“The influence of consumer, manager, and investor sentiment on US stock market returns”

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ARTICLE INFO	Pedro Manuel Nogueira Reis, Antonio Pedro Soares Pinto and Andre Guimaraes (2025). The influence of consumer, manager, and investor sentiment on US stock market returns. *Investment Management and Financial Innovations*, *22*(1), 231-256. doi:10.21511/imfi.22(1).2025.18
DOI	http://dx.doi.org/10.21511/imfi.22(1).2025.18
RELEASED ON	Thursday, 13 February 2025
RECEIVED ON	Thursday, 05 September 2024
ACCEPTED ON	Monday, 09 December 2024

JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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THE INFLUENCE OF CONSUMER, MANAGER, AND INVESTOR SENTIMENT ON US STOCK MARKET RETURNS

Abstract

This study examines how consumer, investor, and manager sentiment explain US stock excess returns over 23 years. Its novelty resides in integrating the sentiments of three different types of economic and financial agents. It also performs a segmented temporal analysis using rolling window techniques, to assess sentiment's impact across different time horizons. The empirical analysis utilizes the Paris-Winsten and Newey-West estimators, along with the ARMAX model to address autocorrelation and heteroscedasticity in linear regression, providing robust standard errors and reliable statistical inferences. The autoregressive moving average models estimate excess return based on the past values, shocks, and external variables. Combining the Fama-French five-factor model with the sentiment factor enriches the analysis. The study's findings indicate that higher consumer optimism negatively impacts excess returns, as investors may anticipate a future decline in the stock market due to an existing overheated economy. Investor sentiment exhibits mixed behavior, where higher uncertainty may increase stock returns due to previous oversold markets creating opportunities for investors or due to the closing of short positions, which will also increase stock demand. It is also related to decreased stock returns depending on the proxy used. As for managers' sentiment, this work did not demonstrate a relevant relationship between this sentiment and stock returns. The study also reveals that the importance of sentiment determinants of those three agents changes over time. The findings support behavioral models of asset pricing, which incorporate both market fundamentals and the psychological characteristics (sentiment) of different market participants.

Keywords behavior, mood, pricing, profit, risk, markets, portfolio

JEL Classification G12, G14, G40

Received on: 5th of September, 2024
Accepted on: 9th of December, 2024
Published on: 13th of February, 2025

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Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

Despite the significant contributions to the relationship between sentiment and excess returns, several issues require further research. One such issue is the difficulty in achieving consensus on the most effective metrics for measuring sentiment. The heterogeneity of sentiment highlights the need to assess how different stakeholders (consumers, investors, and managers) and their specificities affect financial markets. Moreover, the role that sentiment plays in periods of turbulence, such as financial crises, political tensions, and pandemics, needs to be more understood, limiting the applicability of traditional models in these contexts for a period between 2000 and 2023, characterized by significant global events, including the subprime mortgage crisis, the COVID-19 pandemic, Brexit, and the Russia-Ukraine war.

The analysis integrates sentiment from three types of economic agents using the Fama-French five-factor model, recognized for capturing multiple dimensions of market risk and traditional financial variables. Consumer sentiment is assessed based on car sales, house purchases, credit card loans, and consumer opinions. Investor sentiment is evaluated using variables, such as the Equity Market Volatility (EMV) tracker derived from newspaper reports, and the Volatility Index (VIX), which measures expectations of short-term market volatility. Manager sentiment reflects economic activity and is captured through variables such as employment, the business perspective from the entrepreneur's point of view, and industrial production.

By incorporating these three sentiment dimensions, this study provides a more comprehensive understanding of their impacts on financial markets, particularly excess stock returns in increasingly unstable markets. To ensure the robustness of the analysis, the study employs econometric techniques such as the Prais-Winsten estimator, Newey-West corrections, and ARMAX models (Autoregressive Moving Average), addressing autocorrelation and heteroscedasticity in time series data. These methodologies allow for more rigorous statistical inferences and the evaluation of dynamic relationships over time.

The findings reveal that the impact of consumer and investor sentiment through the selected proxies strongly influences the US stock returns when the whole period of 2000 to 2023 is considered. Consumer sentiment proxied by new houses, and monthly consumer loan shifts produce significant negative impacts on excess stock returns. This may indicate a price overheated by demand, increased debt by market players and potential bubbles, which may retract investors that sell shares, decreasing stock returns. Concerning Investor sentiment, the proxies used to capture different volatility issues: one for the short term (Equity Volatility tracker) and one for the longer term (expected volatility, the VIX). The first one, which had a negative impact on stock returns, shows that the market incorporates in stock prices the relevant news of optimism and pessimism. The VIX with a positive relationship with the stock returns may indicate a persistent higher VIX that can show previous oversold markets, creating investor opportunities and increasing daily stock returns. Moreover, a higher VIX may lead to a higher excess stock return due to the closing of short positions that increase stock demand.

Furthermore, the study evaluates fluctuations in the sentiment factor over time, highlighting its relevance during global events and the need for new variables and methodologies capable of interpreting how sentiment conditions market evolution. This approach integrates behavioral and subjective factors often neglected in traditional models, which enriches the understanding of market dynamics.

1. LITERATURE REVIEW

The studies conducted by Fama (1970) advocate that markets are efficient and that investors are rational and have no feelings or emotions. The classical theory acknowledges the existence of irrational and less-informed investors but claims that their actions are largely neutralized by arbitrageurs. However, a large number of anomalies have been identified across stock markets, raising doubts about the capacity of traditional economic theories to explain the fluctuation in financial asset prices. Since then, behavioral finance has sought to establish a relationship between investor behavior and price dynamics in the financial market by introducing the concept of market sentiment. On the other hand, consumer sentiment has emerged as an important tool for understanding economic developments and aggregating expectations about current and future demand conditions (Benhabib & Spiegel, 2019; Hartlieb, 2023). Sentiment in the financial context includes the investors' emotions or attitudes toward a particular market or a specific asset (Mili et al., 2023). As a consequence, a relevant field of research has emerged within behavioral finance, specifically addressing the connection between sentiment and excess returns (Li, 2021; Birru & Young, 2022). Their work points out that sentiment has a significant impact on excess returns and emphasizes the importance of considering investor sentiment when assessing short-term assets. The studies by Li (2021) and Kuo and Huang (2022), among others, combine the sentiment factor with the Fama-French model in order to address a set of anomalies and more effectively explain excess returns.

The five-factor asset pricing model proposed by Fama and French (2015) has been used to capture the effect of market risk, size, book-to-market eq-

http://dx.doi.org/10.21511/imfi.22(1).2025.18

uity ratio, profitability, and investment on average stock returns. The performance of the five-factor model on country-specific and geographically diversified portfolios was tested by Mosoeu and Kodongo (2022). The authors conclude that the profitability factor is particularly useful for explaining emerging market equity returns, but that the five-factor model has little explanatory power. The study also reveals that the average stock returns of large-size firms exceed those of small-size companies.

Investor sentiment significantly influences the size and profitability factors suggested by Fama and French (2015), according to the results of Kuo and Huang (2022). In turn, the sentiment factor can impact the variation of excess returns more intensely compared to the size and book-to-market factors (Li, 2021). Investment strategies known as long-short anomaly portfolio returns (strategies in which researchers buy stocks they believe to be priced too low and sell stocks they believe to be priced too high) can help predict stock market performance (Dong et al., 2022). The study suggests that investors can adopt various investment strategies to forecast market developments using different methodologies, such as special computational methods like machine learning, combining simple forecasts to produce more robust ones, identifying the most relevant patterns, testing them against the current stock market conditions, and making adjustments where needed.

A study by Kurz et al. (2013) evaluates how the average of the absolute excess return, stock market volatility, and the level of the stock price affect excess returns. Their article states that absolute excess returns can be regarded as an empirical measure of financial investors' herding behavior. Investors adopt this behavior when they feel insecure and believe that other investors are in possession of relevant information. They conclude that the absolute excess return of the German stock index significantly depends on the average of the absolute excess return, the level of the stock price, and stock market volatility. According to their findings, volatility is a significant factor that strongly impacts herding behavior. The amateur and professional investors exhibit herding behavior, but professionals show less propensity to herd, with this behavior being influenced by a firm's systematic risk and size. Differences likely stem from professionals' superior financial training, and herding, especially by amateurs, is correlated with and contributes to stock market volatility (Veneza et al., 2011).

Sentiment indicators based on the news source have undergone significant developments over the last decade (Shi et al., 2016). In the literature, Baker and Wurgler (2007) proposed one of the most widely recognized indicators for measuring the indirect proxy of sentiment using market data. Traditional sentiment measures include the consumer confidence index, investor sentiment, and business sentiment (Symitsi & Stamolampros, 2021).

For the literature review, a bibliometric analysis was applied using the Scopus (2024) database to find the most relevant articles about consumer, manager, and investor sentiment. The data were processed and analyzed using tools such as VOSviewer (Van & Waltman, 2018) and Bibliometrix R (Aria & Cuccurullo, 2017). The analysis identified 10 of the most relevant articles from recent years (the number of citations appears in parenthesis): Daniel et al. (2002) (1101); Zaremba et al. (2022) (54); Sun et al. (2020) (52); Mishra and Mishra (2021) (46); Ahmed (2020) (42); Koçak et al. (2022) (26); Chen et al. (2017) (22); Trichilli et al. (2020) (17); Zaremba et al. (2020) (14); Berninger et al. (2021) (10).

After bibliometric analysis, the study first evaluates the impact of Consumer sentiment on excess returns. In an economy characterized by market imperfections and increasing levels of uncertainty, consumer sentiment regarding economic developments continues to be an important cause for concern and study. People's decisions to consume, save, or invest are strongly influenced by their expectations of short-term economic developments, particularly if they lack reliable information. If consumers are optimistic (pessimistic) about the economic outlook, they naturally tend to spend more (less). Consumer sentiment indicators reveal how a diverse set of heterogeneous agents reflects the current and future evolution of the economy (Ahmed, 2020).

Consumer sentiment plays a crucial role in the stock market. Consumer confidence indices reveal how households perceive the current and future economic environment and a wide array of related factors, such as the rising cost of living, savings plans, the purchase of durable goods, and the inflation rate. High levels of consumer confidence are generally associated with better stock market performance (Ludvigson, 2004).

The relevance of confidence indicators lies in their capacity to provide professionals and policymakers with significant insight into the sentiment of the different agents toward market changes. The evaluation of the impact of consumer sentiment indicators on economic activity has been the subject of numerous studies. Sentiment indicators significantly contribute to predicting the evolution of business cycles (Moran et al., 2019). Confidence indicators play an important role in transmitting the effects of US uncertainty shocks to the real economy (Zhang, 2017). Confidence indicators, derived from the Michigan consumer surveys, play a relevant role in forecasting the future trajectory of US economic activity.

The empirical evidence used to assess the interaction between consumer confidence or sentiment indicators and financial asset returns clearly demonstrates how challenging it has been to reach a consensus on this issue. An increase in the Michigan index of consumer sentiment (a proxy for the economic outlook of individual investors) in January increases monthly market excess returns from February to December by about 20 basis points (Chen & Daves, 2018). The positive short-term relationship between consumer confidence and stock returns in 9 European countries is also documented by Jansen and Nahuis (2003). For their part, Chen et al. (2021b) found that the S&P500 index is more sensitive to shifts in consumer confidence during periods of recession than during periods of expansion.

The index of consumer sentiment has a positive relation with new car sales. An increase in car sales reflects high consumer sentiment (Utama, 2003). Conversely, Singh et al. (2022) claim that negative consumer sentiment significantly impacts car sales. The authors highlight the importance of monitoring negative consumer perceptions to improve car sales performance. In their article on home purchase attitudes, Baghestani et al. (2013) conclude that consumer surveys contain predictive information for changes in the real estate market, considering the long-term commitment involved in that specific process. Positive consumer sentiment triggers an increase in new home sales. The authors further claim that consumers' perception of borrowing limitations may have an impact on house demand.

Based on a monthly panel data analysis covering 29 countries, from January 2003 through December 2018, Ahmed (2020) found that changes in consumer sentiment have positive effects on stock returns, particularly in the short term. The author also concludes that higher levels of consumer confidence boost stock prices in both developed and developing economies. Announcements of lower-than-expected consumer sentiment have a significant negative effect on the Australian stock market on the day of the release, whereas higher sentiment index values have no notable impact (Akhtar et al., 2011). In contrast, Lemmon and Portniaguina (2006) suggest that confidence-based sentiment measures lack predictive power for the book-to-market factor. However, high levels of sentiment predict lower returns for value stocks. In turn, Kenneth and Meir (2003) also point out that the index of consumer confidence has a substantial negative impact on the subsequent Nasdaq and small-cap returns. In line with previous studies, Gric et al. (2023) identify a negative relation between consumer sentiment and stock returns. The authors argue that due to limits on arbitrage, the initial overvaluation effect does not disappear immediately. Other studies (e.g., Hengelbrock et al., 2013; Rakovská, 2021) present additional empirical evidence associated with this type of relationship.

The next step analyses the relationship between Investor sentiment and excess returns. Investor sentiment has a strong influence on asset pricing in the US financial market. This relation occurs because investor optimism or pessimism can result in asset valuation errors in stock markets. According to Yang and Wu's model (2019), investors trade stocks regardless of their intrinsic value, thereby amplifying the prevailing sentiment. If the initial sentiment is optimistic (pessimistic), investors tend to replicate the prevailing sentiment, even if the asset is overvalued (undervalued), further increasing (decreasing) its value (Baker et

http://dx.doi.org/10.21511/imfi.22(1).2025.18

al., 2012; Rzeszutek et al., 2020). Optimistic sentiment leads to overvaluation (pessimistic sentiment leads to undervaluation) of asset prices, assigning value significantly above (below) the underlying intrinsic value (Gaies et al., 2021; Mili et al., 2023). The authors point out the importance of incorporating sentiment into portfolio managers' strategies, which may pose a challenge for regulators since sentiment can be manipulated. The results indicate that volatility has a negative impact not only on returns but also on investor attitudes. There is also evidence that long-term interest rate has a positive impact on both asset returns and investor attitudes. Shifts in investor sentiment can lead to a temporary increase in stock returns, and the most significant impact is observed in the following two months, returning to normal levels after six months (Mili et al., 2023).

The way investors perceive risk is also associated with the salience or prominence of the news, insofar as geopolitical events with broader visibility are more emotionally charged, attract greater attention, and cause market agents to overestimate actual risk, leading them to react more intensely than warranted (Zaremba et al., 2019). Emotional responses are, in many circumstances, associated with fear and anxiety. These emotions can influence value judgments and lead to irrational decision-making, causing investors to panic sell stocks or buy excessively when the perceived risk decreases (Dessaint & Matray, 2017).

In financial markets characterized by financial information, the media plays an important role in disseminating information to the market (Sun et al., 2020). The study of the relationship between media and stock markets has focused on two main issues: the attention effect and the sharing of humorous content (Deng et al., 2018). Studies conducted on the attention effect suggest that individuals have a limited capacity to process information and tend to make decisions under time pressure. According to this principle, the information dissemination speed is linked to the level of attention, prompting individuals to make decisions almost instantaneously. Media share information and convey humor, as discussed by Gentzkow and Shapiro (2010), who focus primarily on the relationship between media and investors. Stock markets are often driven by the emotions of their participants (Akhtar, et al., 2012). Investors' emotions, combined with the role of the media, have a direct impact on stock pricing (Sun et al., 2020). They also point out that interactions on digital platforms amplify the relationship between investor emotions and stock returns. Through emotional contagion, investors can share the same feelings as those around them, which can significantly influence their decisions. On the other hand, Sustein and Zeckhauser (2011) argue that media coverage of military conflicts or terrorist attacks often amplifies the frequency and perceived severity of these events, often triggering exaggerated reactions across the stock market.

In a study conducted to assess the explanatory power of Google searches on investor behavior regarding market index returns, Trichilli et al. (2020) found that collective sentiment can influence market trends. The information collected can be used to develop more informed investment strategies by taking into account the psychological factors that influence market movements. The authors conclude that Google search trends, particularly those related to investor sentiment, exhibit strong predictive power for market index returns in the MENA (Middle East and North African) region, especially during instability periods such as the Arab Spring in 2011 or the 2014 oil crisis. An investor sentiment index using Google Trends, which was based on the combination of several proxy measures, was constructed by Reis and Pinho (2020). According to the study, there is a negative correlation between returns in the US global index and an increase in negative sentiment (fear, pessimism, and panic). Europe exhibits a similar response, although the impact is less pronounced compared to the US.

The relationship between investor sentiment and future stock returns was studied by Baker and Wurgler (2006). The authors identified a negative relationship for unprofitable stocks, high volatility stocks, small stocks, extreme growth stocks, distressed stocks, non-dividend-paying stocks, and young stocks. In a study focusing on the Chinese economy, Han and Li (2017) concluded that investor sentiment measures can predict local Chinese market returns and can have a negative impact, particularly over longer time horizons. Investor sentiment-induced buying and selling is an important determinant of stock price variation Chau et al., 2016). The authors also note those investors' reactions to waves of pessimism and optimism in the US market are uneven. On the other hand, according to Chen et al. (2019), investor sentiment positively influences the probability of firms conducting seasoned equity offerings (SEOs). They also found that this influence is stronger for young and small firms. The authors also point out that investor sentiment has a positive impact on abnormal returns around the issuance (SEO) but may result in more severe post-issue long-run underperformance. In turn, Zhang et al. (2019) draw the conclusion that, in contrast to the conventional macroeconomic variables, investor mood has a more pronounced positive influence on stock market crises.

Investor sentiment has little explanatory power for weekly and monthly returns in the Chinese market, except during boom periods (2006–2008), as shown by Cheema et al. (2019). Brown and Cliff (2004) report similar evidence for the US stock market.

Reis and Pinho (2021) evaluated significant sentiment measures, including VIX, VSTOXX, put and call ratios, gold, and government bond spreads, identifying a causal relationship between sentiment proxies and stock returns. They find that investor sentiment, as measured by the VIX, provides valuable insights into future market behavior and can help predict stock returns based on expected levels of market volatility. High volatility (high VIX) is associated with lower future stock returns (Reis & Pinho, 2021).

In their studies on bitcoin volatility, Jareño et al. (2020), López-Cabarcos et al. (2021), and Dias et al. (2022) concluded that the VIX index is the most appropriate predictor of investor sentiment. A nonlinear relationship is identified between investor sentiment and bitcoin returns, with the predictive power of volatility changing according to market conditions (Dias et al., 2022). However, other authors highlight a negative relationship between the VIX and bitcoin returns, noting that increased market fear reduces bitcoin returns (Subramaniam & Chakraborty, 2020; Chen et al., 2021a).

Using the Equity Market Volatility Tracker, Lee et al. (2002) demonstrate that excess returns are positively correlated with shifts in investor sentiment. Upward (downward) changes in sentiment are associated with higher (lower) future excess returns. Similarly, Jiang and Jin (2021) identify a positive relationship between the Equity Market Volatility Tracker and excess returns in the Shanghai stock market. In turn, Alqahtani et al. (2020) find that US stock market volatility significantly and negatively affects stock market returns, while in China, Hong Kong, and India, the effects are adverse but not significant.

Finally, the study incorporates the last measure of sentiment, economic environment (business managers' sentiment), and relates it to excess returns. Business sentiment reflects the way in which company managers assess the future of their businesses. When business sentiment is favorable, investors exhibit greater optimism about the evolution of companies and economic activity. This optimism leads to increased demand for stocks and, consequently, higher stock prices. In a study conducted in the UK, Salhin et al. (2016) found that manager sentiment has a positive impact on profitability indices. A manager sentiment index based on firms' financial disclosure reports was developed to measure its impact on US stock prices (Jiang et al., 2019). They discovered that future total stock market returns are significantly and negatively predicted by managers' attitudes. In a study carried out in different countries, Zaremba et al. (2020) state that markets with high sentiment perform better than those with low sentiment. The authors also conclude that the impact of manager sentiment on market profitability is greater in countries with stronger collective sentiment. In a study carried out in the European Union, Klein and Özmucur (2010) show that bringing together surveys of production expectations to models that use only past values of manufacturing growth improves forecasting performance, suggesting that using both the headline index and sentiment indicators can enhance predictions of manufacturing growth. Consequently, business leaders' expectations can be a key determinant of oil price movements, especially during periods of increased global oil demand (Byrne et al., 2019).

News about geopolitical uncertainty, such as the risk of wars and terrorist attacks, affects the valuation of market stocks. In a study focusing on emerging markets, Zaremba, et al. (2022) reported that in-

http://dx.doi.org/10.21511/imfi.22(1).2025.18

vestors tend to overreact to recent geopolitical news, leading to temporary stock mispricing and abnormal returns, which are subsequently corrected in the following months. Investors' overreaction is due to the availability heuristic, as they assess the likelihood of an event based on how easy it is for them to recall a similar event. The availability heuristic is a mechanism that pushes people to act in two different directions: i) when relevant adverse risk events occur people will typically take action to lessen the likelihood or the consequences of the risk, overestimate the threat posed by the risk, and take unnecessary precautions; ii) if relevant events are not available, people will undervalue the risk and take less action (Sunstein & Zeckhauser, 2011).

In their study conducted in Portugal, Italy, Greece, and Spain, Atukeren et al. (2013) found a positive causal relationship between business confidence indicators and stock returns. Business confidence indices, particularly within industry sectors, hold significant influence, especially during market recession and expansion cycles in the USA (Çevik et al., 2012). A positive relationship between the economic sentiment indicator and excess stock returns is documented, with strong effects in the short term than in the long term (Keiber & Samyschew, 2019; Ahmed, 2020). A positive relationship between market sentiment and short-term returns in the Korean stock market was identified by Seok et al. (2019). They also demonstrate that this relationship is more evident for smaller firms with high earnings volatility and higher book-to-market ratios. In a study focused on developed countries, Belke and Beckmann (2015) identify a positive long-term relationship between US stock returns and business sentiment. On the other hand, Collins (2001) found no evidence of a relationship between business confidence and stock market performance in South Africa, Japan, Germany, and the USA. In turn, Friesner, et al. (2013) consider that the impact of business sentiment on stock returns is merely indirect. The implications of manager sentiment on stock returns in the US market were also assessed by Jiang, et al. (2019). These authors discovered that future aggregate stock market returns negatively correlate with manager sentiment. precedes Lower aggregate returns are preceded by higher manager sentiment, especially for enterprises with significant arbitrage costs or those that are hard to evaluate.

As the literature review documents, studies around sentiment have gained increasing relevance, particularly in the last four years. The relationship between sentiment, in its different dimensions, and excess returns, although it has been the subject of different studies, needs a holistic approach incorporating new variables and methodologies. Considering the literature review, gathering consensus around this topic is not easy. This leads the authors to evaluate the impact of the Fama-French five-factor model with the sentiment factors (investor, consumer, and manager's sentiment) over a 23-year period on the US stock excess returns.

2. METHOD

All the explanatory variables, 7 to 15 in Table 1A, are standardized with a mean of 0 and standard deviation of 1. This procedure is explained further in the article. The Economic and Statistical Rationale for dividing the explanatory variables into three groups yielded the following results:

Group 1 includes variables related to consumer behavior and the housing market (stdCarssold, stdNewhouses, stdLoans, stdConsumerOpinion). These variables can reflect consumer sentiment, or in other words, their confidence and perception of economic health and are capable of influencing market returns. They serve as indicators of consumer confidence and spending patterns. An increase in car sales or new house purchases often signals positive consumer sentiment, as these are significant financial commitments consumers are more likely to make when they feel confident about their financial future. A rise in credit card loans indicates optimism about the economy's prospects. Similarly, consumer opinions provide a direct measure of sentiment, influencing and reflecting the overall economic outlook from the consumer's perspective.

Group 2 encompasses variables related to market sentiment and volatility (stdEquityTracker, stdvix). These variables are more directly related to market conditions and investor sentiment, potentially affecting market risk and returns. The stdEquityTracker variable represents the standardized movement of equity prices or indices, which can directly reflect investor sentiment. It is constructed using news from eleven major U.S. newspapers and captures the journalists' moods regarding Macroeconomic News, Monetary Strategy, Tax Policy, and Financial Regulation. Higher values of this index indicate higher risk or pessimism. Investors are willing to pay more for stocks in anticipation of future growth before rising equity prices, which may indicate positive investor sentiment. The opposite was also verified. The stdVIX variable, or VIX, also known as the "fear index", measures expected volatility for the following 30 days. A higher VIX indicates higher expected volatility, often associated with increased uncertainty and negative investor sentiment. A lower VIX implies that investors believe in steady market conditions and reflects positive sentiment.

Group 3 incorporates variables related to employment, business outlook, and industrial production (stdEmployees, stdBusinessSurveys, stdindpro). These indicators reflect overall economic activity and productivity, which are fundamental determinants of market performance. The stdEmployees variable, which corresponds to the number of employees in the air transportation sector, indicates the labor market's health in a pivotal sector that encompasses business and leisure travel. An increase in employment suggests that businesses are expanding and reflects a positive sentiment among managers and a robust economic outlook. The stdBusinessSurveys variable indicates the results of surveys conducted with business managers and provides insights into their expectations for future business conditions, including turnover, earnings, and investment plans. Positive survey results indicate optimistic business sentiment, while negative results suggest caution or pessimism. The stdIndPro variable represents the standardized industrial production and measures the industrial sector's output. It serves as a key indicator of economic activity and productivity. Growing industrial production shows strong economic growth and positive sentiment among business managers. It suggests high demand for goods and that businesses are operating at or near full capacity.

In summary, Group 1 variables address consumer sentiment. Group 2 variables capture the mood and expectations of investors, reflecting how they perceive current and future market conditions. Group 3 variables, on the other hand, offer insight into the economic environment from the perspective of business managers, indicating their confidence in the economy's health and their expectations for future business activity. Together, these three sets of variables are essential for understanding the dynamics of market risk and return, as they reflect the underlying sentiments driving the economic and market behavior of three different economic actors (see Table A1 in the Appendix).

Table 1 shows the descriptive statistics, where the monthly excess market return has a median of 1,14% and a mean of 0,55%. For almost all the explanatory variables, the median and the average exhibit close values that support a normal distribution. The standard deviation of the variables is low, and the existence of outliers is limited, as the 95th percentile is not so far from the average. Financial market factors (MktRF, SMB, HML, RMW, CMA, and Rf) and volatility indicators (VIX, Equity Market Volatility Tracker) exhibit significant volatility. For instance, the VIX has a maximum value of 68.51, highlighting periods of high market stress. Variables like air transportation employees, Consumer Opinion Surveys, and new houses show less volatility than financial market factors but their respective domains are quite wide in range. For example, the new houses variable ranges from 478 thousand monthly units to 2273 thousand, reflecting fluctuations in housing market activity. For most variables, the median (p50) is close to the mean, suggesting a relatively symmetrical distribution of values. The 95th percentile values (p95) provide insights into the upper extremes of each variable. For instance, the Equity Market Volatility Tracker's p95 value is 5.11 (more than twice the mean), suggesting that volatility spikes are greater than those in the VIX, which has a p95 value of 34.77 (about 70% above the mean). These values are also confirmed by the dispersion coefficient ratio (mean divided by the standard deviation). The stationarity column indicates whether the time series is stationary based on the Augmented Dickey-Fuller test. Non-stationary variables like RF and air transportation employees sector show fewer extreme fluctuations compared to some stationary variables, suggesting that stationarity does not necessarily imply higher volatility.

http://dx.doi.org/10.21511/imfi.22(1).2025.18

Table 1. Descriptive statistics

Variable	Mean	SD	Min	Max	p95	p50	Stationarity Augmented Dickey–Fuller test
MktRF	0.55	4.63	–17.23	13.65	7.72	1.14	Yes
SMB	0.24	3.12	–15.32	18.28	4.98	0.16	Yes
HML	0.21	3.51	–13.87	12.75	7.09	–0.03	Yes
RMW	0.45	2.94	–18.65	13.07	4.99	0.45	Yes
CMA	0.28	2.24	–7.22	9.07	4.40	0.00	Yes
RF	0.14	0.16	0.00	0.56	0.44	0.08	No
Carssold	15.96	2.25	8.83	22.06	18.29	16.66	Yes
Newhouses	1303.08	440.55	478.00	2273.00	2042.00	1302.50	No
Loans	539.14	237.47	211.50	1029.06	924.90	606.47	No
Consumer Opinion Surveys	99.70	1.53	96.19	102.85	101.59	99.90	No
Equity Market Volatility Tracker	2.05	1.51	0.26	11.21	5.11	1.66	Yes
VIX	20.06	8.35	9.51	68.51	34.77	17.84	Yes
Air transportation Employees	496.20	49.05	391.00	633.60	612.60	489.85	No
Business Tendency Surveys (Manufacturing)	99.94	1.15	95.79	102.12	101.58	99.97	No
indpro	97.03	4.97	84.60	104.12	103.19	98.37	No

Note: 288 monthly observations.

Table A2 in the Appendix shows fewer correlations, over 50%, which may indicate the absence of multicollinearity. However, further testing is warranted.

For the methodology, this work used the Prais-Winsten (1954) estimator that corrects the autocorrelation of residuals in a linear regression model. It is particularly effective when dealing with autocorrelation that follows a first-order autoregressive [AR(1)] process. It transforms the model to remove first-order autocorrelation, enabling the use of ordinary least squares (OLS) on the transformed model. The Prais-Winsten estimation is a variation of the Cochrane-Orcutt procedure; both are used to repair first-order autocorrelation of residuals in a regression model. Unlike the Cochrane-Orcutt procedure, the Prais-Winsten estimator allows for including all observations by transforming the data to correct for autocorrelation. The Prais-Winsten estimator is a method used for estimating expected returns, which was particularly useful in analyzing expected returns on Treasury securities and stock returns (Elton, 1999).

The Newey-West (1987) estimator applied addresses autocorrelation and heteroskedasticity of residuals in a regression model without requiring a specific form for autocorrelation or heteroskedasticity. It adjusts the standard errors of the coefficients in a linear regression model to account for autocorrelation up to a certain lag and heteroskedasticity, making the inference more robust. This method is more flexible than the Prais-Winsten estimator as it does not assume a specific form of autocorrelation. It is appropriate for models with both autocorrelation and heteroskedasticity concerns, providing robust standard errors that can lead to more reliable statistical inference. The Newey-West estimator is more robust and less sensitive to outliers than traditional least squares estimators, improving performance in regression models (Mcdonald and White, 1993). Recent works, such as those by Ofoeda et al. (2022) and Kim et al. (2012), have applied those methods in their estimations.

The ARMAX models used extend ARMA (Autoregressive Moving Average) models by incorporating exogenous variables (X) to model a dependent variable based on its past values and past errors (shocks) and take into account the influence of external variables. The model can be represented as:

$$\Delta y_t = \phi_1 \Delta y_{t-1} + \phi_2 \Delta y_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots \theta_p \varepsilon_{t-p} + \beta_1 \Delta x_{1,t} + \ldots \beta_k \Delta x_{k,t} + \varepsilon_t, \quad (1)$$

where Δy_t is the dependent variable in the first difference, ϕ_1, ϕ_2 are the parameters of the autoregressive part of the model, $\theta_1 \ldots \theta_p$ are the parameters of the moving average part, $\varepsilon_{t-1}, \ldots \varepsilon_{t-p}$, are the lagged forecast errors, β_k is the parameter associated with the exogenous inputs $\Delta x_{k,t}$ (in first differences), ε_t is the error term. Δ means the first difference of variables.

ARMAX models are beneficial when the goal is to forecast a variable that is influenced by its past values and external factors. They provide a flexible framework for modeling complex dynamics in time series data. This is the standard model in studies such as Lim et al. (2009) and Lapitskaya et al. (2022).

In the analysis, all the explanatory variables were standardized. Standardized values, often called z-scores in statistical analysis, are common in various fields, including economics, psychology, and machine learning. Standardization involves rescaling the values of a variable so that they have a mean of 0 and a standard deviation of 1. This process is beneficial for several reasons, particularly in estimation and modeling, as it enables the comparison of variables that are measured on different scales (Kuhn & Johnson, 2013; Aikenet al., 1991). For instance, Baker and Wurgler (2006) also employed a standardized variables approach in constructing their sentiment index.

After using the three models for estimation, and in accordance with the adjusted R2 selection, this study conducted a Newey-West rolling regression with a 60-month window to assess the evolution of the significance of the explanatory variables along the period under study, a method also applied by Reis and Pinho (2020). This robust procedure tests the stability or shift in the significance levels of the estimators over time.

2.1. Models

Due to the unit root of some variables (see Table 1), this work used the first differences of the variables, as they were found to be stationary on that level.

Model 1: Group 1 Variables

$$\begin{aligned}&\Delta mktrf\_t = \alpha + \beta 1 \Delta SMB\_t\\&+\beta 2 \Delta HML\_t + \beta 3 \Delta RMW\_t + \beta 4 \Delta CMA\_t\\&+\beta 5 \Delta RF\_t + \gamma_1 \Delta stdCarssold\_t\\&+\gamma_2 \Delta stdNewhouses\_t + \gamma_3 \Delta stdLoans\_t\\&+\gamma_4 \Delta stdConsumerOpinion\_t + \varepsilon\_t.\end{aligned} \tag{2}$$

Model 2: Group 2 Variables

$$\begin{aligned}&\Delta mktrf\_t = \alpha + \beta_1 \Delta SMB\_t\\&+\beta_2 \Delta HML\_t + \beta_3 \Delta RMW\_t + \beta_4 \Delta CMA\_t\\&+\beta_5 \Delta RF\_t + \gamma_1 \Delta stdEquityTracker\_t\\&+\gamma_2 \Delta stdVIX\_t + \varepsilon\_t.\end{aligned} \tag{3}$$

Model 3: Group 3 Variables

$$\begin{aligned}&\Delta mktrf\_t = \alpha + \beta_1 \Delta SMB\_t\\&+\beta_2 \Delta HML\_t + \beta_3 \Delta RMW\_t + \beta_4 \Delta CMA\_t\\&+\beta_5 \Delta RF\_t + \gamma_1 \Delta stdEmployees\_t\\&+\gamma_2 \Delta stdBusinessSurveys\_t\\&+\gamma_3 \Delta stdIndPro\_t + \varepsilon\_t.\end{aligned} \tag{4}$$

where $\Delta mktrf_{\_t}$, is the excess return over the risk-free rate at time t, in first differences, $\Delta SMB_{\_t}$, $\Delta HML_{\_t}$, $\Delta RMW_{\_t}$, $\Delta CMA_{\_t}$, $\Delta RF_{\_t}$ are the Fama and French five factors at time t (See Table A1 for more detail), $std\ldots\ldots_{\_i}$ represents each standardized variable included as an explanatory variable in the model, please see Table A1, α, β_i, and γ_i are the coefficients to be estimated, ε_t is the error term at time t.

3. RESULTS

The estimation results, according to the methods section, are reproduced in Table 2.

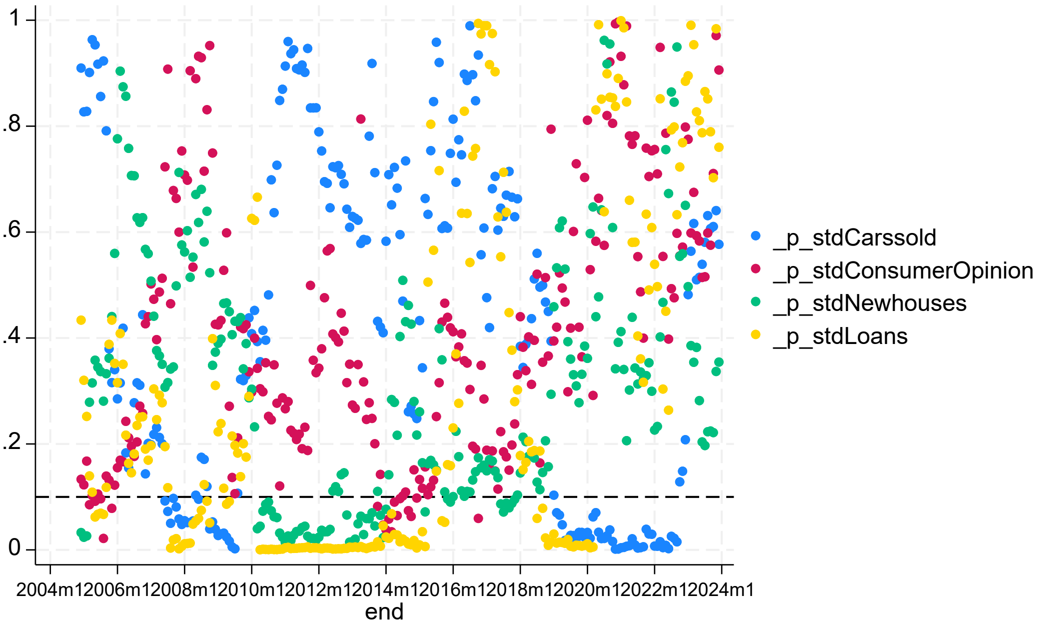
The analysis presented in Table 2 covers the period from 2000 to 2023. However, considering the different crises and other dramatic events that have occurred during this particular period of time, such as financial crises and epidemics, the different sentiment measures may have differing impacts on excess stock returns during specific sub-periods of the sample. Bearing this in mind, the paper applied rolling regressions using the Newey-West model (selected for its highest adjusted R^2) with a rolling window of 60 months, as detailed in the method section. Before proceeding with the next step, it was important to consider the key events that have taken place within this timeframe and are documented in the literature. The results analysis, explanation, and respective confrontation with the literature review will be presented in the next section in a more detailed manner.

http://dx.doi.org/10.21511/imfi.22(1).2025.18

Table 2. Newey, Prais and Arima estimation robust results

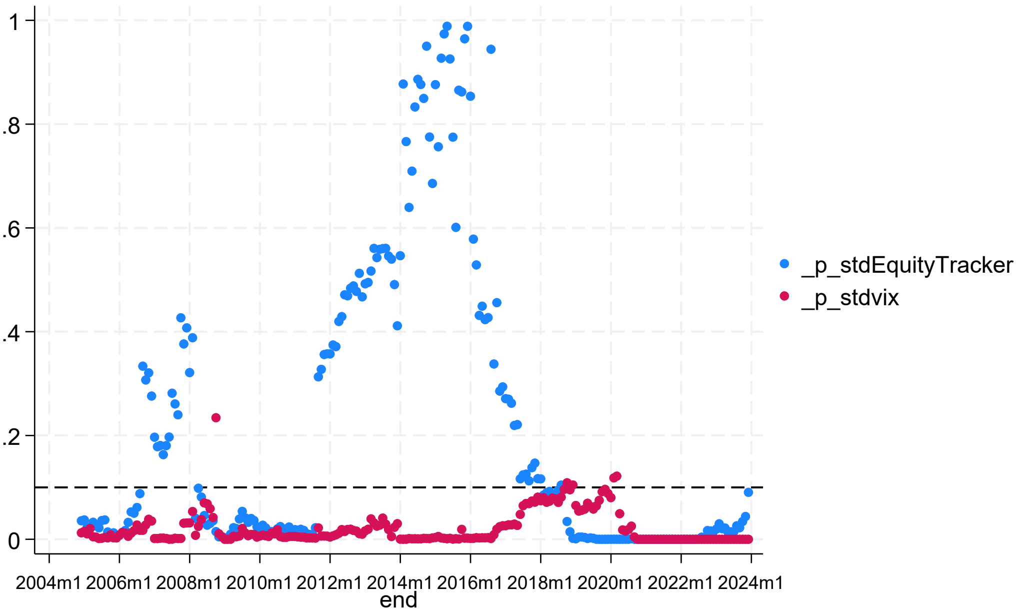
Variable code	Newey 1	Newey 2	Newey 3	Prais 1	Prais 2	Prais 3	Armax 1	Armax 2	Armax 3
	D.MktRF	**D.MktRF**	**D.MktRF**	**D.MktRF**	**D.MktRF**	**D.MktRF**	**D.MktRF**	**D.MktRF**	**D.MktRF**
D.SMB	0.128	0.0238	0.0986	0.168	0.0646	0.137	0.229+	0.139	0.201
	(0.92)	(0.19)	(0.70)	(1.13)	(0.47)	(0.93)	(1.74)	(1.08)	(1.59)
D.HML	0.374**	0.301**	0.352**	0.358*	0.330**	0.338*	0.373**	0.403***	0.347**
	(2.83)	(2.61)	(2.66)	(2.44)	(2.63)	(2.31)	(3.02)	(3.52)	(2.91)
D.RMW	–0.471**	–0.465**	–0.488**	–0.401*	–0.432**	–0.429**	–0.453**	–0.472***	–0.468***
	(–2.84)	(–3.07)	(–2.84)	(–2.46)	(–2.97)	(–2.69)	(–3.16)	(–3.61)	(–3.49)
D.CMA	–0.749***	–0.577**	–0.708**	–0.673**	–0.599**	–0.656**	–0.613**	–0.636***	–0.605**
	(–3.57)	(–2.98)	(–3.30)	(–3.02)	(–2.93)	(–2.89)	(–3.05)	(–3.47)	(–3.06)
D.RF	–9.226	–4.196	–7.820	–3.774	4.810	0.428	–2.461	3.720	6.677
	(–0.76)	(–0.37)	(–0.68)	(–0.27)	(0.38)	(0.03)	(–0.32)	(0.48)	(0.89)
D.stdCarssold	–0.516			0.0854			–0.185		
	(–0.57)			(0.10)			(–0.27)		
D.stdNewhouses	–4.080*			–3.380*			–2.121+		
	(–2.41)			(–2.15)			(–1.81)		
D.stdLoans	–3.949+			–5.241			–4.283+		
	(–1.85)			(–1.03)			(–1.71)		
D.stdConsumerOpinion	–1.665			–1.297			–0.126		
	(–1.06)			(–0.88)			(–0.15)		
D.stdEquityTracker		–1.126**			–1.608***			–1.515***	
		(–2.63)			(–4.39)			(–4.54)	
D.stdvix		3.991***			3.069***			1.719***	
		(7.03)			(5.29)			(3.65)	
D.stdEmployees			–0.892			–2.357			–2.972**
			(–0.31)			(–0.89)			(–2.96)
D.stdBusinessSurveys			0.445			0.224			0.351
			(0.35)			(0.17)			(0.64)
D.stdindpro			–3.330			–2.262			–1.577
			(–1.27)			(–0.85)			(–1.43)
_cons	0.0387	0.0440	0.0482	0.0673	0.0368	0.0389	0.0546	0.0123	0.0121
	(0.20)	(0.21)	(0.24)	(0.31)	(0.19)	(0.18)	(0.58)	(0.13)	(0.13)
ARMA									
L.ar							–0.780***	–0.763***	–0.813***
							(–11.86)	(–10.78)	(–12.46)
L2.ar							–0.639***	–0.59***	–0.675***
							(–9.13)	(–7.61)	(–9.62)
L3.ar							–0.327***	–0.327***	–0.353***
							(–5.65)	(–5.6)	(–6.02)
sigma									
_cons							4.398***	4.210***	4.339***
							(20.83)	(21.78)	(20.53)
N	287	287	287	286	286	286	287	287	287
R^2	0.216	0.353	0.198	0.207	0.326	0.199	–	–	–
adj. R^2	0.190	0.337	0.174	0.182	0.309	0.176	–	–	–
AIC	1832	1773	1836	1764.7	1714	1765.7	1693.6	1664.5	1684.0

Note: t statistics in the parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. For the Armax model, the p-value associated with the Chi-square statistic below 0.05 indicates that the null hypothesis can be rejected, suggesting that the model's predictors, as a group, have a statistically significant association with the dependent variable. In this case, a p-value of 0.000 for all estimations supports the model's significance. The AIC is a measure of the relative quality of statistical models for a given set of data and provides a trade-off between the goodness of the model's fit and complexity. A lower AIC value indicates a better model. The AIC is particularly useful for model selection, where you compare the AIC of different models built from the same dataset. In this case, all the AICs are very close, denoting that all models can reasonably be applied. The adjusted R^2 is slightly better for the Newey-West models. The goal is not to compare models based on their predictive performance, and if that were the case, the AIC criteria would be better compared to the R^2. The primary purpose is to evaluate how well the model explains the variability of the data, and this work argues that the adjusted R^2 is more appropriate. James et al. (2013) discuss AIC and adjusted R^2 measures in this context. $d.mktrf_t$ is the excess return over the risk-free rate at time t, in first differences, - $d.SMB_t$, $d.HML_t$, $d.RMW_t$, $d.CMA_t$, and $d.RF_t$ are the Fama and French five factors at time t (see Table A1 for more detail), *D.stdCarssold* is the Total Vehicle Sales, *D.stdNewhouses* is the New Privately-Owned Housing Units Started in Total Units, *d.stdLoans* is the Credit Cards and Other Revolving Plans loans, *D.stdConsumerOpinion* is the Consumer Opinion Surveys: Confidence Indicators, *D.stdEquityTracker* the Equity Market Volatility Tracker, *d.stdVIX* measures market expectation of near-term volatility conveyed by stock index option prices, *D.stdEmployees* is the Number of Air Transportation employees in the US, *D.stdBusinessSurveys* is the Business Tendency Surveys (Manufacturing), and finally, the *D.stdindpro* is the Industrial production index. The prefix D means first difference, and std is standardization (see Table A1 for more detail).



Note: On the y-axis, the significance level (p-value) with the dashed line indicates the threshold for 10%. On the x-axis is the end period of each 60-month rolling regression. In blue is the value of the stdcarssold variable; in red, the value of the *stdconsumeropinion* variable; in green is the value of the new houses sold variable; and in yellow is the value of the *stdloans* variable. *stdCarssold* is the Total Vehicle Sales, *stdNewhouses* is the New Privately-Owned Housing Units Started in Total Units, *stdLoans* is the Credit Cards and Other Revolving Plans loans, *stdConsumerOpinion* is the Consumer Opinion Surveys: Confidence Indicators.

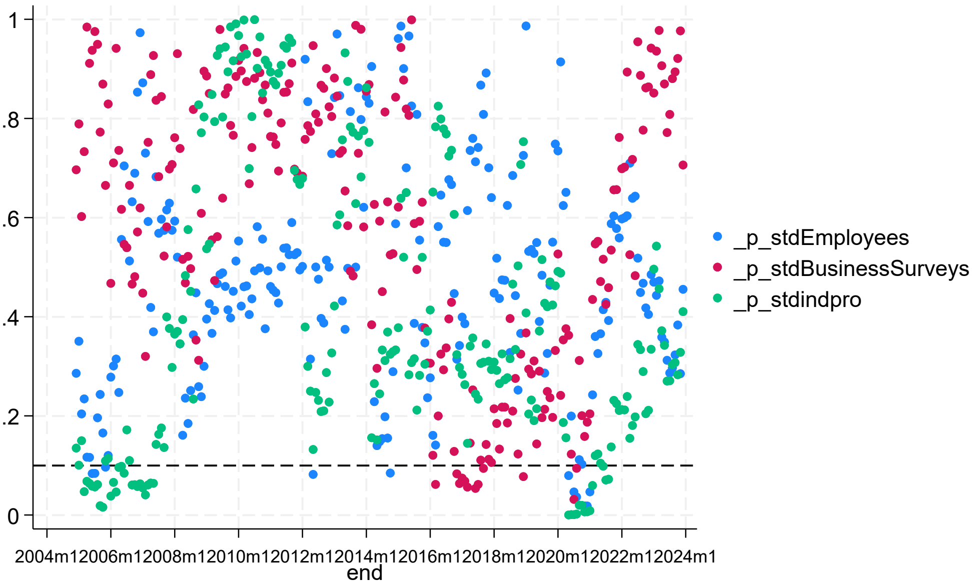
Figure 1. Rolling Newey-West regression for consumer sentiment proxies



Note: On the y-axis, the significance level with the dashed line indicates the threshold for 10%. On the x-axis is the end period of each 60-month rolling regression. In blue is the p-value of the *stdequitytracker* variable; in red is the p-value of the *stdvix* variable. *stdEquityTracker* the Equity Market Volatility Tracker, *stdVIX* measures market expectation of near-term volatility conveyed by stock index option prices.

Figure 2. Rolling Newey-West regression for investor sentiment proxies

http://dx.doi.org/10.21511/imfi.22(1).2025.18



Note: On the y-axis, the significance level with the dashed line indicates the threshold for 10%. On the x-axis is the end period of each 60-month rolling regression. In blue is the p-value of the *stdemployees* variable (airline employees), in red is the p-value of the *stdbusiness* surveys variable, and in green is the p-value of the *stdindpro* variable (industrial production index). *stdEmployees* is the Number of Air Transportation employees in the US, *stdBusinessSurveys* is the Business Tendency Surveys (Manufacturing), and finally, the *stdindpro* is the Industrial production index (see Table A1 for more details).

Figure 3. Rolling Newey-West regression for manager sentiment proxies

4. DISCUSSION

The explanatory variables related to consumer sentiment, new houses, and monthly consumer loan shifts produce significant negative impacts on excess stock returns (for all three types of estimation models, except for Prais regarding consumer loans). Although an increase in those values would typically indicate a positive consumer sentiment about the economy, there are reasons for the market to react negatively. An increase in new houses sold and consumer loans might indicate higher demand, leading to higher property prices, potential bubbles in the housing market, and, consequently, inflationary tensions. Such consumer behavior would impact investor decisions, who may anticipate that central banks will respond by raising interest rates to control inflation. This reaction could negatively impact stock returns by increasing borrowing costs, enforcing stricter lending regulations, or implementing cooling measures for both companies and consumers that will ultimately reduce consumer spending. These measures can diminish investor sentiment and decrease investments and earnings, lowering stock prices. Investors may adopt more cautious strategies and start to sell off stocks in anticipation of a market correction, thereby contributing to negative stock returns. While an increase in consumer loans indicates confidence and willingness to spend, it also suggests that consumers may be taking on excessive debt. Investors may then fear a credit crisis or defaults that would negatively impact stock returns, especially for companies heavily dependent on consumer spending.

Lemmon and Portniaguina (2006) and Gric et al. (2023) state that greater consumer confidence is associated with lower future returns. When consumer confidence is high, investors tend to become overly optimistic, leading to overvaluation of stocks. When stocks exceed their actual value, future returns decrease as the market corrects these valuations to more realistic levels. During periods of high consumer confidence, investors may exhibit irrational biases. Other studies (e.g., Hengelbrock et al., 2013; Rakovská, 2021) have provided similar empirical evidence. Rakovská (2021) states that the effect of sentiment predictability is not immediate and manifests after one or three months. High sentiment levels create an environment in which stock prices may be inflated due to excessive optimism, potentially giving rise to future corrections. These corrections generate lower returns when stocks have been previously overvalued. Overly optimistic consumers tend to make decisions based on their emotions (irrational exuberance), often disregarding independent analysis and warning signs.

Regarding investor sentiment, the estimation models reveal that changes in stdEquityTracker (Equity Market Volatility Tracker) and changes in stdvix (VIX index), as proxies, reflect opposite expected excess return variations. The first presents a significant negative impact, while the second has a strong and positive influence. The Equity Market Volatility (EMV) tracker uses the news from eleven major U.S. newspapers. It draws on the articles to calculate the journalist's perceptions of the strengths underlying stock market volatility and its trends over time. The index classifies those forces into thirty categories containing: Macroeconomic News, Monetary Policy, Tax Policy, and Financial Regulation (Baker et al., 2019). This broader perspective may lead to a different risk assessment and, consequently, the risk premium demanded by investors. The different influences of the CBOE Volatility VIX indicator and the Equity Market Volatility Tracker can be attributed to their distinct sources of information and integration into market perceptions. The VIX focuses primarily on the market's expectation of volatility derived from S&P 500 index options. It measures market sentiment and investor expectations of future volatility, often reacting to immediate market conditions and investor sentiment.

On the other hand, the Equity Market Volatility Tracker incorporates a broader range of information, including the realized volatility of returns on the S&P 500 and macroeconomic news and outlook related to different economic policies. This reflects current market conditions and integrates broader economic indicators that may influence market volatility. While some news may increase uncertainty and volatility (reflected in a higher VIX), others may stabilize or reduce uncertainty, influencing the Equity Market Volatility Tracker differently. Including the macroeconomic outlook in the tracker allows it to dampen or amplify the response to such news compared to the VIX. The VIX can be highly sensitive to short-term market movements and sentiment shifts, leading to rapid changes in expected volatility. In contrast, the Equity Market Volatility Tracker's broader scope can make it less sensitive to short-term fluctuations but more reflective of underlying economic trends and their impact on market volatility.

When the Equity Volatility Tracker is high, it indicates the presence of uncertainty that is rapidly absorbed by the markets, as market investors will rapidly price the assets according to this uncertainty, often leading to declining returns. However, the VIX represents the market's expectation for volatility over the near term conveyed by stock index option prices, which may serve as a lag inducer of falling returns in the future. A persistent higher VIX may indicate previous oversold markets, creating investor opportunities and increasing daily stock returns. Moreover, a higher VIX may lead to a higher excess stock return due to the closing of short positions that increase stock demand.

Sarwar (2014) found a powerful negative contemporary relation between VIX changes and European stock returns, which tends to be even more pronounced during a crisis. The same approach was later confirmed by Sarwar and Khan (2017), who argued that increases in the VIX lead to substantial immediate and delayed declines in emerging market returns for all periods under study. However, changes in the VIX explain a more significant percentage of shifts in emerging market returns during financial crises compared to other periods. Qadan et al. (2019) argue that an increase in the VIX demonstrates a negative relationship between idiosyncratic volatility and future returns. In contrast, Bagchi (2012) found that the VIX in India yields a positive and significant relationship with portfolio returns. Contrary to our results, Wang et al. (2021) found that during the COVID-19 crisis period, the VIX hurt the S&P 500 equity returns. However, the "equity market volatility tracker" was positively associated with stock market returns.

As for the influence of manager sentiment on excess stock returns, the studies show that none of the proxies significantly impact stock returns, except for the ARMAX model, and only when changes in the number of employees are considered. This consistently demonstrates that excess

http://dx.doi.org/10.21511/imfi.22(1).2025.18

returns are not sensitive to this type of sentiment during the period under analysis. Contrary to expectations, an increase in employees in air transportation firms does not drive stock excess returns. Additionally, the business confidence surveys administered to managers do not show any association with excess returns and, consequently, cannot be considered a good proxy for manager sentiment. This conclusion is further supported by the industrial production index, which does not perceive them as a good proxy for manager sentiment expected to influence excess stock returns over the whole period. The results of our study align with those conducted by Collins (2001), who states that manager sentiment is not a predictor of the evolution of the stock market.

Contrary to the results of this study, Ahmed (2020) concludes that business sentiment positively affects returns in developed markets over short- and long-term time horizons. However, in emerging markets, the impact of business sentiment on stock prices is significant in the short term but not in the long term. The results of the current study differ from those of many authors (e.g., Greenwood & Shleifer, 2014; Hirshleifer & Yu, 2015; Jiang et al., 2019), who consider that manager sentiment can significantly improve investment decisions and portfolio performance. Jiang et al. (2019) state that manager sentiment is a relevant negative foreteller of future aggregate stock market returns, with greater predictive power than other previously studied macroeconomic variables. Higher manager sentiment precedes lower aggregate returns, particularly for companies that are difficult to value and have high arbitrage costs. According to Chen et al. (2022), manager sentiment significantly impacts firms' future stock returns differently. An optimistic sentiment regarding the evolution of business results positively impacts excess returns, while a pessimistic sentiment negatively impacts stock returns. Verma et al. (2008) investigate the relationship between manager sentiment and excess returns, revealing a complex interplay between rational and irrational components. They suggest that managers' irrational sentiments can cause immediate fluctuations in excess returns, but these initial effects tend to be corrected over time as markets adjust. Additionally, the influence of manager sentiment on excess returns is neither direct nor consistent, as multiple market factors and investor behaviors contribute to the varying impacts of sentiment on excess returns. Other authors, such as Friesner et al. (2013), state that although business sentiment provides valuable information, its impact on stock returns will be indirect and influenced by many other factors.

By using rolling regression for Group 1 (consumer sentiment, Figure 1), this study observes that the number of cars sold and consumer loans are relevant for explaining excess returns during the periods surrounding the subprime crisis, China-US Trade War, the COVID-19 pandemic, and the Russia-Ukraine war. Houses sold and Consumer loans strongly impacted excess returns during the sovereign crisis period and the Chinese Stock Market Crash. While the relevance of different economic indicators fluctuates depending on the nature and context of the crisis, consumer loans consistently emerge as a critical factor, underscoring their pivotal role in shaping market dynamics during tumultuous periods. Real estate transactions involving significant sums of money contribute to the wealth effects experienced by consumers and investors. House prices and transaction volumes influence perceptions of wealth and financial well-being, which, in turn, affects spending and investment decisions. In times of crisis, shifts in housing market dynamics can amplify wealth effects, influencing excess returns in financial markets. Consumer loans and housing market activity are closely linked to systemic risk and financial stability. Excessive leverage in the housing market and high consumer debt levels can exacerbate systemic risks during periods of economic stress.

For Group II (investor sentiment, Figure 2), the VIX was a relevant predictor for stock performance. In contrast, the Equity tracker was not considered relevant for the period between 2012 and 2017, characterized by a calmer environment. During periods of uncertainty or distress, such as economic crises or geopolitical tensions, investors typically become more risk-averse, leading to increased stock price volatility. The VIX tends to rise during such times, making it a valuable market sentiment indicator. A possible explanation for the irrelevance of the Equity volatility tracker during calmer periods (2012–2017) is that it primarily focuses on journalist perceptions about Macroeconomic News, Monetary Policy, Tax Policy, and Financial Regulation, variables that are more significant during macroeconomic crises, such as government debt levels, political instability, or credit risk.

In the case of Group III (manager sentiment, Figure 3), the industrial production index was found to be the most relevant factor during the subprime crisis and the COVID-19 pandemic. In contrast, business surveys were irrelevant during the Brexit announcement and the USA trade war. The importance of the industrial production index during the subprime crisis and the COVID-19 period stems from its sensitivity to economic downturns. This index is a crucial barometer of overall economic health, reflecting changes in manufacturing activity, capacity utilization, and overall industrial output. During times of crisis, such as the subprime mortgage crisis and the COVID-19 pandemic, investors closely monitor industrial production trends as they provide valuable insights into broader economic conditions and potential market vulnerabilities. Similarly, the heightened relevance of business surveys during events like the Brexit announcement and the China-USA trade war underscores their role as leading indicators of sentiment and economic expectations. Business surveys, which capture sentiment among executives and managers regarding future business conditions, offer timely insights into how geopolitical events and policy decisions may impact corporate decision-making, investment plans, and consumer sentiment.

Overall, the patterns observed highlight the dynamic nature of market influences and the importance of considering various economic indicators and sentiment proxies to understand how different events can shape market behavior across various periods. The analysis reveals that specific sentiment proxies can significantly influence excess stock returns across various periods. This underscores the importance of expanding sentiment behavior analysis to encompass a broader range of sentiment measure proxies tailored to diverse stakeholder groups, such as consumers, managers, and investors. Examining how each sentiment measure correlates with different events is crucial to gaining deeper insights into market dynamics. By incorporating these enhancements, researchers can develop a more comprehensive understanding of the impact of sentiment on financial markets and implement more nuanced investment strategies.

CONCLUSION

This study evaluated the impact of consumer sentiment, investor sentiment, and manager sentiment (economic environment) on US stock excess returns by analyzing a set of time series data from 2000 to 2023. This study evaluated the impact of consumer sentiment, investor sentiment, and manager sentiment (economic environment) on US stock excess returns by analyzing a set of time series data from 2000 to 2023. This study emphasizes the importance of behavioral factors, such as the sentiment of economic agents, that complement and enrich traditional approaches based exclusively on market fundamentals. It addresses important issues like autocorrelation and heteroscedasticity of residuals and dynamic modeling by applying advanced techniques, including the Paris-Winsten, Newey-West estimators, and ARMAX models. Additionally, rolling regressions analyze the temporal evolution of sentiment's impact during significant global events, such as financial crises, pandemics, and geopolitical conflicts.

The results indicate that consumer sentiment, measured using proxies such as new home sales and monthly change in consumer loans, negatively impacts excess returns. The impact is particularly relevant during the subprime crisis, the China-US trade war, and the COVID-19 pandemic. Proxies such as the number of cars sold and consumer loans are important consumer sentiment indicators, reflecting the economic and agent's emotional response in periods of instability (the sovereign crisis period and the Chinese Stock Market Crash). When optimistically, these proxies can indicate bubbles and excess debt and may lead to stocks selling off, diminishing stock returns. These results suggest that significant

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external events influence consumer sentiment and play a key role in translating subjective perceptions that have concrete impacts on financial markets. These results highlight the importance of including robust proxies to assess consumer sentiment in forecasting models when analyzing markets, especially in contexts of high economic uncertainty.

Investor sentiment shows the opposite effect: The Equity Market Volatility Tracker reduces excess returns, while the VIX index substantially positively affects them. When persistent, the latter signals the market with good market opportunities, which may lead to stock buying opportunities or result from the close of short positions that may increase demand for shares, thus increasing returns. These findings suggest that different proxies capture distinct dimensions of investor sentiment, reflecting varied behaviors and perceptions over time. For example, the VIX has consistently influenced market performance throughout the period analyzed, emerging as a significant determinant. At the same time, the Equity Market Volatility Tracker played a less relevant role between 2012 and 2017. This contrasting behavior underscores the importance of using multiple indicators to comprehensively capture the impact of investor sentiment on excess equity returns.

Manager sentiment plays a less prominent role, showing significance only when measured by variations in the number of employees, which negatively impact excess returns. In the rolling regression analysis, the industrial production index variable (the manager's proxy of sentiment) becomes particularly relevant during times of economic crisis, such as the subprime crisis and the COVID-19 pandemic.

One of the main contributions of this study arises from the integrated assessment of the impact of consumer, investor, and manager sentiment on US equity excess returns. This multidimensional approach captures the perceptions and expectations of different economic agents, enriching the understanding of financial market dynamics. Traditionally, research in this area tends to focus on a single type of sentiment, often investor sentiment. However, the study provides a broad perspective on the behavioral factors that influence markets by including consumer and manager sentiments. The evidence that the relevance of sentiment indicators fluctuates over time, influenced by the context of specific global events, constitutes another relevant contribution to this investigation. The simultaneous analysis of these three types of sentiment, combined with robust methodologies applied to time series, which include periods marked by significant global events, such as financial crises and pandemics, highlights the relevance of considering multiple sentiment dimensions. This innovative approach contributes to a broader understanding of the relationships between behavioral factors and the performance of financial markets, opening new challenges for future analyses.

The theoretical contribution of this study arises from the multidimensional analysis of the impact of consumer, investor, and manager sentiment on US excess returns, suggesting that the relevance of each type of sentiment varies according to global events, such as crises and pandemics. The study enhances understanding of the dynamic relationships between sentiment and market performance by using different proxies, rolling regressions, and robust methodologies. In practice, the results show that i) investors should integrate behavioral factors when evaluating portfolios, ii) portfolio managers should consider sentiment indicators when building their strategies, and iii) policymakers should use these indicators to supervise the markets and stabilize them in periods of high sentiment-driven volatility. This study combines theoretical and practical perspectives, offering a comprehensive view of the behavioral dimensions of financial markets.

This study's limitations arise from using specific proxies to gauge the sentiment of consumers, investors, and managers, who may need to capture the perceptions and behaviors of these agents. Although the study plays an important role in revealing the significant effects of sentiment on excess returns, it does not account for the specific characteristics of the different types of industries in its estimations. Alternative proxies, built from social media data or news analysis, can complete this assessment.

Furthermore, the geographic scope, limited only to the US market, conditions the generalization of results to other markets, especially emerging economies, where sentiment dynamics can differ significantly. Another area for improvement is the predominance of a linear approach, which, although robust, may not capture non-linear relationships and more complex interactions associated with behavioral factors. The study does not explicitly consider external factors such as geopolitical crises, cybercrime, or climate change to help assess the role sentiment has in stock performance.

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ACKNOWLEDGMENTS

This work is funded by National Funds through the FCT – Foundation for Science and Technology, I.P., within the scope of the project Ref. UIDB/05583/2020. Furthermore, we would like to thank the Research Centre in Digital Services (CISeD) and the Instituto Politécnico de Viseu for their support.

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APPENDIX A

Table A1. Variables description

Code	Variable name	Description	Period	Frequency	Data source	Measure
(1) MktRF	Mkt–RF	Market Risk (Mkt – RF): This factor represents stock market excess returns over the risk-free rate (Fama & French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(2) SMB	SMB	Size (SMB – Small Minus Big): This factor captures the historical outperformance of small-cap stocks over large-cap stocks. It measures the excess returns of small-cap stocks compared to large-cap stocks (Fama & French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(3) HML	HML	Value (HML – High Minus Low): The value factor captures the excess returns of value stocks over growth stocks. Value stocks are those with low price-to-book ratios, indicating that they are priced relatively low compared to their book value. Growth stocks, on the other hand, have higher price-to-book ratios (Fama 7 French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(4) RMW	RMW	Profitability (RMW – Robust Minus Weak): This factor reflects the historical outperformance of profitable firms over unprofitable ones. Profitability is typically measured by factors such as operating income over book equity (Fama & French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(5) CMA	CMA	Investment (CMA – Conservative Minus Aggressive): The investment factor captures the historical outperformance of firms with conservative investment policies over those with aggressive ones. Conservative firms tend to invest less in capital expenditures and growth opportunities compared to aggressive ones. This factor aims to capture the impact of firms' investment decisions on their stock returns (Fama & French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(6) RF	RF	The risk–free rate represents the theoretical return on an investment that carries no risk of financial loss. 10-year Treasury Bond Yield (Fama & French, 1993, 2015)	2000–2023	Monthly	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f–f_5_factors_2x3.html	%
(7) Carssold	Cars sold	Total Vehicle Sales	2000–2023	Monthly	U.S. Bureau of Economic Analysis, Total Vehicle Sales [TOTALSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TOTALSA, February 9, 2024	Millions

http://dx.doi.org/10.21511/imfi.22(1).2025.18

http://dx.doi.org/10.21511/imfi.22(1).2025.18

Table A1 (cont.). Variables description

Code	Variable name	Description	Period	Frequency	Data source	Measure
(8) Newhouses	New houses	New Privately-Owned Housing Units Started: Total Units	2000–2023	Monthly	U.S. Census Bureau and U.S. Department of Housing and Urban Development, New Privately-Owned Housing Units Started: Total Units [HOUST], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/HOUST, February 7, 2024	Thousand units
(9) Loans	Loans	Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks, Billions of U.S. Dollars, Weekly, Seasonally Adjusted	2000–2023	Monthly	Board of Governors of the Federal Reserve System (US), Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks [CCLACBW027SBOG], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CCLACBW027SBOG, March 18, 2024	Billions of U.S. Dollars
(10) ConsumerOpini~s	Consumer Opinion Surveys	Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States	2000–2023	Monthly	Organization for Economic Co-operation and Development, Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for United States [CSCICP03USM665S], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CSCICP03USM665S, February 9, 2024	Higher values higher confidence (normalized=100)
(11) EquityMarketVo~e	Equity Market Volatility Tracker	Equity Market Volatility Tracker: Macroeconomic News and Outlook: Consumer Spending And Sentiment Index, Monthly. The Equity Market Volatility tracker moves with the VIX and with the realized volatility of returns on the S&P 500. It is constructed using news from eleven major U.S. newspapers	2000–2023	Monthly	Baker, Scott R., Bloom, Nick and Davis, Stephen J., (2024) Equity Market Volatility Tracker: Macroeconomic News and Outlook: Consumer Spending And Sentiment [EMVMACROCONSUME], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/EMVMACROCONSUME, February 9, 2024	Higher values higher risk or pessimism
(12) VIX	VIX	The VIX measures market expectation of near-term volatility conveyed by stock index option prices	2000–2023	Monthly	Chicago Board Options Exchange, CBOE Volatility Index: VIX [VIXCLS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/VIXCLS, February 9, 2024	Higher values higher risk or pessimism
(13) Employeesairtr~t	Employees air transport	Number of Air Transportation employees in the US	2000–2023	Monthly	U.S. Bureau of Labor Statistics, All Employees, Air Transportation [CES4348100001], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CES4348100001, February 8, 2024	Thousand employees
(14) BusinessTende~u	Business Tendency Surveys (Manufacturing	Business Tendency Surveys (Manufacturing): Confidence Indicators: Composite Indicators: OECD Indicator for the United States	2000–2023	Monthly	Organization for Economic Co-operation and Development, Business Tendency Surveys (Manufacturing): Confidence Indicators: Composite Indicators: OECD Indicator for United States [BSCICP03USM665S], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BSCICP03USM665S, February 9, 2024	Higher values higher confidence (normalized=100)
(15) indpro	Industrial production index	The industrial production (IP) index measures the real output of all relevant establishments located in the United States, regardless of their ownership, but not those located in U.S. territories	2000–2023	Monthly	Board of Governors of the Federal Reserve System (US), Industrial Production: Total Index [INDPRO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/INDPRO, March 3, 2024	Index;2017=100

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Table A2. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) MktRF	1.000														
(2) SMB	0.277*	1.000													
(3) HML	–0.019	0.058	1.000												
(4) RMW	–0.346*	–0.493*	0.345*	1.000											
(5) CMA	–0.232*	0.034	0.622*	0.227*	1.000										
(6) RF	–0.123*	–0.021	0.096	0.090	0.083	1.000									
(7) Carssold	0.007	0.033	0.097	–0.059	–0.013	0.340*	1.000								
(8) Newhouses	–0.062	0.046	0.139*	0.022	0.092	0.474*	0.607*	1.000							
(9) Loans	0.100	–0.117*	–0.130*	–0.050	–0.144*	–0.292*	–0.072	–0.287*	1.000						
(10) ConsumerOpini~s	0.006	0.031	0.071	–0.031	0.053	0.273*	0.747*	0.435*	–0.260*	1.000					
(11) EquityMarketV~k	–0.294*	–0.108	–0.039	0.107	0.076	0.229*	–0.076	0.066	–0.313*	–0.069	1.000				
(12) VIX	0.039	0.083	–0.070	0.024	0.044	–0.154*	–0.549*	–0.260*	–0.133*	–0.439*	0.480*	1.000			
(13) Employeesairt~t	–0.204*	0.044	0.147*	0.127*	0.191*	0.696*	0.363*	0.505*	–0.402*	0.371*	0.390*	0.055	1.000		
(14) BusinessTende~u	0.140*	0.006	0.079	–0.059	–0.006	–0.282*	0.222*	0.207*	0.146*	0.267*	–0.429*	–0.492*	–0.308*	1.000	
(15) indpro	–0.026	–0.183*	–0.085	–0.041	–0.135*	0.090	0.353*	0.033	0.636*	0.028	–0.284*	–0.509*	–0.263*	0.226*	1.000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

http://dx.doi.org/10.21511/imfi.22(1).2025.18