

Information Priorities for investment decision-making and fear during market crashes: Analyzing East Asian Countries with Bayesian Mindsong Framework Analytics

Minh-Hoang Nguyen ¹, Dan Li ^{2,*}, Thien-Vu Tran ³, Phuong-Tri Nguyen ⁴, Thi Mai Anh Tran ⁵, Quan-Hoang Vuong ^{1,6}

¹ Centre for Interdisciplinary Social Research, Phenikaa University, Hanoi, Vietnam

² Yan'an University, Yan'an, China

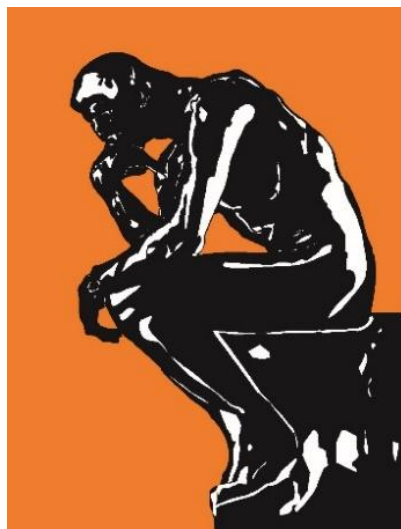
³ Vietnam-Korea University of Information and Communication Technology, the University of Danang, Da Nang, Vietnam

⁴ Securities Research and Training Center, State Security Commission, Ho Chi Minh City, Vietnam

⁵ College of Forest Resources and Environmental Science, Michigan Technological University, Houghton, USA

⁶ Adjunct Professor, University College, Korea University, Seoul, South Korea

*Corresponding Email: dellelee103@gmail.com (Dan Li)



December 12, 2024

[Original working draft v2 / Un-peer-reviewed]

“It is difficult to have a grasp of philosophy in life. Well, because everyone knows only bits here and there. And generalization would likely end up false. Such bad philosophizing in the bird village has brought harm to numerous birds.”

— In “The Philosopher Bird”; *Wild Wise Weird* (2024)

Abstract

Market crises amplify fear, disrupting rational decision-making of stock investment. This study examines the relationship between investors' information priorities—such as intuition, company performance, technical analysis, and other factors—and their fear responses (freeze, flight, and hiding) during market crashes. Using the Bayesian Mindsponge Framework (BMF) to analyze data from 1,526 investors in China and Vietnam, the findings reveal complex dynamics. We found positive associations between investors' prioritization of social influence and intuition for investment decision-making with being freeze (i.e., not knowing what to do with the owned stock), between prioritization of professionals' evaluation and intuition with fleeing (i.e. giving up stock investment permanently), and between prioritization of professionals' evaluation and social influence with hiding (i.e., stopping investing in stock for a while). In contrast, prioritization of companies' performance metrics (e.g., net profit, debt, etc.) was negatively associated with being freeze, fleeing, and hiding. Meanwhile, prioritization of professionals' evaluation, technical analysis, and liquidity was negatively associated with being freeze, fleeing, and hiding, respectively. The study highlights the importance of disseminating transparent, accurate information through government and media channels, along with implementing financial education programs, to promote rational investment decisions and reduce fear-driven behaviors.

Keywords: information priorities; investment decision-making; fear responses, crises; mindsponge theory

1. Introduction

Financial crises disrupt markets globally. One of their most profound impacts lies in the emotional responses they trigger, particularly fear and anxiety (Mansoor & Jalal, 2010). Recent events, such as the 2022 cryptocurrency crash and the market volatility following the COVID-19 pandemic, have intensified these emotional reactions among investors (Sattar et al., 2020; Vasileiou, 2021; Gaies et al., 2023). While fear is an essential survival mechanism, during financial crises, it can become a destructive force that paralyzes rational decision-making (Soydemir et al., 2017; LeDoux & Daw, 2018; Ali et al., 2023). Common behavioral expressions of fear include freeze (decision paralysis), flight (panic selling), and hiding (market withdrawal) (Adolphs, 2013; Sutejo et al., 2023; Lal et al., 2024). These reactions can lead to suboptimal investment decisions, with studies showing that median investors earn a zero to negative return after panic selling, and many panic sellers who reinvest often repurchase equities at higher prices than they sold for (Elkind et al., 2021). Moreover, when fear grips a large number of investors simultaneously, it can trigger systemic risks, inflate stock price bubbles, destabilize financial institutions, and precipitate cycles of market volatility, ultimately slowing economic recovery (Schulmerich et al., 2015; Neuhauser, 2015; Lehnert, 2020; Elkind et al., 2021; So et al., 2022).

During financial crises, investors often prioritize specific sources of information to guide their decisions, such as profit and liquidity, company performance, social influence, intuition, professional evaluations, and technical analysis (Hoffmann et al., 2013; Arand &

Kerl, 2012; Spyrou, 2013; Feuerriegel & Prendinger, 2016). Profit and liquidity are among the primary considerations driving investment choices (Hidayat et al., 2018; Shrestha, 2020). Dash (2010) found that modern investors are generally well-informed and tend to align their investments with their risk tolerance levels, especially during periods of market volatility. Company performance metrics, such as earnings reports and return ratios, also influence investor decisions by providing insights into an organization's financial health and growth potential (Huang, 2019). Jasiniak et al. (2023) found that during the COVID-19 pandemic, investors' fear responses and market trends closely influenced each other, with sectors like energy, financials, and real estate showing a stronger correlation with fear indices than others. Furthermore, social influence also impacts investor behavior, often leading to herding (Spyrou, 2013; Dang & Lin, 2016). Biel et al. (2010) explore two types of social influence on stock market dynamics, with direct influence explicitly following other's actions and indirect influence stemming from common knowledge or shared investment strategies. The author suggests that investors are concerned about their reputation and tend to align their decisions with the majority to avoid negative social consequences. Andersson et al. (2014) and Sudrajat (2022) added that social influence can arise from a desire for conformity or a fear of missing out.

Intuition, often described as a gut feeling or experiential knowledge, represents a more subjective element in guiding investor decisions. While difficult to quantify, intuitive judgments can be useful in situations of uncertainty or incomplete information (Huang & Pearce, 2015). Taffler et al. (2017) reveal that despite having rigorous investment processes, fund managers often incorporate intuitive judgments into their decisions. Professional evaluation, including analyst reports, expert opinions, and financial advisories, also guides investors' decisions by providing specialized insights (Yukselturk & Tucker, 2015). These evaluations can serve as valuable inputs for decision-making, especially for investors lacking the time or expertise to conduct in-depth analyses (Sharda, 2021). Finally, technical analysis, involving the study of historical price movements and trading volumes, offers a systematic approach to predicting future market behavior, which influences investor's decisions (Pompian, 2023). Prorokowski (2011) found that technical analysis is a preferred tool utilized by non-professional investors.

While existing research provides valuable insights into the impacts of fear on investors' decision-making and performance (Chiu et al., 2014; Lee & Andrade, 2014; Guiso et al., 2018; Vasileiou, 2021; Zargar & Kumar, 2021), little is known about factors contributing to investors' fear response during the financial crises. Specifically, the impacts of investors' information source priorities on different fear responses, such as freeze, flight, and hiding behaviors. To address this research gap, in this study, we aim to explore the relationship between investors' information source priorities and their fear responses during market crashes, utilizing a 2022 dataset of 1,526 Chinese and Vietnamese investors. The specific objectives of the study are:

- To investigate the influence of prioritized information sources on investors' freeze response during market crashes.
- To investigate the influence of prioritized information sources on investors' flight response during market crashes.

- To investigate the influence of prioritized information sources on investors' hiding responses during market crashes.

By examining different sources of information and expressions of fear response, we offer a comprehensive understanding of how information priorities shape fear responses during crises. Given the lack of prior research on this topic, this study serves as a pioneering inquiry into these relationships. For academia, this study contributes to expanding the existing literature on behavioral finance and the psychology of fear, especially in non-Western contexts. For investors, the study findings offer recommendations to improve decision-making effectiveness through emotional regulation strategies. For policymakers, the study results are expected to inform the development of strategies aimed at designing interventions that stabilize markets and mitigate the negative impacts of market crashes on the economy.

2. Methodology

We embraced the mindsponge theory for the conceptual framework and used Bayesian inference to validate this model empirically (Nguyen et al., 2022; Vuong et al., 2020). Particularly, the Bayesian Mindsponge Framework (BMF) analytic was used for statistical analysis on a dataset of 1526 Chinese and Vietnamese investors (Vuong et al., 2024). This dataset describes the emotions of investors and the driving elements of investors' behavior. Particularly, the factors that alleviated investors' fear during the market crash in China and Vietnam in 2022 and their regulation in the aftermath of the crisis are detailed in this dataset. We aim to investigate factors impacting the investors' fear in terms of freeze, flight, and hide, with the rationalization following.

2.1. Mindsponge-based rationalization

The mindsponge theory, developed by Vuong and Napier (2015), proposes a mechanism for how individuals absorb, filter, and rationalize information to shape their values and belief (Vuong & Napier, 2015). The information penetrates the layers of cultural and ideological setting (environment), comfort zone (filtering), and mindset (individual perception and belief). The mindsponge theory is particularly explained in interdisciplinary studies such as psychology, humanity, and social sciences (Vuong & Nguyen, 2024a, 2024b). The fear of individuals (i.e., investors) is a psychological phenomenon that individuals react or confront with the unpredicted financial situation (García-Monleón et al., 2024; Pixley, 2002). The behaviors of fear in the market volatility have exposed them to freeze or paralyze, flee or escape from the market, and hide or delay their investments. Facing the financial risks, investors tend to refrain from investing. In a mental process, the perceived fear might be affected by several factors.

First, the intuition or hunch of investors plays an important factor in the information process of the mind. This is because emotional responses could lead to irrational investment behaviors, and intuition could drive the decision-making process (Fenton-O'Creevy et al., 2011). Second, the evaluation from experts and professional groups could be an important hint to make decisions (Chen et al., 2023). Third, the impact of technology analysis on investor fear in the market is multifaceted, influencing both decision-making and emotional responses. Technical indicators and financial technologies shape investor

behavior, strengthening or alleviating fears in decision-making (Lee & Andrade, 2011). Fourth, Le and Andrade (2011) stated that people's tendency to believe that others are likely to feel, think, and behave like them. Hence, other people, such as acquaintances and friends, can influence investors' decisions. Finally, financial performance metrics are crucial factors in shaping investor perceptions and decisions, including company performance and profit liquidity. The positive financial performance of a company thrusts investors to decide; however, in the case of poor performance, investors tend to delay or escape from their investments (Bird et al., 2023). The description of the variables is presented in Table 1.

Thus, we hypothesized that factors of intuition, professional evaluation, technology analysis, social influence, company performance, and profit liquidity impacting freeze, flight, and hide are conceptualized in models 1, 2, and 3, respectively, as follows:

Model 1:

$$Fear_Freeze \sim normal(\mu, \sigma) \quad (1.1)$$

$$\mu = \beta_0 + \beta_1 * Priority_Intuition + \beta_2 * Priority_ProfessionalEvaluation + \beta_3 * Priority_TechAnalysis + \beta_4 * Priority_SocialInfluence + \beta_5 * Priority_CompanyPerformance + \beta_6 * Priority_ProfitLiquidity \quad (1.2)$$

$$\beta \sim normal(M, S) \quad (1.3)$$

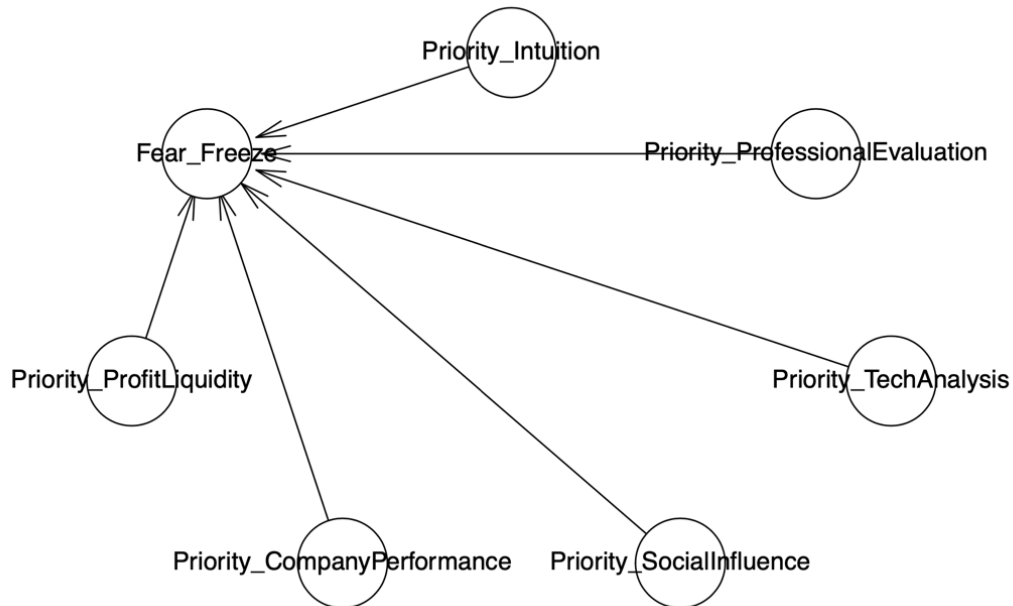


Figure 1: The logical network of the constructed model 1

Model 2:

$$Fear_Flight \sim normal(\mu, \sigma) \quad (2.1)$$

$$\mu = \beta_0 + \beta_1 * Priority_Intuition + \beta_2 * Priority_ProfessionalEvaluation + \beta_3 * Priority_TechAnalysis + \beta_4 * Priority_SocialInfluence + \beta_5 * Priority_CompanyPerformance + \beta_6 * Priority_ProfitLiquidity \quad (2.2)$$

$$\beta \sim normal(M, S) \quad (2.3)$$

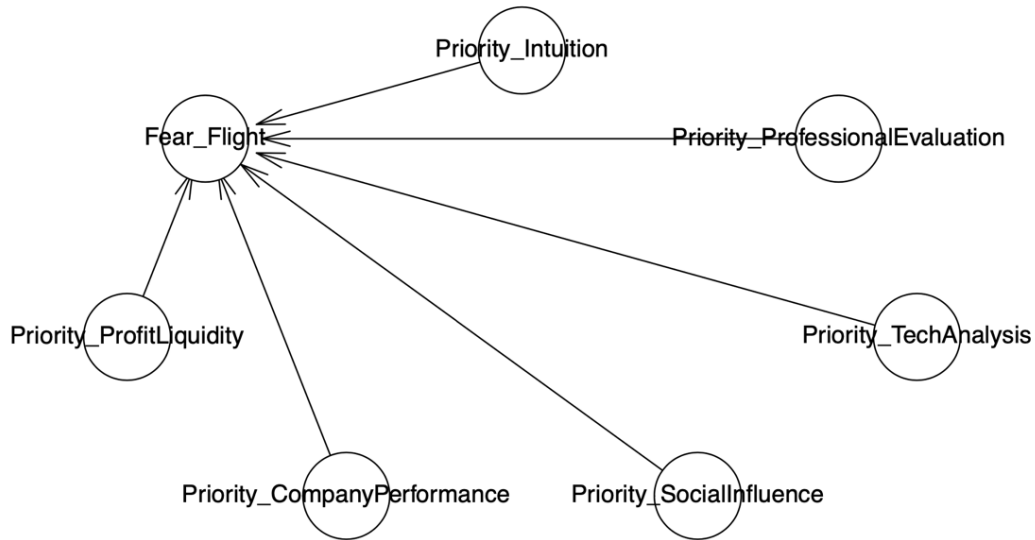


Figure 2: The logical network of the constructed model 2

Model 3:

$$Fear_Hide \sim normal(\mu, \sigma) \quad (3.1)$$

$$\mu = \beta_0 + \beta_1 * Priority_Intuition + \beta_2 * Priority_ProfessionalEvaluation + \beta_3 * Priority_TechAnalysis + \beta_4 * Priority_SocialInfluence + \beta_5 * Priority_CompanyPerformance + \beta_6 * Priority_ProfitLiquidity \quad (3.2)$$

$$\beta \sim normal(M, S) \quad (3.3)$$

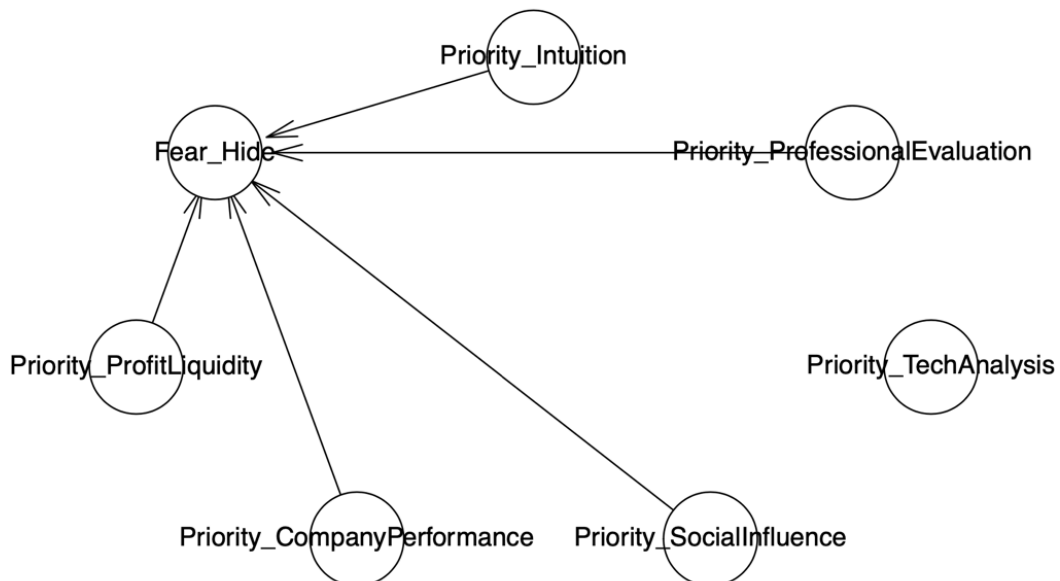


Figure 3: The logical network of the constructed model 3

Table 1. Variable description

Variable	Description	Data type	Coding
<i>Fear_Freeze</i>	Do not know what to do with owned stocks (E1_5)	Continuous	1 – No 2 – Yes, a few times 3 – Yes, many times
<i>Fear_Flight</i>	Give up stock investment permanently (E1_2)	Continuous	1 – No 2 – Yes, a few times 3 – Yes, many times
<i>Fear_Hide</i>	Stop investing in stocks for a while (E1_3)	Continuous	1 – No 2 – Yes, a few times 3 – Yes, many times
<i>Priority_Intuition</i>	Intuition/ hunch (D1_16)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
<i>Priority_ProfessionalEvaluation</i>	Experts' evaluation (D1_12)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree

	Investment groups' evaluation (D1_13)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
<i>Priority_TechnologyAnalysis</i>	Technical analysis (D1_11)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
<i>Priority_SocialInfluence</i>	Acquaintances' evaluation (D1_14)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
	Friends' investment behavior (D_15)		
<i>Priority_CompanyPerformance</i>	Net profit (D1_4)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
	Debt (D1_5)		
	Financial metrics (D1_6)		
<i>Priority_ProfitLiquidity</i>	Dividends (D1_1)	Continuous	1 – strongly disagree 2 – disagree 3 – Agree 4 – Strongly agree
	Cash dividends (D1_2)		
	Stock liquidity (D1_3)		

2.2 Materials and Methods

The dataset was collected from two countries, China and Vietnam, in the aftermath of the market crisis in 2022. The questionnaire survey includes six components: Environment,

trust evaluation, information collection and processing, mindset, outcomes, and socio-demographic information, which reflect the information-processing perspective of Mindsponge Theory (Vuong et al., 2024). In total, 1526 Chinese and Vietnamese investors responded to this questionnaire, of which 75 participants were Vietnamese, accounting for 5%, and 1451 participants were Chinese, accounting for 95%. The dataset was collected through Google Forms at the Securities Research and Training Center of the State Security Commission in Ho Chi Minh City, Vietnam, between March and May 2023. On the other hand, the survey in China was conducted through the WeChat mini-app ‘Survey Star,’ targeting members of 10 WeChat stock trading groups from April to May 2023.

In terms of gender, the ratio of males and females in the dataset accounts for 51.38% and 48.62%, respectively. Most of them had achieved university-level degrees (51.09%) and graduate level (14.81%), while the remaining respondents hold the K-12 educational level. 44.17% of investors had attended the training courses and classes to learn finance knowledge and skills, while 28.96% of investors had not. The remaining are currently enrolled in these courses and classes (26.87%). The average of surveyed participants is 40.09 years old, ranging from 21 to 58, with a standard deviation of 7.15 years old.

From the dataset, three dependent variables related to investors’ fear are included in our test. First, the *Fear_Freeze* (variable *E1_5*) is a variable demonstrating the psychological aspect of investors that they feel paralyzed by fear and are unable to make decisions, even if they are able to perceive the potential benefits from these invested actions. This variable expresses investors “do not know what to do with owned stocks.” Different from the *Fear_Freeze*, the *Fear_Flight* (variable *E1_2*) variable illustrates the psychological reactions of investors to withdraw their investments or exit the market. “Flight” means escaping from a threatening situation and refraining from investments. The *Fear_Flight* shows “give up stock investment permanently.” Third, the *Fear_Hide* (variable *E1_3*) is also a psychological behavior in which investors postpone their actions against the perceived financial risk. The *Fear_Hide* describes “stop investing in stocks for a while.”

For the independent variables, six constructs are incorporated in the conceptual framework. First, intuition (*Priory_Intuition*) refers to the priority of investors in making decisions relying on their feelings, instinct, or subconscious judgment rather than analysis. Second, the professional evaluation (*Priority_ProfessionalEvaluation*) represents the priority of making decisions contingent on the specialized knowledge of experts and investment groups’ evaluation. Third, the technology analysis (*Priority_TechAnalysis*) refers to the priority of using the findings and results of technical analyses in the decision-making process. Fourth, the social influence (*Priority_SocialInfluence*) expresses the investors’ prioritization of their acquaintances and friends’ influences in decision-making processes. Fifth, investors need information about company performance (*Priority_CompanyPerformance*), such as net profit, debt, and financial metrics to decide their investments. Finally, the *Priority_ProfitLiquidity* variable demonstrates the investors’ priority of profit liquidity of a company, such as dividends, cash dividends, and stock liquidity, to make investment decisions. All dependent and independent variables are illuminated in Table 1.

We employed the BMF in this current study for a couple of things. The BMF incorporates the Bayesian analysis and the Mindsponge theory. First, the Bayesian analysis was conducted using the bayesvl R package, which is aided by the Markov chain Monte Carlo (MCMC) algorithm. Unlike frequentist statistics, Bayesian analysis is more advantageous because it is applied to a wide range of models, and the interpretation of findings is more flexible. Furthermore, the bayesvl R package has a user-friendly interface, and visually eye-catching graphics, and is open-source software (Nguyen et al., 2022; Vuong et al., 2022). Second, the Mindsponge Theory describes the mechanism to accept or reject information based on personal perception, which fits the study on psychological aspects and human behavior (Nguyen et al., 2023). The models were fitted with three Markov chains. Each chain has 2000 iterations for warmup and 5000 iterations. We also checked the validity of the analysis to avoid the subjective bias.

We examined the robustness of models in two ways. First, the model's goodness-of-fit was shown in the Pareto smoothed importance-sampling leave-one-out cross-validation (PSIS-LOO) (Vehtari A & Gabry J, 2024), following the criteria for goodness-of-fit.

Table 2. PSIS-LOO test evaluation

k-values	Status
All below 0.5	Good
More than 0.5 and below 0.7	'OK'
More than 0.7 and below 1	'Bad'
More than 1	'Very bad'

PSIS-LOO diagnostics is computed as follows:

$$LOO = -2LPPD_{loo} = -2 \sum_{i=1}^n \log \int p(y_i | \theta) p_{post(-i)}(\theta) d\theta$$

The second approach is to check the Markov chain central limit theorem using two diagnostic statistics: effective sample size (n_{eff}) and Gelman-Rubin shrink value ($Rhat$).

Table 3. Markov chain convergence evaluation

Indicators	Status
n_{eff} values are larger than 1,000	Good convergence
Rhat value equals 1	

The Markov chain convergence was visual in the trace plots.

3. Results

3.1. Model 1

To interpret the findings, it is crucial to assess the model's goodness of fit for Model 1 against the data. As illustrated in Figure 4, all estimated k -values fall below the 0.5 threshold, indicating a strong fit between the model and the observed data.

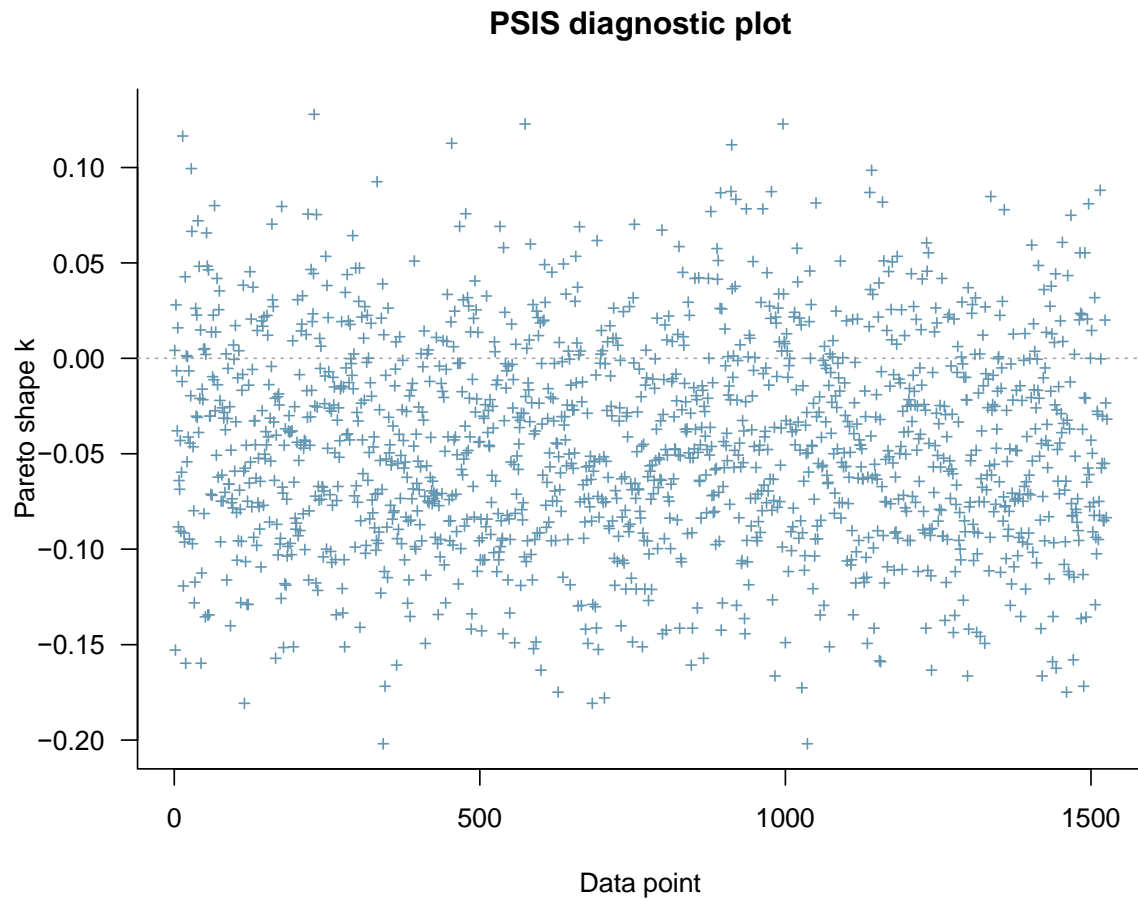


Figure 4: Model 1's PSIS-LOO diagnosis

The computed posterior distributions for Model 1 are shown in Table 4. All effective sample size (n_{eff}) values are above 1,000, and the $Rhat$ values are precisely 1, indicating the convergence of the Markov chains in Model 1. This convergence is additionally corroborated by the trace plots presented in Figure 5, where all chain values achieve stability around a central equilibrium following the 2,000th iteration.

Table 4. Estimated results of Model 1

Parameters	Mean	SD	n_{eff}	$Rhat$
<i>Fear_Freeze</i>	2.03	0.07	13043	1
<i>Priority_ProfitLiquidity_Fear_Freeze</i>	-0.01	0.06	8842	1
<i>Priority_CompanyPerformance_Fear_Freeze</i>	-0.07	0.06	9683	1
<i>Priority_SocialInfluence_Fear_Freeze</i>	0.08	0.05	10499	1
<i>Priority_TechAnalysis_Fear_Freeze</i>	0.01	0.04	11698	1

<i>Priority_ProfessionalEvaluation_Fear_Freeze</i>	-0.05	0.05	11107	1
<i>Priority_Intuition_Fear_Freeze</i>	0.04	0.04	11947	1

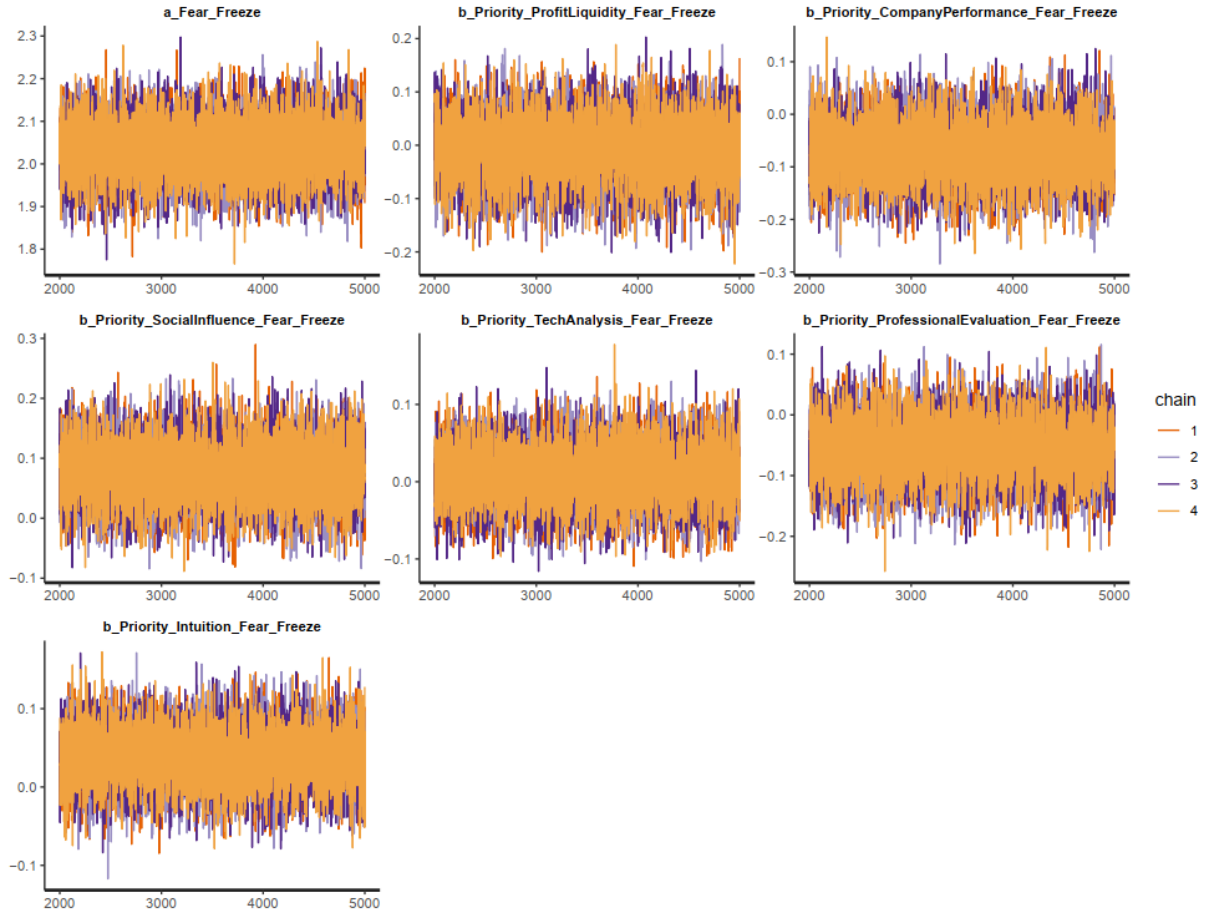


Figure 5: Model 1's trace plots

As all diagnostic tests validate the convergence of the Markov chains, the simulation outcomes are appropriate for analysis. The estimated results from Model 1 show that different information priorities for investment decision-making have different impacts on investors' fear freeze during the financial crisis. If the investment decision was based on social influence and intuition, they were more likely to freeze when the crisis occurred ($M_{Priority_SocialInfluence_Fear_Freeze} = 0.08$ and $S_{Priority_SocialInfluence_Fear_Freeze} = 0.05$; $M_{Priority_Intuition_Fear_Freeze} = 0.04$ and $S_{Priority_Intuition_Fear_Freeze} = 0.04$); meanwhile, if the investors based on the company's performance and professional evaluation to make their investment decision, they were less likely to freeze when the crisis happens ($M_{Priority_CompanyPerformance_Fear_Freeze} = -0.07$ and $S_{Priority_CompanyPerformance_Fear_Freeze} = 0.06$; $M_{Priority_ProfessionalEvaluation_Fear_Freeze} = -0.05$ and $S_{Priority_ProfessionalEvaluation_Fear_Freeze} = 0.05$). Additionally, profit liquidity and technology analysis the investors based on to make their investment decision had an unclear association with their degree of fear freeze ($M_{Priority_ProfitLiquidity_Fear_Freeze} = -$

0.01 and $S_{Priority_ProfitLiquidity_Fear_Freeze} = 0.06$ and $M_{Priority_TechAnalysis_Fear_Freeze} = -0.01$ and $S_{Priority_TechAnalysis_Fear_Freeze} = 0.04$).

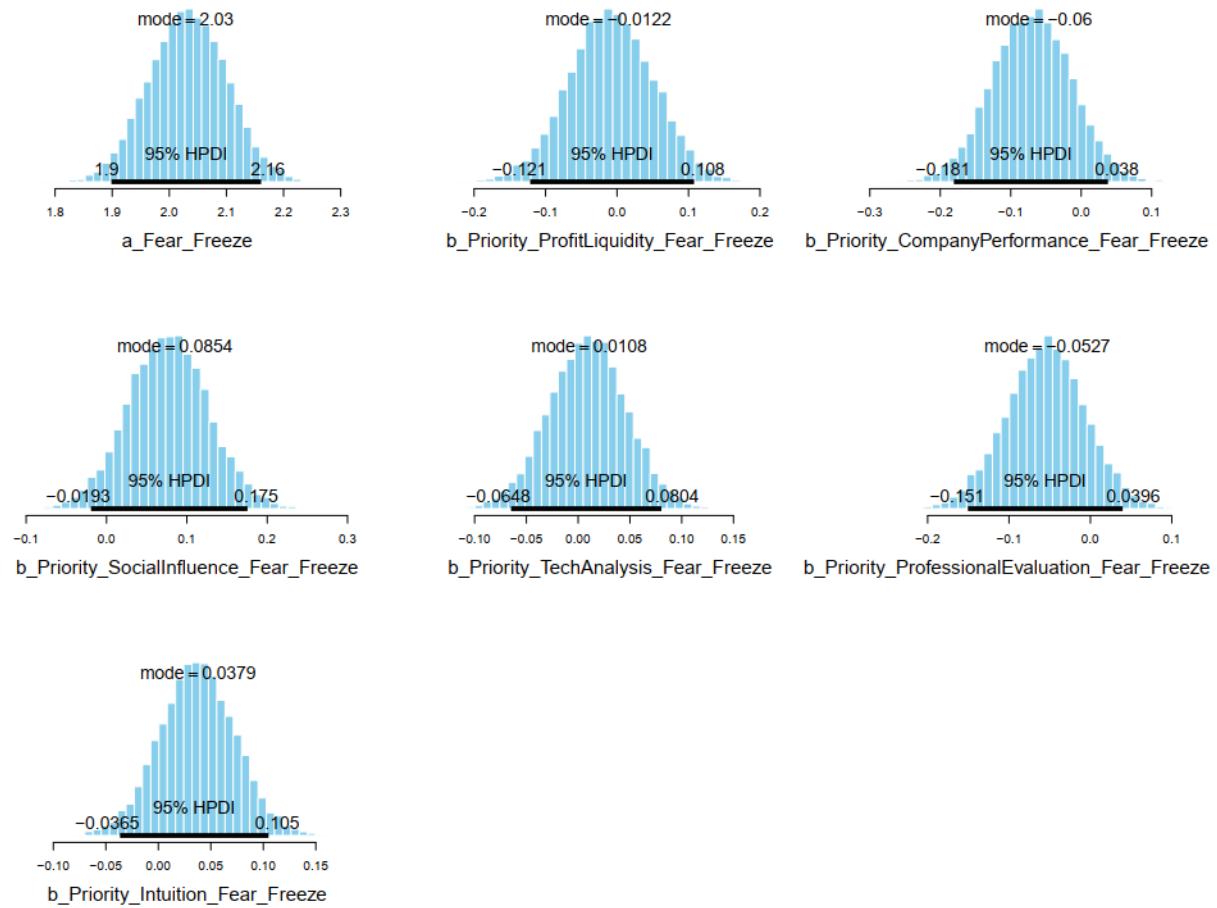


Figure 6: Model 1's posterior distributions

Figure 6 illustrates the posterior distributions of the coefficients, with their 95% Highest Posterior Density Intervals (HPDIs) depicted by bold blue lines. The posterior distributions for *Priority_SocialInfluence_Fear_Freeze* and *Priority_Intuition_Fear_Freeze* are on the positive side of the x-axis. A proportion of *Priority_SocialInfluence_Fear_Freeze* is still located on the negative side, but it is negligible; thus, its positive association is deemed highly reliable. Meanwhile, a proportion of *Priority_Intuition_Fear_Freeze* still lies on the negative side, and its mean value is equal to its standard deviation, indicating moderate reliability.

The posterior distributions of *Priority_CompanyPerformance_Fear_Freeze* and *Priority_ProfessionalEvaluation_Fear_Freeze* are on the negative side. However, a proportion of their distributions are still on the positive side, and their mean value is equal and not much higher than their standard deviation. Therefore, their negative associations are deemed moderately reliable.

3.2. Model 2

The results of the PSIS-LOO test for Model 2 are illustrated in Figure A1. All calculated k-values fall beneath the 0.5 threshold, signifying that the model exhibits an adequate goodness of fit with the observed data.

The statistical metrics of n_{eff} (exceeding 1000) and $Rhat$ (equal to 1) presented in Table 3 demonstrate the convergence of Model 2's Markov chains. Furthermore, the trace plots provide additional confirmation of convergence (refer to Figure A2). As a result, the simulated outcomes of Model 2 are appropriate for analysis.

Table 5: Estimated results of Model 2

Parameters	Mean	SD	n_{eff}	$Rhat$
<i>Fear_Flight</i>	1.86	0.07	11810	1
<i>Priority_ProfitLiquidity_Fear_Flight</i>	-0.02	0.06	9707	1
<i>Priority_CompanyPerformance_Fear_Flight</i>	-0.07	0.06	10145	1
<i>Priority_SocialInfluence_Fear_Flight</i>	0.01	0.05	10427	1
<i>Priority_TechAnalysis_Fear_Flight</i>	-0.04	0.04	11649	1
<i>Priority_ProfessionalEvaluation_Fear_Flight</i>	0.06	0.05	10829	1
<i>Priority_Intuition_Fear_Flight</i>	0.07	0.04	11618	1

The simulated results in Table 5 indicate different information priorities for investment decision-making have different impacts on investors' fleeing response during the financial crisis. If the investment decision was based on professional evaluation and intuition, they were more likely to flee when the crisis occurred ($M_{Priority_ProfessionalEvaluation_Fear_Flight} = 0.06$ and $S_{Priority_ProfessionalEvaluation_Fear_Flight} = 0.05$; $M_{Priority_Intuition_Fear_Flight} = 0.07$ and $S_{Priority_Intuition_Fear_Flight} = 0.04$); meanwhile, if the investors based on the company's performance and technical analysis to make their investment decision, they were less likely to flee when the crisis happens ($M_{Priority_CompanyPerformance_Fear_Flight} = -0.07$ and $S_{Priority_CompanyPerformance_Fear_Flight} = 0.06$; $M_{Priority_TechAnalysis_Fear_Flight} = -0.04$ and $S_{Priority_TechAnalysis_Fear_Flight} = 0.04$). Additionally, prioritizing profit liquidity and social influence to make their investment decision had unclear associations with their degree of fleeing response ($M_{Priority_ProfitLiquidity_Fear_Flight} = -0.02$ and $S_{Priority_ProfitLiquidity_Fear_Flight} = 0.06$ and $M_{Priority_SocialInfluence_Fear_Flight} = 0.01$ and $S_{Priority_SocialInfluence_Fear_Flight} = 0.05$).

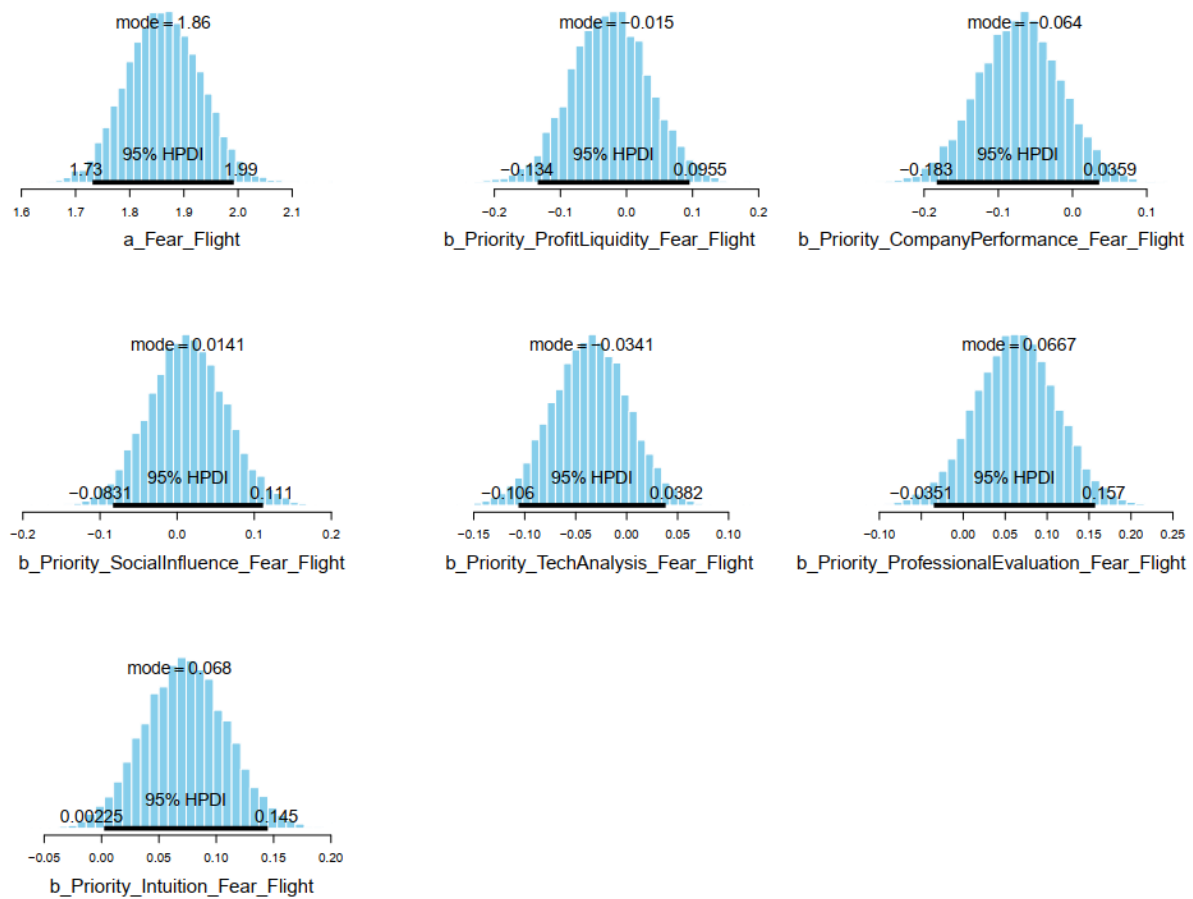


Figure 7: Model 2's posterior distributions

Figure 7 displays the posterior distributions along with their 95% HPDIs. The posterior distribution of *Priority_ProfessionalEvaluation_Fear_Flight* and *Priority_Intuition_Fear_Flight* are on the positive side of the x-axis. The HPDI of *Priority_Intuition_Fear_Flight* is located entirely on the positive side, underscoring the high reliability. Meanwhile, a proportion of *Priority_ProfessionalEvaluation_Fear_Flight*'s distribution is still located on the negative side, and its mean value is not much higher than its standard deviation, indicating moderate reliability.

The posterior distributions of *Priority_CompanyPerformance_Flight* and *Priority_TechAnalysis_Fear_Flight* are on the negative side. However, a proportion of their distributions is still on the positive side, and their absolute mean values are equal and not much higher than their standard deviation, so their negative associations can be deemed moderately reliable.

3.3. Model 3

The PSIS-LOO test outcomes for Model 3 are illustrated in Figure A3. All calculated k -values fall below the 0.5 threshold, signifying that the model exhibits an adequate goodness of fit with the dataset.

The statistical metrics of n_{eff} (exceeding 1000) and $Rhat$ (equal to 1) presented in Table 4 demonstrate the convergence of the Markov chains for Model 3. Furthermore, the trace plots offer additional confirmation of this convergence (refer to Figure A4). As a result, the simulated findings from Model 3 are appropriate for interpretation.

Table 6: Estimated results of Model 3

Parameters	Mean	SD	n_{eff}	$Rhat$
<i>Fear_Hide</i>	2.06	0.07	12800	1
<i>Priority_ProfitLiquidity_Fear_Hide</i>	-0.05	0.06	9929	1
<i>Priority_CompanyPerformance_Fear_Hide</i>	-0.09	0.06	9565	1
<i>Priority_SocialInfluence_Fear_Hide</i>	0.05	0.05	10905	1
<i>Priority_TechAnalysis_Fear_Hide</i>	0.01	0.04	12763	1
<i>Priority_ProfessionalEvaluation_Fear_Hide</i>	0.04	0.05	11872	1
<i>Priority_Intuition_Fear_Hide</i>	0.01	0.04	12493	1

The simulated results in Table 6 indicate different information priorities for investment decision-making have different impacts on investors' hiding responses during the financial crisis. If the investment decision was based on professional evaluation and social influence, they were more likely to hide when the crisis occurred ($M_{Priority_ProfessionalEvaluation_Fear_Hide} = 0.04$ and $S_{Priority_ProfessionalEvaluation_Fear_Hide} = 0.05$; $M_{Priority_SocialInfluence_Fear_Hide} = 0.05$ and $S_{Priority_SocialInfluence_Fear_Hide} = 0.05$); meanwhile, if the investors based on profit liquidity and company performance to make their investment decision, they were less likely to hide when the crisis happens ($M_{Priority_CompanyPerformance_Fear_Hide} = -0.09$ and $S_{Priority_CompanyPerformance_Fear_Hide} = 0.06$; $M_{Priority_ProfitLiquidity_Fear_Hide} = -0.05$ and $S_{Priority_ProfitLiquidity_Fear_Hide} = 0.06$). Additionally, technical analysis and intuition the investors based on to make their investment decision had unclear associations with their degree of fear flight ($M_{Priority_TechAnalysis_Fear_Hide} = 0.01$ and $S_{Priority_TechAnalysis_Fear_Hide} = 0.04$ and $M_{Priority_Intuition_Fear_Hide} = 0.01$ and $S_{Priority_Intuition_Fear_Hide} = 0.04$).

Figure 8 illustrates the posterior distributions accompanied by their 95% HPDIs. The HPDI of *Priority_SocialInfluence_Fear_Hide* is on the positive side, and its mean value is equal to its standard deviation, implying the association's moderate reliability. A majority of *Priority_ProfessionalEvaluation_Fear_Hide*'s HPDI is also located on the positive side, but its mean value is lower than its standard deviation, suggesting weak reliability.

Most HPDIs of *Priority_CompanyPerformance_Fear_Hide* and *Priority_ProfitLiquidity_Fear_Hide* are on the negative side of the x-axis. Although a proportion of *Priority_CompanyPerformance_Fear_Hide* is on the positive side, that proportion is negligible; hence, the association can be deemed highly reliable. Meanwhile, the absolute mean value of *Priority_TechAnalysis_Fear_Hide* is lower than its standard deviation, so its negative association is weakly reliable.

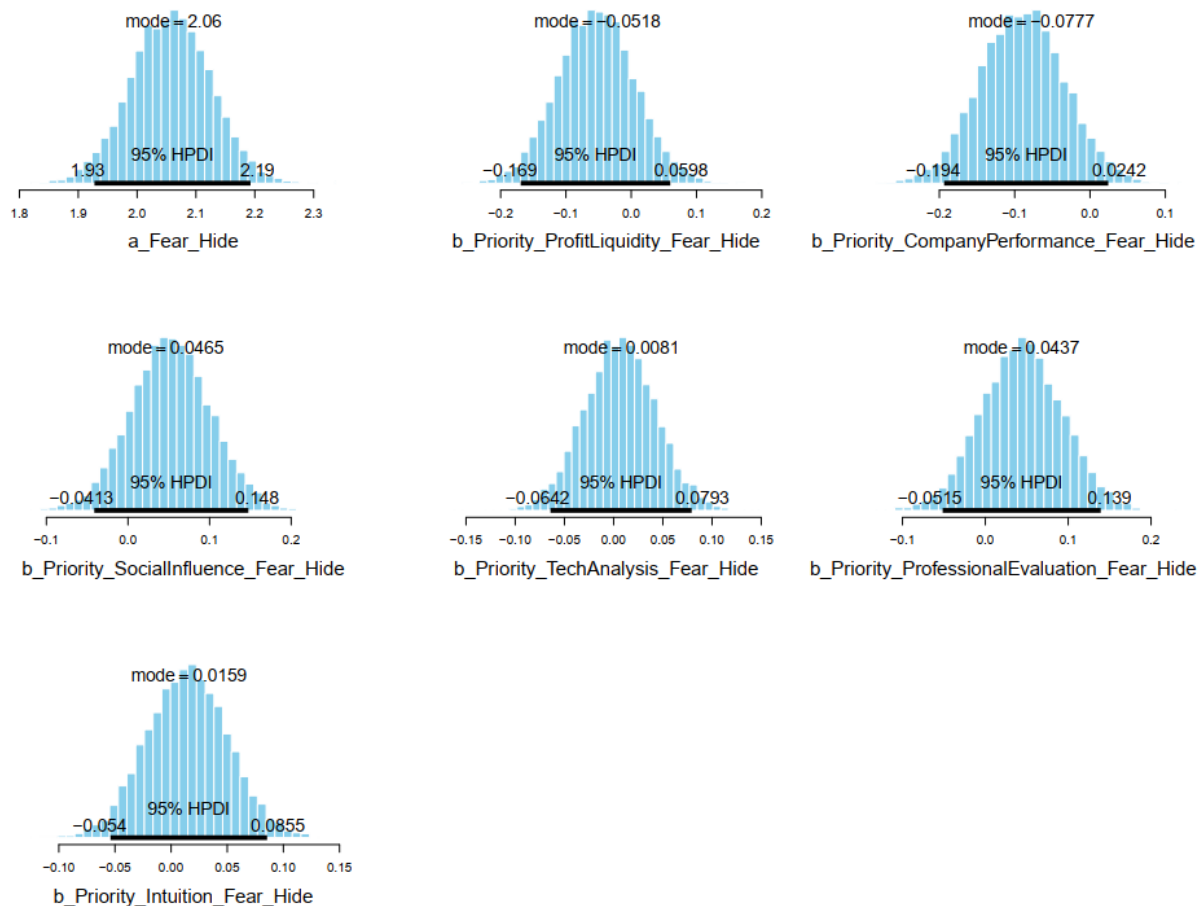


Figure 8: Model 3's posterior distributions

4. Discussion

The research employed the Bayesian Mindsponge Framework (BMF) to analyze how investors' information priorities in investment decision-making influence their fear responses during a market crisis. A statistical analysis of a dataset consisting of 1,526 investors from Vietnam and China revealed that different information priorities—such as professional evaluation, social influence, company performance, technical analysis, profit and liquidity, and intuition—had distinct effects on investors' fear responses, categorized as freeze, flight, and hide, amid financial turmoil.

Concerning the freeze response, investors who prioritized social influence and intuition in their investment decisions were more likely to freeze during crises. Conversely, those who made decisions based on company performance and professional evaluations were less likely to experience this freeze response. Regarding the fleeing response, investors relying on professional evaluation and intuition were more inclined to flee during crises, while

those who prioritized company performance and technical analysis were less likely to do so. For the hiding response, investors who based their decisions on professional evaluations and social influence were more prone to retreat, while those focused on profit, liquidity, and company performance were less likely to hide during crises.

The study's findings align with the initial hypotheses of the Mindsponge theory. Notably, investors influenced by social dynamics and intuition were more prone to freeze during crises. Social contexts, such as social preferences, signaling, and responsibility, can significantly impact investment decisions (Brodback et al., 2019; Riedl & Smeets, 2017). Negative portrayals of social situations, including unaddressed unfavorable behaviors from acquaintances, can trigger fear responses in investors, causing reluctance to engage with sustainable investments (Vanwalleghem & Mirowska, 2020). Additionally, unconscious processes, including emotions and intuitions, play a vital role in human decision-making (Bargh & Morsella, 2008). During crises, investors instinctively focus on negative scenarios to avoid, with fear being the dominant emotion. This fear often triggers a freeze response, deterring even proactive investors from pursuing sustainable investment options (Vanwalleghem & Mirowska, 2020).

In contrast, investors guided by company performance and professional evaluations were significantly less likely to freeze. The human brain's capacity for information processing and memory retention plays a central role in decision-making (VanderPal & Brazie, 2022). Rational investors typically benefit from the efficient market hypothesis by relying on both internal company performance and expert assessments. When evaluating all available information in the stock market, they make decisions aimed at optimizing expected returns. This enables them to act decisively, avoiding a freeze response and potentially engaging in either the repurchase or disposition effect. (Dermawan & Trisnawati 2023; VanderPal & Brazie, 2022).

Regarding the fleeing response, investors dependent on professional evaluation and intuition were more likely to overreact to negative news during crises, driven by risk aversion (Cohn et al., 2015). Such overreactions can lead to pessimism, prompting investors to sell off assets in a bid to avoid further losses. Decision-making in these cases is influenced by contextual factors, where fear of loss activates the autonomic nervous system, triggering flight behaviors (Porges, 2021). In contrast, those who made investment decisions based on company performance and technical analysis were less prone to flight during market downturns, even when faced with traumatic experiences. These investors tend to rely more on factual analysis than emotional reactions, resulting in a more measured approach to crisis-driven volatility (VanderPal, 2021; VanderPal & Brazie, 2022).

For the hiding response, investors influenced by professional evaluations and social influence were more likely to hide during crises. According to the mindsponge theory, fear responses are shaped by cognitive processing patterns embedded in the mindset, affecting information prioritization in investment decisions (Vuong, 2023). Negative professional evaluations, combined with social influences, tend to exacerbate the tendency to withdraw from investments. Cognitive biases, such as overreaction and underreaction, along with herding behaviors, can divert investors from rational decision-making during crises (Metawa et al., 2019).

Conversely, investors who prioritize profit, liquidity, and company performance in their decisions are less likely to resort to hiding during times of crisis. Essentially, an individual's risk-taking behavior is closely linked to their cognitive and analytical abilities (VanderPal, 2021). Sullivan (2011) found that individuals exposed to neutral imagery, as opposed to only negative financial scenarios, were less inclined to make conservative investment choices. When investors perceive a generally favorable outlook in terms of profit, liquidity, and other positive indicators of company performance, they are less likely to withdraw or conceal their investments, even amid crises. However, this tendency can sometimes lead to unfavorable investment outcomes due to cognitive biases like anchoring and confirmation biases. Anchoring bias occurs when individuals rely too heavily on pre-existing data as a benchmark for evaluating new information, which can distort decision-making (VanderPal & Brazie, 2022). This overreliance on historical data related to profit, liquidity, and company performance can lead investors to overlook evolving market conditions, causing them to continue investing rather than withdraw. Similarly, confirmation bias leads investors to seek out information that supports their pre-existing beliefs (VanderPal & Brazie, 2022). For example, when investors believe in the strong performance of companies based on past crises, they may disregard contradictory information from the current crisis, making them hesitant to divest from their shares or avoid high-yield, albeit risky, investments.

These findings have important implications for mitigating investors' fear responses and improving investment decision-making during crises, especially when confronted with varying information priorities. To optimize the use of these priorities, providing accurate and transparent data regarding crises and market downturns can significantly alleviate fear responses, such as freezing, fleeing, and hiding. Governments and regulatory bodies must take responsibility for interventions that facilitate the dissemination of reliable information, helping guide investors toward more rational, well-informed decisions during periods of uncertainty and crisis (Rehman et al., 2024).

Policies that raise awareness of crises, market news, and trends are crucial for shaping the behavioral biases influencing investment choices (Khurshid et al., 2021). For instance, coverage of government stimulus initiatives, economic recovery efforts, stock market fluctuations, and other relevant topics directly impact investment decisions. This is particularly true when investors face conflicting information priorities, such as social influences, company performance, intuition, professional assessments, and technical analysis, all of which are compounded by cognitive and behavioral biases in crisis situations.

Therefore, policies promoting transparency in crisis-related reporting by mainstream and social media can help counteract the negative effects of exaggerated news coverage on investor decision-making. Practically, it is essential for companies and organizations to engage in comprehensive financial education programs aimed at enhancing investors' financial literacy, sound investment practices, and ability to navigate cognitive biases, especially during crises. This approach empowers investors to better leverage available information and make more informed decisions during volatile market conditions (Rehman et al., 2024; Nguyen et al., 2022).

The current study has several limitations, which are outlined for transparency (Vuong, 2020). This analysis, focusing on investors' viewpoints on how information priorities affect decision-making during crises, relies on survey methodologies and self-reported data. Such an approach is susceptible to personal biases and may not fully capture the complex dynamics between investors' fear responses and their information priorities in investment decisions. Future research could address these limitations by employing experimental methodologies. Additionally, the dataset is composed solely of samples from China and Vietnam, so it may not accurately represent the investment climates of other nations or regions. Caution is therefore advised when generalizing the findings to diverse international contexts. Subsequent research should focus on exploring the informational priorities related to investment decision-making using the mindsponge theory across a broader range of regions and countries.

Appendix

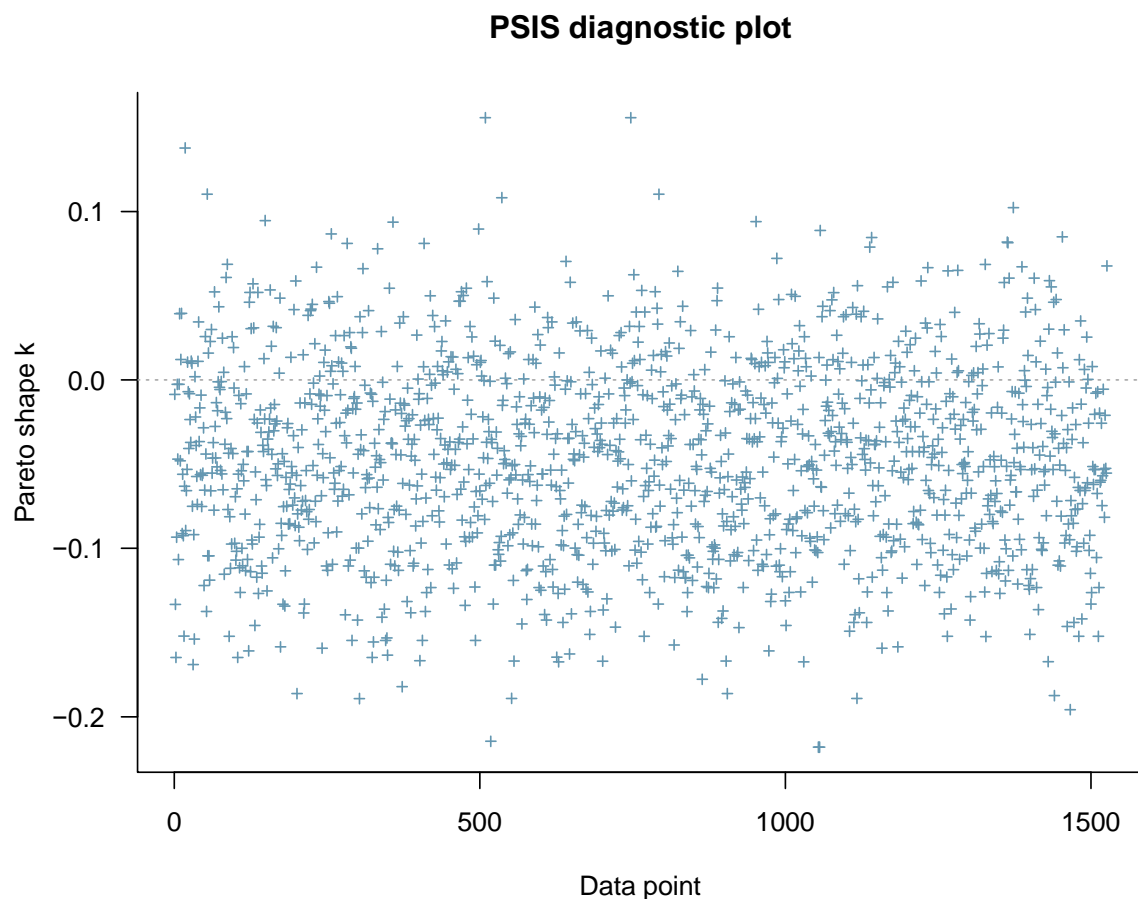


Figure A1: Model 2's PSIS-LOO diagnosis

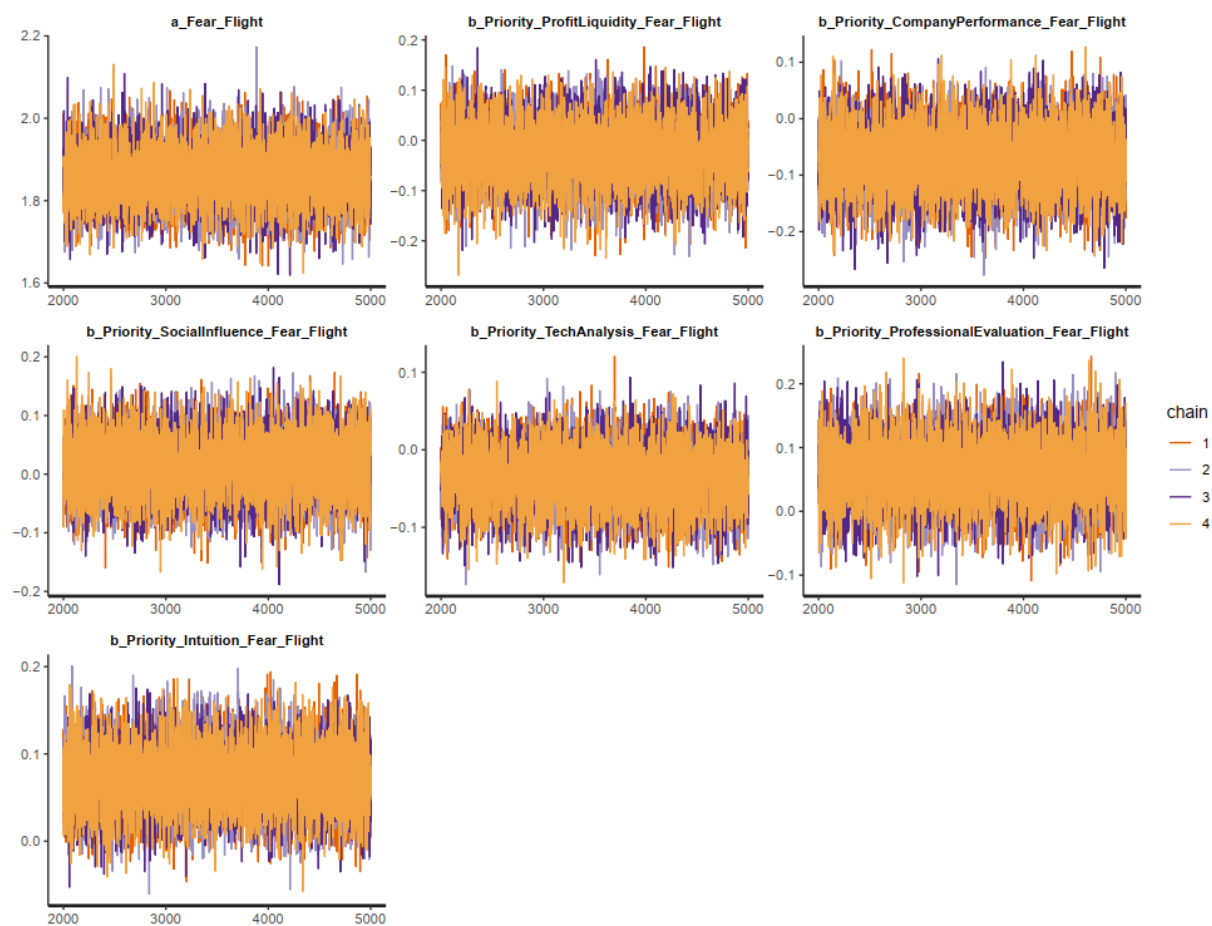


Figure A2: Model 2's trace plots

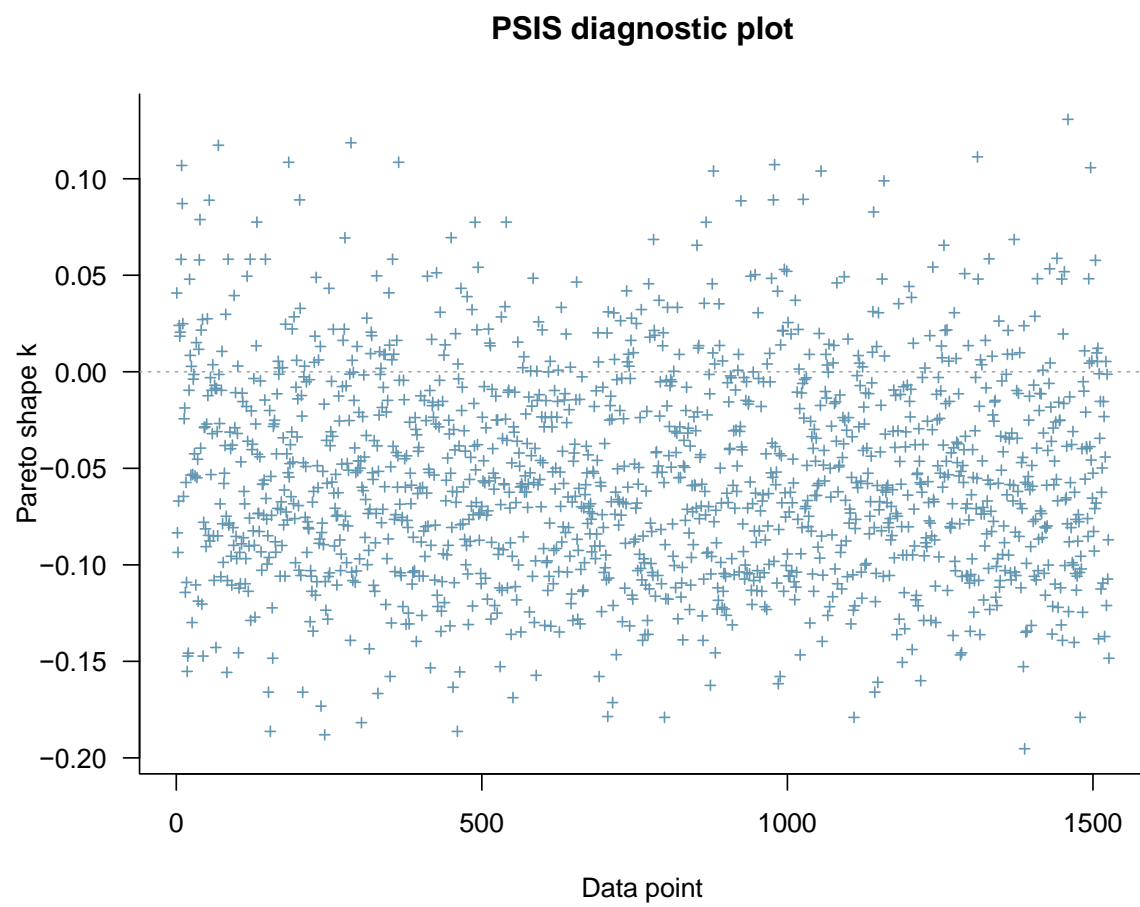


Figure A3: Model 3's PSIS-LOO diagnosis

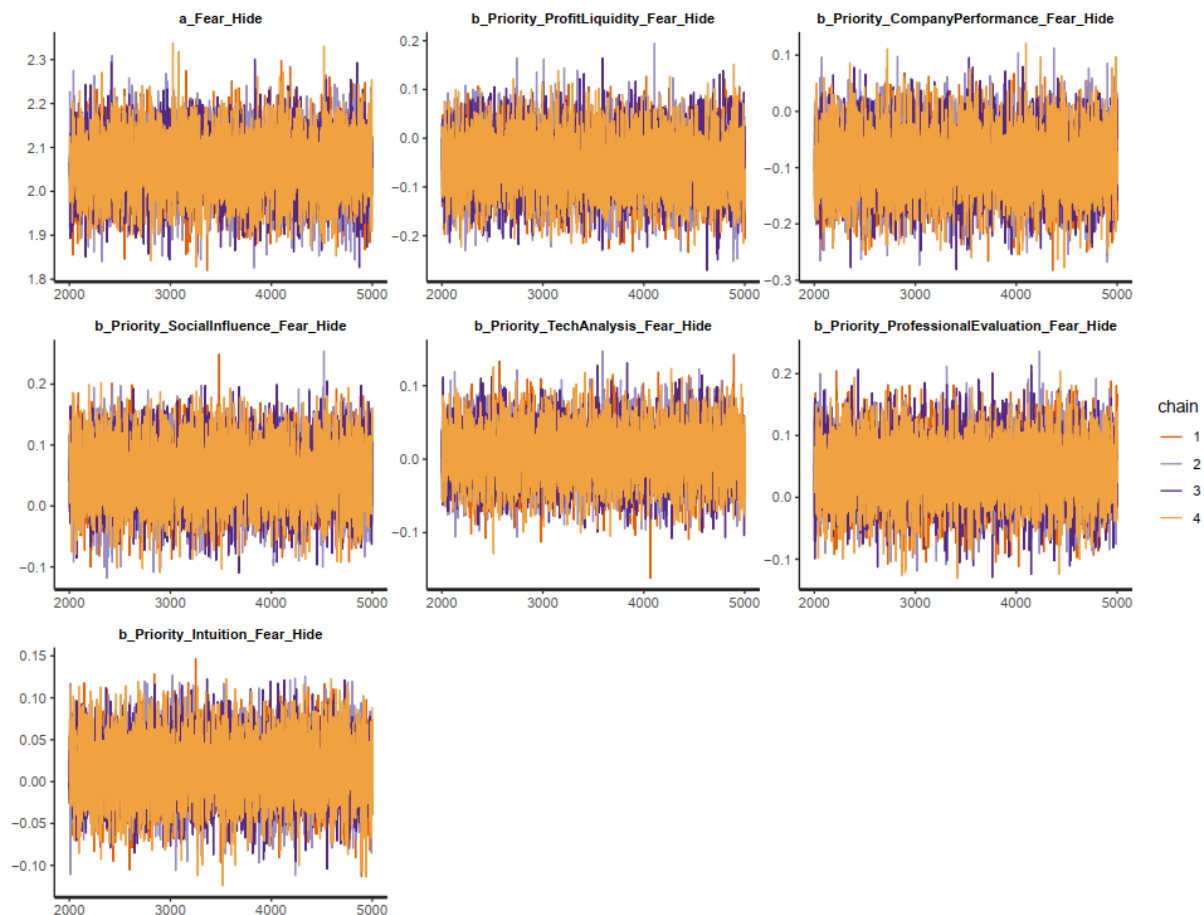


Figure A4: Model 3's trace plots

Reference

- Adolphs, R. (2013). The Biology of Fear. *Current Biology*, 23(2), R79–R93.
<https://doi.org/10.1016/j.cub.2012.11.055>
- Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly*, 107-136.
- Andersson, M., Hedesström, M., & Gärling, T. (2014). A Social-Psychological Perspective on Herding in Stock Markets. *Journal of Behavioral Finance*, 15(3), 226–234.
<https://doi.org/10.1080/15427560.2014.941062>
- Arand, D., & Kerl, A. G. (2012). Analyst Research and Investor Reactions: Evidence from the 2008 Financial Crisis. *SSRN Electronic Journal*.
<https://doi.org/10.2139/ssrn.2126605>
- Bargh, J. A., & Morsella, E. (2008). The unconscious mind. *Perspectives on psychological science*, 3(1), 73-79.
- Barker, R., Hendry, J., Roberts, J., & Sanderson, P. (2012). Can company-fund manager meetings convey informational benefits? Exploring the rationalisation of equity investment decision making by UK fund managers. *Accounting, Organizations and Society*, 37(4), 207-222.

- Bird, R., Gallagher, D. R., Khan, A., & Yeung, D. (2023). Do Emotions Influence Investor Behavior? In *Journal of Behavioral Finance*. <https://doi.org/10.1080/15427560.2023.2282966>
- Brodback, D., N. Guenster, and D. Mezger (2019). Altruism and egoism in investment decisions. *Review of Financial Economics* 37 (1), 118–148.
- Burchett, H. E., Mayhew, S. H., Lavis, J. N., & Dobrow, M. J. (2013). When can research from one setting be useful in another? Understanding perceptions of the applicability and transferability of research. *Health Promotion International*, 28(3), 418-430. <https://doi.org/10.1093/heapro/das026>
- Chen, Y., Liu, J., Gao, Y., He, W., Li, H., Zhang, G., & Wei, H. (2023). A new stock market analysis method based on evidential reasoning and hierarchical belief rule base to support investment decision making. *Frontiers in Psychology*, 14(February), 1–18. <https://doi.org/10.3389/fpsyg.2023.1123578>
- Chiu, J., Chung, H., & Ho, K.-Y. (2014). Fear Sentiment, Liquidity, and Trading Behavior: Evidence from the Index ETF Market. *Review of Pacific Basin Financial Markets and Policies*, 17(03), 1450017. <https://doi.org/10.1142/s0219091514500179>
- Cohn, A., Engelmann, J., Fehr, E., & Maréchal, M.A. (2015). Evidence for countercyclical risk aversion: An experiment with financial professionals. *American Economic Review*, 105(2), 860–85. <https://doi.org/10.1257/aer.20131314>
- Dang, H. V., & Lin, M. (2016). Herd mentality in the stock market: On the role of idiosyncratic participants with heterogeneous information. *International Review of Financial Analysis*, 48, 247–260. <https://doi.org/10.1016/j.irfa.2016.10.005>
- Dash, M. (2010). Factors Influencing Investment Decision of Generations in India: An Econometric Study. <https://www.ijbmer.com/docs/volumes/vol1issue1/ijbmer2010010103.pdf>
- Dermawan, E. S., & Trisnawati, E. (2023). Investment decisions in the era of the COVID-19 pandemic. *International Journal of Application on Economics and Business*, 1(1), 70-79.
- Elkind, D., Kaminski, K., Lo, A. W., Siah, K. W., & Wong, C. H. (2021). When Do Investors Freak Out? Machine Learning Predictions of Panic Selling. *The Journal of Financial Data Science*, jfds.2021.1.085. <https://doi.org/10.3905/jfds.2021.1.085>
- Fenton-O'Creevy, M., Soane, E., Nicholson, N., & Willman, P. (2011). Thinking, feeling and deciding: The influence of emotions on the decision making and performance of traders. *Journal of Organizational Behavior*, 32(8), 1044–1061. <https://doi.org/10.1002/job.720>
- Feuerriegel, S., & Prendinger, H. (2016). News-based trading strategies. *Decision Support Systems*, 90, 65–74. <https://doi.org/10.1016/j.dss.2016.06.020>
- Forbes, W. (2024). Unconscious thoughts as a spur and halt on good financial decisioning making. *International Review of Financial Analysis*, 91, 103012.

- Gaies, B., Nakhli, M. S., Sahut, J.-M., & Schweizer, D. (2023). Interactions between investors' fear and greed sentiment and Bitcoin prices. *The North American Journal of Economics and Finance*, 67, 101924. <https://doi.org/10.1016/j.najef.2023.101924>
- García-Monleón, F., González-Rodrigo, E., & Bordonado-Bermejo, M. J. (2024). Investor behavior in crisis: a comparative study of fear-driven downtrends and confidence-led recoveries. *Journal of Risk Finance*, 25(5), 10–11. <https://doi.org/10.1108/JRF-07-2024-0189>
- Guiso, L., Sapienza, P., & Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics*, 128(3), 403–421. <https://doi.org/10.1016/j.jfineco.2018.02.007>
- Hedesström, M. (2010, July). Social Influence in Stockmarkets: A Conceptual Analysis of Social Influence Processes in Stock Markets. Sustainable Investment and Corporate Governance Working Papers; Sustainable Investment Research Platform. https://ideas.repec.org/p/hhb/sicgwp/2010_013.html
- Hidayat, R., Wahyudi, S., & Muharam, H. (2018). Sensitivity of Liquidity, Investment Decision, and Financial Constraints. *Indonesian Capital Market Review*, 10(1). <https://doi.org/10.21002/icmr.v10i1.10872>
- Hoffmann, A. O. I., Post, T., & Pennings, J. M. E. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, 37(1), 60–74. <https://doi.org/10.1016/j.jbankfin.2012.08.007>
- Huang, L., & Pearce, J. L. (2015). Managing the Unknowable: the Effectiveness of Early-stage Investor Gut Feel in Entrepreneurial Investment Decisions. *Administrative Science Quarterly*, 60(4), 634–670. <https://doi.org/10.1177/0001839215597270>
- Huang, Z. (2019, December 1). Analyzing the Value Investment Based on Financial Data in Retailer Market. *IEEE Xplore*. <https://doi.org/10.1109/ICEMME49371.2019.00011>
- Imam, S., & Spence, C. (2016). Context, not predictions: a field study of financial analysts. *Accounting, Auditing & Accountability Journal*, 29(2), 226–247.
- Jasiniak, M., Krzeczewska, O., & Pluskota, A. (2023). Is It a Real COVID-19 Fear? A Cross-Industry Study of Fear on the Stock Market. *Annales Universitatis Mariae Curie-Skłodowska, Sectio H – Oeconomia*, 57(3), 123–138. <https://doi.org/10.17951/h.2023.57.3.123-138>
- Khurshid, S., Ahmed, A., & Irrum, L. (2021). An Examination of Behavioral Factors Affecting the Retail Investor's Investment Decisions: The Moderating Role of Covid-19. *Journal of ISOSS*, 7(1), 105–120.
- Lal, S., Xuan, T., Aliyu Ali Bawalle, Mostafa, & Yoshihiko Kadoya. (2024). Unraveling Investor Behavior: The Role of Hyperbolic Discounting in Panic Selling Behavior on

- the Global COVID-19 Financial Crisis. *Behavioral Sciences*, 14(9), 795–795. <https://doi.org/10.3390/bs14090795>
- Laungratanamas, K., & Nuangjamnong, C. (2023). Behavioral biases and fear of missing out impact investment decisions in Thailand during COVID-19 pandemic. *Universal Journal of Financial Economics*, 2(2), 1-20.
- LeDoux, J., & Daw, N. D. (2018). Surviving threats: neural circuit and computational implications of a new taxonomy of defensive behaviour. *Nature Reviews Neuroscience*, 19(5), 269–282. <https://doi.org/10.1038/nrn.2018.22>
- Lee, C. J., & Andrade, E. B. (2014). Fear, excitement, and financial risk-taking. *Cognition and Emotion*, 29(1), 178–187. <https://doi.org/10.1080/02699931.2014.898611>
- Lee, C. J., & Andrade, E. B. (2011). Lee, Chan J. / Andrade, Eduardo B. (2011): Fear, Social Projection, and Financial Decision Making, *Journal of Marketing Research* 40, 121-129. *Journal of Marketing Research*, 48(SPL), S121–S129.
- Lehnert, T. (2020). Fear and stock price bubbles. *PLOS ONE*, 15(5), e0233024. <https://doi.org/10.1371/journal.pone.0233024>
- Lim, Y., and Kim, K.T. (2019). Afraid of the stock market. *Review of Quantitative Finance and Accounting*, 53(3), 773–810. <https://doi.org/10.1007/s11156-018-0766-x>
- Mansoor, D., & Jalal, A. (2010). The Global Business Crisis and Consumer Behavior: Kingdom of Bahrain as a Case Study. *International Journal of Business and Management*, 6(1). <https://doi.org/10.5539/ijbm.v6n1p104>
- Metawa N, Hassan MK, Metawa S, Safa MF (2019) Impact of behavioral factors on investors' financial decisions: case of the Egyptian stock market. *Int J Islamic Middle East Financ Manag* 12(1):30–55
- Neuhauser, K. L. (2015). The Global Financial Crisis: what have we learned so far? *International Journal of Managerial Finance*, 11(2), 134–161. <https://doi.org/10.1108/ijmf-02-2015-0014>
- Nguyen, M. H., La, V. P., Le, T. T., & Vuong, Q. H. (2022). Introduction to Bayesian Mindsponge Framework analytics: An innovative method for social and psychological research. *MethodsX*, 9, 101808. <https://doi.org/10.1016/j.mex.2022.101808>
- Nguyen, M. H., Khuc, Q. V., La, V. P., Le, T. T., Nguyen, Q. L., Jin, R., Nguyen, P. T., & Vuong, Q. H. (2022). Mindsponge-based reasoning of households' financial resilience during the COVID-19 crisis. *Journal of Risk and Financial Management*, 15(11), 542. <https://doi.org/10.3390/jrfm15110542>
- Nguyen, M. H., Le, T. T., & Vuong, Q. H. (2023). Ecomindsponge: A Novel Perspective on Human Psychology and Behavior in the Ecosystem. *Urban Science*, 7(1), 1–32. <https://doi.org/10.3390/urbansci7010031>
- None Muhammad Ali, Ansari, H., Chishty, A., None Chin-Hong Puah, & None Muhammad Ashfaq. (2023). Investor behaviour and investment decisions: Evidence from

- Pakistan Stock Exchange. *Asian Academy of Management Journal/Asian Academy of Management Journal*, 28(2), 1–28.
<https://doi.org/10.21315/aamj2023.28.2.1>
- Pixley, J. (2002). Finance organizations, decisions and emotions. *British Journal of Sociology*, 53(1), 41–65. <https://doi.org/10.1080/00071310120109320>
- Pompian, M. M. (2023). Behavioral finance and investor types: managing behavior to make better investment decisions. CiNii Books; Wiley.
<http://ci.nii.ac.jp/ncid/BB11663565>
- Porges, S.W. (2021). Polyvagal Theory: A biobehavioral journey to sociality. *Comprehensive Psychoneuroendocrinology*, 100069.
<https://doi.org/10.1016/j.cpnec.2021.100069>
- Potsaid, T., & Venkataraman, S. (2022). Trading restrictions and investor reaction to non-gains, non-losses, and the fear of missing out: Experimental evidence. *Journal of Behavioral and Experimental Finance*, 33, 100597.
- Prorokowski, L. (2011). Trading strategies of individual investors in times of financial crisis. *Qualitative Research in Financial Markets*, 3(1), 34–50.
<https://doi.org/10.1108/17554171111124603>
- Riedl, A. and P. Smeets (2017). Why do investors hold socially responsible mutual funds? *The Journal of Finance* 72 (6), 2505–2550.
- Rehman, W.U., Saltik, O., Jalil, F., & Degirmen, S. (2024). Viral decisions: unmasking the impact of COVID-19 info and behavioral quirks on investment choices. *Humanities and Social Sciences Communications*, 11(1), 1-20.
- Sattar, M., Toseef, M., & Fahad Sattar, M. (2020). Behavioral Finance Biases in Investment Decision Making. *International Journal of Accounting, Finance and Risk Management*, 5(2), 69. <https://doi.org/10.11648/j.ijafrm.20200502.11>
- Schulmerich, M., Leporcher, Y.-M., & Eu, C.-H. (2015). Applied Asset and Risk Management. In *Management for Professionals*. Springer Berlin Heidelberg.
<https://doi.org/10.1007/978-3-642-55444-5>
- Sharda, S. (2021). The short-term impact of analyst recommendations: evidence from the Indian stock market. *Vilakshan - XIMB Journal of Management*, ahead-of-print(ahead-of-print). <https://doi.org/10.1108/xjm-12-2020-0239>
- Shrestha, P. M. (2020). Factors Influencing Investment Decisions of Nepalese Investors. *Management Dynamics*, 23(2), 145–160.
<https://doi.org/10.3126/md.v23i2.35818>
- So, M. K. P., Mak, A. S. W., & Chu, A. M. Y. (2022). Assessing systemic risk in financial markets using dynamic topic networks. *Scientific Reports*, 12(1), 2668.
<https://doi.org/10.1038/s41598-022-06399-x>

- Soydemir, G., Verma, R., & Wagner, A. (2017). The asymmetric impact of rational and irrational components of fear index on S&P 500 index returns. *Review of Behavioral Finance*, 9(3), 278–291. <https://doi.org/10.1108/rbf-05-2016-0025>
- Spyrou, S. (2013). Herding in financial markets: a review of the literature. *Review of Behavioural Finance*, 5(2), 175–194. <https://doi.org/10.1108/rbf-02-2013-0009>
- Sudrajat, D. (2022). Fear of Missing Out and Student Interest in Stocks Investment during Covid-19 Pandemic. *Journal of Economics Research and Social Sciences*, 6(2), 115–123. <https://doi.org/10.18196/jerss.v6i2.15319>
- Sullivan, R.N. (2011). Deploying financial emotional intelligence. *Financial Analysts Journal*, 67(6), 4–10.
- Sutejo, B. S., Sumiati, Wijayanti, R., & Ananda, C. F. (2023). Five Basic Human Emotions and Investment Decisions on Generation Z in Surabaya-Indonesia. *Proceedings of the 20th International Symposium on Management (INSYMA 2023)*, 9–15. https://doi.org/10.2991/978-94-6463-244-6_3
- Taffler, R. J., Spence, C., & Eshraghi, A. (2017). Emotional economic man: Calculation and anxiety in fund management. *Accounting, Organizations and Society*, 61, 53–67. <https://doi.org/10.1016/j.aos.2017.07.003>
- Uthayakumar, J., Metawa, N., Shankar, K., & Lakshmanaprabu, S. K. (2020). Financial crisis prediction model using ant colony optimization. *International Journal of Information Management*, 50, 538–556.
- VanderPal, G.A. (2021). Emotional Quotient and Intelligence Quotient on Behavioral Finance and Investment Performance. *Journal of Marketing Development and Competitiveness*, 15(2).
- VanderPal, G., & Brazie, R. (2022). Influence of basic human behaviors (influenced by brain architecture and function), and past traumatic events on investor behavior and financial bias. *Journal of Accounting and Finance*, 22(2).
- Vanwalleghem, D., & Mirowska, A. (2020). The investor that could and would: The effect of proactive personality on sustainable investment choice. *Journal of Behavioral and Experimental Finance*, 26, 100313.
- Vasileiou, E. (2021). Explaining stock markets' performance during the COVID-19 crisis: Could Google searches be a significant behavioral indicator? *Intelligent Systems in Accounting, Finance and Management*. <https://doi.org/10.1002/isaf.1499>
- Vehtari A, & Gabry J. (2024). *Bayesian Stacking and Pseudo-BMA weights using the loo package* (pp. 1–14). <https://mc-stan.org/loo/articles/loo2-weights.html>
- Vuong, Q.-H. (2020). Reform retractions to make them more transparent. *Nature*, 582(7811), 149. <https://doi.org/10.1038/d41586-020-01694-x>
- Vuong, Q. H., La, V. P., Nguyen, M. H., Ho, M. T., Ho, M. T., & Mantello, P. (2020). Improving Bayesian statistics understanding in the age of Big Data with the bayesvl R package. *Software Impacts*, 4, 100016. <https://doi.org/10.1016/j.simpa.2020.100016>

- Vuong, Q. H., & Napier, N. K. (2015). Acculturation and global mindsponge: An emerging market perspective. *International Journal of Intercultural Relations*, 49, 354–367. <https://doi.org/10.1016/j.ijintrel.2015.06.003>
- Vuong, Q. H., Nguyen, M.-H., & La, V. P. (2022). *The mindsponge and BMF analytics for innovative thinking in social sciences and humanities*. Walter de Gruyter GmbH.
- Vuong, Q. H. (2023). *Mindsponge theory*. Walter de Gruyter GmbH.
- Vuong, Q. H., Nguyen, P.-T., Jin, R., Giang, H., La, V.-P., & Nguyen, M.-H. (2024). Fear and fear regulation of Chinese and Vietnamese investors in the extremely volatile markets: A dataset. <https://doi.org/10.17605/OSF.IO/A2Z9X>
- Vuong, Q. H., & Nguyen, M. H. (2024a). Better economics for the Earth: A lesson from quantum and information theories. <https://www.amazon.com/dp/BOD98L5K44>
- Vuong, Q. H., & Nguyen, M. H. (2024b). Further on informational quanta, interactions, and entropy under the granular view of value formation. <https://dx.doi.org/10.2139/ssrn.4922461>
- Vuong, Q. H. (2024). *Wild Wise Weird*. <https://www.amazon.com/dp/B0BG2NNHY6/>
- Yukselturk, O., & Tucker, J. (2015). The impact of analyst sentiment on UK stock recommendations and target prices. *Accounting and Business Research*, 45(6-7), 869–904. <https://doi.org/10.1080/00014788.2015.1044496>
- Zargar, F. N., & Kumar, D. (2021). Market fear, investor mood, sentiment, economic uncertainty and tourism sector in the United States amid COVID-19 pandemic: A spillover analysis. *Tourism Economics*, 135481662110528. <https://doi.org/10.1177/13548166211052803>