Research Article

Investigating the Predictive Role of the Equity Market Sentiment Index (EMSI): Industry-Level Return Responses in the Thai Equity Market

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ABSTRACT

This study explores the predictive power of investor sentiment on stock returns in the Thai equity market using the Equity Market Sentiment Index (EMSI), a high-frequency, market-implied indicator derived from return-volatility dynamics. Applying Vector Autoregression (VAR) and Granger causality tests to daily data from 2019 to 2024, the results reveal that EMSI significantly Granger-causes market returns at both the aggregate and sectoral levels, supporting the hypothesis that sentiment is a forward-looking driver of return behavior. Impulse response functions show that positive sentiment shocks lead to sustained increases in returns, particularly in financial and consumer-related sectors, while other industries show shorter-lived or asymmetric responses. Notably, in the property and technology sectors, sentiment is incorporated contemporaneously, precluding VAR-based modeling and impulse response analysis. These findings highlight the heterogeneous transmission of sentiments across industries and reinforce the relevance of behavioral signals in return predictability, especially in emerging markets where informational inefficiencies persist.

Keywords: Investor Sentiment, Equity Market Sentiment Index (EMSI), Industrial Impulse Response, Behavioral Finance

บทความวิจัย

การศึกษาความสามารถในการพยากรณ์ของดัชนีที่สะท้อนอารมณ์การลงทุนในตลาดทุน (EMSI) ต่อการตอบสนองของผลตอบแทนของหลักทรัพย์รายอุตสาหกรรมในตลาดทุนไทย

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บทคัดย่อ

การศึกษานี้มีวัตถุประสงค์ เพื่อวิเคราะห์ความสามารถในการทำนายผลตอบแทนของตลาดหุ้นไทยโดยใช้ดัชนีอารมณ์การลงทุนในตลาดทุน ซึ่งวัดผ่านดัชนี Equity Market Sentiment Index (EMSI) ที่พัฒนาขึ้นจากความสัมพันธ์เชิงพลวัตระหว่างผลตอบแทนและความผันผวนของราคา การวิเคราะห์ข้อมูลอาศัยแบบจำลองเวกเตอร์ออโตรีเกรสซีฟ (VAR) และการทดสอบเชิงสาเหตุแบบแกรนเจอร์ (Granger Causality Test) โดยใช้ข้อมูลผลตอบแทนรายวันในช่วงปี พ.ศ. 2562 ถึง 2567 ผลการศึกษาพบว่า EMSI มีอิทธิพลเชิงสาเหตุที่มีนัยสำคัญต่อผลตอบแทนของตลาดทั้งในระดับภาพรวมและระดับอุตสาหกรรม ซึ่งสนับสนุนสมมติฐานที่ว่าอารมณ์นักลงทุนมีบทบาทสำคัญต่อพฤติกรรมของราคาหลักทรัพย์ นอกจากนี้ การวิเคราะห์การตอบสนองต่อแรงกระตุ้น (Impulse Response Function) แสดงให้เห็นว่าเมื่อดัชนี EMSI ปรับตัวในทางบวก มีผลต่อผลตอบแทนในกลุ่มอุตสาหกรรมการเงินและสินค้าอุปโภคบริโภคจะเพิ่มขึ้นอย่างต่อเนื่อง ขณะที่อุตสาหกรรมอื่น ๆ มีการตอบสนองที่สั้นกว่าและไม่สมมาตร อย่างไรก็ตาม ในกลุ่มอุตสาหกรรมอสังหาริมทรัพย์และเทคโนโลยี ไม่สามารถดำเนินการวิเคราะห์ด้วยแบบจำลอง VAR ได้ เนื่องจากไม่มีโครงสร้างความสัมพันธ์เชิงเวลาอย่างมีนัยสำคัญ ผลการศึกษานี้สะท้อนให้เห็นถึงความแตกต่างในการส่งผ่านอารมณ์ระหว่างอุตสาหกรรมต่าง ๆ และเน้นย้ำถึงความสำคัญของการนำปัจจัยเชิงพฤติกรรมมาประกอบการพยากรณ์ผลตอบแทน โดยเฉพาะในตลาดเกิดใหม่ที่ยังมีข้อจำกัดด้านประสิทธิภาพของข้อมูล

คำสำคัญ : อารมณ์นักลงทุน ดัชนีอารมณ์การลงทุนในตลาดทุน การตอบสนองของผลตอบแทนอุตสาหกรรมต่อแรงกระตุ้น การเงินเชิงพฤติกรรม

1. INTRODUCTION

Investor sentiment is increasingly recognized as a significant driver of asset price movements, particularly in markets with high retail investor participation. Rooted in behavioral finance theory, this perspective challenges the assumption of purely rational expectations by emphasizing the systematic influence of psychological biases. Seminal contributions such as Shiller (1983) and Baker and Wurgler (2006) highlight that stock prices often deviate from fundamentals due to investor mood. Shiller (1983) showed that stock price volatility exceeds what can be justified by dividend changes, suggesting the influence of non-fundamental factors. Baker and Wurgler (2006) further developed a sentiment-based asset pricing model, showing that sentiment disproportionately affects stocks that are hard to arbitrage.

Building on this foundation, Calzadilla et al. (2021) conducted a comprehensive review of behavioral biases among retail investors, noting the central role of sentiment in driving decisions and contributing to anomalies such as overconfidence, the disposition effect, and confirmation bias. These biases can distort asset pricing and create mispricing opportunities. Their review also emphasized the rising importance of real-time sentiment measures derived from digital sources, particularly for predicting short-term volatility. In support, Da et al. (2015) show that sentiment-driven trading not only forecasts market movements but also responds to volatility shocks, reinforcing a feedback loop in price formation.

The need to quantify sentiment has led to the development of diverse indicators. These include survey-based tools like the University of Michigan Consumer Sentiment Index, market-based proxies such as the CBOE Volatility Index (VIX), and textual sentiment measures using financial news and social media. For instance, Tetlock (2007) showed that the pessimistic tone in Wall Street Journal articles could predict market returns, while Baker et al. (2016) constructed the Economic Policy Uncertainty Index, which captures macro-level investor anxiety. Da et al. (2011) introduced Google search volume as a proxy for investor attention and mood, enabling high-frequency monitoring of sentiment shifts.

Despite these advances, many sentiment indices still rely on indirect proxies, such as media coverage, trading activity, or search queries, which may not fully capture investor sentiment embedded in actual market behavior. Addressing this limitation, Bandopadhyaya and Jones (2006) proposed the Equity Market Sentiment Index (EMSI), which measures sentiment through the cross-sectional correlation between stock return rankings and volatility rankings. EMSI provides a high-frequency, market-implied indicator of investor mood, reflecting risk appetite through observable trading patterns. This approach aligns with behavioral finance theory, which posits that during periods of elevated sentiment, investors are more likely to chase returns and underprice risk, thereby increasing the comovement of return and volatility.

While EMSI has attracted academic interest, its predictive power has not been widely tested using robust econometric methods. Recent studies show its empirical relevance. Debata et al. (2021), for example, show that sentiment, captured through EMSI-like measures, significantly affects stock market liquidity in India, particularly in volatile periods. Chu and Gu (2024) further confirm that high-frequency sentiment indicators enhance return forecasts using MIDAS models, reinforcing the usefulness of real-time sentiment data. Nevertheless, the application of EMSI remains limited in Southeast Asia, especially in studies that explore sector-specific dynamics.

Emerging markets offer a particularly relevant context for sentiment analysis due to lower market efficiency and higher information asymmetry. For instance, Amiri Hosseini (2023) found that heightened investor sentiment led to increased volatility in the Tehran Stock Exchange. In line with this, Debata et al. (2021) emphasized that both local and global sentiment shocks can impact liquidity. Zhu et al. (2022), using wavelet quantiles, revealed that sentiment interacts with macroeconomic uncertainty and commodity prices to affect stock returns across different time horizons. These findings underscore the complex and time-dependent influence of investor sentiment on financial market behavior.

To address the existing research gap, this study applies the EMSI to the Thai equity market to assess its causal impact on sectoral stock returns using a Vector Autoregression (VAR) and Granger causality framework. Unlike earlier studies focusing on aggregate indices, this research disaggregates sentiment by industry, allowing for a more granular assessment of how behavioral factors influence different sectors in an emerging market. Our findings not only highlight the estimated value of EMSI but also provide empirical support for behavioral finance in the Thai context.

Specifically, this study examines whether EMSI holds statistically significant predictive power for future market returns, contributing to the ongoing debate between efficient markets and sentiment-driven pricing anomalies. Although EMSI has appeared in previous research (Piñeiro-Chousa et al., 2021; Shahid & Abbas, 2019), this study offers both methodological and contextual advancements. First, by disaggregating EMSI at the industry level, the study uncovers sector-specific sentiment spillovers often obscured in aggregate analyses, particularly relevant in Thailand, where investor composition and sectoral performance vary widely. Second, the use of VAR and Granger causality methods enables dynamic, time-sensitive testing of lead–lag relationships between sentiment and returns, a relatively underused approach in this domain. Third, applying EMSI in the Thai market, characterized by high retail trading and uneven liquidity, contributes novel insights to the literature on sentiment dynamics in less-developed financial environments.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature Review

Investor sentiment has long been recognized as a key explanatory variable in asset pricing, especially in markets where retail investor participation is high and information asymmetry is prevalent. Drawing from the theoretical framework of behavioral finance, this study is grounded in the view that investor decisions are influenced by cognitive biases, emotional heuristics, and bounded rationality (Barberis et al., 1998; Loewenstein et al., 2001). These behavioral irregularities often lead to mispricing, excess volatility, and non-linear market dynamics that traditional rational models, such as the Efficient Market Hypothesis (Fama, 1970), do not fully explain.

Among the most influential contributions to this domain is the sentiment-based asset pricing model developed by Baker and Wurgler (2006), which shows that sentiment has a disproportionate impact on stocks that are hard to arbitrage and difficult to value. Their framework provides a basis for understanding how investor sentiment can exert cross-sectional and time-varying effects on asset returns. Recent empirical studies have expanded upon this foundation by investigating behavioral biases among ordinary investors. For instance, Calzadilla et al. (2021) conducted a systematic review that links sentiment with biases such as overconfidence, disposition effect, and confirmation bias. These biases not only explain deviations from rational investing behavior but also give rise to asset bubbles and market anomalies.

To empirically capture sentiment, earlier studies have employed a range of proxies. Survey-based indices like the University of Michigan Consumer Sentiment Index provide subjective measures of consumer outlook (Brown & Cliff, 2004), while market-derived indicators such as the CBOE Volatility Index (VIX) reflect forward-looking expectations of market risk (Whaley, 2000). Text-based models have also gained popularity. For example, Tetlock (2007) demonstrated that media pessimism in Wall Street Journal columns could predict future market returns. Da et al. (2011) introduced a Google Search Volume Index, showing that search trends serve as a real-time proxy for investor attention and behavioral biases. While these tools offer valuable insights, they are not without limitations; many are infrequently updated, subjective, or difficult to apply across different markets and industries.

Recognizing these limitations, the Equity Market Sentiment Index (EMSI) has appeared to be a promising alternative. EMSI is a market-implied, high-frequency sentiment indicator calculated from the cross-sectional correlation between stock return and volatility rankings. Unlike surveys or textual sentiment indices, EMSI is grounded in observable investor behavior and can be computed daily, making it highly suitable for time-series econometric applications such as VAR or GARCH (Da et al., 2015; Smales, 2017). Additionally, EMSI is adaptable at both the market and industry levels, allowing researchers to investigate industry-specific sentiment spillovers (Kumar & Lee, 2006). Its design also avoids semantic ambiguities commonly found in natural language processing approaches (Tetlock, 2007).

Despite its advantages, EMSI has some notable constraints. It offers little insight into the narrative or psychological drivers behind shifts in investor behavior—an area where survey and text-based approaches may offer more context (Baker et al., 2016). Furthermore, EMSI relies heavily on daily volatility estimates, which may introduce noise due to microstructure effects, particularly in thin or illiquid markets (Jin & Sui, 2022). It is also inherently backward-looking, capturing historical co-movement rather than forward-looking expectations like those embedded in VIX (Whaley, 2000). Finally, interpreting EMSI requires caution: a high EMSI value could stem from multiple investor behaviors such as risk-seeking, momentum chasing, or volatility targeting, necessitating complementary diagnostics for accurate interpretation (Antoniou et al., 2013).

Recent literature has also advanced our understanding of the drivers of investor sentiment. Macroeconomic uncertainty plays a pivotal role in shaping sentiment and market volatility (Pastor & Veronesi, 2012), while psychological constructs such as risk perception, affective heuristics, and emotions like fear and optimism significantly affect financial decision-making (Loewenstein et al., 2001; Peterson, 2007). These findings emphasize the multidimensional nature of sentiment and its influence on investor behavior and financial outcomes.

Moreover, sentiment analysis has become increasingly relevant for corporate decision-making and market strategy. Recent studies have shown that understanding sentiment can enhance customer engagement, guide investor relations, and improve market forecasting. For instance, financial sentiment models trained on domain-specific corpora have demonstrated superior forecasting ability, especially in volatile conditions (Chen et al., 2014; Nassirtoussi et al., 2014). Similarly, tracking consumer sentiment through user-generated content has been shown to inform corporate responses, enhance customer satisfaction, and foster long-term loyalty (Bing, 2012).

However, Mishev et al. (2020) found that general-purpose models frequently have trouble understanding the complex terminology and context-specific meanings found in financial texts. For instance, standard sentiment models commonly misclassify words like “liability” or “debt,” which might have neutral or positive meanings in the finance industry, as negative. This emphasizes the necessity of domain-specific strategies designed for financial terminology. In addition, Du et al. (2024) examined a number of sentiment analysis methods and highlighted enduring difficulties, such as the lack of sizable, labeled financial datasets and the intricacy of financial language. These restrictions lead to an excessive dependence on sentiment indicators, which raises the possibility of misunderstanding, especially during times when the market is emotionally volatile. To increase accuracy and decision-making in financial forecasting, this research collectively highlights the need for more sophisticated, context-aware sentiment models.

2.2 Hypothesis Development

This study's hypotheses are grounded in the theoretical frameworks of behavioral finance, particularly the noise trader model (De Long et al., 1990) and the investor sentiment model by Barberis et al. (1998). These frameworks posit that sentiment-driven investors, those influenced by psychological biases rather than fundamentals, can move prices away from intrinsic values in predictable ways. Such effects are more pronounced in emerging markets like Thailand, where retail trading dominates and arbitrage is limited. The Equity Market Sentiment Index (EMSI), by capturing the correlation between return and volatility rankings, serves as a market-implied proxy for shifts in investor mood and risk appetite. Consistent with these theories, we expect EMSI to have predictive power over future stock returns, particularly across different industry sectors where sentiment intensity and sensitivity may vary.

In an emerging market context, sentiment-induced anomalies are amplified due to weaker institutional frameworks and greater retail dominance. Amiri Hosseini (2023), using data from the Tehran Stock Exchange, found that heightened investor sentiment leads to increased market volatility. This mirrors the structure of Thailand's equity market, where sentiment-driven trading is prevalent and sectoral dynamics are pronounced.

Considering the existing literature, the Equity Market Sentiment Index (EMSI) presents a behaviorally grounded and empirically tractable measure of investor sentiment. Despite its conceptual appeal and high-frequency design, EMSI's application in emerging market contexts and its validation using dynamic econometric models are still underexplored. This study addresses that gap by employing a Vector Autoregression (VAR) framework to examine the predictive power of EMSI and its temporal interactions with both market-wide and sectoral stock returns in Thailand.

At the market microstructure level, Debata et al. (2021) emphasize that both local and global sentiment shocks significantly influence liquidity, highlighting the importance of capturing real-time investor behavior. However, most existing sentiment measures, such as VIX, survey-based indices, or textual sentiment models, lack behavioral grounding or do not reflect sector-specific dynamics, particularly in sentiment-sensitive markets like Thailand.

To overcome these limitations, this study applies EMSI as a high-frequency proxy for investor sentiment that reflects cross-sectional investor behavior based on volatility and return co-movements (Bandopadhyaya & Jones, 2006). Furthermore, to enhance theoretical contribution, the study adopts a sentiment, return feedback loop perspective, recognizing that sentiment not only predicts return volatility but is also endogenously influenced by it, as discussed in Da et al. (2015) and Smales (2017). This bidirectional structure underpins the justification for using VAR and Granger causality methodologies in this context. Synthesizing prior literature and behavioral theory, we develop two testable hypotheses:

H1: Investor sentiment, as captured by EMSI, has predictive power over aggregate market returns.

H2: The effect of EMSI on returns varies significantly across industry sectors due to differences in volatility, investor attention, and sentiment sensitivity.

By addressing both theoretical and empirical gaps, this research provides a novel behavioral asset pricing perspective tailored to the Thai stock market and contributes to the expanding literature on sentiment-based financial modeling in emerging markets.

3. DATA AND EMPIRICAL METHODOLOGY

3.1. Data

The EMSI is adapted from Bandopadhyaya and Jones (2006) but is modified to suit the Thai stock market's institutional characteristics and trading structure. Specifically, EMSI is constructed using daily stock return and volatility rankings across all listed firms on the Stock Exchange of Thailand (SET), encompassing a wide array of industries and firm sizes. Utilizing a comprehensive dataset including 257,021 firm-day observations from 2019 to 2024, daily log returns are calculated for each firm, accompanied by a five-day rolling standard deviation of returns to measure historical volatility.

3.2 Construction of the Equity Market Sentiment Index (EMSI)

For each trading day t, the EMSI is computed as the Spearman rank correlation between cross-sectional stock return ranks R_{it} and volatility ranks V_{it}. This correlation is then scaled by a factor of one hundred to generate the daily EMSI value. Over the sample period from 2019 to 2024, this method yields 1,396 daily EMSI observations, corresponding to trading days with sufficient firm-level data coverage. The EMSI thus serves as a market-implied proxy for aggregate investor sentiment: higher EMSI values suggest elevated risk appetite and potential overconfidence, while lower values reflect rising risk aversion and more conservative market positioning. Thus, the EMSI is calculated as follows:

$$EMSI_t = Spearman\ (R_{it}, V_{it}) \tag{1}$$

While the EMSI construction follows the core method established by Bandopadhyaya and Jones (2006), Our study adapts it to the Thai market context in two important ways. First, the EMSI is calculated using firm-level data from all companies listed on the Stock Exchange of Thailand (SET), thereby reflecting the broad sectoral composition and investor base of Thailand's capital market. Second, the reliance on high-frequency (daily) data and the use of a five-day rolling volatility measure are calibrated to match the liquidity patterns and short-term sentiment cycles observed in markets dominated by retail investors. These design choices ensure that the index captures locally relevant dynamics of investor mood and risk appetite. Although the index formula is not fundamentally altered, its application in this study is tailored to exploit the unique features of an emerging market with shallow arbitrage, high behavioral trading, and uneven information dissemination.

3.3 Econometric Framework

To empirically investigate the dynamic interplay between investor sentiment and sectoral stock returns in Thailand's equity market, this study employs a Vector Autoregression (VAR) model. This approach is chosen not only for its statistical flexibility but also for its alignment with behavioral finance theory, which posits that variables like sentiment and returns are endogenously determined and evolve together over time. The VAR model captures these feedback effects without imposing strict assumptions about the direction of causality, an essential feature in markets shaped by investor psychology and limited arbitrage. Given Thailand's market structure, characterized by high retail participation, low institutional buffering, and pronounced sectoral dynamics, the VAR model provides an appropriate framework to study how sentiment shocks transmit through different industries. Unlike static models or single-equation regressions that assume exogenous regressors, VAR treats all variables as potentially endogenous, reflecting the complexity and interdependence typical of sentiment-driven markets.

Furthermore, disaggregating the analysis at the sectoral level allows us to assess heterogeneous responses to sentiment, acknowledging that sectors differ in terms of volatility, investor familiarity, and liquidity. These features influence how sentiment manifests across the market. Using sectoral returns rather than aggregate indices provides more refined insights into which industries are particularly sensitive to shifts in investor sentiment.

To investigate the dynamic relationship between EMSI and sectoral stock returns, the general form of the Vector Autoregression (VAR) model is specified as

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{2}$$

Where Y_t is a vector comprising EMSI and sectoral return indices at time t, A_i are coefficient matrices, p is the optimal lag length, and ε_t is a vector of white noise errors. This structure allows us to estimate how past values of sentiment and returns influence their future paths in a mutually dependent system.

Lag selection is performed using the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC), which optimize the balance between model fit and parsimony. This ensures that the VAR system captures meaningful dynamics without overfitting, especially important when modeling high-frequency financial data.

3.4 Granger Causality Testing

To further investigate the directionality of the relationship between investor sentiment and sectoral stock returns, this study applies Granger causality tests. These tests assess whether past values of one time series contain statistically significant information useful for forecasting another. In this context, we examine whether lagged values of the Equity Market Sentiment Index (EMSI) can predict future sectoral returns and, conversely, whether past stock returns influence EMSI.

The use of Granger causality is theoretically grounded in behavioral finance, which posits a dynamic feedback loop between sentiment and market performance. As highlighted by Da et al. (2015) and Smales (2017)), sentiment may not only drive future market outcomes but may also be shaped by prior price movements and volatility. Thus, identifying causality in either direction provides empirical support for the notion that sentiment is both a source and a consequence of asset pricing behavior. The Granger causality tests are conducted within the previously estimated VAR framework, maintaining the optimal lag length determined by the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). Significance levels are evaluated at conventional thresholds (1%, 5%, and 10%), ensuring robust inference.

This methodological approach enables us to determine whether EMSI offers forward-looking information relevant for market participants and whether return-based feedback effects play a role in shaping investor mood. Evidence of bidirectional causality would reinforce the theoretical claim of endogenous sentiment dynamics in emerging markets such as Thailand.

3.5 Robustness Checks and Diagnostics

To reinforce the credibility and stability of the empirical findings, this study conducts essential diagnostic and robustness checks. These procedures are critical for validating the underlying assumptions of the Vector Autoregression (VAR) model and ensuring that the estimated relationships are statistically sound.

First, the stationarity of all time-series variables used in the VAR model, namely EMSI and sectoral return indices, is examined using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Establishing stationarity is a prerequisite for valid inference in VAR models, as non-stationary series may produce spurious regression results. The results of both tests confirm that the series are stationary in levels, thus satisfying the requirement for VAR estimation.

Next, a series of residual diagnostics are applied to assess the statistical adequacy of the VAR model. Autocorrelation is assessed using the Durbin-Watson statistics and the Ljung-Box Q-test, while normality of residuals is evaluated using the Jarque-Bera test. In addition, the ARCH-LM test is conducted to examine the presence of conditional heteroskedasticity. The outcomes of these tests indicate that the residuals do not violate key assumptions, supporting the validity of the impulse response functions and Granger causality analyses.

These diagnostic checks collectively strengthen the empirical credibility of the model by confirming that it meets the necessary econometric assumptions. The results thereby provide robust support for the study's conclusions regarding the dynamic interaction between investor sentiment and sectoral stock returns in Thailand.

4. EMPIRICAL RESULTS

4.1 The EMSI (Equity Market Sentiment Index)

The EMSI (Equity Market Sentiment Index) chart captures the dynamic shifts in investor sentiment across the Thai stock market from 2019 to 2024, highlighting periods of excessive optimism and deep fear through the "Greed Zone" (above +30) and "Fear Zone" (below –30). The most striking feature in the chart is the dramatic spike in EMSI volatility during the year 2020, which coincides with the onset of the COVID-19 pandemic, as shown in Figure 1.

Throughout 2020, the EMSI exhibits both extreme positive and negative values, indicating heightened investor uncertainty and rapidly changing risk preferences. This period is marked by sharp plunges into the fear zone, reflecting widespread panic and flight-to-safety behavior during the early stages of the pandemic, followed by abrupt rebounds into the greed zone as markets responded to stimulus measures, vaccine announcements, and expectations of recovery. The intensity and frequency of these sentiment swings during 2020 far exceed those in other years, underscoring the exceptional market turbulence brought on by COVID-19.

These extreme EMSI fluctuations support the hypothesis that sentiment becomes more reactive and volatile in times of systemic crisis. The EMSI's ability to reflect such rapid shifts in investor behavior reinforces its value as a real-time sentiment proxy, particularly during episodes of financial stress. As such, the 2020 data validate EMSI's usefulness in capturing behavioral dynamics that traditional fundamentals or survey-based measures may overlook, providing empirical motivation for its inclusion in time-series models of return predictability and industrial risk sensitivity.

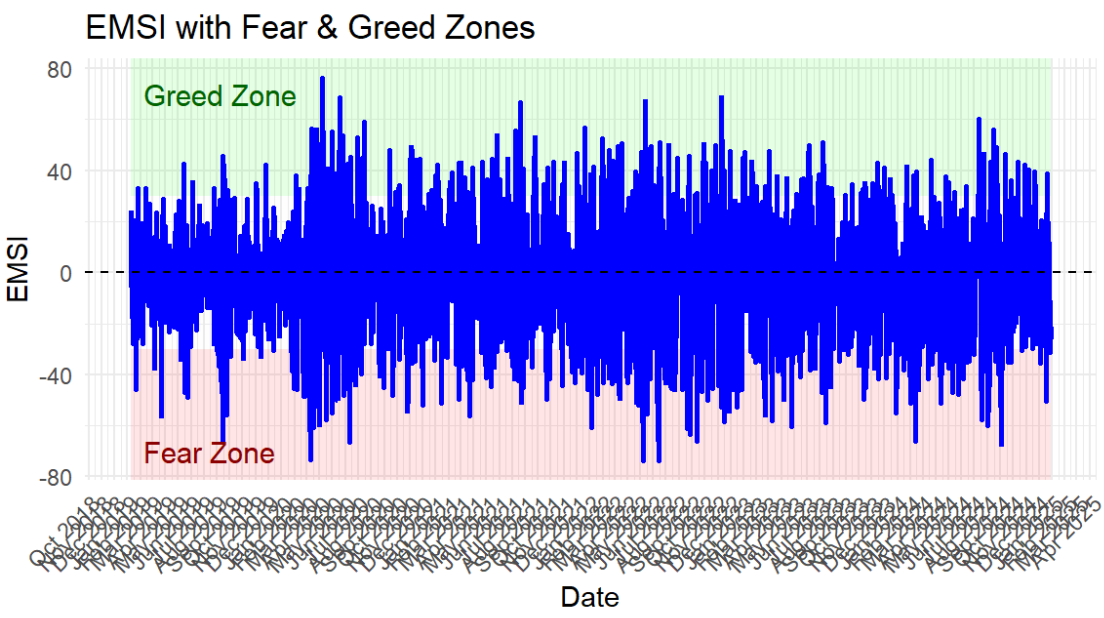

Figure 1: Daily Equity Market Sentiment Index (EMSI) with Fear and Greed Zones (2019–2024)

4.2 Descriptive Statistics

Table 1 presents descriptive statistics for the Equity Market Sentiment Index (EMSI) and daily log returns across the overall Thai equity market and each industry from 2019 to 2024. The EMSI captures day-to-day investor sentiment based on return-volatility rankings, while market return refers to daily changes in the market index, serving as a proxy for market performance.

The overall mean EMSI is -0.0202, showing a slight but persistent tilt toward negative sentiment across the sample period. This negative average reflects a general risk-averse tone among investors, which may stem from macroeconomic uncertainties and crisis periods, notably the COVID-19 pandemic. The EMSI exhibits substantial variation, with values ranging from –0.7377 to 0.6927 and a standard deviation of 0.2692, illustrating wide swings between periods of fear and greed in the market. The overall market return mean is –0.00013, with a standard deviation of 1.00%, suggesting low average daily performance but moderate volatility consistent with daily data from emerging equity markets. The range of returns (–11.43% to +7.65%) captures significant market shocks, again consistent with major stressful events during the sample period.

Across industries, EMSI values are tightly clustered around the overall mean, with only minimal differences in average sentiment levels. For instance, the FINCIAL industry records the lowest average EMSI (–0.0203), while the AGRO and INDUS industries are slightly more neutral (–0.0201 and –0.0201, respectively). Although its impact may vary in size or length, this consistency shows that sentiment, as gauged by EMSI, tends to move broadly in parallel across industries.

Market returns are similarly consistent across industries in terms of mean and dispersion, reinforcing the interpretation that aggregate market dynamics drive much of the short-term return behavior, while industry-specific effects may appear through higher-order analyses such as impulse response functions. The standard deviation of returns is still close to 1% across industries, showing homogeneous risk levels in terms of day-to-day price variation.

Table 1: Descriptive Statistics of EMSI and Stock Returns by Industry

Industry	Variable	Observations	Mean	Min	Max	Std. Dev.
Overall	EMSI	257,021	−0.0202196	−0.7376623	0.6926808	0.2692034
	Market Return	257,021	−0.0001314	−0.1142818	0.0765307	0.0100318
AGRO	EMSI	25,388	−0.0201124	−0.7376623	0.6926808	0.2688399
	Market Return	25,388	−0.0001278	−0.1142818	0.0765307	0.0100489
CONSUMP	EMSI	23,076	−0.0202075	−0.7376623	0.6926808	0.2687363
	Market Return	23,076	−0.0001318	−0.1142818	0.0765307	0.0101131
FINCIAL	EMSI	32,559	−0.0203391	−0.7376623	0.6926808	0.0100643
	Market Return	32,559	−0.0001398	−0.1142818	.0765307	0.0100643
INDUS	EMSI	40,290	−0.0201449	−0.7376623	0.6926808	0.269505
	Market Return	40,290	−0.0001303	−0.1142818	0.0765307	0.0101384
PROPCON	EMSI	41,918	−0.0201495	−0.7376623	0.6926808	0.2694718
	Market Return	41,918	−0.0001272	−0.1142818	0.0765307	0.0099028
RESOURC	EMSI	23,076	−0.0204087	−0.7376623	0.6926808	0.2695672
	Market Return	23,076	−0.0001401	−0.1142818	0.0765307	0.0099762
SERVICE	EMSI	54,451	−0.0202126	−0.7376623	0.6926808	0.2688803
	Market Return	54,451	−0.0001293	−0.1142818	0.0765307	0.0100067
TECH	EMSI	16,263	−0.0202865	−0.7376623	0.6926808	0.2688547
	Market Return	16,263	−0.0001271	−0.1142818	0.0765307	0.010053

Note: EMSI refers to the Equity Market Sentiment Index; Market Return is the daily log return. Overall statistics reflect the full market aggregate, while industry-level values are disaggregated by industry. Observations are based on daily data from 2019 to 2024.

Notably, the FINCIAL, RESOURC, and TECH industries show slightly more negative return means and higher return standard deviations, which may reflect their sensitivity to sentiment-driven trading, macroeconomic news, or industry-specific volatility (e.g., financial regulations, commodity prices, or tech cycles).

4.3 Augmented Dickey-Fuller Test Results

The results presented in Table 2 provide robust evidence that both the Equity Market Sentiment Index (EMSI) and Market Return series are stationary across all industries and in the overall sample. The Augmented Dickey-Fuller (ADF) test is a standard tool used to assess whether a time series possesses a unit root, which would show non-stationarity. Stationarity is a critical assumption for time series modeling, particularly in Vector Autoregressive (VAR) frameworks, as it ensures that the statistical properties of the series (mean, variance, autocorrelation) remain constant over time.

The ADF test statistics for EMSI and Market Return are all highly negative, and the associated p-values are consistently below 0.01, clearly rejecting the null hypothesis of a unit root at the 1% significance level for every industry. This implies that both variables revert to a stable mean over time and do not show stochastic trends, making them suitable for inclusion in level-based VAR models.

Table 2: Augmented Dickey-Fuller Test Results (ADF-test)

Industry	Variable	ADF Statistic	p-value
Overall	EMSI	−29.560	< 0.01
	Market Return	−30.539	< 0.01
AGRO	EMSI	−27.292	< 0.01
	Market Return	−37.559	< 0.01
CONSUMP	EMSI	−27.520	< 0.01
	Market Return	−23.357	< 0.01
FINCIAL	EMSI	−27.079	< 0.01
	Market Return	−39.551	< 0.01
INDUS	EMSI	−25.560	< 0.01
	Market Return	−29.800	< 0.01
PROPCON	EMSI	−24.909	< 0.01
	Market Return	−30.222	< 0.01
RESOURC	EMSI	−22.991	< 0.01
	Market Return	−25.086	< 0.01
SERVICE	EMSI	−24.596	< 0.01
	Market Return	−56.941	< 0.01
TECH	EMSI	−23.459	< 0.01
	Market Return	−23.260	< 0.01

Note: ADF Statistic is the test statistic from the Augmented Dickey-Fuller test. A p-value < 0.05 suggests stationarity, i.e., rejection of the null hypothesis of a unit root.

Notably, the Market Return series in some industries, such as SERVICE (−56.94) and FINCIAL (−39.55), show particularly large ADF statistics, suggesting even stronger stationarity and more pronounced mean-reversion behavior. Similarly, the EMSI displays robust stationarity across all industries, supporting its role as a behaviorally grounded sentiment proxy that fluctuates around a stable long-run level rather than drifting without bound. Thus, these findings confirm the econometric soundness of the subsequent VAR and Granger causality analyses. They also reinforce the reliability of EMSI as a dynamic indicator of investor sentiment whose properties are consistent across both aggregate and industrial levels in the Thai equity market.

4.4 Lag Length Selection Based on Information Criteria

The lag-order selection results for the vector autoregressive (VAR) model, which includes EMSI and Market return as endogenous variables, are evaluated using four widely recognized information criteria: Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan–Quinn Information Criterion (HQIC), and Schwarz Bayesian Information Criterion (SBIC). These criteria are employed to determine the optimal number of lags that best capture the underlying dynamics without overfitting the model.

Among the evaluated lag structures, the fourth lag appears to be the most suitable. Specifically, Lag 4 yields the minimum values across all model selection metrics, including the FPE (0.000016), AIC (−5.36615), HQIC (−5.26590), and SBIC (−5.11688), showing a superior in-sample fit compared to shorter lag specifications, as shown in Table 4. This optimality is further reinforced by the results of the Likelihood Ratio (LR) test, which reveals a statistically significant improvement in model fit between Lag 3 and Lag 4, with an LR statistic of 144.340 and a corresponding p-value below 0.001, as shown in Table 3.

The trend in model performance across lags is consistent with theoretical expectations: as the number of lags increases from zero to four, all selection criteria show a steady decline, suggesting that the inclusion of additional lag terms enhances the explanatory power of the VAR model. While Lag 3 already offers noteworthy improvements shown by both the reduction in information criteria and a significant LR test, the gains are more pronounced at Lag 4, which decisively outperforms earlier specifications. In contrast, the selection of Lag 2 does not provide a statistically significant improvement over Lag 1 ($p = 0.190$), implying that the marginal benefit of additional lags becomes substantial only at the fourth lag.

These findings show Lag 4 as the optimal lag length for the VAR specification. This choice captures the dynamic interactions between investor sentiment and market returns over a four-period horizon, which may reflect behavioral inertia, delayed sentiment transmission, or staggered information processing in the Thai equity market. The results highlight the importance of selecting a suitable lag structure to uncover meaningful temporal dependencies in sentiment-driven return behavior.

Table 3: Lag Length Selection Based on Information Criteria

Lag	Log-Likelihood (LL)	Likelihood Ratio (LR)	df	p-value	Final Prediction Error (FPE)	AIC	HQIC	SBIC
0	609.646	–	–	–	0.000030	−4.74724	−4.73610	−4.71954
1	622.298	25.304	4	0.000	0.000028	−4.81483	−4.78141	−4.73174
2	625.359	6.1222	4	0.190	0.000028	−4.80749	−4.75180	−4.66901
3	632.698	14.678	4	0.005	0.000027	−4.83358	−4.75560	−4.63970
4	704.868	144.340*	4	0.000	0.000016	−5.36615	−5.26590	−5.11688

Note: Optimal lag order based on minimum values of FPE, AIC, HQIC, and SBIC. Sample period: 18 January 2019 to 20 December 2024, with gaps; N = 256.

The results in Table 4 reveal considerable heterogeneity across industries in terms of the proper lag structure. In the AGRO, CONSUMP, FINCIAL, and SERVICE industries, the information criteria uniformly select a fourth-order lag, showing that the dynamics of investor sentiment and return interactions in these industries unfold over a longer temporal horizon. This suggests that market reactions within these industries are characterized by gradual adjustment processes and potentially prolonged behavioral responses to sentiment shocks.

By contrast, the optimal lag for the INDUS industry is found to be two, which reflects a more intermediate memory in the return-sentiment relationship. Interestingly, the RESOURC industry displays an optimal lag of one, suggesting that investor sentiment is incorporated into return dynamics more quickly, potentially due to the high frequency of speculative activity or the sensitivity of this industry to immediate external signals such as commodity price fluctuations.

The best model for the PROPCON and TECH sectors has a lag duration of zero, suggesting that the dynamics in these sectors are dominated by contemporaneous interactions between sentiment and returns. In highly liquid or transparent markets, where investor reactions are instantaneous and less susceptible to lagged behavioral inertia, sentiment may be quickly incorporated into price mechanisms. As the optimal lag selection criteria (AIC, HQIC, SBIC, and FPE) uniformly identify zero lags, this shows that past values of sentiment and returns do not provide additional explanatory power beyond current-period information. Consequently, a Vector Autoregressive (VAR) framework, designed to model temporal interdependencies and feedback effects across multiple lags, is not applicable in this context. As a result, it is not feasible to estimate impulse response functions (IRFs) for the PROPCON and TECH sectors, since IRFs rely on dynamic lag structures to trace the effect of shocks over time. Instead, a static regression approach is more proper for capturing the immediate influence of sentiment on market returns in these sectors, as the absence of meaningful lagged relationships renders impulse response analysis both theoretically and empirically unjustified.

Table 4: Lag Length Selection Criteria for VAR Model by Industry

Industry	Optimal Lag	AIC	HQIC	SBIC	FPE
AGRO	4	−1.56643*	−1.46618*	−1.31716*	0.000716*
CONSUMP	4	−6.24889*	−6.14863	−5.99962	0.000006*
FINCIAL	4	−2.4885*	−2.38825*	−2.23923*	0.000285*
INDUS	2	−6.64054*	−6.58484	−6.50206	0.000005*
PROPCON	0	−6.4324*	−6.42126*	−6.4047*	0.000006*
RESOURC	1	−4.89946*	−4.86605	−4.81637	0.000026*
SERVICE	4	−4.14485*	−4.0446*	−3.89558*	0.000054*
TECH	0	−5.44691*	−5.43577*	−5.41921*	0.000015*

Note: Optimal lag length determined by the lowest value of AIC, HQIC, SBIC, and FPE in each industry. The sample period may vary depending on data availability. AGRO refers to the agriculture and food industry; CONSUMP refers to the consumer products industry; FINCIAL represents financials; INDUS refers to industrials; PROPCON captures the property and construction industry; RESOURC denotes resources; SERVICE includes services such as tourism and healthcare; TECH covers technology-related firms. The asterisk (*) denotes the optimal lag order as selected by the minimum value of each respective criterion (AIC, HQIC, SBIC, or FPE).

Given the dynamic and interdependent nature of financial markets, understanding how investor sentiment influences stock returns require models that can capture both contemporaneous and lagged effects. Vector Autoregressive (VAR) models offer a flexible framework for examining such temporal interactions, as they allow for endogenous variables to influence one another over multiple periods. In the context of this study, the VAR approach is employed to assess the predictive relationship between the Equity Market Sentiment Index (EMSI) and stock returns across various industries of the Thai equity market. These findings underscore the importance of tailoring the time series model specifications to industrial characteristics, as the optimal lag structure varies not only in length but also in the degree to which sentiment-induced behaviors persist. The variation in lag length across industries highlights the differing speeds at which information is processed and priced, reinforcing the need for industry-specific modeling approaches in sentiment-driven return analysis. By applying industry-level VAR models, the analysis seeks to identify how quickly and persistently investor sentiment is incorporated into return dynamics across heterogeneous industry environments.

4.5 Vector Autoregression (VAR) Results

The results presented in Table 5 from the Vector Autoregression (VAR) analysis offer critical insights into the dynamic relationship between investor sentiment, as captured by the Equity Market Sentiment Index (EMSI), and the daily return of the SET Index over four lags.

In the EMSI equation, none of the lagged EMSI variables are statistically significant, showing that sentiment itself does not show strong autoregressive behavior over the four-day window. However, lagged market returns do influence sentiment, with the first lag of SET return having a negative and statistically significant effect at the 5% level (–2.6412, $p < 0.05$). This suggests that a market decline on the previous day leads to a decline in sentiment today. The third lag in market return is also marginally significant (–2.1377, $p < 0.10$), reinforcing the idea that negative market performance depresses sentiment with a slight delay. The constant term is weakly significant, suggesting a persistent mild downward trend in sentiment.

In the Market return equation, EMSI appears as a strong predictor. The first lag of EMSI has a positive and highly significant effect on SET returns (0.0199, $p < 0.01$), suggesting that positive shifts in sentiment today are associated with higher returns tomorrow. Similarly, the fourth lag of EMSI is also significant at the 1% level (0.0298, $p < 0.01$), showing that sentiment has a delayed and reinforcing effect on returns, reflecting behavioral persistence or feedback trading. This supports the forward-looking role of sentiment, consistent with behavioral finance theories that suggest investor mood can drive asset prices beyond fundamentals.

Additionally, the return equation shows a strong mean-reversion pattern, with the first (–0.4216, $p < 0.01$) and fourth (–0.5981, $p < 0.01$) lags of market return being significantly negative. This implies that positive returns tend to be followed by corrections, a common feature in emerging markets with limited arbitrage efficiency. The constant term in this equation is also statistically significant, showing a slight negative drift in average daily returns.

Therefore, the VAR results provide robust evidence for a bidirectional relationship between sentiment and returns. Investor sentiment not only forecasts market returns but is also influenced by past market behavior, highlighting a feedback loop. These findings reinforce the behavioral foundations of financial market dynamics in the Thai context and confirm the use of EMSI as a forward-looking tool for monitoring and forecasting stock market performance.

Table A1 (Appendix 1) summarizes the dynamic relationship between investor sentiment, as measured by EMSI, and stock returns across different Thai industries. Most sectors were analyzed using VAR models, revealing both lagged and contemporaneous effects, while static regressions were applied to PROPCON and TECH due to optimal lag lengths of zero, showing that sentiment in these sectors is incorporated instantly into prices.

Table 5: Vector Autoregression (VAR) Results, EMSI and Market Return

Dependent Variable	Independent Variable	Coefficient	Std. Error	Z-stat
EMSI	EMSI, Lag 1	0.0965	0.0872	1.11
	EMSI, Lag 2	−0.0267	0.0865	−0.31
	EMSI, Lag 3	−0.0640	0.0796	−0.80
	EMSI, Lag 4	−0.1129	0.0785	−1.44
	Market return, Lag 1	−2.6412**	1.3080	−2.02
	Market return, Lag 2	−1.4229	1.3448	−1.06
	Market return, Lag 3	−2.1377*	1.2744	−1.68
	Market return, Lag 4	0.6454	0.8236	0.78
	Constant	−0.0367*	0.0212	−1.73
Market return	EMSI, Lag 1	0.0199***	0.0061	3.28
	EMSI, Lag 2	0.0057	0.0060	0.95
	EMSI, Lag 3	0.0064	0.0055	1.15
	EMSI, Lag 4	0.0298***	0.0055	5.45
	Market return, Lag 1	−0.4216***	0.0910	−4.63
	Market return, Lag 2	−0.1299	0.0936	−1.39
	Market return, Lag 3	−0.2515**	0.0887	−2.84
	Market return, Lag 4	−0.5981***	0.0573	−10.44
	Constant	−0.0059***	0.0015	−3.98

Note: **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed test). EMSI refers to the Equity Market Sentiment Index. Market return is measured as the daily logarithmic return of the SET Index.

Key findings highlight that the FINCIAL sector shows the strongest forward-looking predictive power of sentiment, with EMSI significantly affecting returns at multiple lags, particularly lag 4 (0.0755, z = 5.02). This aligns with the notion that financial stocks are extremely sensitive to expectations and macroeconomic outlooks.

The SERVICE sector also shows a robust delayed response, with EMSI at lag 4 significantly influencing returns (0.0483, z = 6.99), while returns show persistent autoregressive patterns (e.g., lag 4: −0.9458, z = −39.11), suggesting longer behavioral adjustment periods.

In CONSUMP, EMSI is predictive at earlier lags (lag 2: 0.0176, z = 3.12), with sentiment playing a role in short-term price dynamics. In contrast, sentiment only has an impact in INDUS at lag 1 (0.0063, z = 2.3), showing faster information absorption by the market.

For AGRO, EMSI is shaped by prior returns (e.g., lag 2: –1.0879, z = –2.35), but its predictive power for returns is weak, appearing only at lag 4 (0.0486, z = 2.00). RESOURC follows a similar pattern, where EMSI is driven by past returns (–1.0389, z = –2.29), but lacks predictive strength.

Static regression estimates for PROPCON (0.0375, t = 42.9) and TECH (0.0437, t = 32.85) confirm that sentiment influences return instantaneously in these sectors, due to higher liquidity or speculative trading. However, the absence of lagged dynamics rules out the estimation of IRFs.

Therefore, these results underscore the heterogeneity in sentiment transmission across industries. Some sectors respond quickly and persistently to sentiment (e.g., FINCIAL, SERVICE), while others reflect sentiment reactively (e.g., AGRO, RESOURC), and in some, sentiment effects are immediate but not sustained (e.g., PROPCON, TECH). This diversity calls for sector-specific modeling strategies when applying behavioral finance principles in emerging markets.

4.6 Granger Causality Test

Table 6 reports the results of Granger causality Wald tests to evaluate the temporal predictive relationship between investor sentiment—measured by the Equity Market Sentiment Index (EMSI)—and sectoral stock returns in the Thai equity market. The analysis reveals important cross-industry differences in the causal linkages, with results reported at the 5% significance threshold.

At the overall market level, EMSI is found to Granger-cause stock returns (p = 0.000), confirming the forward-looking predictive power of sentiment. This finding supports the hypothesis that sentiment can serve as a leading indicator of market behavior, in line with behavioral finance theory.

At the sector level, several industries show statistically significant Granger-causal relationships at the 5% level. In the consumer products (CONSUMP) sector, bidirectional causality is observed: EMSI both influences (p = 0.010) and is influenced by (p = 0.018) stock returns. This feedback loop implies dynamic interactions between investor mood and consumer sector valuation.

In the financial (FINCIAL) sector, EMSI significantly Granger-causes stock returns (p = 0.000), with no reverse effect. This unidirectional pattern suggests that sentiment in this sector is exogenous and forward-looking, due to its link with macroeconomic expectations and investor confidence. The industrial (INDUS) sector also displays significant causality from EMSI to returns (p = 0.030), while no evidence of reverse causality is found. Similarly, in the resources (RESOURC) sector, past market returns significantly Granger-cause EMSI (p = 0.022), showing that sentiment in this industry is more reactive than predictive.

For other sectors such as AGRO and SERVICE, no statistically significant Granger causality is detected at the 5% level. Finally, PROPCON and TECH are excluded from Granger causality testing due to an optimal lag length of zero, which shows that the relationship between sentiment and returns is contemporaneous, thus violating the lag-dependent structure required for Granger causality tests. Thus, these results underscore the importance of sector-specific modeling in sentiment analysis and highlight EMSI's role as a valid predictor of returns in key segments of the Thai equity market.

While the statistical findings show that EMSI significantly Granger-causes stock returns in several sectors, the economic size of these effects calls for further scrutiny. For example, although coefficients are statistically significant at conventional levels, the actual effect sizes are modest in industries such as Industrials and ICT, suggesting limited practical predictability. Moreover, the lack of statistical significance in certain sectors (e.g., Property and Finance) calls for caution in overgeneralizing the results. This pattern may reflect structural differences in how sentiment is transmitted across industries with varying liquidity, investor composition, and exposure to global factors.

Table 6: Granger Causality Wald Test Results by Industry

Industry	Dependent Variable	Excluded Variable	Chi-Square	Degrees of Freedom	p-value	Granger-Causal Direction
Overall	EMSI	Market return	6.806	4	0.146	No
	Market return	EMSI	37.860	4	0.000	Yes
AGRO	EMSI	Market return	8.132	4	0.087	No
	Market return	EMSI	6.326	4	0.176	No
CONSUMP	EMSI	Market return	11.901	4	0.018	Yes
	Market return	EMSI	13.232	4	0.010	Yes
FINCIAL	EMSI	Market return	0.816	4	0.936	No
	Market return	EMSI	31.618	4	0.000	Yes
INDUS	EMSI	Market return	0.374	2	0.830	No
	Market return	EMSI	7.007	2	0.030	Yes
RESOURC	EMSI	Market return	5.223	1	0.022	Yes
	Market return	EMSI	0.0531	1	0.818	No
SERVICE	EMSI	Market return	9.200	4	0.056	No
	Market return	EMSI	50.129	4	0.000	Yes

Note: EMSI denotes the Equity Market Sentiment Index. A p-value less than 0.05 indicates rejection of the null hypothesis that the excluded variable does not Granger-cause the dependent variable. Granger causality tests assess whether lagged values of one variable help predict another, and with no lag structure in PROPCON and TECH industries, such a test is not applicable.

To strengthen the robustness of the findings, this study incorporates impulse response functions (IRFs), which trace the dynamic responses of sectoral returns to EMSI shocks over time. These IRFs provide valuable insight into the temporal structure of the sentiment–return relationship, beyond what is captured by contemporaneous correlations. However, the analysis does not include additional robustness procedures such as variance decomposition, out-of-sample forecast evaluations, or structural stability tests. These omitted checks represent important avenues for future research. Furthermore, while several coefficients are statistically significant, their economic size is still modest in certain sectors, highlighting the importance of interpreting significance in conjunction with effect size and practical relevance.

4.7 Impulse Response Function (IRF) of SET Returns to EMSI Shocks

Impulse response functions (IRFs) are included to trace the dynamic reaction of returns to EMSI shocks over time, helping validate the temporal relationship beyond contemporaneous effects. The impulse response function (IRF) depicted in Figure 2 illustrates the dynamic effect of a one-standard-deviation shock in the Equity Market Sentiment Index (EMSI) on overall market returns (SET Index) over a 10-day horizon. The IRF traces how an exogenous sentiment innovation influences stock return movements through time, with the shaded area representing the 95% confidence interval around the orthogonalized impulse response estimate.

As shown in Figure 2, a positive EMSI shock generates an immediate increase in market returns, with the response peaking sharply in the first period. This suggests that the Thai stock market reacts quickly to changes in investor sentiment, aligning with behavioral finance theories that emphasize sentiment-driven return formation in the short run. The positive effect, although gradually declining over subsequent steps, is still above zero across the forecast horizon, showing a persistent influence of sentiment.

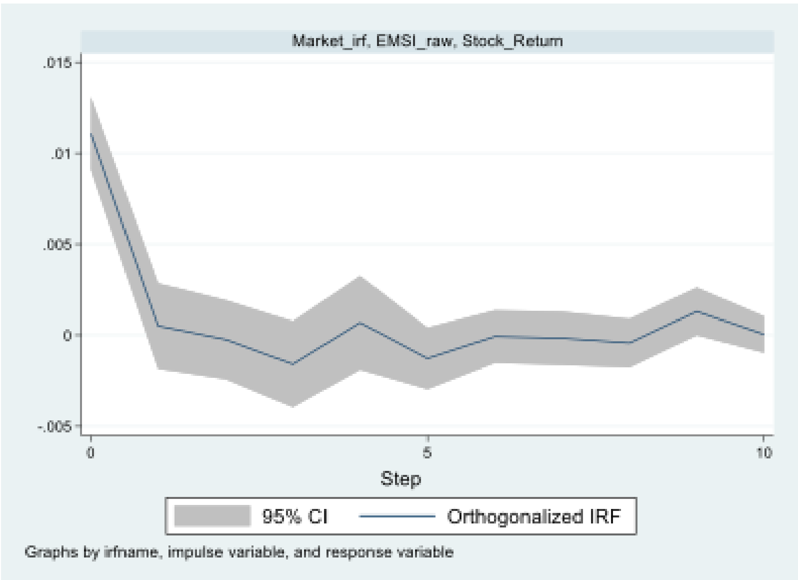

Figure 2: Impulse Response Function (IRF) of SET Returns to EMSI Shocks

However, while the first response is clearly distinguishable and statistically significant, the confidence band widens after the third step, and the response trajectory flattens. This pattern reflects growing uncertainty in the long-run effect and potential mean reversion as fundamental drivers regain dominance. Overall, the results reinforce the predictive and contemporaneous value of EMSI in modeling stock return dynamics and underscore the importance of sentiment as a behavioral determinant in Thailand's equity market.

4.8 Industrial Impulse Response Functions of Stock Returns to EMSI Shocks

Figure 3 presents the impulse response functions of stock returns to EMSI shocks across six Thai industries. In the AGRO sector (top left panel) and FINCIAL sector (top right panel), stock returns exhibit pronounced volatility in response to sentiment shocks. AGRO shows a first surge followed by a reversal, suggesting overreaction and subsequent correction, while FINCIAL displays a cyclical and persistent response, implying a delayed and extended sentiment effect typical of finance-related assets that are more sensitive to macroeconomic expectations.

In contrast, the CONSUMP sector (top middle panel), INDUS sector (bottom left panel), and RESOURC sector (bottom middle panel) show weak and short-lived responses. CONSUMP and INDUS register brief positive reactions that quickly revert to baseline, showing limited behavioral amplification and efficient sentiment absorption, while RESOURC shows almost no reaction, due to the sector's dependence on external commodity prices rather than domestic investor sentiment.

The SERVICE sector (bottom right panel) reveals a fluctuating pattern with alternating positive and negative responses over time, suggesting cyclical investor behavior and delayed sentiment transmission. Overall, these patterns confirm that the transmission of sentiment shocks varies across sectors in both timing and intensity, reinforcing the relevance of tailoring sentiment-based investment strategies to industry-specific dynamics in emerging markets.

Therefore, the figure of IRF results underscores that sentiment shocks, as captured by EMSI, affect industries differently in both size and duration. These sectoral disparities emphasize the need for sentiment-aware portfolio strategies that are tailored to industry-specific behavior in emerging markets like Thailand.

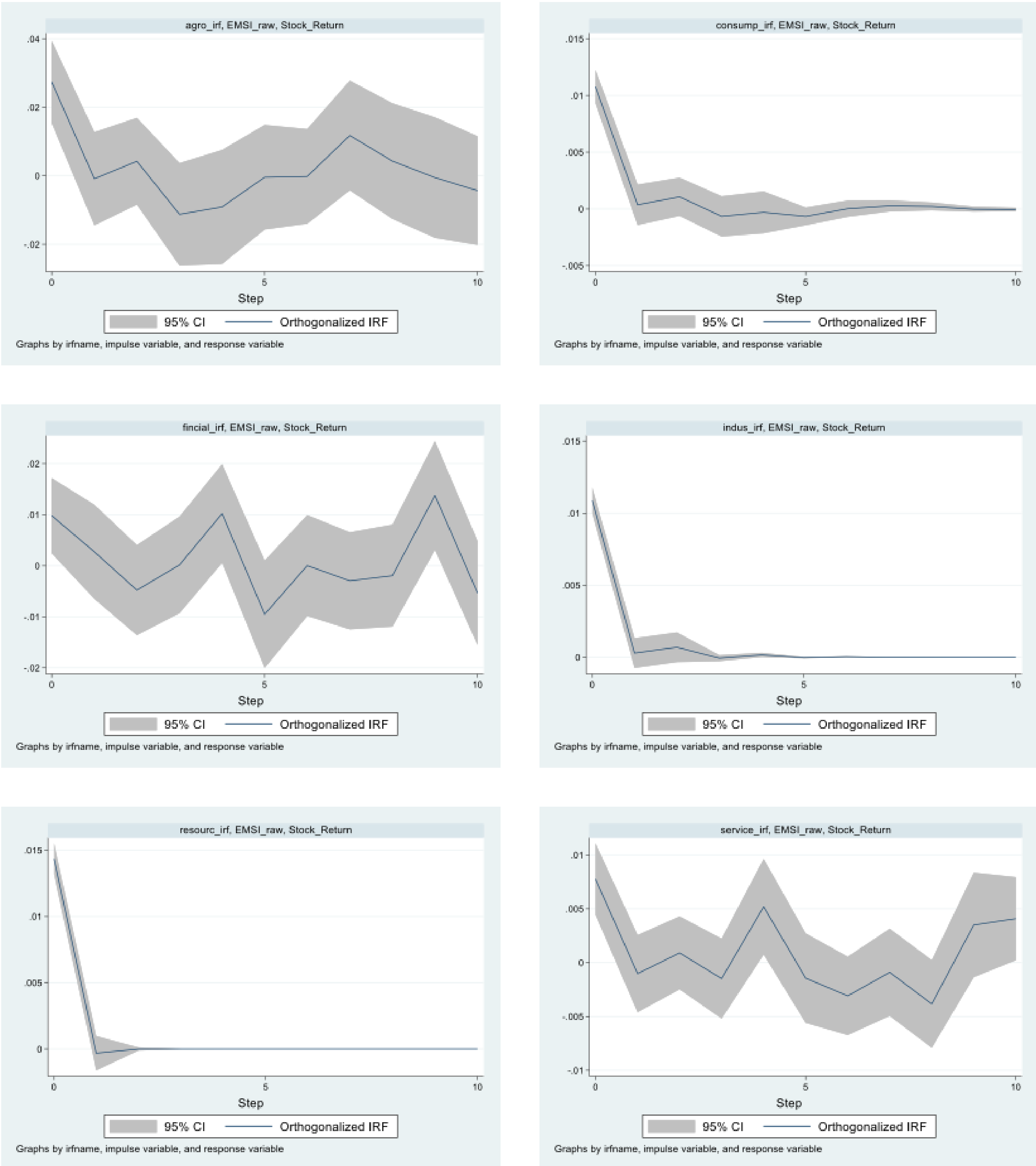

Figure 3: Industrial Impulse Response Functions of Stock Returns to EMSI Shocks

5. CONCLUSION AND DISCUSSION

This study investigates the predictive ability of the Equity Market Sentiment Index (EMSI) for stock returns in the Thai equity market, with a particular focus on sectoral heterogeneity. By applying Vector Autoregression (VAR) and Granger causality tests to daily data from 2019 to 2024, the findings reveal that EMSI Granger-causes returns in several sectors, most notably in finance and consumer-related industries, while other sectors show weaker or contemporaneous sentiment-return relationships. The impulse response analysis further confirms that positive sentiment shocks tend to produce short-term increases in returns, reinforcing the behavioral finance view that investor mood influences price dynamics, especially in markets with high retail participation and limited informational efficiency.

These results are consistent with prior research. For instance, Debata et al. (2021) found that sentiment indicators significantly affect liquidity and volatility in India, especially under uncertainty. Similarly, Amiri Hosseini (2023) reported that investor sentiment drives volatility in the Tehran Stock Exchange, and Zhu et al. (2022) emphasized that sentiment interacts with macroeconomic uncertainty to influence stock returns across different time horizons. Chu and Gu (2024) demonstrated that high-frequency sentiment indices improve return forecasts when embedded in MIDAS models. Our study aligns with these findings and extends them by focusing on Thailand, a Southeast Asian emerging market that remains underrepresented in the sentiment literature. Importantly, this study moves beyond aggregate sentiment-return relationships by uncovering how sentiment transmission varies across industries. This sectoral disaggregation provides a more nuanced understanding of market behavior and offers practical insights for investors and policymakers. For example, sector-specific sentiment effects are particularly relevant in Thailand, where retail investors dominate trading in some industries, leading to heterogeneous behavioral patterns and return predictability. This approach responds to calls in the literature for more disaggregated and context-specific analysis of sentiment dynamics (Piñeiro-Chousa et al., 2021; Shahid & Abbas, 2019).

From a theoretical standpoint, the study draws on behavioral asset pricing theory, which suggests that investor sentiment can lead to mispricing, particularly in environments where arbitrage is limited (Baker & Wurgler, 2006). The results underscore the importance of interpreting statistical outcomes within a broader economic and behavioral framework, emphasizing effect sizes and practical relevance rather than relying solely on p-values or mechanical significance thresholds. This helps ensure that the findings contribute meaningfully to investor decision-making and policy considerations in sentiment-sensitive markets like Thailand.

Despite these contributions, the study has several limitations. First, the analysis relies on in-sample testing and does not incorporate out-of-sample forecasting or rolling-window model stability assessments, which may affect the generalizability of the results. Second, while impulse response functions are used to trace the effect of sentiment shocks, the study does not include other complementary robustness diagnostics such as forecast error variance decomposition, structural break tests, or alternative model specifications.

From a policy perspective, the results suggest that financial regulators and market monitoring units should consider integrating real-time, market-implied sentiment indicators like EMSI into early warning systems. Unlike media-based or search-engine sentiment proxies, which may reflect delayed or noisy signals, EMSI captures actual trading behavior and thus offers a timelier and behaviorally grounded tool for predicting market stress. For institutional investors, the differential impact of sentiment across sectors reinforces the need for adaptive strategies that account for behavioral asymmetries, echoing insights from Da et al. (2015) and Calzadilla et al. (2021) regarding the feedback loop between mood and market volatility.

Future research could build on these findings by refining EMSI's construction to account for local trading patterns and investor composition. While EMSI already improves upon indirect sentiment proxies, incorporating sector-specific features, such as the dominance of retail investors in certain industries or trading frequency metrics, could enhance its precision. Additionally, combining EMSI with advanced econometric or machine learning techniques (Chu & Gu, 2024) may improve its forecasting power under nonlinear and high-frequency conditions. Comparative analyses across ASEAN markets could provide deeper insights into regional differences in sentiment transmission and investor behavior.

REFERENCES

Amiri Hosseini, M. (2023). Impact of Investors' Sentiments on Volatility of Stock Exchange Index in Tehran Stock Exchange. *Advances in Mathematical Finance and Applications, 5*(1), 291.

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

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

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636.

Bandopadhyaya, A., & Jones, A. L. (2006). Measuring investor sentiment in equity markets. In *Asset Management: Portfolio Construction, Performance and Returns* (pp. 258–269). Springer.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307–343.

Bing, L. (2012). Sentiment analysis and opinion mining (synthesis lectures on human language technologies). *University of Illinois: Chicago, IL, USA*.

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

Calzadilla, J., Bordonado-Bermejo, M., & González-Rodrigo, E. (2021). A systematic review of ordinary people, behavioural financial biases. *Economic Research-Ekonomska Istraživanja, 34*(1), 2767–2789.

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

Chu, X., & Gu, Y. (2024). Does intraday high-frequency investor sentiment help forecast stock returns? Evidence from the MIDAS models. *China Finance Review International, 14*(2), 123–145.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance, 66*(5), 1461–1499.

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

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

Debata, B., Dash, S. R., & Mahakud, J. (2021). Stock market liquidity: Implication of local and global investor sentiment. *Journal of Public Affairs, 21*(3), e2231.

Du, K., Xing, F., Mao, R., & Cambria, E. (2024). Financial sentiment analysis: Techniques and applications. *ACM Computing Surveys, 56*(9), 1–42.

Fama, E. F. (1970). Efficient capital markets. *The Journal of Finance, 25*(2), 383–417.

Jin, L. J., & Sui, P. (2022). Asset pricing with return extrapolation. *Journal of Financial Economics, 145*(2), 273–295.

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

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin, 127*(2), 267.

Mishev, K., Gjorgjevikj, A., Vodenska, I., Chitkushev, L. T., & Trajanov, D. (2020). Evaluation of sentiment analysis in finance: from lexicons to transformers. *IEEE access, 8*, 131662–131682.

Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y., & Ngo, D. C. L. (2014). Text mining for market prediction: A systematic review. *Expert Systems with Applications, 41*(16), 7653–7670.

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The Journal of Finance, 67*(4), 1219–1264.

Peterson, R. L. (2007). Affect and financial decision-making: How neuroscience can inform market participants. *The Journal of Behavioral Finance, 8*(2), 70–78.

Piñeiro-Chousa, J., López-Cabarcos, M. Á., Caby, J., & Šević, A. (2021). The influence of investor sentiment on the green bond market. *Technological Forecasting and Social Change, 162*, 120351.

Shahid, M. S., & Abbas, M. (2019). Does corporate governance play any role in investor confidence, corporate investment decisions relationship? Evidence from Pakistan and India. *Journal of Economics and Business, 105*, 105839.

Shiller, R. J. (1983). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?: Reply. *American Economic Review, 73*(1).

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

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

Whaley, R. E. (2000). The investor fear gauge. *Journal of Portfolio Management, 26*(3), 12.

Zhu, H., Wu, H., Ren, Y., & Yu, D. (2022). Time-frequency effect of investor sentiment, economic policy uncertainty, and crude oil on international stock markets: evidence from wavelet quantile analysis. *Applied Economics, 54*(53), 6116–6146.

Appendix 1

Table A1: Vector Autoregression (VAR) Results, EMSI and Market Return, by Industry

Industry	Dependent Variable	Independent Variable	Coefficient	Std. Error	Z-stat / t-stat
ARGO	EMSI	EMSI, Lag 1	0.0160	0.0662	0.24
		EMSI, Lag 2	–0.0396	0.0638	–0.62
		EMSI, Lag 3	–0.1311**	0.0620	–2.11
		EMSI, Lag 4	–0.1065*	0.0631	–1.69
		Market return, Lag 1	–0.8350**	0.4065	–2.05
		Market return, Lag 2	–1.0879**	0.4630	–2.35
		Market return, Lag 3	–0.7294**	0.3122	–2.34
		Market return, Lag 4	0.0336	0.0882	0.38
		Constant	–0.0272	0.0196	–1.39
	Market return	EMSI, Lag 1	0.0331	0.0254	1.30
		EMSI, Lag 2	0.0272	0.0245	1.11
		EMSI, Lag 3	0.0121	0.0238	0.51
		EMSI, Lag 4	0.0486**	0.0242	2.00
		Market return, Lag 1	–0.3459**	0.1562	–2.21
		Market return, Lag 2	–0.0907	0.1779	–0.51
		Market return, Lag 3	–0.4089***	0.1200	–3.41
		Market return, Lag 4	–0.8182***	0.0339	–24.13
		Constant	0.0301***	0.0075	3.99
COMSUMP	EMSI	EMSI, Lag 1	0.0728	0.0986	0.74
		EMSI, Lag 2	0.1628	0.1022	1.59
		EMSI, Lag 3	–0.1049	0.0900	–1.17
		EMSI, Lag 4	–0.0902	0.0937	–0.96
		Market return, Lag 1	–2.3580	1.5986	–1.48
		Market return, Lag 2	–5.4614***	1.8940	–2.88
		Market return, Lag 3	–0.5872	1.7172	–0.34
		Market return, Lag 4	1.0708	1.4404	0.74
		Constant	–0.0244	0.0168	–1.45
	Market return	EMSI, Lag 1	0.0094*	0.0054	1.72
		EMSI, Lag 2	0.0176***	0.0056	3.12
		EMSI, Lag 3	0.0020	0.0050	0.4
		EMSI, Lag 4	–0.0041	0.0052	–0.79
		Market return, Lag 1	–0.1909**	0.0882	–2.16
		Market return, Lag 2	–0.3106***	0.1045	–2.97
		Market return, Lag 3	–0.0524	0.0948	–0.55
		Market return, Lag 4	0.1562**	0.0795	1.97
		Constant	0.0007	0.0009	0.81

Table A1: Vector Autoregression (VAR) Results, EMSI and Market Return, by Industry (Cont.)

Industry	Dependent Variable	Independent Variable	Coefficient	Std. Error	Z-stat / t-stat
FINCIAL	EMSI	EMSI, Lag 1	−0.0195	0.0661	−0.29
		EMSI, Lag 2	−0.0971	0.0627	−1.55
		EMSI, Lag 3	−0.1507**	0.0650	−2.32
		EMSI, Lag 4	−0.1054	0.0654	−1.61
		Market return, Lag 1	−0.1636	0.3644	−0.45
		Market return, Lag 2	−0.0386	0.3410	−0.11
		Market return, Lag 3	−0.2102	0.3403	−0.62
		Market return, Lag 4	0.0335	0.1124	0.3
		Constant	−0.0358	0.0224	−1.6
	Market return	EMSI, Lag 1	0.0371**	0.0152	2.44
		EMSI, Lag 2	0.0194	0.0144	1.34
		EMSI, Lag 3	0.0261*	0.0149	1.75
		EMSI, Lag 4	0.0755***	0.0150	5.02
		Market return, Lag 1	−0.7184***	0.0837	−8.59
		Market return, Lag 2	−0.7829***	0.0783	−10
		Market return, Lag 3	−0.7044***	0.0781	−9.02
		Market return, Lag 4	−0.9394***	0.0258	−36.41
		Constant	−0.0123**	0.0051	−2.4
INDUS	EMSI	EMSI, Lag 1	−0.0350	0.0473	−0.74
		EMSI, Lag 2	−0.0337	0.0474	−0.71
		Market return, Lag 1	−0.4415	0.8105	−0.54
		Market return, Lag 2	−0.2233	0.8509	−0.26
		Constant	−0.0257***	0.0092	−2.79
	Market Return	EMSI, Lag 1	0.0063**	0.0027	2.3
		EMSI, Lag 2	−0.0034	0.0027	−1.23
		Market return, Lag 1	−0.1277***	0.0466	−2.74
		Market return, Lag 2	0.1577***	0.0489	3.22
		Constant	−0.0002	0.0005	−0.43
PROPCON	EMSI	Market return	14.6691***	0.3420	42.9
		Constant	−0.0178***	0.0046	−3.86
	Market return	EMSI	0.0375***	0.0009	42.9
		Constant	0.0006**	0.0002	2.58
RESOURC	EMSI	EMSI, Lag 1	0.0033	0.0383	0.09
		Market return, Lag 1	−1.0389**	0.4546	−2.29
		Constant	−0.0220***	0.0078	−2.82
	Market return	EMSI, Lag 1	0.0008	0.0033	0.23
		Market return, Lag 1	−0.0361	0.0388	−0.93
		Constant	−0.0005	0.0007	−0.79

Table A1: Vector Autoregression (VAR) Results, EMSI and Market Return, by Industry (Cont.)

Industry	Dependent Variable	Independent Variable	Coefficient	Std. Error	Z-stat / t-stat
SERVICE	EMSI	EMSI, Lag 1	0.0673	0.0734	0.92
		EMSI, Lag 2	–0.0953	0.0708	–1.35
		EMSI, Lag 3	–0.0861	0.0744	–1.16
		EMSI, Lag 4	–0.0851	0.0649	–1.31
		Market return, Lag 1	–2.8574***	1.0284	–2.78
		Market return, Lag 2	–0.1957	0.8709	–0.22
		Market return, Lag 3	–2.0022*	1.0343	–1.94
		Market return, Lag 4	0.0288	0.2271	0.13
		Constant	–0.0287	0.0216	–1.33
	Market return	EMSI, Lag 1	0.0058	0.0078	0.74
		EMSI, Lag 2	0.0116	0.0075	1.53
		EMSI, Lag 3	0.0044	0.0079	0.55
		EMSI, Lag 4	0.0483	0.0069	6.99
		Market return, Lag 1	–0.3254***	0.1095	–2.97
		Market return, Lag 2	–0.3106***	0.0928	–3.35
		Market return, Lag 3	–0.3162***	0.1102	–2.87
		Market return, Lag 4	–0.9458***	0.0242	–39.11
		Constant	–0.0046**	0.0023	–1.99
TECH	EMSI	Market return	9.5627***	0.2911	32.85
		Constant	–0.0224***	0.0053	–4.26
	Market return	EMSI	0.0437***	0.0013	32.85
		Constant	0.0011***	0.0004	3.16

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed test). EMSI refers to the Equity Market Sentiment Index; Market return is the daily return of the SET Index. For the PROPCON and TECH industries, static regression models are employed instead of VAR, as the optimal lag selection criteria indicate no significant lag structure, making VAR modeling inappropriate.