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Investor negativity derived from news shapes firm distress dynamics under bounded rationality

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Abstract

Purpose – This study examines and explains the two-phase mechanisms through which investor negativity derived from news affects firm distress, drawing on prospect theory, bounded rationality and regret theory.

Design/methodology/approach – We apply prompt-based large language models (LLMs) to over 80,000 Vietnamese-language news articles to measure firm-level negativity sentiment. To test the proposed inverted U-shaped effect, we used ordered probit and logit regressions, which not only match the ordinal structure of distress levels but also enable the identification of threshold turning points in the sentiment–distress relationship. The sample included 80 listed Vietnamese firms that experienced and recovered from at least one distress episode between 2010 and 2022, ensuring sensitivity across distress intensities.

Findings – The results provide reliable empirical evidence for our proposed hypothesis: negative sentiment independently and nonlinearly influences distress outcomes. This is an inverted U-shaped relationship between negativity and firm distress.

Research limitations/implications – This study focused only on a tight, specific sample, which included only Vietnamese-listed non-financial firms that have operated continuously from 2008 until now and have experienced at least one instance of distress. Future research can be extended to a larger number of firms in other emerging economies.

Practical implications – Risk management should take into account the investor sentiment derived from news in their risk analysis and distress prediction models to enhance predictive accuracy.

Originality/value – This study integrates loss aversion and regret theories to demonstrate novel nonlinear dynamics linking negativity sentiment to firm distress, advancing our understanding of how behavioral responses evolve across different sentiment intensities.

Keywords Investor sentiment, Bounded rationality, Prospect theory, Loss aversion, Financial distress, Behavioral finance in emerging markets

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1. Introduction

Traditionally, the market efficiency theory posits that information plays a central role in shaping investor behavior and asset prices. Investors with earlier and more complete access to

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information are believed to hold advantages in decision making and benefit-taking (Fama, 1970). Building on this background, the recent research continues to emphasize the critical role of information in shaping financial behavior (Pham *et al.*, 2025). From a different perspective, behavioral finance highlights that investor behavior is not purely rational but is significantly influenced by their emotions (Akin and Akin, 2024; Hirshleifer, 2015; Ritter, 2003). Within this framework, the concept of investor sentiment emerged and has been increasingly recognized for its impact on market behaviors (De Long *et al.*, 1990). Subsequent studies have connected the two theoretical schools, showing that information not only directly affects markets but also triggers changes in investor psychology, thereby influencing their investor behaviors (Ángeles López-Cabarcos *et al.*, 2020; Lo, 2004; Shiller, 2003).

Foundational theories, from market efficiency to behavioral finance, all converge on the focal point that information shapes investment behavior, not only through rationality but also through sentimentality. Accordingly, empirical studies continuously provide evidence to reinforce that argument and affirm that investor psychology is formed by the information they receive and thereby has a significant influence on financial markets through their investment behavior (Akin and Akin, 2024; Hirshleifer, 2015; Ritter, 2003). From there, a sufficiently solid foundation is established to use investor sentiment shaped by news in various fields, specifically in designing quantitative models to analyze financial behavior or stock forecasting models. One of those applications is financial distress modeling. Notably, although the analysis of firm financial distress has become a classic topic, with many studies having been meticulously conducted, new research continues to emerge, still aiming to improve the ability to identify new risks or signs of latent risks. Typically, Wang *et al.* (2014), Mai *et al.* (2019) and Zhao *et al.* (2022) have included investor sentiment as input in their financial distress analyses. Interestingly, they found reliable evidence that investor sentiment is not only an explanatory variable but also a predictive one, improving the forecasting accuracy for firm financial distress. However, these studies implemented machine learning and deep learning approaches, aiming to optimize for accuracy prediction rather than hypothesis testing.

Even though machine learning models do not impose any structural assumptions, they can capture complex and nonlinear patterns between investor sentiment and financial distress. In doing so, they hint at the possibility of a nonlinear link between sentiment and distress. However, their "*black box*" nature means they provide neither interpretable coefficients nor marginal effects nor allow robustness testing. As a result, prior studies improve predictive accuracy but fail to demonstrate the specific form of the sentiment and distress relationship. This leaves a clear gap: the nonlinear impact of investor negativity, particularly the possibility of an inverted U-shaped pattern consistent with bounded rationality and saturation effects, remains theoretically plausible but empirically untested. To address this gap, our study is the first to move beyond black box prediction and explicitly test an inverted U-shaped relationship between investor negativity and firm distress, grounding the analysis in behavioral theories of bounded rationality and saturation. To our knowledge, this is the first study to test an inverted U-shaped relationship between investor sentiment and distress in an emerging market context, using an ordinal distress framework with regulatory compliance included.

Vietnam represents a critical case study, sharing structural similarities with many other emerging markets, most notably, the predominance of retail investors, who account for approximately 99.5% of the investor population (Bui and Nguyen, 2019). These individual investors typically have limited access to complex or institutional grade information sources and instead rely heavily on low-cost, rapid news on the Internet (Bui and Nguyen, 2019). The Vietnamese stock market thus provides a uniquely suitable context for examining how news influences investor behavior. Moreover, the market exhibits pronounced sentiment driven volatility (Nguyen *et al.*, 2025; Pham *et al.*, 2025). Consequently, Vietnam should not be viewed merely as a local case, but rather as a strategic empirical setting, one that functions as a natural laboratory for investigating nonlinear dynamics between investor sentiment and firm distress. Insights derived from this context are highly transferable to other emerging markets and, more broadly, contribute meaningfully to global discourses on financial market behavior.

In addition, our contribution is twofold: first, we extend the conventional notion of financial distress to a broader concept of firm distress, explicitly incorporating regulatory compliance distress, a widespread but underexplored phenomenon in listed firms; second, we develop a tailored prompt base large language models (LLMs) for estimating investor sentiment from news, which aligns more closely with the firm distress framework. Taken together, these contributions position our study as the first to move beyond black-box prediction and provide theoretically grounded, empirically interpretable evidence of an inverted U-shaped sentiment–distress relationship in an emerging market context (Nguyen *et al.*, 2025).

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework and develops the hypotheses, focusing on how negative investor sentiment, through loss aversion, bounded rationality and regret theory affects firm distress. Section 3 describes the research design and methodology. Section 4 reports the empirical findings. Section 5 discusses the theoretical and practical implications and concludes with the study's limitations and directions for future research.

2. Theoretical framework and hypothesis development

Addressing the gaps identified in emerging markets where the Vietnamese case is particularly informative because it shares structural characteristics with many other markets, notably the prevalence of sentiment-driven volatility triggered by news flows (Nguyen *et al.*, 2025 and Pham *et al.*, 2025), we focus on the underexplored nonlinear effects of investor negative sentiment at the firm level of distress that have been hinted at in previous studies but without explicit testing (Singh and Arora, 2024; Wang *et al.*, 2014; Mai *et al.*, 2019; Zhao *et al.*, 2022). Earlier research by Mai *et al.* (2019) emphasized that AI-based models such as deep learning and kernel SVM outperform linear approaches when processing multidimensional textual data, suggesting that the relationship between textual information and financial outcomes is inherently complex and nonlinear. Zhao *et al.* (2022) later provided stronger empirical evidence: when investor sentiment between social media and traditional news remains stable, the probability of default decreases, whereas large fluctuations in this divergence significantly increase financial risk, indicating the presence of a hidden nonlinear mechanism. Furthermore, Zhao *et al.* (2022) employed the CatBoost model, specifically designed to capture complex and nonlinear interactions, and demonstrated that incorporating these nonlinear relationships among sentiment features substantially improves the prediction of firm distress compared with traditional linear models. This finding reinforces that the link between investor sentiment and corporate financial distress is fundamentally nonlinear. More recently, Garcia (2025) advanced this line of research by introducing sentiment divergence**,** the difference between social media and news-based sentiment, as a predictive variable. Garcia (2025) found that a one-standard-deviation increase in the level of divergence reduces default probability by 7 basis points, while the same increase in divergence volatility raises it by 46 basis points. Moreover, heightened institutional investor attention amplifies default risk by as much as 869 basis points, further confirming and extending the evidence that the relationship between investor sentiment and financial distress is far from linear, governed instead by nonlinear mechanisms. Therefore, we develop a testable hypothesis and explain a two-phase mechanism by which news-driven investor behavior affects firm distress. In the first phase, rising negativity increases pressure and distress risk. In the second phase, once negativity crosses a threshold, contrarian reactions reduce distress. This two-phase framework provides a clear basis for quantitative testing and offers important theoretical contributions. Accordingly, the following hypothesis is proposed: *Investor negativity derived from news has a nonlinear effect on firm distress, following an inverted U-shaped pattern.*

We focus specifically on negative sentiment derived from firm specific news, because this is the form of sentiment most capable of driving investor reactions and shaping market outcomes (Kahneman and Tversky, 1979; Kahneman, 2003; Dunham and Garcia, 2021). Prospect theory shows that individuals react more strongly to losses than to equivalent gains,

creating the loss aversion effect; accordingly, negative firm specific sentiment is weighted more heavily than positive sentiment in shaping investor behavior (Kahneman and Tversky, 1979). In parallel, Bounded Rationality emphasizes that under imperfect information, investors cannot optimize their decisions, making them prone to overreaction and irrational responses (Kahneman, 2003). Together, these theories explain why negativity derived from news plays a dominant role in driving investor decisions.

Behavioral mechanisms underlying an inverted U-shaped effect involve two phases: negativity increases firm distress at a diminishing rate, and after negativity reaches a certain threshold, it reduces firm distress. The threshold at which the inverted U-shaped effect turns can be interpreted as the collective crossing of individual psychological thresholds described in agent-based market frameworks (Cross *et al.*, 2005). In these agent-based models, each investor is represented as an agent endowed with simple psychological features, specifically, tensions such as cowardice *(the stress of being in a minority position) and inaction (the growing urge to reevaluate one's position)* and a threshold level for each of these tensions. According to Cross *et al.* (2005), "*This personality consists of a threshold level for each of the tensions being modeled, and the agent reacts whenever a tension threshold is reached.*" Each agent "*reacts by re-evaluating their market position whenever one of these emotional levels breaches their individual tolerance level.*" Furthermore, "*whenever a particular tension reaches an agent's pre-defined tolerance level, then that agent will be forced to switch position in order to eliminate that tension.*" For the cowardice tension, "*when this agent's tolerance threshold is exceeded, the agent will switch positions to (attempt to) join the majority. At that time, the cowardice tension is reset to zero since that participant has now extinguished that particular source of tension.*" These behavioral rules imply that agents change their reactions when their internal emotional pressures surpass their personal thresholds, causing discrete, stepwise shifts in market behavior. As sentiment negativity accumulates across the market, more agents exceed their tolerance levels and simultaneously reevaluate or switch positions, leading to a collective transition in aggregate dynamics. This synchronization of micro level threshold breaches generates a macro-level turning point, the apex of the inverted U-shaped relationship. Beyond this threshold, most agents have already adjusted their positions; the remaining market participants, often more tolerant or contrarian, begin perceiving undervaluation and act in stabilizing ways, which reduce overall firm distress. This behavioral logic has recently found empirical support in momentum-based analyses of market turning points. Goulding *et al.* (2023) demonstrate that investors' heterogeneous sensitivities to new information captured through "*fast*" and "*slow*" momentum signals, can collectively produce regime shifts at market turning points. These regime transitions mirror the threshold-triggered switching behavior proposed by Cross *et al.* (2005), wherein agents alter positions once their emotional tension thresholds are breached. The observed alignment between micro-level psychological thresholds and macro-level momentum dynamics provides empirical grounding for the emergence of nonlinear patterns in market sentiment and performance.

The first phase can be explained by bounded rationality (Kahneman, 2003), in which investors process information imperfectly and are prone to cognitive biases. When negative sentiment rises, investors often overreact by selling off shares, which depresses stock prices and increases firms' cost of capital (Dunham and Garcia, 2021). Falling valuations reduce collateral values, weaken borrowing capacity and may trigger margin calls, while uncertainty and pessimism lead firms to delay investments, disrupt cash flows and amplify liquidity stress (Garcia, 2025). Together, these channels show how rising negativity directly translates into heightened financial and operational distress.

Therefore, when negativity reaches a certain threshold, investors become emotionally numb. They no longer react as strongly as before, and their responses diminish due to saturation, leading to inertia and paralysis of action. At this stage, contrarian mechanisms begin to emerge. Many investors interpret the market's reaction as an overreaction (De Bondt and Richard, 1985), with stock prices falling well below their fundamental values. Empirical evidence shows that noise trading can push prices far from fundamentals, thereby creating

conditions for reversal once pessimism peaks (De Long *et al.*, 1990). In this context, the belief arises that the worst of the bad news has already been priced in and that further downside risk is limited. Regret theory provides further insight that when faced with historically low prices under extreme pessimism, investors anticipate the regret they might feel if they fail to buy before a rebound and act to avoid that regret (Loomes and Sugden, 1982). These mechanisms encourage renewed buying activity, which offsets earlier selling momentum, stabilizes prices and alleviates financial distress. In this phase, the relationship between negativity and distress reverses, thereby completing the inverted U-shaped dynamic. Taken together, these behavioral mechanisms provide a rigorous theoretical foundation for our main hypothesis that investor negativity derived from news exerts an inverted U-shaped effect on firm distress.

This theoretical framework also constitutes a contribution in itself. Our theoretical contribution lies in integrating previously fragmented perspectives into a coherent framework. While prior research has separately invoked prospect theory, bounded rationality, or regret theory, no study has combined them to explain the full chain from news sentiment to investor reactions and ultimately to firm-level distress. By articulating this two-phase mechanism and formulating a testable inverted U-shaped hypothesis, we provide an integrated behavioral framework that advances our understanding of how sentiment translates into corporate vulnerability.

We address the important possibility of a reverse causal relationship, where firm distress precedes and amplifies negative news sentiment. While this endogeneity concern is valid, we argue that the temporal sequencing of news sentiment provides a stronger causal narrative. News typically emerges earlier and shapes investor perceptions in real time, whereas distress materializes more gradually in financial statements and regulatory outcomes. Thus, although reverse causality cannot be fully ruled out, it is less likely to dominate the dynamic. This recognition further motivates our hypothesis and empirical design, which uses news ahead of distress announcements to ensure the correct ordering of cause and effect.

3. Methodologies

3.1 Model specifications

We tested the proposed hypothesis using ordered probit and ordered logit models. These models are appropriate because the dependent variable, firm distress ($Distress_{it}$) is defined on a six-level ordinal scale (0 = no distress to 5 = severe distress with delisting), consistent with Vietnamese stock exchange regulations. Crucially, ordered models (probit and logit) not only fit the ordinal nature of the data but also provide threshold estimates that enable us to examine the inverted U-shaped relationship between investor negativity and firm distress, which is the main focus of this study. Jones and Hensher (2004) have demonstrated and provided strong empirical evidence that logit models are well suited for financial distress analysis, precisely because they account for nonlinear effects in firm outcomes. Building on this precedent, ordered response models such as ordered probit and ordered logit are widely recognized as appropriate tools for analyzing ordinal rating scales, since the dependent variable inherently requires a nonlinear link function (logit or probit). This makes them a natural and theoretical choice for capturing the inverted U-shaped relationship between investor negativity and firm distress in our study.

The models include firm distress ($Distress_{it}$) as the dependent variable and two groups of variables: Negativity_{it} as the key independent variable, representing investor negativity sentiment derived from news, and a set of control variables capturing standard financial ratios. Specifically, the controls consist of the effective tax rate (ETR_{it}) (Lundberg and Lee, 2017), return on invested capital ($ROIC_{it-1}$) (Sun *et al.*, 2021), average payables days (ADA_{it-2}) (Jabeur *et al.*, 2021), quick ratio (QR_{it}) (Tran *et al.*, 2022), interest coverage ratio (ICR_{it}) (Jabeur *et al.*, 2021), current ratio (CR_{it-2}) (Brédart, 2014; Jabeur *et al.*, 2021; Tran *et al.*, 2022) and net margin (NM_{it-1}) (Jabeur *et al.*, 2021). These variables cover leverage, profitability, liquidity, efficiency and risk amplification, and each is grounded in prior distress prediction

studies. Notably, the inclusion of ICR is particularly important because it directly reflects a firm's ability to service debt from core operations. An ICR below 1 indicates that earnings before interest and taxes (EBIT) are insufficient to cover interest payments-a clear sign of financial stress. This interpretation aligns with the empirical definition of financial distress adopted by Nguyen *et al.* (2025), who consider a firm distressed if it records EBIT lower than interest expense for two consecutive years. By incorporating ICR into our model, we capture an early warning indicator of insolvency risk that is both financially intuitive and widely supported in corporate finance literature. This ensures that our specification is theoretically justified and empirically consistent with established corporate finance and distress literature.

We first test the hypothesis that higher negativity in investor sentiment derived from news increases the likelihood of firm distress. This will provide the basis to test for the non-linear relationship, as we need to confirm that there exists a statistically significant relationship between these variables. The model specification is as follows:

$$\mathrm{P(Distress)}_{it} = \sum \text{financial ratios}_{it} + \alpha_1 \mathrm{Negativity}_{it} + \varepsilon_{it} \quad (1)$$

We expect a statistically significant and positive α_1.

Next, we test our main hypothesis that the relationship between investor negativity and firm distress is non-linear, following an inverted U-shaped pattern. The specification is as follows:

$$\mathrm{P(Distress)}_{it} = \sum \text{financial ratios}_{it} + \alpha_1 \mathrm{Negativity}_{it} + \alpha_2 \mathrm{Negativity}_{it}^{2} + \varepsilon_{it} \quad (2)$$

The inclusion of the quadratic term $Negativity_{it}^2$ serves as a formal test of nonlinearity. This approach is grounded in the principle demonstrated by Boyar *et al.* (2013), who showed that the presence of squared terms is direct evidence of nonlinearity. Consistent with our hypothesis, we expect a statistically significant, positive α_1, and a negative α_2. Definitions and measurements of the investor sentiment variable are provided in Section 3.2.

3.2 Measuring investor sentiment

To measure investor sentiment, we use prompt-based LLMs, specifically GPT-4o-mini. This method is implemented on financial news from Cafef.vn, a reputable source in Vietnam, covering 80 listed companies during 2010–2022. A carefully designed prompt guides GPT-4o-mini to evaluate each article based on five financial distress indicators: (1) continuous cash shortage and negative cash flow; (2) reduction in profit and continuous revenue decline; (3) high short-term borrowing and leverage; (4) failure to meet debt obligations and (5) financial statements being rejected or receiving a qualified opinion from auditors. For each indicator, the model assigns a score from 0 *(no distress)* to 5 *(severe distress)*. These scores are then mapped to the six levels of firm distress as defined by Vietnam's legal obligations for companies listed on HOSE, HNX and UPCOM. For example, an article reporting that a firm's accumulated losses exceed its charter capital and has been suspended from trading would be quantified into a negative sentiment score corresponding to "*financial distress level 2*." The level of negativity that investors derive from each article, denoted as $Negativity_{it}$, is calculated as the total score aggregated across the five indicators, thereby capturing both explicit and implicit signals of financial distress.

The choice of prompt-based LLMs is optimal for measuring investor sentiment, as the literature consistently shows their superiority over traditional methods. "Comparative studies have consistently shown that LLMs outperform traditional Natural Language Processing (NLP) techniques in financial sentiment analysis" (Leechewyuwasorn and Wangpratham, 2024; Moreno and Ordieres-Meré, 2025). LLMs not only enhance predictive accuracy but also minimize biases, since "unlike human analysts, LLMs are not influenced by emotional or overconfidence biases" (Tjuatja *et al.*, 2024). Empirical evidence further confirms this

advantage: "*the Gemini and GPT-4o models excel in handling negative sentiment, demonstrating superior performance in terms of precision, recall, and F1 score*" (Leechewyuwasorn and Wangpratham, 2024). Moreover, technical efficiency strengthens their suitability, as "prompt-based LLMs offer several advantages in sentiment financial context ... they are flexible, interpretable, and resource-saving" (Chen and Kawashima, 2025). Taken together, these findings provide strong scholarly support for our decision to use GPT-4o-mini, ensuring both robustness and practical relevance in capturing negativity from financial news.

To validate the reliability of the prompt based LLM sentiment scores, we conducted a manual labeling exercise on a randomly selected gold standard subset of 150 news articles. This sample size ensures sufficient representativeness at a 95% confidence level with an accepted margin of error of ±8%, consistent with standard statistical practices. Three finance experts independently classified each article as *positive*, *neutral* or *negative* based on standardized criteria. The labeling results showed a high level of agreement, with consistent classifications in 78% of the cases, indicating strong convergence in human judgment. Furthermore, the sentiment labels generated by the prompt-based LLMs matched the majority expert labels in 84% of the cases. While the high match rate confirms the validity of the prompt based LLMs sentiment measure, future research should explore additional robustness criteria beyond expert labeled references to ensure construct reliability.

3.3 Samples

This study works on a sample of 80 listed non-financial firms that have continuously operated, experienced and recovered from distress from 2010 until now. This specific sample meets the nature of threshold distress, ensuring sensitivity and focused on analysis. This sampling approach is consistent with prior research showing that firm distress is highly sensitive to investor sentiment and is shaped by speculative trading, capital costs and market volatility (Baker *et al.*, 2016; Bollen *et al.*, 2011; Vogel and Xie, 2023). We manually collect the distress data from HOSE and HNX announcements. Financial ratios were collected from Thomson Reuters Eikon and investor negativity was estimated using news from Cafef.vn.

4. Empirical findings

4.1 Empirical confirmation of the inverted U-shaped relationship between investor negativity and firm distress

This section presents empirical evidence confirming the hypothesis that investor negativity and firm distress are related through a non-linear, inverted U-shaped function, using results from the full set of regression models and marginal effects analysis. Model 1, which does not include the squared term for investor negativity ($Negativity_{it}^2$), cannot formally test for a non-linear relationship. However, it serves as a critical baseline specification for assessing the linear impact of investor negativity on firm distress. The coefficient for $Negativity_{it}$ is positive and statistically significant in both the probit (+0.490***) and Logit (+0.912***) specifications, indicating that higher investor negativity is associated with greater levels of distress (see Table 1). Although Model 1 is restricted to a linear form, its marginal effects across distress levels exhibit a non-monotonic pattern. As shown in Table II in the Supplementary Material, the marginal effects increase to a peak at Distress Level 2 (+0.049) and then gradually decline through higher levels of distress (+0.035 at Distress 3, +0.010 at Distress 4), before showing a minor uptick at Distress 5 (+0.023). While the uptick may be attributed to noise or category overlap, the general shape reflects the first phase of an inverted U. This suggests that Model 1 weakly signals a latent non-linear relationship, which is later formally validated by Model 2. Model 2, estimated using both ordered probit and logit models, incorporates both Negativity and Negativity^2, and provides direct statistical confirmation of the hypothesized non-linear dynamic. The coefficient for $Negativity_{it}$ is positive and

Table 1. Main empirical evidence from ordered probit and logit models

Variable	Expectation	Model 1 Probit	Logit	Model 2 Probit	Logit
$Negativity_{it}^2$	$\alpha 2 < 0$			−0.600***	−1.187***
$Negativity_{it}$	$\alpha 1 > 0$	0.490***	0.912***	1.067***	2.033***
ETR_{it}		−0.084**	−0.159**	−0.081**	−0.157**
$ROIC_{it-1}$		−0.405***	−0.688***	−0.430***	−0.749***
ADA_{it-2}		−0.233***	−0.462***	−0.179***	−0.324***
QR_{it}		0.292***	0.489***	0.294***	0.493***
ICR_{it}		−0.115**	−0.186*	−0.090*	−0.144
CR_{it-2}		−0.157**	−0.249**	−0.172***	−0.273**
NM_{it-1}		−0.062	−0.127	−0.092*	−0.157*

Note(s): All models are estimated using ordered probit and logit methods. Standard errors are clustered at firm level

$Negativity_{it}$ is strongly positive and significant in all models, confirming that higher investors' negativity increases distress probability

$Negativity_{it}^2$ is significantly negative, supporting the hypothesis of diminishing marginal impact of extreme negativity

Source(s): Estimated by authors

significant (probit: +1.067***; logit: +2.033***). The coefficient for $Negativity_{it}^2$ is negative and significant (probit: −0.600***; logit: −1.187***). This combination of a negative linear term and a positive quadratic term, supports the existence of an inverted U-shaped relationship within ordered response models, where higher distress levels indicate more severe financial conditions. In this context, the results imply that the probability of distress initially increases with negativity, reaches a maximum, and then declines beyond a certain threshold.

The marginal effects in Model 2 (Table II) further validate this structure. Distress probability peaks at intermediate levels (Distress 2: +0.102; Distress 3: +0.075) and then gradually declines (Distress 4: +0.022; Distress 5: +0.052). This pattern reflects the predicted saturation and reversal in investor responses as negativity intensifies, confirming the concave (inverted U) shape. The cut points from Table III in the Supplementary Material reinforce this evidence (Threshold_2: −0.318 (probit), 0.256 (logit) and Threshold_3: −0.387 (probit), 0.241 (logit). These estimates identify the inflection point of the inverted U-curve between these thresholds, indicating that the peak probability of distress occurs between moderate levels of negativity, after which the marginal impact declines. Together, these findings offer strong and statistically valid confirmation of the hypothesis: (1) A negative linear and positive quadratic coefficient structure, (2) Peak marginal effects at intermediate distress levels and (3) inflection points localized between Thresholds 2 and 3. All provide consistent evidence for the inverted U-shaped relationship between investor negativity and firm distress. The model is both statistically robust and economically interpretable. These findings are fully consistent with the theoretical foundations. prospect theory and bounded rationality explain the initial phase of the inverted U-shape, where increasing negativity prompts strong investor reactions, exerting pressure on firms through multiple channels. The saturation effect and desensitization account for the diminishing responses at higher levels of negativity, accurately capturing the turning point of the model. Furthermore, this reversal phase is reinforced by the bottom fishing strategy and regret theory, where investors seek buying opportunities at perceived market bottoms, thereby easing corporate distress. As such, the model not only achieves quantitative validity but also demonstrates strong consistency with the theoretical basis used to formulate the hypothesis. This provides clear evidence that the study has constructed a well-founded analytical framework that tightly integrates behavioral finance theory with empirical results, contributing meaningful academic value.

4.2 Robustness checks and model fit statistics

The statistical robustness of the models is clearly supported by the results from Table IV (Model Fit Statistics) and Table V (Variance Inflation Factors) in the Supplementary Material. Taken together, these outputs affirm that the empirical specifications are both stable and well-fitted. Table IV provides detailed model fit statistics. Specifically, the fit statistics for Models 1 and 2, using both probit and logit regressions, indicate a clear improvement in model performance from Model 1 to Model 2. This enhancement is reflected in the following key indicators: Log-Likelihood improves from −921.337 (probit) and −922.236 (logit) in Model 1 to −904.657 (probit) and −904.213 (logit) in Model 2. This increase (i.e. less negative values) reflects a better fit to the data. Akaike Information Criterion (AIC) declined from 1868.674 (probit) and 1870.472 (logit) in Model 1 to 1837.314 (probit) and 1836.427 (logit) in Model 2. A lower AIC indicates that Model 2 achieves a better balance between explanatory power and parsimony. Bayesian information criterion (BIC) also decreases, from 1932.985 to 1934.783 in Model 1 to 1906.572 and 1905.684 in Model 2, further reinforcing that the improved fit is not merely a result of overfitting. Pseudo R^2 increases from 0.162 (probit) and 0.161 (logit) in Model 1 to 0.177 (probit) and 0.178 (logit) in Model 2, suggesting enhanced explanatory power with the inclusion of additional predictors, especially those reflecting sentiment and nonlinear effects. Together, these metrics provide robust evidence that Model 2 significantly outperforms Model 1 in terms of goodness-of-fit. In addition, Table V presents the results of the multicollinearity check using Variance Inflation Factors (VIFs). The VIFs were assessed before and after mean-centering to ensure reliable coefficient estimation. In Model 2, the highest VIFs before centering are 10.174 and 7.542, which might raise concerns. However, after mean-centering, these values are substantially reduced to 5.192 and 6.638, respectively. Moreover, all other variables display VIFs well below the conventional threshold of 10, with most falling in the range of 1.2–5.0 both before and after centering. These results confirm that the centering correction is effective in mitigating multicollinearity, particularly for polynomial terms like Negativity^2, where raw scores tend to inflate VIFs. As a result, acceptable levels of multicollinearity were achieved, ensuring stability in the regression coefficients. In conclusion, the combination of improved fit indices (LL, AIC, BIC, Pseudo R^2) and VIF values demonstrated strong statistical robustness of the empirical models. Notably, Model 2 exhibits superior performance without multicollinearity distortion, confirming its validity and reliability for estimating the relationship under investigation.

5. Conclusion

5.1 Theoretical implications

This study investigates how investors' negative sentiments derived from news affects the firm's distress likelihood. Through this, on one hand, it provides reliable empirical evidence and on the other hand, it enriches important theories within the behavioral finance school, such as loss aversion of prospect theory and the anchoring and adjustment process of bounded rationality theory and regret theory.

First, this study bridges the efficient market hypothesis with behavioral finance. Both schools of thought together confirm that information is a factor shaping investor behavior, not only through rationality but also through investor sentiment. This study reinforces that argument by demonstrating that investor sentiment, shaped by news, directly influences investor behavior in the market, resulting in an increase in the firm's risk of falling into distress.

Second, the study enriches the theories in the behavioral finance school with significant contributions. On one hand, the study challenges the traditional assumption of a linear relationship between negative sentiment and firm distress by demonstrating that the relationship is non-linear, following an inverted U-shaped pattern. Thereby, the study expands the understanding of investor behavior at different levels of negativity sentiment, showing investor sentiment has a positive and diminishing marginal effect until reaching a certain threshold of negativity, and the relationship reverses. The inverted U-shape investigated

in this study is really a significant novel contribution, linking the loss aversion effect, bounded rationality and regret aversion to explain the mechanism by which investor negativity affects firm distress through the lens that investor rationality is limited by a threshold.

In sum, this study not only re-affirms existing findings that news-driven negative sentiment escalates firm distress risk but also provides new insights into the non-linear nature of this relationship. By doing so, it enriches behavioral finance theory, offering a more nuanced understanding of how investor sentiment derived from news, mediated by bounded rationality, can dynamically influence corporate distress.

5.2 Practical implications

In addition to its theoretical contributions, this study also provides practical implications. As shown in empirical results, negative investor sentiment derived from news plays an important role in explaining distress risk; therefore, it can be directly used as a predictor for firm distress modeling. It is important to note that sentiment variables serve as the best predictors only when they are combined with financial metrics. Prediction models become more effective with this combination, as the impact of negative sentiment varies across firms depending on internal characteristics such as profitability. This investigation highlights the value of integrating behavioral proxies with fundamental financial data. Doing so improves prediction accuracy and offers a more realistic view of market behavior, especially when investor sentiment strongly drives a firm's distress. Overall, this study helps bridge behavioral finance with distress modeling and supports the development of more responsive risk management engines.

5.3 Limitations and further research

This study is not without limitations. First, our analysis uses a highly specific sample of listed non-financial firms in Vietnam that have operated continuously since 2008 and experienced at least one instance of distress. This design ensures a high-quality sample for identifying multi-level thresholds of distress, but its narrow scope limits generalization. Second, although our dataset consists of more than 80,000 Vietnamese news articles, a massive and novel corpus, it remains confined to Vietnam. Although we strongly wish to extend the analysis to other emerging economies in order to further generalize the theoretical inverted U-shaped relationship, this is not yet feasible because such cross-country research is technically demanding: sentiment extraction must be conducted in each market's native language (e.g. Hindi for India) to ensure objectivity and validity. Third, in terms of model specification, our approach relies on a quadratic term to capture the inverted U-shaped relationship. While the inclusion of such a term is widely accepted as a standard method for testing nonlinearity, we recognize that it may be considered simplistic compared to more advanced structural approaches. More complex nonlinear models (e.g. spline regressions or threshold models) could provide additional insights into distress dynamics.

For further research, three directions are particularly promising. First, future studies should seek more empirical evidence to support the inverted U-shaped relationship between negative sentiment derived from news and firm distress, extending the analysis beyond Vietnam to other economies and developing multilingual sentiment frameworks that respect native-language contexts to ensure cross-country comparability. Second, as LLM-based sentiment analysis is advancing at remarkable speed, further work should both leverage these technological developments and broaden robustness verification by integrating multiple LLMs and combining prompt-based methods with alternative sentiment measures. Third, future research should explore richer nonlinear specifications beyond quadratic terms, including spline or threshold models, to test whether the observed relationship holds under more flexible structural assumptions.

5.4 Conclusion

This study was set out to examine the effect of investor negativity derived from news on firm distress through the lens of bounded rationality, aiming to determine if negative sentiment has an independent, nonlinear impact. The empirical findings provide reliable evidence supporting

our main hypothesis. First, the study demonstrates a nonlinear, inverted U-shaped relationship between investor negativity and firm distress. Distress risk initially increases with rising negativity but then gradually drops after negativity reaches a certain threshold. This is strongly consistent with effects from loss aversion of prospect theory in the context of bounded rationality and regret theory. The marginal effects analysis further supports this, showing the impact peaking at moderate distress levels (specifically Distress 2 in Vietnamese case) before weakening at higher levels. Theoretically, this study bridges the efficient market hypothesis and behavioral finance by showing that information shapes investor behavior through both rationality and sentiment and has significant impacts on firm distress. It also significantly contributes to behavioral finance by challenging the traditional linear view, revealing the novel inverted U-shaped nonlinear relationship between negative sentiment and firm distress and explaining this through the lens of loss aversion and bounded rationality theory. This also pointed out the existence of the anchoring effect. From a practical standpoint, the study highlights that investor sentiment derived from news is an important predictor of distress risk, becoming more effective when combined with traditional financial metrics, improving the accuracy of prediction models and offering a more realistic view of market behavior. However, the study has limitations, including the specific sample of listed non-financial firms in Vietnam that experienced distress, which limits further generalizability.

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Supplementary material

The supplementary material for this article can be found online.

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