey-based or direct measures

The survey-based measures that researchers commonly use include Investor Intelligence (II), Association of Individual Investors (AAII), Investor Dashboard index (ING), Investors Intelligence index (II), Consumer ISI of the University of Michigan, the UBS/GALLUP Investor Optimism Index (Pandey & Sehgal, 2019; Lemmon & Portniaguina, 2006; Baker & Stein, 2004; Brown & Cliff, 2004, 2005; Lee et al., 2002; Fisher & Statman, 2000; Clarke & Statman, 1998), used by Solt and Statman (1988), Grigaliūnienė and Cibulskienė (2010), Shi et al. (2022), among others. One of the earlier studies by Solt and Statman (1988) investigated the Bearish Sentiment Index in the US and suggested that its construction from II's survey makes it a partial reflector of upcoming changes in stock price. Grigaliūnienė and Cibulskienė (2010) studied the stock markets in Scandinavia and observed a negative association of the consumer confidence index with total market returns. Schmeling (2009) and Bathia and Bredin (2013) suggested similar outcomes in connection with 18 industrialised economies and the G7 members respectively. Likewise, Vuong and Suzuki (2022) embodied the consumer confidence index (CCI), advance/decline ratio (ADR), and volatility premium (VP) to construct the composite sentiment index (CSI). They investigated the forecasting power of the CSI in 12 Asian and European markets from 2004 to 2016, and observed a solid but negative connectedness of investor sentiment with the stock returns over the upcoming 3–24 months. On the contrary, Shi et al. (2022) found positive and significant influence of local sentiment on the expected stock returns of a diverse range of industrial sectors. Researchers also used a variety of direct proxies of investor sentiment such as "investor mood" (Kim, 2017; Yuan et al., 2006), "option implied volatility" (Bekaert & Hoerova, 2014), and "text-based indices" (Gao et al., 2020; Kim & Kim, 2014; Antweiler & Frank, 2004), and produced divergent results corresponding to various study contexts.

With the fast proliferation of IT in the recent years, researchers have increasingly been able to make a rich collection of textual information such as frequency of web searches (popularity) and volume of comments on social networks and use proxies of investor sentiment (Gui et al., 2022; Sun et al., 2021). Antweiler and Frank (2004) and Tetlock et al. (2008) were the pioneers in introducing computer analysis methods to quantify investor sentiment and examine possible association of text-based information with stock prices. Antweiler and Frank (2004) in particular used a million US-based Yahoo! Finance posts/messages to develop a sentiment index and emphasised the ability of a positive shock to a post/conversation to forecast negative yields on the following day. Bollen et al. (2011) developed six emotional reflectors (namely, calm, alert, sure, vital, kind, happy) using 9.85 million blog communication on twitter. Based on an emotional analysis tool, they predicted influence of "calm" index on the stock market asset return. Following Bollen et al. (2011), analysing personal user-generated sentiment (i.e., daily frequency data of investor opinions and stock reviews) to construct indices has gained popularity in behavioural finance (Gui et al., 2022; Loughran & Mcdonald, 2016). For instance, Mao et al. (2015) used the linguistic analysis of the results of an extensive search of "bullish" and "bearish" on twitter and Google for the 2010–2012 period to construct a twitter bullish sentiment index. They observed a positive nexus between the index on the day of investigation and stock prices on the following day. On the contrary, Corea (2016) conducted a trend model analysis of tweets data in seconds for Apple, Google and Facebook for 2 months, and postulated a direct link between negative sentiment and its negative influence on stock prices. Renault (2020) scrutinised a large dataset of stock investor posts on a micro blogging platform (namely, StockTwits) to build a lexicon of terms used by investors and suggested that the first 30-min variations in investor sentiment were able to forecast S&P 500 ETF returns in the following 30 min. Gao et al. (2020) studied Google search behaviour of global households to create weekly ISI for 38 markets and emphasised their ISI as a contrarian forecaster of stock returns on country levels. By creating Gubalex of a databank of over 200 million posts regarding stocks and making an extensive analysis, Sun et al. (2021) stressed that GubaSenti associates better with stock market returns than the BW models (Baker & Wurgler, 2006) in the context of China. Gui et al. (2022) took the ERNIE model to construct the ISI (based on investor comments) and suggested a positive nexus of investor sentiment with GEM index returns in China. A very recent development in behavioural finance is the use of the latest neural network algorithm to quantify textual contents and analyse the investors' sentiment on web-based forums (Gui et al., 2022).

As Vuong and Suzuki (2022) argued, there are methodological complexities associated with quantifying such data (e.g., text contents) which are unstructured and noisy in nature. This observation sets the background of one of the core aims of this study related to the accuracy of investor sentiment measurement in the context of Korea where it has been a long-standing issue.

2.2 | Market-based or indirect measures

Review of empirical literature highlights use of market-based proxies as an indirect measure of investor sentiment, such as trading quantity (Baker & Stein, 2004), dividend premium (Baker & Wurgler, 2004), and first day returns from initial public offering (IPO) (Ljungqvist et al., 2006). However, the most influential measure of all so far has been the BW-ISI, which Baker and Wurgler (2006, 2007) constructed using principal component analysis (CPA) of six proxies that included the above three indicators, along with the closed-end fund discount, the number of IPOs and the equity share in new issues. The BW-ISI index is commonly applied in various financial circumstances in the US, such as stock market irregularities, mean–variance nexus, macro-risk pricing, high-beta low-return puzzle for studies (Han et al., 2022). Similar to the BW index, Yi and Mao (2009) developed a Composite Index of Chinese ISI to study investor sentiment in the Chinese stock exchange. The performance of BW-ISI (S^{BW}) in predicting stock market returns has been examined in the past studies. Although Baker and Wurgler (2007) documented the similar finding, that is, strong sentiment envisages worse future stock market return, their finding lacked strong statistical evidence. Similarly, Baker et al. (2012) combined four single market-based proxies (volatility premium, aggregate issuance of IPO, first day IPO returns, and market yield) into ISI (S^{RW}s) related to six leading global equity markets and revealed that (S^{BW}) fails to forecast the future stock returns significantly in the US market alone. Huang et al. (2015) constructed a superior ISI employing the similar proxies as used in (S^{BW}) and found that their sentiment index (S^{PLS}) significantly predicts negative future stock returns whereas (S^{BW}) exhibited no forecasting ability. A more extreme result is documented in Bekiros et al. (2016).

Given the parameter instability in the association of investor sentiment with stock returns, they employed a non-linear approach and found that both (S^{BW}) and (S^{PLS}) do not predict future stock returns and its volatility. In contrast, Balcilar et al. (2017) also used a non-linear approach but stressed that both indexes have predictive power over the stock market returns. Gizelis and Chowdhury (2016) used closed-end fund discount to create an ISI, which partially elucidated returns in the Athens Stock Exchange. Dash and Maitra (2018) employed a wide range of indirect sentiment proxies and value-weighted market indices to develop an ISI, and noticed a robust short and long term sentiment impact on the stock returns in India. Cheema et al. (2020) created an ISI from the price-earnings ratio, turnover ratio, and some recently opened individual investor accounts, which identified a robust and positive connectedness of investor sentiment with succeeding returns during the bubble period in China. Vuong and Suzuki (2022) however pointed out that the influence of sentiment on future returns is insignificant when the bubble period is excluded from the analysis.

The BW index and similar market-based sentiment indices are based on the notion that individual investors are influenced by their sentiments and hence misprice stocks, implying that the behavioural outcome of investor sentiment affects stock market performance. A common weakness of these metrics has been their limited availability for the overall market and also their limited frequency due to monthly updating of the market indicators. Moreover, the indices only cover the institutional investors and the way demand shocks influence their investment behaviour. This has an important implication on our study as the existing measures have limited applicability in Korea, a country classified as a developed economy by the World Bank but reflective of a developing economy feature in terms of its investor population (e.g., 87% of the trading done by individual investors). This reiterates the need of constructing a better measure for Korean stock exchange and other stock markets that display similar features.

2.3 | Meta measures

The last category is called meta measures. This is known to be an innovative and non-standard measure which is developed in the form of a composite investor sentiment index (ISI), based on a mix of the above measures. A number of authors (e.g., Sun et al., 2021; Feldman, 2010; Baker & Wurgler, 2007; Brown & Cliff, 2004, 2005, among others) created such an amalgam to examine the nexus of investor sentiment with stock returns and/or to check the effectiveness of the measures in forecasting upcoming stock returns. For example, Brown and Cliff (2004) pooled 12 survey and market sentiment assessment tools to develop an ISI and applied it on both contemporary and near-term stock markets. Their research established the fact that embedding different sentiment proxies in one place enables composition of a better quantifying tool for investor sentiment. Other studies also followed Brown and Cliff (2004), Baker and Wurgler (2006) and Baker et al. (2012), and blended direct and indirect measures to assess the likely impact of investor sentiment on various stock markets (e.g., Chen et al., 2010 for Hong Kong; Finter et al., 2012 for Germany; Li, 2015 for China; Yang & Zhou, 2015, 2016 for China; Ryu et al., 2017a for Korean Republic, among others). More recently, Khan and Ahmad (2019) employed Google search volume index (GSVI) as a direct proxy and nine other indirect proxies to investigate bi-directional contemporary and lead–lag association of investor sentiment with stock returns in Pakistan over the 2006–2016 period. The authors noticed considerable traces of investors' irrational conduct in dragging the thin market away from its sustainable path of convergence. Some of the other studies collected information from conventional mainstream media, for example, daily newspaper contents (Tetlock et al., 2008) and newsletter write-ups (Fisher & Statman, 2000) and integrated those in forming meta measures. As discussed in Section 2.1, with the emergence of big data technology, researchers switched to collecting data through IT-based means in the recent years (Sun et al., 2021), for example, stock-related viewpoints on virtual chatrooms (Antweiler & Frank, 2004); blog contents, microblogs and Facebook activity (Bollen et al., 2011; Mao et al., 2015); Yahoo-driven messages (Kim & Kim, 2014); Wikipedia users (Moat et al., 2013).

The above review develops a clear understanding of the significance of the BM index (Baker & Wurgler, 2006, 2007) as a guiding principle of developing investor sentiment measures in various research and their implications in finance. A series of studies such as Yi and Mao (2009), Baker et al. (2012), Huang et al. (2015), Bekiros et al. (2016), Gizelis and Chowdhury (2016), Balcilar et al. (2017), Dash and Maitra (2018), Cheema et al. (2020), among others followed the BM index as a pioneer to construct ISI in various contexts. However, Yang et al. (2017) argued BM index to be an inadequate measure having limited applicability. In light of this backdrop, we adopt and amend the ISI constructed by Yang et al. (2017), besides considering the BM index as well as a number of proxy variables (deemed suitable from the above review) in constructing a purpose-built ISI. Due to flurry of studies in specific advanced nations in which the investor sentiment is recognised to have played a great role and added values in the asset pricing framework and elucidated the portfolio of returns, we find it rational to think about extending the work in the context of a fast-transitioning market from the developed world, that is, Korea where the topic is only nominally examined.

3 | METHODOLOGY

Huang et al. (2015) point out that the methodology explained in the study of Baker and Wurgler (2006, 2007), specifically the principal component analysis (CPA), does not clearly separate different components that are included in their sentiment index, that is, asset return forecasting component and the common approximation error component. They criticise that the latter (i.e., the common approximation error for all sentiment proxies) is irrelevant to asset returns and that Baker and Wurgler's (2006, 2007) measure does not properly filter out the effects of this component. To overcome such drawbacks, Huang et al. (2015) apply the partial least squares (PLS) approach to extract in effective manner the former (i.e., the component that is valuable to forecast asset returns). In light of this backdrop, we construct a new sentiment index based on the methodology of Huang et al. (2015), the align index of sentiment.

3.1 | Building an aligned index of investor sentiment ($\mathrm{SENT}^{\mathrm{PLS}}$)

The construction method of sentiment index in Huang et al. (2015) is as follows:

First, we select five sentiment proxies that could be applied in the framework of the Korean stock market: the relative strength index (RSI) which computes the magnitudes of gains/losses for investors like the ratio of rising to declining stock prices in 14 trading days (Wong et al., 2003; Chong & Ng, 2008; Chen et al., 2010; Zhou & Yang, 2020). $\mathrm{RSI}_{\mathrm{i,t}}$ is equal to 100 if a denominator of $\mathrm{RS}_{\mathrm{i,t}}$ is 0. When the RSI is higher (lower) than 80 (20), sentiment of investor is optimistic (pessimistic).

$$RSI_{i,t} = \frac{RS_{i,t}}{(1+RS_{i,t})} \times 100, \text{where } RS_{i,t} = \frac{\sum_{k=0}^{13} \max(P_{i,t-k} - P_{i,t-k-1}, 0)}{\sum_{k=0}^{13} \max(P_{i,t-k-1} - P_{i,t-k}, 0)} \tag{1}$$

The psychological line index (PLI) reflects psychological stability of investors through measuring short-term price reversals and measures psychological changes of investors by computing the number of trading days of price increases over the past 12 trading days (Yang & Gao, 2014; Gao & Liu, 2020). $PLI_{i,t}$ is equal to 100 if a denominator is 0. When the (PLI) is higher (lower) than 75 (25), sentiment of investor is optimistic (pessimistic).

$$PLI_{i,t} = \left[\sum_{k=0}^{11} \left\{ \frac{\max(P_{i,t-k} - P_{i,t-k-1}, 0)}{P_{i,t-k} - P_{i,t-k-1}} \right\} / 12 \right] \times 100 \tag{2}$$

The buy-sell imbalance (BSI) reflects the trading behaviour of the domestic individual investors (Kumar & Lee, 2006) who are more easily impacted through behavioural bias and sentiment compared with their institutional counterparts. A BSI of a stock that is positive or negative, means that sentiment of investor of the said stock is optimistic or pessimistic respectively.

$$BSI_{i,t} = \frac{BV_{i,t} - SV_{i,t}}{BV_{i,t} + SV_{i,t}} \tag{3}$$

The trading volume's logarithm (LVOL) in which a great trading volume normally implies that investors trading that stock exhibit great sentiment,

$$LVOL_{i,t} = ln(VOL_{i,t}) \tag{4}$$

The turnover adjusted ratio (ATR) is considered as a suitable sentiment proxy due to the fact that the turnover ratio is claimed to show the state of sentiment of investor (Baker and Stein, 2004). ATR is positive or negative when stock returns are positive or negative and this indicates a bullish (bearish) state of market.

$$ATR_{i,t} = \frac{VOL_{i,t}}{\#\text{of outstanding stocks}_{i,t}} \times \frac{R_{i,t}}{|R_{i,t}|} \tag{5}$$

We utilise the residuals of these proxy variables after estimating them on a set of macroeconomic terms: the market excess return, the VKOSPI index, the exchange rate, the credit spread, and the term spread. Here, the return on the KOSPI index beyond the risk-free rate (the 91-day certificate of deposit rate) denotes the market excess return; the market volatility implied by spot and index options prices shows the VKOSPI; USD/KRW represents the exchange rate between the Korean won and the US dollar; subtraction of the return on BBB- credit bonds from the return on AA- credit bonds defines the credit spread; and subtraction of the risk-free rate from the return on 5-year government bond provides the term spread.

Second, standardising these residual processes so that these outputs will be following stationary processes. In this stage, we consider and check the stationarity of the implied volatility series (i.e., the VKOSPI) and the other macroeconomic variables.

Third, we create the firm-level index of investor sentiment following the method of Huang et al. (2015) who run linear estimations to get the covariance terms of proxies of sentiment index for the market return (see Equation 6). In the equation, we strictly extract the components that are valuable to the predicting of asset returns, and therefore we could exclude other irrelevant components, which is observed as a problem associated with the PCA, and get unbiased index of sentiment.

$$SENT_{i,t-1} = \beta_{i,0} + \beta_i R_t + \varepsilon_{i,t-1} \tag{6}$$

Where $SENT_{i,t-1}$ denotes the investor sentiment proxy i at time $t-1$, R_t is the one-period market excess return at time t, and β_i indicates the sensitivity of each proxy of sentiment (i.e., the covariance of lagged proxies of sentiment and the return process). Then, they develop the final index of sentiment through a linear combination of these covariance values with the proxies of sentiment. Given that the aligned index of sentiment suggested by Huang et al. (2015) is a market-wide and index-relevant sentiment index but our research investigates individual firms rather than the market index, we further develop and modify the methodology of Huang et al. (2015) to construct a new firm-level sentiment measure, as shown in Equation (7).

$$SENT_{f,i,t-1} = \beta_{f,i,0} + \beta_{f,i} R_{f,t} + \varepsilon_{f,i,t-1} \tag{7}$$

Where $SENT_{f,i,t-1}$ refers to the firm-level proxy of sentiment i for firm f in time $t-1$, $R_{f,t}$ is firm f's one-period stock return i, time t, and $\beta_{f,i}$ refers the covariance of lagged proxy of sentiment i and the process of return.

Lastly, we develop our novel index of sentiment through the linear combination of regressed covariance values and proxies of sentiment, as denoted by Equation (8).

$$SENT^{PLS}_{f,t} = \widehat{\beta}_{f,RSI} RSI_{f,t} + \widehat{\beta}_{f,PLI} PLI_{f,t} + \widehat{\beta}_{f,LVOL} LVOL_{f,t} + \widehat{\beta}_{f,BSI} BSI_{f,t} + \widehat{\beta}_{f,ATR} ATR_{f,t} \tag{8}$$

Where $SENT^{PLS}_{f,t}$ is the linearly combined sentiment index. $RSI_{f,t}$, $PLI_{f,t}$, $LVOL_{f,t}$, $BSI_{f,t}$, and $ATR_{f,t}$ denote the RSI, PLI, $LVOL$, BSI, and ATR values for firm $f$at time t respectively. $\widehat{\beta}_{f,i}$ is the fitted coefficient of $R_{f,t}$ for proxy of sentiment i in Equation (7). Table 1 presents the summary statistics of the proxies of investor sentiment and the aligned index of sentiment. The mean of ($SENT^{PLS}$) is 0.0479 and it is the variable in equation (8).

Following Baker and Wurgler (2006, 2007) and Huang et al. (2015), a number of studies (e.g., Hengelbrock et al., 2013; Huang et al., 2015; Kim et al., 2014; Smales, 2016, 2017) analysed the relationships between sentiment of investor, stock returns and firm-specific news, and revealed that previous sentiment significantly predicts the reaction of stock returns to firm-specific news around the announcement dates (t = 0) (Mian & Sankaraguruswamy, 2012; Kim et al., 2019). Thus, we check whether the aligned index of investor sentiment that we constructed have forecasting ability on the market index returns or stock returns by employing an additional regression, as shown in Equation (9). We follow the suggestion of the previous literature that the implied volatility forecasts the stock market (Whaley, 2009; Konstantinidi & Skiadopoulos, 2011), and accordingly include the implied volatility as economic predictors.

$$R_{m,t} = \beta_0 + \beta_1 SENT^{PLS}_{t-1} + \beta_2 VKOSPI_{t-1} + \beta_3 EXCH_{t-1} + \beta_4 CREDIT_{t-1} + \beta_5 TERM_{t-1} + \beta_6 RF_{t-1} + \varepsilon_{i,t} \tag{9}$$

Where $R_{m,t}$ denotes the stock market return at time t, $SENT^{PLS}_{t-1}$ is the aligned investor sentiment indicator at time $t-1$, $VKOSPI_{t-1}$ is the level of market volatility index at time $t-1$, which is calculated from the spot and index options prices, $EXCH_{t-1}$ is the USD/KRW exchange rate at time $t-1$, $CREDIT_{t-1}$ is the return of BBB- credit bonds subtracted from the return of AA-

TABLE 1 Summary statistics.

	Mean	Std.	P25	Median	P75	Max
RSI	0.0060	0.9987	−0.7512	−0.0098	0.7530	4.0097
BSI	−0.0009	0.9998	−0.5020	0.0275	0.5061	17.0951
LVOL	0.0026	0.9911	−0.6991	−0.0413	0.6551	10.3828
PLI	0.0064	0.9992	−0.7748	−0.0796	0.7328	4.5302
ATR	0.0003	0.9917	−0.3035	−0.0469	0.2388	50.0065
$SENT^{PLS}$	0.0479	12.8667	−4.5429	−0.0551	4.3560	518.2304

Note: This table presents summary statistics for the investor sentiment proxies (RSI, BSI, LVOL, PLI, and ATR) and the aligned sentiment index ($SENT^{PLS}$) based on data from January 2006 to December 2021. The summary statistics include the mean (Mean), standard deviation (Std), minimum (Min), 25th percentile (P25), 50th percentile (P50), 75th percentile (P75), and maximum (Max).

credit bonds at time $t-1$, $TERM_{t-1}$ is the return of the 5-year government bond after subtracting the risk-free rate at time $t-1$, RF_{t-1} is the rate of the 91-day certificate deposit at time $t-1$, and $\varepsilon_{i,t}$represents the error term.

3.2 | Asset pricing with investor sentiment

Three sets of stylised portfolios are constructed based on firm size, firm value, and price momentum (i.e., market capitalization, P/B ratio, and past 6-month average returns respectively). Following the legal requirement in South Korea, we form the size and value portfolios in March of year t (December of year t−1) on an annual basis but realign the momentum portfolios on a 6-monthly basis, and rank the securities based on market capitalization and P/B ratio. As P/B ratio is an accounting measure and generally, there is a delay in submission of financial statements from the financial closing date, that is, the 31st of December, we keep 3 months gap between portfolio construction and holding period. This is explained by the fact that investors may need time interval to get the required information for portfolio construction purpose. We classify the ranked securities into five portfolios (quintiles) from P1 (the highest) to P5 (the lowest) and we estimate the equally weighted monthly excess returns to these portfolios for the coming 12 months, beginning from April of year t. Hence, we refer P1 and P5 as corner portfolios in this study and represent top 5% and bottom 5% stocks based on market capitalization and P/B ratio. Concerning momentum portfolios, in March of year t, the sample stocks are ranked in ascending order based on their average returns during last 6 months and form quintiles as follows: P1 the highest represents the winner and P5 the lowest represents the loser. We estimate equally weighted monthly excess returns to these portfolios for the coming 6 months. Again, we rebalance the portfolios in September of year t to form the winners and losers. Indeed, we follow a momentum strategy (6–6) where: formation period and holding period equal 6 months each. We make robustness check tests for the partition sensitivity of anomalies of asset pricing such as size, value and price momentum due to alternative portfolio formations. As discussed previously, we now classify the securities into 10 portfolios (deciles) P1 to P10 and 20 portfolios (vigintiles) P1 to P20, based on stylised properties. The portfolio P1 composes the highest (10%–5%) (decile-vigintile) of firms having greatest attribute while P10-P20 (decile-vigintile) composes the lowest (10%–5%) firms having lowest attribute.

We estimate the model of Capital asset pricing (CAPM) on the sample portfolios utilising the excess return of the market model as follows:

$$R_{p,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \varepsilon_t \tag{10}$$

Where $R_{p,t}$ and $R_{f,t}$ denotes the excess returns by month on the portfolio and risk-free rate return, respectively. $R_{m,t}$ denotes the monthly excess market return.

We then utilise three-factor Fama–French model (3F-FF) to verify the possibility of reflecting the missed returns by one factor (CAPM) model, using the following equation:

$$R_{p,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t + \varepsilon_t \tag{11}$$

Where SMB_t and LMH_t symbolise the monthly return on the size and value (book to market ratio) mimicking portfolios. For measurement of value factor, we employ LMH factor instead of HML factor in the 3F-FF model and thus the value factor's interpretation will be opposite. The correlation between the measures of SMB and LMH is weak and negative (−0.19) and thus the construction of non-overlapping factors. We develop a 2*2 size-value partition to create SMB and LMH portfolios following Sehgal et al. (2012) where a detailed outline of the construction methodology of the SMB and LMH factors is provided.

At this stage, our aim is to clean the extra normal returns of the portfolios that were not explained by 3F-FF modelling, so we examine the 3F-FF by adding a momentum factor (MOM). Following Carhart (1997), we construct four factor model capturing the patterns of the anomaly in returns, as observed in equation:

$$\begin{aligned} R_{p,t} - R_{f,t} = {} & \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t \\ & + \lambda MOM_t + \varepsilon_t \end{aligned} \tag{12}$$

Where MOM_t symbolises the excess return by month of the winner minus loser on the basis of quintile formation of portfolio. Fama and French (2015) brings two additional factors (i.e., investment and profitability) and propose a five-factor model (5F-FF), as indicated below:

$$\begin{aligned} R_{p,t} - R_{f,t} = {} & \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t \\ & + \varphi RMW_t + \nu CMA_t + \varepsilon_t \end{aligned} \tag{13}$$

Where RMW_t captures the potential profitability premium and is the excess returns by month of low profitability minus high profitability portfolios (measured by ROE), and $CMA_t$is the monthly excess returns of a portfolio of stocks having low investment minus a portfolio of stocks having high investment (measured by change in total assets). The findings are found in line for both proxies of quality of firm, namely profitability (ROE) and cash flow change (Walkshäusl, 2013), and hence the role of firm quality factor to explain returns on sorted portfolio by volatility is confirmed. Motivated by the results from Walkshäusl (2013) who additionally add a firm quality factor (proxied by either ROE and cash flow change) to extend the 3F-FF modelling, we rank portfolios on new cash flow change factor instead of profitability factor (ROE), resulting in the following modified five-factor model (5F-FF):

$$R_{p,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t + \eta RMW_t^{*} + \nu CMA_t + \varepsilon_t \tag{14}$$

Where RMW_t^{*} is the excess returns by month of low cash flow change minus high cash flow change portfolios (measured by 'σ' of cash flow operations trailing 5 years).

The 3F-FF and the 5F-FF models are estimated utilising a sentimental factor, namely the composite ISI. A dummy variable ($SENT_{Dummy}^{PLS}$) (taking a value of 1 if composite ISI is higher compared to its long-term average value and 0 otherwise) is added to both model regressions. It is given by,

$$R_{p,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t + \omega SENT_{Dummy}^{PLS} + \varepsilon_t \tag{15}$$

$$R_{p,t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \gamma SMB_t + \delta LMH_t + \varphi RMW_t + \nu CMA_t + \omega SENT_{Dummy}^{PLS} + \varepsilon_t \tag{16}$$

$SENT_{Dummy}^{PLS}$ relates to the sentimental factor, which is based on our constructed composite ISI. The results of the sentimental factor on portfolios appear encouraging and meaningful enough to be presented for further discussion.

3.3 | Data

To construct proxies for investor sentiment, daily transaction and price data for individual companies during the period of our sample are collected. The raw dataset contains data on the stocks of all manufacturing companies, which are listed in the Korea Composite Stock Price Index (KOSPI). This is in alignment with other recent behavioural finance studies focusing on the Korean market (Yang & Zhou, 2015, 2016; Ryu et al., 2017a; Yang et al., 2017; Seok et al., 2019a, 2019b) which employed similar indicators of sentiment (i.e., firm specific sentiment indices). The study employs month end closing adjusted stock prices during the January 2006–December 2021 period, the time when proxies were well available in this market. The dataset also covers the period of the pandemic in Korea where the first case was confirmed on 20 January 2020, and finally 277,989 confirmed cases and 2380 deaths were reported on 15 September 2021 (Source: Korea Disease Control and Prevention Agency). In order to remove ambiguity, the stocks with suspended trading or administrative problems and also the stocks with no indicators of investor sentiment were deleted from the whole sample. By filtrating, our final sample included the stocks of 636 KOSPI companies. The stock prices data which is adjusted to variations in capitalization like dividends, stock splits and rights problem is used. For further regression, we transform the end of month stock price series into percentage return series. We use the CD91 (91-day certificate of deposit) rate to measure the risk-free rate of return. We gather the data to follow company characteristics that are considered to form stylised portfolios and these risk factors: Market capitalization for proxy of size is computed as the natural log of price times shares outstanding, Price to book value per share which is the inverse of (Book Equity/Market Equity) for value proxy indicating the security price over a firm's book value, the average trailing 6 month's returns computed as momentum proxy, the income available to common stockholders for the most recent fiscal year divided by the average common equity and is represented as a percentage to calculate the return on equity (ROE) for profitability proxy, a standard deviation (σ) of trailing 5 years cash flow from operations for the different firms is computed to get Cash Flow variability as proxy of quality of firm, and Total Assets change (i.e., total asset variations between t and t−1 years) as proxy of investment. The sample is completed by hand-collecting financial and stock price data from the Data Guide monthly reports on the KOSPI firms, provided by Bloomberg.

4 | FINDINGS AND DISCUSSION

First of all, we attempt to support the use of the aligned ISI ($SENT^{PLS}$) constructed by the PLS method and claim its validity as a forecasting index, as emphasised by Huang et al. (2015). Table 2 illustrates an analysis in this regard.

In model 4, we document that the forecasting ability of the aligned indicator of sentiment is still significantly positive after adding a set of macroeconomic control variables, which are often known to determine future market returns. This result is in line with Sun et al. (2016)

TABLE 2 Performance of investor sentiment as a predictor for future stock returns.

	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	−0.0057	−0.0057	−0.0057	−0.0057
	(−0.222)	(−0.222)	(−0.222)	(−0.222)
$\mathbf{SENT^{PLS}_{t-1}}$		**0.0665****		**0.0701****
		(2.459)		**(2.533)**
$VKOSPI_{t-1}$	−0.7218***	−0.7227***	−0.7209***	−0.7220***
	(−31.45)	(−31.55)	(−31.40)	(−31.50)
$EXCH_{t-1}$			−0.0240	−0.0188
			(−0.992)	(−0.770)
$CREDIT_{t-1}$			−0.0316	−0.0324
			(−0.902)	(−0.943)
$TERM_{t-1}$			−0.0261	−0.0190
			(−1.045)	(−0.741)
RF_{t-1}			−0.0274	−0.0380
			(−1.135)	(−1.545)
R^2	0.4943	0.4972	0.4961	0.4992

Note: This table presents estimation results of the prediction models relative to the market return ($R_{m,t}$) for the aligned investor sentiment index ($SENT^{PLS}$) and the other economic predictors (VKOSPI, EXCH, CREDIT, TERM, and RF) based on data from January 2006 to December 2021.Thet-statistics are reported in parentheses while *, ** and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

suggesting that the effect of sentiment on future stock returns is positive in the short term. Also, even though it turns negative in the long term, the effect has a tendency to be long-lasting when the sentiment effect is stronger. The positive coefficient of ($SENT^{PLS}_{t-1}$) is therefore attributable to the strong sentiment effect in the Korean market. In addition, the R-square values in models 2 and 4 are clearly higher than those in models 1 and 3 respectively, indicating that the adding of the ($SENT^{PLS}_{t-1}$) improves the explanatory powers of the models even after controlling for macroeconomic variables. Further, following Hengelbrock et al. (2013), we utilise the bootstrap simulation to test the robustness of this result and reveal an alignment of the outcome with Table 2. Overall, we find that investor sentiment ($SENT^{PLS}$) forecasts stock returns within our period of sample. We now share and discuss our findings on asset pricing with investor sentiment, starting with stylised portfolios of asset returns.

Table 3 shows the unadjusted average returns on size, value and momentum for alternative portfolio formations (quintiles, deciles, vigintiles). The average unadjusted monthly returns on size sorted portfolios for quintiles show a 2.95% monthly return differential between small and large stocks, resulting from the monotonic increase from large stocks (1.56%) to small stocks (4.51%), and hence corroborate the size effect proposed by Banz (1981), Lettau and Ludvigson (2001), Roll (1981), and Sehgal and Tripathi (2005). Likewise, the unadjusted average returns for quintiles are monotonically rising from 2.12% per month for high P/B ratio stocks (low BE/ME) to 3.39% per month for low P/B ratio stocks (high BE/ME), displaying a 1.27% monthly return differential and approving the existence of strong value impact, as argued by Stattman (1980), De Bondt and Thaler (1987), and Lakonishok et al. (1994). We also see that size effect dominates the value effect by 2.32 times, in consistence with the results of the emerging markets such as South Korea (Sehgal et al., 2012). The unadjusted returns on momentum sorted portfolios indicate that the monthly mean returns for the winner's portfolio (P1) is 3.04% while the same for the loser's portfolio (P5) is 1.64%, hence generating a 1.40% momentum profit. Consequently, the size, value and momentum impacts are empirically approved for the quintile portfolio in the South Korean market.

In Panel B and C from Table 3, the unadjusted average returns on properties-based portfolios for deciles and vigintiles formations are shown respectively. The negative relation among size and average returns is confirmed because the unadjusted return differential among small and large stocks (in terms of deleting P1 from decile and P1, P2 from vigintile) is (3.33%–3.79%) monthly for both decile-vigintile portfolios. P1 is comprised of large firm stocks chased by institutional investors since we observe raw returns for deciles and the excess demand for them makes positive reaction of price leading to greater

TABLE 3 Unadjusted returns of portfolios sorted by size, value, and momentum.

Panel A: Quintiles										
Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**					
Size	0.0156	0.0193	0.0221	0.0300	0.0451					
Value	0.0212	0.0225	0.0251	0.0292	0.0339					
Momentum	0.0304	0.0202	0.0180	0.0203	0.0164					
Panel B: Deciles										
Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Size	0.0313	0.0180	0.0203	0.0184	0.0227	0.0218	0.0291	0.0316	0.0398	0.0513
Value	0.0296	0.0194	0.0225	0.0237	0.0258	0.0241	0.0287	0.0296	0.0313	0.0376
Momentum	0.0216	0.0294	0.0219	0.0190	0.0193	0.0170	0.0196	0.0214	0.0220	0.0120
Panel C: Vigintiles										
Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Size	0.0293	0.0326	0.0148	0.0217	0.0203	0.0209	0.0187	0.0186	0.0214	0.0249
Value	0.0277	0.0312	0.0196	0.0195	0.0210	0.0246	0.0250	0.0234	0.0271	0.0260
Momentum	0.0205	0.0161	0.0369	0.0224	0.0237	0.0211	0.0176	0.0209	0.0206	0.0188
Portfolio	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
Size	0.0206	0.0242	0.0289	0.0308	0.0309	0.0341	0.0383	0.0430	0.0497	0.0527
Value	0.0271	0.0223	0.0274	0.0314	0.0310	0.0292	0.0266	0.0378	0.0316	0.0458
Momentum	0.0141	0.0208	0.0233	0.0171	0.0243	0.0200	0.0217	0.0245	0.0200	0.0046

Note: This table presents estimation results of the unadjusted returns for size, value, and momentum sorted portfolios measured on a monthly basis data from January 2006 to December 2021.

expected returns. The result in increasing activity of trading and the additional returns may be a simple compensation for raised volatility. The findings are re-approved for vigintile portfolio in which P1 and P2 portfolios are equal to decile P1 portfolio in number of constituent stocks. Therefore, the size impact is almost monotonic from P2 to P10 in deciles and from P3 to P20 in vigintiles. In terms of excluding P1 from decile and P1, P2 from vigintile, the monthly unadjusted return differential among low P/B ratio and high P/B ratio stocks is (1.82%–2.62%) for decile-vigintile portfolios thus approving the existence of value effect. We can notice that for the decile portfolios and the vigintile portfolio, the size impact is therefore 1.83 times, and 1.44 times the value effect respectively. Another time relating to P/B ranked stocks, P1 with high P/B ratio stocks are in fact growth stocks that attract the enthusiasm of institutional investors. While greater demand makes positive reactions of price and greater returns, in general greater activity of trading leads to higher volatility in price, and the additional returns observed may be simple compensation for additional risk. The relation is mainly monotonic from P2 to P10 for deciles when P1 is removed. Likewise, by deleting P1 and P2 equals to decile portfolio P1, returns increase almost monotonically from P3 to P20. In case of removing P1 from decile and P1, P2 from vigintile, the monthly unadjusted return differential among winners and losers' portfolios is (1.74%–3.23%) for decile-vigintile portfolios, approving the existence of the effect of momentum. Looking at raw returns, we see that P1 winners exhibit moderate expected returns as probably investors do not believe that they are able to support the greater returns, so the correction of price process will force their returns to reduce and stabilise. In case of deciles, the momentum relation is mainly monotonic from P2 to P10. Likewise, by deleting P1 and P2 equals to decile portfolio P1, returns decrease mainly monotonically from P3 to P20. In resume, the stylised property premiums are powerful for vigintile portfolios, hence approving that performance of portfolio sorted by characteristics is sensitive to construction of alternate portfolios.

Table 4 tests the Capital asset pricing model (CAPM) for all formations of alternate portfolio. For instance, for quintiles, the small size stocks on an average earn a monthly 3.01% return, with statistical significance in comparison with 0.21% of big stocks. The adjusted R^2 is low for small stock quintile portfolio (P5) compared to large stock portfolio (P1), implying that the first has a very large variance not explained in their returns. The high P/B ratio portfolios have a lower intercept term than low P/B ratio portfolios, suggesting that the latter is giving greater market risk adjusted returns than the former.

TABLE 4 Testing results of capital asset pricing model (CAPM) for sample portfolios.

Panel A: Quintiles											
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**					
Size	α	0.0021	0.0046	0.0072*	0.0151*	0.0301*					
		(1.30)	(1.76)	(2.24)	(3.93)	(5.53)					
	β	1.0677*	1.1527*	1.1671*	1.1574*	1.1574*					
		(75.1)	(44.2)	(36.5)	(30.5)	(22.9)					
	Adjusted R^2	0.9823	0.9127	0.8690	0.8028	0.6656					
Value	α	0.0088*	0.0084*	0.0108*	0.0139*	0.0174*					
		(2.89)	(3.46)	(3.73)	(3.91)	(3.62)					
	β	0.9707*	1.1068*	1.1150*	1.1948*	1.3076*					
		(32.6)	(44.5)	(38.1)	(33.6)	(27.8)					
	Adjusted R^2	0.8300	0.9137	0.8815	0.8416	0.7679					
Momentum	α	0.0185*	0.0084*	0.0054	0.0073	0.0019					
		(3.49)	(2.00)	(1.37)	(1.67)	(0.30)					
	β	0.9277*	0.9049*	0.9684*	0.9987*	1.1216*					
		(14.5)	(18.4)	(21.2)	(19.6)	(16.1)					
	Adjusted R^2	0.6051	0.7207	0.7833	0.7472	0.6554					
Panel B: Deciles											
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Size	α	0.0178*	0.0042	0.0058*	0.0036	0.0075*	0.0066	0.0139*	0.0162	0.0236*	0.0366*
		(4.93)	(1.88)	(2.26)	(1.07)	(2.31)	(1.83)	(3.38)	(1.80)	(5.00)	(4.84)
	β	1.0638*	1.0858*	1.1372*	1.1649*	1.1650*	1.1707*	1.1528*	1.1678*	1.2261*	1.0815*
		(30.1)	(49.5)	(44.6)	(37.3)	(35.7)	(33.3)	(28.9)	(28.9)	(26.9)	(17.1)
	Adjusted R^2	0.8046	0.9348	0.9146	0.8755	0.8620	0.8387	0.7849	0.7852	0.7505	0.4710
Value	α	0.0151*	0.0070*	0.0077*	0.0098*	0.0116*	0.0092*	0.0134*	0.0136*	0.0148*	0.0201*
		(4.03)	(2.89)	(2.88)	(3.56)	(4.24)	(2.48)	(3.67)	(3.33)	(3.25)	(3.52)
	β	1.1523*	0.9568*	1.1285*	1.0772*	1.0836*	1.1409*	1.1653*	1.2081*	1.2473*	1.3218*
		(31.4)	(39.5)	(40.2)	(39.2)	(38.8)	(31.5)	(31.4)	(30.4)	(28.4)	(24.8)
	Adjusted R^2	0.8171	0.8919	0.8960	0.8893	0.8868	0.8183	0.8289	0.8018	0.7766	0.7061
Momentum	α	0.0082	0.0181*	0.0103*	0.0069	0.0066	0.0039	0.0065	0.0078	0.0069	−0.0090
		(1.55)	(2.90)	(2.31)	(1.58)	(1.69)	(0.88)	(1.43)	(1.63)	(1.25)	(−0.59)
	β	1.0509*	0.8720*	0.8927*	0.9183*	0.9551*	0.9790*	0.9696*	0.9989*	1.1311*	1.1152*
		(22.0)	(17.0)	(22.2)	(23.4)	(26.4)	(24.9)	(24.3)	(23.4)	(22.91)	(19.20)
	Adjusted R^2	0.6453	0.4608	0.6483	0.6805	0.7449	0.7101	0.7038	0.6791	0.6676	0.5503
Panel C: Vigintiles											
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Size	α	0.0146*	0.0194*	0.0018	0.0067*	0.0052	0.0064	0.0029	0.0040	0.0069	0.0084
		(4.46)	(3.20)	(0.61)	(2.30)	(1.81)	(1.92)	(0.67)	(1.23)	(1.91)	(1.18)
	β	1.1726*	1.0181*	1.0112*	1.1602*	1.1678*	1.1069*	1.2193*	1.1147*	1.0793*	1.2487*
		(24.9)	(19.3)	(42.3)	(39.4)	(42.3)	(34.3)	(30.9)	(36.4)	(31.3)	(33.5)
	Adjusted R^2	0.8601	0.5561	0.9045	0.8914	0.9024	0.8481	0.8096	0.8681	0.8150	0.8411
		P11	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
	α	0.0041	0.0092*	0.0133*	0.0148*	0.0145*	0.0179*	0.0211*	0.0260*	0.0324*	0.0388*
		(0.97)	(2.42)	(2.97)	(3.23)	(3.25)	(3.86)	(4.26)	(4.87)	(5.39)	(3.09)

TABLE 4 (Continued)

Panel A: Quintiles											
	β	1.2445*	1.0928*	1.1400*	1.1659*	1.1768*	1.1604*	1.2372*	1.2144*	1.2279*	
		(31.3)	(29.8)	(26.7)	(26.7)	(27.3)	(26.1)	(26.0)	(24.1)	(22.2)	(6.16)
	Adjusted R^2	0.8143	0.8005	0.7474	0.7460	0.7601	0.7365	0.7335	0.6973	0.6449	0.1950
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Value	α	0.0130*	0.0161*	0.0071*	0.0069*	0.0066	0.0095*	0.0108*	0.0088*	0.0120*	0.0118*
		(4.02)	(4.01)	(2.42)	(2.38)	(2.02)	(2.86)	(3.31)	(2.61)	(3.72)	(3.28)
	β	1.1721*	1.1895*	0.9634*	0.9697*	1.1041*	1.1667*	1.0790*	1.0959*	1.1305*	1.0560*
		(35.9)	(30.0)	(33.1)	(34.2)	(34.7)	(35.1)	(33.1)	(32.6)	(34.6)	(29.9)
	Adjusted R^2	0.8632	0.8031	0.8363	0.8473	0.8534	0.8568	0.8370	0.8308	0.8518	0.8014
		P11	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
	α	0.0121	0.0066	0.0113*	0.0157*	0.0144*	0.0122*	0.0097*	0.0199*	0.0137*	0.0266*
		(1.81)	(1.52)	(2.94)	(3.71)	(3.06)	(2.59)	(2.18)	(3.49)	(2.46)	(3.63)
	β	1.1369*	1.1545*	1.1920*	1.1456*	1.2044*	1.2389*	1.2113*	1.3019*	1.2902*	1.3922*
		(28.7)	(28.1)	(31.7)	(28.1)	(26.5)	(27.5)	(28.2)	(24.1)	(25.9)	(20.9)
	Adjusted R^2	0.8209	0.8110	0.8635	0.8108	0.7843	0.8009	0.8151	0.7312	0.7419	0.6397
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Momentum	α	0.0075	0.0028	0.0261*	0.0102	0.0116*	0.0089	0.0051	0.0086	0.0080	0.0053
		(1.72)	(0.46)	(2.71)	(2.00)	(2.43)	(1.92)	(1.08)	(1.85)	(1.94)	(1.22)
	β	1.0255*	1.0337*	0.8123*	0.9271*	0.8819*	0.9026*	0.9621*	0.9128*	0.9326*	0.9780*
		(25.5)	(20.6)	(7.04)	(20.7)	(20.8)	(21.6)	(22.2)	(22.0)	(24.9)	(24.9)
	Adjusted R^2	0.7624	0.6295	0.2469	0.6330	0.6367	0.6616	0.6774	0.6761	0.7478	0.7493
	Portfolio	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
	α	0.0008	0.0071	0.0098*	0.0033	0.0098	0.0059	0.0052	0.0087	0.0042	−0.018
		(0.10)	(1.42)	(2.12)	(0.65)	(1.91)	(1.19)	(0.91)	(1.48)	(0.65)	(−1.45)
	β	0.9708*	0.9877*	0.9620*	0.9762*	1.0127*	0.9970*	1.1690*	1.0994*	1.1053*	1.1445*
		(25.4)	(21.8)	(23.0)	(22.5)	(22.1)	(23.1)	(22.9)	(22.1)	(21.2)	(16.0)
	Adjusted R^2	0.7590	0.6705	0.7012	0.6894	0.6771	0.7033	0.6969	0.6433	0.6100	0.4468

Note: The table shows (OLS) results for the coefficient values based on Newey-West estimation of least squares with heteroskedasticity-and-autocorrelation-consistent standard errors. * indicates statistical significance at 5% level, t-statistics are reported in parentheses, and $R^2$is the adjusted coefficient of determination. The sample period covers from January 2006 to December 2021.

However, the cross-sectional return differences on any of the value sorted portfolios for quintiles seem to be not absorbed by the CAPM model. For momentum sorted portfolios (quintiles), the CAPM findings indicate that market factor is not explaining momentum due to the statistically significant intercept terms of winner portfolio. Leaning on Jegadeesh and Titman (1993), and Chordia and Shivkumar (2002), this approves the existence of strong momentum profits.

In Table 4 (Panel B and C), the CAPM findings for decile-vigintile (P10-P20) portfolios are shown respectively. The small stocks portfolio in P10-P20 earns greater returns on an average (3.66%–3.88%) vis-a-vis large stocks (P1) (1.78%–1.46%). The size effect is thus confirmed in both decile and vigintile because small stock portfolios earn positive extra risk adjusted returns with statistical significance. The intercept term is shown to be lower for high P/B ratio portfolios (P1) than for low P/B ratio portfolios (P10-P20) suggesting that the latter generates higher market risk adjusted returns than the former in both deciles-vigintile portfolios. The result also indicates that the intercept terms of winner (P1) and loser (P10-P20) are often not statistically significant in the CAPM model, which helps to capture the momentum effect. In Summary, we find that the CAPM framework is capable to clarify only 45 out of the total 105 portfolios (5–10–20 sorted portfolios by size, value and momentum properties, respectively), whereas it is not capable of

TABLE 5 Testing results of three-factor Fama–French model for sample portfolios whose returns are missed by CAPM.

Panel A: Quintiles							
	Portfolio	**P3**	**P4**	**P5**			
Size	α	−0.007	0.0030	0.0067*			
		[−0.13]	[0.97]	[2.61]			
	β	1.0906*	1.0528*	1.0831*			
		[20.5]	[27.1]	[28.3]			
	γ	0.4996*	0.9190*	1.6668*			
		[12.79]	[16.2]	[18.5]			
	δ	0.4780*	0.6695*	0.5975*			
		[16.0]	[14.61]	[9.45]			
	Adjusted R^2	0.9676	0.9790	0.9848			
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	
Value	α	0.0025	0.0034	0.0036	0.0042	0.0035	
		[1.22]	[1.35]	[1.20]	[1.75]	[1.55]	
	β	1.0329*	1.1065*	1.0406*	1.0629*	1.1004*	
		[24.9]	[26.6]	[40.2]	[27.8]	[31.4]	
	γ	0.4743*	0.3805*	0.5194*	0.6861*	0.9703*	
		[3.96]	[5.32]	[7.33]	[12.4]	[16.0]	
	δ	−0.3607*	0.0254	0.4658*	0.7962*	1.1996*	
		[−3.17]	[0.28]	[7.16]	[14.5]	[19.9]	
	Adjusted R^2	0.9084	0.9331	0.9376	0.9611	0.9693	
	Portfolio	**P1**	**P2**				
Momentum	α	0.0070	0.0025				
		[1.69]	[0.71]				
	β	0.9266*	0.8688*				
		[8.74]	[9.40]				
	γ	0.8386*	0.4229*				
		[4.44]	[3.62]				
	δ	0.1097	0.2833*				
		[0.53]	[2.19]				
	Adjusted R^2	0.6582	0.7151				
Panel B: Deciles							
	Portfolio	**P1**	**P3**	**P5**	**P7**	**P9**	**P10**
Size	α	0.0047	0.0044	0.0025	0.0027	0.0066*	0.0067
		[1.80]	[1.95]	[0.81]	[0.78]	[2.61]	[1.33]
	β	1.0648*	1.0762*	1.0956*	1.0362*	1.0971*	1.0532*
		[39.1]	[32.8]	[21.5]	[23.7]	[30.0]	[26.2]
	γ	0.9405*	0.1020 0.3670*	0.7909*	1.1986*	2.1512*	
		[7.52]	[1.70] [4.94]	[8.53]	[15.7]	[8.42]	
	δ	0.1092	0.3465* 0.4225*	0.7213*	0.8344*	0.3462	
		[0.83]	[6.91] [7.59]	[10.28]	[11.3]	[1.33]	
	Adjusted R^2	0.9177	0.9340 0.8975	0.9033	0.9338	0.8090	

TABLE 5 (Continued)

Panel A: Quintiles											
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Value	α	0.0022	0.0028	0.0033	0.0040	0.0057	0.0012	0.0048	0.0027	0.0049	0.0025
		[0.78]	[1.30]	[1.27]	[1.36]	[1.58]	[0.28]	[1.97]	[0.80]	[1.90]	[0.72]
	β	1.1086*	0.9628*	1.1478*	1.0604*	1.0663*	1.0274*	1.0420*	1.0840*	1.0769*	1.1104*
		[26.8]	[27.3]	[22.6]	[32.2]	[47.3]	[26.9]	[27.7]	[25.4]	[25.9]	[30.1]
	γ	0.9196*	0.3146*	0.3745*	0.4146*	0.4384*	0.5718*	0.5995*	0.7725*	0.6888*	1.2265*
		[6.58]	[4.42]	[4.61]	[5.21]	[6.02]	[6.16]	[6.63]	[10.16]	[9.48]	[14.35]
	δ	0.3483*	−0.0702	−0.0796	0.1535	0.1536	0.7099*	0.7674*	0.8630*	1.0590*	1.3373*
		[2.50]	[−1.18]	[−1.20]	[1.88]	[2.02]	[9.29]	[8.83]	[9.64]	[19.8]	[12.8]
	Adjusted R^2	0.9178	0.9055	0.9081	0.9083	0.9083	0.9122	0.9342	0.9260	0.9243	0.9488
	Portfolio	**P2**	**P3**								
Momentum	α	0.0040	0.0036								
		[0.86]	[0.96]								
	β	0.8784*	0.8386*								
		[7.79]	[8.69]								
	γ	1.0205*	0.4760*								
		[3.05]	[3.73]								
	δ	0.0936	0.3540*								
		[0.25]	[2.15]								
	Adjusted R^2	0.5734	0.6942								
Panel C: Vigintiles											
	Portfolio	**P1**	**P2**	**P4**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	
Size	α	0.0033	0.0025	0.0070*	−0.0011	0.0024	0.0033	0.0025	0.0031	0.0055	
		[1.67]	[0.48]	[2.17]	[−0.23]	[0.70]	[0.73]	[0.65]	[0.93]	[1.82]	
	β	1.0821*	1.0700*	1.1004*	1.0040*	1.0149*	1.0587*	1.0673*	1.0855	*1.1074*	
		[29.3]	[23.3]	[33.4]	[24.6]	[21.8]	[23.0]	[20.7]	[32.4]	[21.9]	
	γ	0.8038*	1.2260*	−0.0311	0.6604*	0.7722*	0.8053*	0.8478*	1.0518*	1.1100*	
		[13.9]	[4.17]	[−0.27]	[10.38]	[7.69]	[6.73]	[8.40]	[10.57]	[13.0]	
	δ	0.5866*	−0.1543	0.3288*	0.5925*	0.7687*	0.6772*	0.6942*	0.5291*	0.8037*	
		[12.4]	[−0.54]	[4.56]	[11.8]	[11.8]	[6.08]	[6.35]	[5.47]	[6.87]	
	Adjusted R^2	0.9657	0.7130	0.9021	0.8886	0.8678	0.8502	0.8696	0.8734	0.8920	
	Portfolio	**P18**	**P19**	**P20**							
	α	0.0080*	0.0115*	−0.0016							
		[2.50]	[3.54]	[−0.15]							
	β	1.0821*	1.1060*	1.0077*							
		[29.9]	[33.9]	[14.82]							
	γ	1.2816*	1.4873*	2.8134*							
		[11.3]	[10.59]	[4.91]							
	δ	0.8682*	0.8244*	−0.1290							
		[12.4]	[7.18]	[−0.25]							
	Adjusted R^2	0.8911	0.8577	0.5240							

(Continues)

TABLE 5 (Continued)

Panel A: Quintiles										
	Portfolio	**P1**	**P2**	**P3**	**P4**	**P6**	**P7**	**P8**	**P9**	**P10**
Value	α	0.0031	0.0040	0.0036	0.0020	0.0046	0.0052	0.0030	0.0065	0.0049
		[1.56]	[1.07]	[1.28]	[0.61]	[1.56]	[1.70]	[0.69]	[1.43]	[1.15]
	β	1.0653*	1.1033*	0.9852*	0.9583*	1.2020*	1.0544*	1.0638*	1.1082*	1.0132*
		[32.0]	[26.5]	[25.4]	[25.5]	[26.2]	[32.6]	[23.9]	[28.8]	[35.7]
	γ	0.7131*	0.8686*	0.2750*	0.3600*	0.3690*	0.4088*	0.4310*	0.4055*	0.5049*
		[10.28]	[9.96]	[3.13]	[4.71]	[3.47]	[4.28]	[4.15]	[3.41]	[4.41]
	δ	0.6622*	0.5547*	−0.1543	0.0295	−0.2132*	0.1393	0.1795	0.0958	0.2431*
		[11.2]	[6.82]	[−2.00]	[0.62]	[−3.12]	[1.68]	[1.40]	[0.78]	[2.20]
	Adjusted R^2	0.9663	0.9045	0.8545	0.8676	0.8821	0.8570	0.8552	0.8710	0.8328
	Portfolio	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**	
	α	0.0036	0.0061	0.0028	0.0022	−0.0016	0.0093*	−0.0016	0.0044	
		[1.14]	[1.91]	[0.67]	[0.57]	[−0.07]	[2.70]	[−0.14]	[0.76]	
	β	1.0820*	1.0054*	1.0788*	1.0963*	1.0729*	1.0776*	1.0812*	1.1484*	
		[25.9]	[24.8]	[20.1]	[25.4]	[30.3]	[20.4]	[25.2]	[27.3]	
	γ	0.5354*	0.6731*	0.8270*	0.7011*	0.6510*	0.7312*	0.9309*	1.5492*	
		[4.45]	[8.68]	[7.10]	[6.72]	[6.21]	[6.86]	[8.56]	[13.8]	
	δ	0.6633*	0.8757*	0.7810*	0.8488*	0.8228*	1.3060*	1.2318*	1.4582*	
		[8.01]	[8.64]	[8.90]	[9.36]	[14.35]	[12.2]	[12.4]	[9.87]	
	Adjusted R^2	0.8982	0.9046	0.8619	0.8721	0.8843	0.8766	0.8992	0.8693	
	Portfolio	**P3**	**P5**	**P13**						
Momentum	α	0.0059	0.0052	0.0053						
		[0.99]	[1.19]	[1.51]						
	β	0.8844*	0.8335*	0.8983*						
		[5.97]	[8.38]	[7.48]						
	γ	1.4637*	0.3192*	0.3185*						
		[2.33]	[3.12]	[2.21]						
	δ	−0.2364	0.3191	0.4158*						
		[−0.37]	[1.74]	[2.65]						
	Adjusted R^2	0.4014	0.6407	0.7011						

Note: The table shows (OLS) results for the coefficient values based on Newey-West estimation of least squares with heteroskedasticity-and-autocorrelation-consistent standard errors. β is the coefficient of excess markets returns, γ of SMB factor, and δ of LMH factor, respectively. We consider that we have observed multicollinearity whether (VIF) higher than 10 and auxiliary regression has been run to transform the variables so that correlations among independent variables do not exceed 0.3. * indicates statistical significance at 5% level, t-statistics are reported in parentheses, and $R^2$is the adjusted coefficient of determination. The sample period covers from January 2006 to December 2021.

absorbing cross-sectional differences on all sorted portfolios by value for mainly all the formations of three alternative portfolios.

Table 5 reports the results of the 3F-FF model for formation of alternate portfolios. For quintiles, the 3F-FF framework explains the size effect only partly because the small stock portfolio (P5) continues to provide an extra normal return with statistical significance of 0.67% per month. Factor loadings for SMB and LMH on the low P/B ratio portfolios (P5) are strongly higher compared to ones for high P/B ratio portfolio (P1), and this confirms the role played by factors of size and value in returns. The 3F-FF framework is able to explain the cross-sectional difference in returns regarding all sorted quintile portfolio by value and the intercept terms, that turn not significant. Likewise, the intercept coefficients for the returns of sorted portfolio by momentum turn statistically not significant, explaining the effect of momentum to quintiles.

In Table 5 (Panel B and C), we report the results of the 3F-FF model for both decile and vigintile portfolios.

TABLE 6 Testing results of four, five, and modified factors models for sample portfolios whose returns are missed by (3F-FF) model.

Panel A: Carhart Model									
Portfolio			**α**	**β**	**γ**	**δ**	**λ**	**Adjusted R^2**	
Quintile	Size	P5	0.0063* (2.42)	1.0888* (31.7)	1.6500* (20.8)	0.6070* (4.88)	0.0571 (0.72)	0.9350	
Decile	Size	P9	0.0074* (2.57)	1.0943* (31.2)	1.2053* (20.6)	0.8261* (10.33)	−0.0771 (−0.92)	0.9338	
Vigintile	Size	P4	0.0074* (2.40)	1.0953* (30.7)	−0.0058 (−0.11)	0.3152* (4.60)	−0.0522 (−0.85)	0.9031	
Vigintile	Size	P18	0.0091* (2.70)	1.0679* (34.1)	1.3150* (16.8)	0.8336* (16.7)	−0.1124 (−1.80)	0.8938	
Vigintile	Size	P19	0.0117* (3.56)	1.1034* (31.2)	1.4969* (16.4)	0.8157* (7.47)	−0.0374 (−0.43)	0.8567	
Vigintile	Value	P18	0.0106* (2.95)	1.0631* (21.0)	0.7740* (6.30)	1.2568* (16.1)	−0.1227 (−1.55)	0.8792	
Panel B: Five Factor Fama–French Model									
Portfolio			**α**	**β**	**γ**	**δ**	**φ**	**ν**	**Adjusted R^2**
Quintile	Size	P5	0.0066* (2.30)	1.0850* (34.9)	1.6781* (18.8)	0.5934* (4.32)	−0.0332 (−0.28)	0.0500 (0.34)	0.9338
Decile	Size	P9	0.0049 (1.80)	1.1099* (30.9)	1.3172* (18.5)	0.8278* (17.6)	−0.2353* (−2.60)	0.2097* (2.85)	0.9400
Vigintile	Size	P4	0.0065 (2.10)	1.1079* (31.02)	−0.1543 (−1.01)	0.3368* (3.31)	−0.0385 (−0.39)	0.1496 (1.50)	0.9055
Vigintile	Size	P18	0.0059 (1.66)	1.1300* (30.9)	1.1312* (7.41)	1.0250* (10.14)	−0.2354* (−2.31)	0.2896* (3.61)	0.8994
Vigintile	Size	P19	0.0118* (3.79)	1.1048* (28.8)	1.0362* (4.57)	0.6830* (5.08)	0.1190 (1.10)	0.4024* (2.49)	0.8700
Vigintile	Value	P18	0.0122* (3.06)	1.0054* (17.3)	0.7924* (4.42)	1.0309* (5.81)	0.3492* (2.17)	−0.2628 (−1.77)	0.8863
Panel C: Modified Five Factor Fama–French Model									
Portfolio			**α**	**β**	**γ**	**δ**	**η**	**ν**	**Adjusted R^2**
Quintile	Size	P5	0.0062* (2.52)	1.0981* (31.3)	1.6992* (19.2)	0.5920* (5.11)	−0.2617* (−2.40)	0.0071 (0.15)	0.9420
Decile	Size	P9	0.0067* (2.55)	1.1055* (30.7)	1.1909* (20.4)	0.8107* (16.9)	0.0395 (0.48)	0.1908* (2.31)	0.9358
Vigintile	Size	P4	0.0070* (2.14)	1.1069* (32.4)	−0.0383 (−0.35)	0.3154* (3.96)	0.0403 (0.53)	0.1498 (1.47)	0.9036
Vigintile	Size	P18	0.0081* (2.42)	1.0924* (29.3)	1.2682* (15.9)	0.8341* (19.3)	0.0715 (0.70)	0.2696* (3.20)	0.8958
Vigintile	Size	P19	0.0112* (3.75)	1.1330* (32.8)	1.5003* (16.4)	0.7745* (8.34)	−0.1838 (−1.45)	0.3951* (2.49)	0.8724
Vigintile	Value	P18	0.0093* (2.52)	1.0669* (20.8)	0.7398* (7.20)	1.3183* (17.1)	−0.0387 (−0.41)	−0.2250 (−1.61)	0.8783

Note: The table shows (OLS) results for the coefficient values based on Newey-West estimation of least squares with heteroskedasticity-and-autocorrelation-consistent standard errors. β is the coefficient of excess markets returns, γ of SMB factor, δ of LMH factor, λ of momentum factor, φ of profitability factor (return on equity), ν of investment factor (change in total assets), and η of cash flow change factor (Std. deviation of trailing 5 years cash flow of operations) consistent with (Walkshäusl, 2013) framework, respectively. We consider that we have observed multicollinearity whether (VIF) higher than 10 and auxiliary regression has been run to transform the variables so that correlations among independent variables do not exceed 0.3. * indicates statistical significance at 5% level, t-statistics are reported in parentheses, and R^2 is the adjusted coefficient of determination. The sample period covers from January 2006 to December 2021.

The cross section of average returns related to different sorted portfolios by size in deciles and vigintiles that were unexplained by the CAPM are absorbed through the 3F-FF model with the exception of portfolio P9 in deciles and P4, P18 and P19 in vigintiles. The coefficient of SMB is greater for P10-P20 in comparison with P1, (2.29–3.50 times coefficient of P1), approving the size factor's role in clarifying the effect of small firm. In Contrast with our predictions, the big firm stocks (P1) seem to load on LMH factor as indicated by LMH loadings in vigintiles. The two factors of size and value help a lot in clarifying the extra normal returns' prior statistical significance that die out once we switch to the 3F-FF model for sorted decile and vigintile portfolios by value with just one exception P18. Consequently, we can say that our model (3F-FF) is capable to assess fully or partly the effect of value in deciles-vigintiles. The 3F-FF model is able to capture with success the cross section of average returns for the sorted portfolios by momentum, which were not explained through CAPM.

The results in Table 5 illustrate the factor of size to be dominant against the reverse effect of value leading to the global success of our (3F-FF) model. Based on the risk adjustment for a portfolio sorted by size, whether excess demand of large stocks by size (P1) conducts to greater volatility due to more active activity of trading activity, the extra returns simply exit to compensate the extra volatility risk. Following the 3F-FF model, size factor and sometimes value factor seem to explain extra returns for these stocks. The additional volatility risk seems to be captured by the size factor of the 3F-FF model. Therefore, as indicated in their greater loadings for factor SMB, P1 stocks in deciles-vigintiles observed to behave similar to small firm stocks. Concerning the 3F-FF model for portfolios sorted by value, the high P/B ratio stocks (P1) that capture institutional frenzy leading to higher volatility in price, the factor size seems to catch this risk of excess volatility and thus depicts their intercept terms. Hence, high P/B ratio stocks (P1) in deciles-vigintiles may be small firms too or seems to behave similar to small firms having high potential of growth.

In Summary, our (3F-FF) modelling is capable explaining the extra normal returns of 54 of the 60 portfolios whose returns were missed by CAPM framework. This shows that the 3F-FF model is much better descriptor for asset returns than the CAPM. Except small stock portfolios by size, namely quintiles P5, deciles P9 and vigintiles P4, P18, P19, the 3F-FF model explains the equity market anomalies for all other portfolios. Given 3F-FF model's failure to fully catch the above portfolios' returns, there is a need to explore an improved factor structure.

Table 6 gives a view of the Carhart model's results, five factors model and its modified version. The intercept coefficients for the Carhart and modified (5F-FF) models show statistical significance, implying that both models are unable to consider the cross section of returns for our portfolios in sample. The 5F-FF model was able to absorb the cross section of returns for the portfolios of small stock P9-P18 from decile-vigintile, and their loadings of factors in profitability and investment are statistically significant but the profitability factor is negative. This finding is mainly same to the work of Sehgal and Subramaniam (2012) who suggested a strongly negative relationship between profitability and returns in one of the emerging markets (e.g., India), yet is not in line with the results from one of the developed markets (e.g., the US). The intercept coefficient related to the size sorted portfolio P4 in vigintile also loses its significance through the 5F-FF model. Concerning the portfolio of small stock (P5 from quintiles and P19 from vigintiles), and low P/B ratio portfolio P18 in vigintile, the extra normal returns are still not explained even by the modified framework (5F-FF). In addition to the estimation models in the current section of our paper, we further investigate if our composite indicator of sentiment ($SENT^{PLS}$) explains the intercept terms of these 3 remaining portfolios. Hence, sentiment of investor is playing a role as a behavioural factor in stock returns.

Table 7 shows the results of the analysis of the significance of sentimental factor in asset pricing. Interestingly, after including our newly introduced sentiment factor, the 5F-FF displays better performance in reflecting average returns for our sample and this is revealed by the intercept coefficient of small size stock portfolio (quintile P5 and vingtile P19) which loses its statistical significance. The 3F-FF with investor sentiment is capable to explain the return on low P/B ratio portfolio P18 because the intercept term dies out (vanish) and as expected we have strongly significant coefficient on sentimental factor. Considering the portfolios P5-P19-P18, we observe a completely statistically significant effect for sentimental factor at the 5% level of significance, implying their economic significance in a multivariate framework. Consequently, there is evidence that investor optimism cached through our sentimental factor is driven by the history of domestic consumption and investment in addition to the

TABLE 7 Testing results of three, five factor Fama–French model plus investor sentiment for sample portfolios whose returns are missed by additional factor models.

Panel A: Five Factor Fama–French Model Plus Sentimental Factor									
Portfolio		**α**	**β**	**γ**	**δ**	**φ**	**ν**	**ω**	**Adjusted R^2**
Quintile Size	P5	0.0020	1.0787	1.6974*	0.5608*	−0.0419	−0.0323	0.0077	0.9344
		[0.38]	[34.6]	[18.6]	[6.16]	[−0.42]	[−0.20]	[3.50]	
Vigintile Size	P19	0.0060	1.1035*	1.5038*	0.8043*	0.1264	0.4131*	0.0137	0.8648
		[1.43]	[28.1]	[17.1]	[7.90]	[1.23]	[2.49]	[3.90]	
Panel B: Three Factor Fama–French Model Plus Sentimental Factor									
Portfolio		**α**	**β**	**γ**	**δ**	**ω**	**Adjusted R^2**		
Vigintile Value	P18	0.0097	1.0766*	0.7963*	1.3148*	0.0030*	0.8840		
		[1.99]	[19.5]	[8.25]	[17.05]	[2.59]			

Note: The table shows (OLS) results for the coefficient values based on Newey-West estimation of least squares with heteroskedasticity-and-autocorrelation-consistent standard errors. β is the coefficient of excess markets returns, γ of SMB factor, δ of LMH factor, φ of profitability factor (return on equity), ν of investment factor (change in total assets), and ω of $SENT^{PLS}_{Dummy}$ investor sentimental factor, respectively. We consider that we have observed multicollinearity whether (VIF) higher than 10 and auxiliary regression has been run to transform the variables so that correlations among independent variables do not exceed 0.3. * indicates statistical significance at 5% level, t-statistics are reported in parentheses, and R^2 is the adjusted coefficient of determination. The sample period covers from January 2006 to December 2021.

country's macroeconomic fundamentals (Kim & Na, 2018), particularly when young investors display positive mindset regarding the future growth prospects of their economy, and hence approximately isolate their economy from the volatile conditions of world market. This is coherent with the specific studies covering the Korean market (e.g., Kang et al., 2019; Rugwiro & Choi, 2019) where Korean investors have consistently been observed to show highly optimistic behaviour over the years compared to others in the Asian region. Thus, it is overall convincing that this optimism should strengthen and boost the confidence of investor in local stock market returns.

To summarise, we find empirically that the 3F-FF model is successful in explaining most of the problems associated with significant anomalies in the equity market, which confirms that stock returns in Korea appear to be primarily driven by rational factors. Looking at the Korean market alone, this does not appear surprising since it is primarily dominated by institutional investors who fully rely on fundamentals. With the exception of low P/B ratio portfolio P18 in vigintile, we observe that both anomalies of value and momentum do not present serious issue for the 3F-FF model. Additionally, applying the 3F-FF framework, we still observe size anomaly, which is partly due to risk and behavioural pattern. The 5F-FF model (including profitability and investment factors) shows fascinating results in capturing size anomaly except small size stock portfolios P5-P19 in quintile-vigintile due to the overreaction in short-term that are caught by our sentimental factor. Hence, in terms of size and value anomaly, it is worth arguing that the new constructed factor of investor sentiment is a good quality proxy to sentiment of investor and it does perform well in asset pricing framework.

5 | CONCLUSION

After the genesis of literature on behavioural finance, many research books and empirical papers all provide invaluable insights on possible relationship of total investor sentiment with stock market returns in the advanced world. In this study, we seek to check this relation in the context of Korea, a country, which has converged its status from a developing into a developed economy as per the World Bank classifications while holding a developing country feature of having considerably higher tail participation in the stock markets. Due to insufficiency of the existing measures for stock markets in economies with such a blend of features, we incorporate a carefully selected mix of direct and indirect sentiment indicators from the extant literature to create the composite investor sentiment index (ISI). Moreover, we considered the recent studies of Yang et al. (2017) and Ryu and Yang (2018) that followed the approaches of Yang and Gao (2014) and Yang and Zhou (2015, 2016), and proposed ISI using firm-level sentiment. We hence reviewed leading empirical studies that employed firm-level sentiment assessment tools to investigate the impacts of investor sentiment on financial markets and the contribution of firm-level sentiment proxies in describing different market behaviours and responses (Kim et al., 2019; Seok et al., 2019a, 2019b). Accordingly, we used daily trading and price data for individual companies from 2006 to 2018 in order to construct investor sentiment proxies.

We have developed an awareness of the use of an inadequate quantity of proxies in the extant studies, which narrowed the explaining power of the newly constructed ISIs. For example, Kim and Byun (2010) constructed an ISI using BSI, stock fund flow, customer expectation index for the economic cycle, customer deposits, logged turnover amount and proportion of newly released KOSPI-listed stocks. Ryu et al. (2017a) created a KOSPI-focused ISI based on a combination of BSI, RSI, PSY, logged trading quantity, and ATR. Kim and Lee (2022) constructed a new ISI to examine its impact on the stock returns of both KOSPI and KOSDAQ-listed companies. Although this study covered two markets with differing features, their index depended only on adjusted turnover amount, buy–sell disparity, relative strength index and some company features (i.e., mobile trading, size and stock price). On the contrary, we claim to have made an important extension to the literature by gathering data corresponding to firm features that are adopted to develop stylised portfolios and handle these risk factors, and total assets change for investment proxy to create a better KOSPI-related ISI.

We have also developed an understanding of the narrow focus that extant literature set to check the influence of investor sentiment. For instance, Nartea et al. (2014) and Byun et al. (2022) limited their focus to only "lottery-like stocks" (overpriced stocks) that have extreme positive returns in Korea and investigated how investor sentiment affects them. Likewise, Chang et al. (2000), Chiang and Zheng (2010), Laih and Liau (2013), and Choi and Yoon (2020) focused only on checking the connection between herding behaviour (i.e., people's tendency to imitate each other) and ISI in the Korean context. On the contrary, we research the effects of investor sentiment on the stocks of all KOSPI-listed manufacturing firms. Additionally, we follow the methodology of Huang et al. (2015) and apply the partial least squares (PLS) approach to overcome the drawbacks of the pioneering Baker and Wurgler (2006, 2007). Our ISI is found to have strong predictive power of market performance and future stock returns in leading the market in the long run, as confirmed by a conventional regression model.

We have delivered a clear observation of sentiment of investor factor and its role in returns, showing that the extra-normal returns of our size-based portfolios are captured by the sentimental factor under the asset pricing multi-factor model. Putting the existence of important asset pricing anomalies to evidence in the Korean stock market, we rank and classify securities into quintiles, deciles and vigintiles function of the stylised characteristics. Looking at behaviour of raw returns for these characteristic sorted portfolios, we find robust size, value and momentum impacts to alternate investment portfolio construction methods. Comparing the results of the three-factor model (3F-FF) with the results of the CAPM model for the Korean equity market, the improvement in explainability is rather important since the former is capable to explain returns on most of the classified portfolios which were missed by CAPM (54 out of 60 remaining sample portfolios). The five-factor model (5F-FF) with additional risk factors or sentimental factor seem to capture the intercept terms of small size stocks portfolio which are not illuminated by the 3F-FF model. At the same time, we note that sentimental factor of the 3F-FF model helps to capture the previously missed extranormal returns of low P/B ratio stocks portfolio. By considering the empirical challenge for the three portfolios (i.e., two size portfolios and one value portfolio) unexplained even by various factor models, and hence capturing the price overreactions of portfolios, our index exhibits superior correcting ability in the short term and the long term. Our improved index also performs better than other well-known investor sentiment predictors because it can reflect mainly all the behavioural aberrations. Thus, compared to the offerings of the extant literature, our ISI is the best measure for the behavioural factor that has strong role and value power for the stock returns in Korea.

The current research paper has relevant implications for academics, researchers and financial regulators. First, it reveals that only a parsimonious asset pricing framework is required for value and momentum effects. However, the use of an expanded factor structure model is justified in the case of size as it presents more complex anomaly. Second, the other academic implication is that we examine both behaviour finance and asset pricing literature in Korea emerging market by dealing with matters related to the ISI development methods and its predictability of the stock returns and pricing financial assets. Moreover, given that our results have shown Korean stock market as fairly well-organised in terms of the availability of the market intelligence, probably due to greater levels of institutional trading, as emphasised by Kim and Lee (2022), we speculate our results to have important managerial implications for regulators in Korea and countries holding similar economic and stock market features. In this connection, we support further research to construct a more comprehensive ISI in light of the changing global economic order with profound impacts on Korea and the emerging economies.

ACKNOWLEDGEMENTS

We express our gratitude to the anonymous referees, the handling editor, and the editor-in-chief for their helpful comments and suggestions in enhancing the quality of our work during the revision process.

DATA AVAILABILITY STATEMENT

The data that supports the findings of the paper are available from the monthly reports, from the DataGuide, of Korean listed firms' financial data.

ORCID

Ahmed Bouteska https://orcid.org/0000-0002-5710-501X

REFERENCES

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, M., Jeffrey, W., & Yu, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, *104*, 272–287.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271–299.

Baker, M., & Wurgler, J. (2004). Appearing and disappearing dividends: The link to catering incentives. *Journal of Financial Economics*, *73*(2), 271–288. https://doi.org/10.1016/j.jfineco.2003.08.001

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

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspective*, *21*(2), 129–151.

Balcilar, M., Cakan, E., & Gupta, R. (2017). Does US news impact asian emerging markets? Evidence from nonparametric causality-in-quantiles test. *The North American Journal of Economics and Finance*, *41*, 32–43.

Banz, R. W. (1981). The relationship between return and market value of common stock. *Journal of Financial Economics*, *9*(1), 3–18.

Bathia, D., & Bredin, D. (2013). An examination of investor sentiment effect on G7 stock market returns. *The European Journal of Finance*, *19*(9), 909–937.

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, *183*(2), 181–192.

Bekiros, S., Gupta, R., & Kyei, C. (2016). On economic uncertainty, stock market predictability and nonlinear spillover effects. *The*

North American Journal of Economics and Finance, *36*, 184–191.

Berger, D., & Turtle, H. J. (2012). Cross-sectional performance and investor sentiment in a multiple risk factor model. *Journal of Banking and Finance*, *36*, 1107–1121.

Black, F. (1986). Noise. *Journal of Finance*, *41*(3), 529–543.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*, 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. *Journal of Business*, *78*(2), 405–440.

Byun, S.-J., Jeon, B., & Kim, D. (2022). Investor sentiment and the MAX effect: Evidence from Korea. *Applied Economics*, *55*, 319–331. https://doi.org/10.1080/00036846.2022.2087858

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

Cevik, E., KirciAltinkeski, B., Cevik, E. I., et al. (2022). Investor sentiments and stock markets during the COVID-19 pandemic. *FinancInnov*, *8*(69), 1–34. https://doi.org/10.1186/s40854-022-00375-0

Chang, E. C., Joseph, W. C., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*, 1651–1679.

Cheema, M. A., Man, Y., & Szulczyk, K. R. (2020). Does investor sentiment predict the near-term returns of the Chinese stock market? *International Review of Finance*, *20*(1), 225–233.

Chen, H., Chong, T. T.-L., & Duan, X. (2010). A principal-component approach to measuring investor sentiment. *Quantitative Finance*, *10*(4), 339–347.

Chen, S. T., & Haga, K. Y. A. (2021). Using E-GARCH to analyze the impact of investor sentiment on stock returns near stock market crashes. *Frontiers in Psychology*, *12*, 1–16. https://doi.org/10.3389/fpsyg.2021.664849

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*, 1911–1921.

Choi, K.-H., & Yoon, S.-M. (2020). Investor sentiment and herding behavior in the Korean stock market. *International Journal of Financial Studies*, *8*(34), 1–14. https://doi.org/10.3390/ijfs8020034

Chong, T. T.-L., & Ng, W. K. (2008). Technical analysis and the London stock exchange: Testing the MACD and RSI rules using the FT30. *Applied Economic Letters*, *15*, 1111–1114.

Chordia, T., & Shivkumar, L. (2002). Momentum, business cycle and time, varying expected returns. *Journal of Finance*, *57*(2), 985–1019.

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. https://doi.org/10.1016/j.jempfin.2012.01.002

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

Corea, F. (2016). Can twitter proxy the Investors' sentiment? The case for the technology sector. *Big Data Research*, *4*, 70–74.

Dash, S. R., & Maitra, D. (2018). Does sentiment matter for stock returns? Evidence from Indian stock market using wavelet approach. *Finance Research Letters*, *26*, 32–39.

De Bondt, W. F., & Thaler, R. (1987). Further evidence of investor overreaction and stock market seasonality. *Journal of Finance*, *42*, 557–581.

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

DeVault, L., Sias, R., & Starks, L. (2019). Sentiment metrics and investor demand. *The Journal of Finance*, *74*(2), 985–1024.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

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

Feldman, T. (2010). A more predictive index of market sentiment. *The Journal of Behavioral Finance*, *11*(4), 211–223.

Ferreira, M. A., & Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, *100*, 514–537.

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2012). The impact of investor sentiment on the German stock market. *ZeitschriftFür-Betriebswirtschaft*, *82*(2), 133–163.

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

Gao, B., & Liu, X. (2020). Intraday sentiment and market returns. *International Review of Economics and Finance*, *69*, 48–62.

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

Gizelis, D. J., & Chowdhury, S. S. H. (2016). Investor sentiment and stock returns: Evidence from the Athens stock exchange. *International Research Journal of Applied Finance*, *7*(7), 137–162.

Greenwood, R., & Shleifer, A. (2014). Expectations of returns and expected returns. *Review of Financial Studies*, *27*, 714–746.

Grigaliūnienė, Ž., & Cibulskienė, D. (2010). Investor sentiment effect on stock returns in Scandinavian stock market. *Economics and Management*, *15*, 929–940.

Gui, J., Pu, J., Naktnasukanjn, N., Yu, X., Mu, L., & Pan, H. (2022). Measuring investor sentiment of China's growth enterprises market with ERNIE. *International Conference on Identification, Information and Knowledge in the Internet of Things, Procedia Computer Science*, *202*, 1–8.

Han, X., Sakkas, N., Danbolt, J., & Eshraghi, A. (2022). Persistence of investor sentiment and market mispricing. *Financial Review*, *57*(3), 617–640. https://doi.org/10.1111/fire.12301

Hengelbrock, J., Theissen, E., & Westheide, C. (2013). Market response to investor sentiment. *Journal of Business Finance and Accounting*, *40*(7–8), 901–917.

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*(1), 791–837.

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

Kang, H., Kang, J., & Kim, W. (2019). A comparison of new factor model in the Korean stock market. *Asia-Pacific Journal of Financial Studies*, *48*, 593–614.

Khan, M. A., & Ahmad, E. (2019). Measurement of investor sentiment and its Bi-directional contemporaneous and Lead–lag relationship with returns: Evidence from Pakistan. *Sustainability*, *2019*(11), 94. https://doi.org/10.3390/su11010094

Kim, D., & Na, H. (2018). Investor sentiment, anomalies, and macroeconomic conditions. *Asia Pacific Journal of Financial Studies*, *47*, 751–804.

Kim, J. H. (2017). Stock returns and investors' mood: Good day sunshine or spurious correlation? *International Review of Financial Analysis*, *52*, 94–103.

Kim, J. S., Ryu, D., & Seo, S. W. (2014). Investor sentiment and return predictability of disagreement. *Journal of Banking and Finance*, *42*, 166–178.

Kim, K., & Byun, J. (2010). Effect of investor sentiment on market response to stock split announcement. *Asia-Pacific Journal of Financial Studies*, *39*, 687–719.

Kim, K., Ryu, D., & Yang, H. (2019). Investor sentiment, stock returns, and analyst recommendation changes: The KOSPI stock market. *Investment Analysts Journal*, *48*(2), 89–101.

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.

Kim, Y., & Lee, K. Y. (2022). Impact of investor sentiment on stock returns. *Asia-Pacific Journal of Financial Studies*, *51*, 132–162. https://doi.org/10.1111/ajfs.12362

Kling, G., & Gao, L. (2008). Chinese institutional investors' sentiment. *Journal of International Financial Markets, Institutions and Money*, *18*(4), 374–387.

Konstantinidi, E., & Skiadopoulos, G. (2011). Are VIX futures prices predictable? An empirical investation. *International Journal of Forecasting*, *27*, 543–560.

Kothari, S., & Shanken, J. (1997). Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial Economics*, *44*, 169–203.

Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, *51*(2), 2451–2486.

Laih, Y.-W., & Liau, Y.-S. (2013). Herding behavior during the subprime mortgage crisis: Evidence from six Asia-Pacific stock markets. *International Journal of Economics and Finance*, *5*, 71–84.

Lakonishok, J., Shliefer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation and risk. *Journal of Finance*, *49*, 1541–1578.

Lee, C., Shleifer, A., & Thaler, R. (1991). Investor sentiment and the closed-end fund puzzle. *Journal of Finance*, *46*, 75–110.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking and Finance*, *26*(12), 2277–2299.

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

Lettau, M., & Ludvigson, S. (2001). Resurrecting the capm: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, *109*, 1238–1287.

Li, J. (2015). The asymmetric effects of investor sentiment and monetary policy on stock prices. *Applied Economics*, *47*(24), 2514–2522.

Ljungqvist, A., Nanda, V., & Singh, R. (2006). Hot markets, investor sentiment, and IPO pricing. *Journal of Business*, *79*(4), 1667–1702.

Loughran, T., & Mcdonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, *54*, 1187–1230.

Mao, H., Scott, C., & Johan, B. (2015). Quantifying the effects of online bullishness on international financial markets. 9, July 2015. ECB Statistics Paper.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*, 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

McLean, R. D., & Zhao, M. (2014). The business cycle, investor sentiment, and costly external finance. *The Journal of Finance*, *69*(3), 1377–1409. https://doi.org/10.1111/jofi.12047

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

Moat, H. S., Curme, C., Avakian, A., Kenett, D. Y., Standley, H. E., & Preis, T. (2013). Quantifying stock market moves. *Scientific Reports*, *3*, 1801.

Nartea, G. V., Wu, J., & Liu, H. T. (2014). Extreme returns in emerging stock markets: Evidence of a MAX effect in South Korea. *Applied Financial Economics*, *24*(6), 425–435. https://doi.org/10.1080/09603107.2014.884696

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

Pandey, P., & Sehgal, S. (2019). Investor sentiment and its role in asset pricing: An empirical study for India. *IIMB Management Review*, *31*, 127–144.

Qiu, L., & Welch, I. (2006). Investor sentiment measures. (Working paper No. 10794).

Renault, T. (2020). Sentiment analysis and machine learning in finance: A comparison of methods and models on one million messages. *Digit Finance*, *2*, 1–13.

Roll, R. (1981). A possible explanation of the small firm effect. *Journal of Finance*, *36*, 879–888.

Ross, S. A. (2013). The arbitrage theory of capital asset pricing. In L. C. MacLean & W. T. Ziemba (Eds.), *Handbook of the fundamentals of financial decision making: Part I*. World.

Rugwiro, S., & Choi, S. B. (2019). Re-examination of Fama–French models in the Korean stock market. *Asia-Pacific Financial Markets*, *26*(1), 23–45.

Ryu, D., Kim, H., & Yang, H. (2017). Investor sentiment, trading behavior and stock returns. *Applied Economics Letters*, *24*(12), 826–830.

Ryu, D., Ryu, D., & Hwang, J. H. (2017). Corporate governance, product-market competition, and stock returns: Evidence from the Korean market. *Asian Business and Management*, *16*(1–2), 50–91.

Ryu, D., & Yang, H. (2018). The directional information content of options volumes. *Journal of Futures Markets*, *38*(12), 1533–1548.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, *16*(3), 394–408.

Sehgal, S., & Subramaniam, S. (2012). An empirical investigation of the profitability anomaly in the Indian stock market. *Asian Journal of Finance and Accounting*, *4*(2), 347–361.

Sehgal, S., Subramaniam, S., & De La Morandiere, L. P. (2012). A search for rational sources of stock return anomalies: Evidence from India. *International Journal of Economics & Finance*, *4*(4), 121–134.

Sehgal, S., & Tripathi, V. (2005). Size effect in Indian stock market: Some empirical evidence. *Vision: The Journal of Business Perspective*, *9*, 27–42.

Seok, S. I., Cho, H., & Ryu, D. (2019a). Firm-specific investor sentiment and the stock market response to earnings news. *North American Journal of Economics and Finance*, *48*, 221–240.

Seok, S. I., Cho, H., & Ryu, D. (2019b). Firm-specific investor sentiment and daily stock returns. *North American Journal of Economics and Finance*, *50*, 100–857.

Shi, J., Ausloos, M., & Zhu, T. (2022). If global or local investor sentiments are prone to developing an impact on stock returns, is there an industry effect? *International Journal of Finance & Economics*, *27*(1), 1309–1320.

Smales, L. A. (2016). Risk-on/risk-off: Financial market response to investor fear. *Finance Research Letters*, *17*, 125–134.

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

Smidt, S. (1968). A new look at the random walk hypothesis. *Journal of Financial & Quantitative Analysis*, *3*(3), 235–261.

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

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

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA – A Journal of Selected Papers*, *4*, 25–45.

Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A highfrequency perspective. *Journal of Banking & Finance*, *73*, 147–164.

Sun, Y., Zeng, X., Zhou, S., Zhao, H., Thomas, P., & Hu, H. (2021). What investors say is what the market says: Measuring China's real investor sentiment. *Personal and Ubiquitous Computing*, *25*(3), 587–599. https://doi.org/10.1007/s00779-021-01542-3

Swaminathan, B. (1996). Time-varying expected small firm returns and closed-end fund discounts. *The Review of Financial Studies*, *9*(3), 845–888.

Taleb, N. N. (2008). *The Black swan: The impact of the highly improbable*. Penguin.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure Firms' fundamentals. *The Journal of Finance*, *63*, 1437–1467.

Vuong, N. B., & Suzuki, Y. (2022). The moderating effect of market-specific factors on the return predictability of investor sentiment. *SAGE Open*, *12*(3), 1–22. https://doi.org/10.1177/21582440221114322

Walkshäusl, C. (2013). The higher returns to low volatility stocks are actually a premium on high quality firms. *Review of Financial Economics*, *22*(4), 180–186.

Wang, Y., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. *International Journal of Forecasting*, *22*, 109–123.

Whaley, R. E. (2009). Understanding the VIX. *Journal of Portfolio Management*, *35*(3), 98–105.

Wong, W. K., Manzur, M., & Chew, B. K. (2003). How rewarding is technical analysis? Evidence from Singapore stock market. *Applied Financial Economics*, *13*, 543–551.

World Bank. (2022). The World Bank in Republic of Korea. March 11, 2022 Update. https://www.worldbank.org/en/country/korea/overview [Online]

Wu, B., Cai, Y., & Zhang, M. (2021). Investor sentiment and stock Price crash risk in the Chinese stock market. *Journal of Mathematics*, *6806304*, 1–10. https://doi.org/10.1155/2021/6806304

Yang, C., & Gao, B. (2014). The term structure of sentiment effect in stock index futures market. *North American Journal of Economics and Finance*, *30*, 171–182.

Yang, C., & Zhou, L. (2015). Investor trading behavior, investor sentiment and asset prices. *North American Journal of Economics and Finance*, *34*, 42–62.

Yang, C., & Zhou, L. (2016). Individual stock crowded trades, individual stock investor sentiment and excess returns. *North American Journal of Economics and Finance*, *38*, 39–53.

Yang, H., Ryu, D., & Ryu, D. (2017). Investor sentiment, asset returns and firm characteristics: Evidence from the Korean stock market. *Investment Analysts Journal*, *46*(2), 132–147.

Yi, Z. G., & Mao, N. (2009). Research on investor sentiment measurement in Chinese stock market: The construction of CICSI. *Financial Research*, *11*, 174–184.

Yuan, K., Zheng, L., & Zhu, Q. (2006). Are investors moonstruck? Lunar phases and stock returns. *Journal of Empirical Finance*, *13*(1), 1–23.

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, *10*, 239–259. https://doi.org/10.1146/annurev-financial-110217-022725

Zhou, L., & Yang, C. (2020). Investor sentiment, investor crowded-trade behavior, and limited arbitrage in the cross-section of stock returns. *Empirical Economics*, *59*, 437–460.

Zweig, M. E. (1973). An investor expectations stock price predictive model using closed-end fund premiums. *Journal of Finance*, *28*(1), 67–78.

How to cite this article: Bouteska, A., Sharif, T., & Abedin, M. Z. (2023). Does investor sentiment create value for asset pricing? An empirical investigation of the KOSPI-listed firms. *International Journal of Finance & Economics*, 1–23. https://doi.org/10.1002/ijfe.2836