

Article

How Framing Susceptibility Is Associated with Investment Grip: Evidence from Japanese Retail Investors

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Abstract

This study builds on the concept of loss tolerance by introducing investment grip, a behavioral interpretation that captures investors' commitment to long-term objectives under adverse market conditions. While loss tolerance traditionally measures the maximum financial loss an investor can withstand, investment grip focuses on the behavioral and psychological dimensions of maintaining long-term investment objectives when facing short-term setbacks, thus providing a more behaviorally grounded and operationalizable approach for evaluating client risk profiles. The investment grip framework integrates insights from self-control theory, emotional regulation research, and goal-commitment models. Using data from 92,792 Japanese retail investors in the 2025 "Survey on Life and Money," we examine how gain-framed and loss-framed messages are associated with investment grip, controlling for digital financial literacy and demographic, socioeconomic, and psychological factors. Our findings reveal that loss framing is robustly associated with stronger investment grip, whereas gain framing demonstrates no statistically meaningful effect. These findings offer new insights into Japanese household financial behavior, explaining why conservative savings patterns persist despite the availability of better investment alternatives. The results underscore the role of information framing in shaping household investment behavior, with implications for investor protection and financial communication policy.

Keywords: investment grip; framing effect; prospect theory; digital financial literacy; behavioral finance; disposition effect; loss tolerance

1. Introduction

Investment loss tolerance is a central yet insufficiently understood construct in personal finance and behavioral investment research. Broadly defined, loss tolerance reflects an investor's psychological and behavioral capacity to endure temporary declines in portfolio value without prematurely altering their investment strategy or exiting the market (Bawalle et al. 2025; van Dolder and Vandenbroucke 2024). It captures the extent to which individuals can absorb short-term losses while maintaining strategic consistency during periods of market volatility (Bawalle et al. 2025; van Dolder and Vandenbroucke 2024).

This concept is closely linked to prospect theory, which highlights the pivotal role of loss aversion—the asymmetry whereby losses loom larger than gains of an equivalent magnitude (Kahneman and Tversky 1979b; Tversky and Kahneman 1992). Substantial empirical studies confirm that loss aversion affects real-world investment choices

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(Dimmock and Kouwenberg 2010; Hwang and Satchell 2010; Iqbal et al. 2021; Lee and Veld-Merkoulova 2016; van Dolder and Vandenbroucke 2024), shaping investors' willingness to bear risk and influencing their portfolio decisions (Khan et al. 2024).

Loss tolerance varies widely across demographic, socioeconomic, and psychological traits. Factors such as age, gender, education, income, and market experience systematically shape investors' responses to losses (Bayar et al. 2020; Dhar and Zhu 2006; Feng and Seasholes 2005; Rieger et al. 2015; Yao et al. 2011). For instance, younger investors tend to show higher tolerance for losses due to longer investment horizons (Bayar et al. 2020; Yao et al. 2011), whereas married investors and parents tend to prioritize capital preservation (Shapira and Venezia 2001). Experience can enhance emotional resilience (List 2003), although sophisticated investors still frequently display loss-averse behavior (Feng and Seasholes 2005; Kaustia and Perttula 2012). Additionally, financial literacy improves the capacity to tolerate short-term losses by strengthening understanding of market fluctuations (Bawalle et al. 2025; Lusardi and Mitchell 2014), though recent work notes that overconfidence may paradoxically decrease loss tolerance (Nabeshima et al. 2025). Collectively, these findings demonstrate the substantial heterogeneity in investor behavior and the need for more nuanced models of loss response.

Traditional finance literature attributes loss tolerance to rational evaluations of financial capacity, portfolio diversification, and investment horizon (Markowitz 1952; Siegel 1998). Behavioral finance, in contrast, emphasizes psychological mechanisms, particularly loss aversion, as the primary determinants of investor behavior (Barberis 2013; Kahneman and Tversky 1979b; Kaushik 2025). Empirical patterns such as the disposition effect (Odean 1998; Shefrin and Statman 1985) further illustrate that investor behavior is often dominated by regret avoidance and an aversion to realizing losses, even among experienced market participants. Consequently, loss tolerance is increasingly understood as dynamic rather than static (Hillen et al. 2017; Hwang and Satchell 2010; Larson et al. 2016; Mukhtar et al. 2023; Walasek and Stewart 2015; Yang 2019).

Building on these insights, this study conceptualizes investment grip as a behavioral reframing of loss tolerance. While the underlying survey item follows the conventional "maximum tolerable loss" format commonly used in the loss-tolerance literature, we interpret this measure from a behavioral perspective. Specifically, the term investment grip is used to emphasize investors' commitment to maintaining long-term objectives under psychologically stressful market conditions, rather than to propose a new psychometric construct or measurement scale. This framework incorporates key elements from self-control theory, emotion regulation research, and goal-commitment models (Gross 1998; Locke and Latham 2002; Tversky and Kahneman 1981). It therefore shifts the analytical focus from the level of loss investors can bear to how effectively they maintain commitment under stress. Investment grip also offers practical value for financial institutions. While regulatory suitability standards in the U.S., Europe, and other markets require consideration of loss aversion (ESMA 2017, 2018; FINRA n.d.; FSA 2011), risk assessments overwhelmingly assume rational expectations and pay insufficient attention to the asymmetric psychological burden of losses. Investment grip provides a more behaviorally grounded and operationalizable approach for evaluating client risk profiles. While our survey measure follows the standard "maximum tolerable loss" format used for loss tolerance, we use the term investment grip to emphasize the behavioral interpretation (i.e., commitment maintenance under stress) rather than proposing a distinct new measurement scale.

Understanding what shapes investment grip is increasingly important in modern financial environments characterized by rapid and continuous information flows. Through financial news, analyst commentary, and social media platforms, retail investors encounter real-time updates that can substantially influence their ability to maintain commitment

(Cantarella et al. 2023; Smales 2021; Tetlock 2007). Young and inexperienced investors, in particular, often respond disproportionately to short-term information, prioritizing immediate reactions over long-term strategy (UK Financial Conduct Authority 2024). These dynamics amplify behavioral biases and heighten vulnerability to emotionally charged content (Cantarella et al. 2023; García 2013; Shao 2025; Wang et al. 2022). Crucially, the effect of information on investor behavior depends not only on its content but also on how it is framed, that is, whether it highlights potential gains or emphasizes prospective losses.

Framing has been shown to significantly influence risk perceptions and investment decisions (D'Angelo 2017; Lecheler and de Vreese 2018; Wang et al. 2025). Moreover, loss framing exerts stronger and more persistent psychological effects (Ding 2024; Ganzach and Karsahi 1995; Shao 2025), intensifying pessimism and accelerating selling behavior during market downturns. Empirical studies show that negative framing, whether through traditional media or online platforms, increases perceived risk and triggers impulsive selling (Ackert et al. 2016; Tetlock 2011; Wang et al. 2022; Zhang et al. 2020). For instance, many retail investors liquidated positions during COVID-19 in response to sustained negative coverage (Kuramoto et al. 2024). Despite extensive research on framing effects in buy–sell decisions, no study has examined whether framing affects investment grip or loss tolerance itself. This represents a critical gap given that investment grip shapes investor resilience during market downturns and influences long-term wealth accumulation. Moreover, prior research has not sufficiently explored how framing operates in real-world information-rich environments where investors simultaneously encounter multiple and often conflicting frames.

This study addresses these gaps by evaluating how gain-framed versus loss-framed information influences investment grip. Using 92,792 investor-level observations from the 2025 Survey on Life and Money conducted by Rakuten Securities and Hiroshima University, we analyze whether exposure to differently framed financial information is associated with variations in investment grip among retail investors. Our contributions are threefold. First, we conceptualize investment grip as a behavioral finance perspective that builds on loss tolerance by highlighting psychological commitment mechanisms. Second, we provide the first empirical evidence of how framing affects investment grip. Third, we investigate heterogeneous effects across investor subgroups, enhancing our understanding of which investors are most susceptible to framing-induced shifts in investment commitment. The remainder of the paper is structured as follows. Section 2 describes the data and empirical method. Section 3 provides the estimation results. Section 4 presents a discussion of the results. Section 5 concludes.

2. Data and Method

2.1. Data

This study utilized data from the 2025 wave of the Survey on Life and Money, jointly conducted by Rakuten Securities, Japan, and the Kadoya Lab of Hiroshima University, Japan. Rakuten Securities is Japan's largest online securities firm. Since 2022, the survey has been administered annually to Rakuten Securities account holders. The 2025 wave was fielded online between January and February 2025 and targeted individuals aged 18 years or older who resided in Japan and had logged into their Rakuten Securities account at least once in the preceding year. The questionnaire collected extensive information on demographic and socioeconomic characteristics, psychological preferences, and investment behaviors. It also included modules designed to measure the respondents' investment grip and their susceptibility to framing effects—the key explanatory variables in this study. After removing observations with missing values for the main analytical variables, the final dataset contained 92,792 unique respondents.

2.2. Variables

2.2.1. Dependent Variable

The dependent variable, *investment grip*, reflects an individual's tolerance of temporary investment losses before deciding to liquidate an asset. This captures the maximum percentage decline in asset value that a respondent reports being able to endure during periods of market volatility. To measure this construct, respondents were presented with a hypothetical scenario in which an investment trust initially valued at JPY 1 million experienced a loss. They were asked to indicate the greatest decline they would be willing to endure before selling. The response options were 1% (JPY 990,000), 10% (JPY 900,000), 20% (JPY 800,000), 30% (JPY 700,000), and 40% or more (JPY 600,000). Based on these responses, we constructed an ordered categorical variable ranging from 1% to 40% or more.

2.2.2. Independent Variable

The primary explanatory variables, *Framing Gain* and *Framing Loss*, were derived from coin-flip-based hypothetical questions adapted from Hayden and Platt (2009) and Blavatsky (2021). Three questions assessed choices between certain and probabilistic outcomes under gain-framed and loss-framed conditions, consistent with prospect theory (Kahneman and Tversky 1979a).

- Respondents who chose gambling *only* in the gain-framed scenario were coded as Framing Gain.
- Respondents who chose gambling *only* in the loss-framed scenario were coded as Framing Loss.

This operationalization is consistent with existing research showing that gain and loss frames systematically shape risk-taking behaviors (Kühberger 1998; Tversky and Kahneman 1981). Empirical evidence from financial settings further supports the robustness of such framing effects (Blavatsky 2021; De Martino et al. 2006). In addition to the framing variables, we include a comprehensive set of controls: gender, age, age squared, marital status, number of children, years of education, employment status, annual household income, annual household assets, digital financial literacy (DFL), risk aversion, and myopic view of the future. Myopic view of the future refers to a short-term investment orientation in which individuals place disproportionate weight on near-term outcomes relative to long-term objectives. This concept captures horizon-based decision-making rather than general risk aversion. Table 1 presents the definitions and measurements of all variables.

Table 1. Definition of variables.

Variable	Definition
Dependent Variable	
Investment Grip	Ordered variable indicating the maximum loss a respondent can tolerate when investing JPY 1 million (1%/10%/20%/30%/40% loss)
Independent Variables	
Framing Gain (positive framing)	1 = gambling action in the gain phase, 0 = otherwise
Framing Loss (negative framing)	1 = gambling action in the loss phase, 0 = otherwise
DFL	Composite index: represents the sum of the average scores of the eight sub-dimensions
Demographic Variables	
Gender	1 = male, 0 = female
Age	respondents' age
Age squared	age squared
Marital status	1 = married, 0 = otherwise

Number of children	Number of children
Socio Economic Variables	
Years of education	Years of education
Having a job	1 = having a full-time job, 0 = otherwise
Household income	Annual earned income before taxes, including bonuses of the entire household (unit: JPY)
Log of household income	Log (household income)
Household assets	Balance of financial assets (savings, stocks, bonds, insurance, and so on) of the entire household (unit: JPY)
Log of household assets	Log (household assets)
Psychological Variables	
Risk aversion	Risk-of-rain preference (percentage score from the question, “Usually, when you go out, how high must the probability of rainfall be before you take an umbrella?”)
Myopic view of the future	Self-reported short-term investment orientation measured on a five-point Likert scale (1–5), where higher values indicate a more myopic investment view

2.3. Descriptive Statistics

Table 2 presents the descriptive statistics of the variables. The mean investment grip is 23.4%, with 5.6% of respondents tolerating only a 1% loss. The summary statistics further reveal that 26.7%, 24.3%, and 14.7% of the respondents tolerate 10%, 20%, and 30% losses, respectively. Notably, 28.7% reported a tolerance of 40% or more, indicating substantial heterogeneity in investors’ loss-absorption capacity. Regarding framing behaviors, 6.86% of respondents exhibited framing-gain behavior, whereas 33.4% were classified as framing loss. The average DFL was 30.0 (range: 7–36). The sample is 64.9% male, with a mean age of 45.2 years and an average of 15.0 years of education. Approximately 67.2% were married, the average number of children was 1.14, and 70.6% were employed full-time. The average annual household income was JPY 7,749,892, and the mean value of household financial assets amounted to JPY 19,700,000. Additionally, the levels of risk aversion and myopic view of the future were 0.53 and 2.42, respectively.

Table 2. Summary of statistics.

Variable	Mean (or %)	Std. Dev.	Min	Max
Investment Grip	0.234717	0.1281467	0.01	0.4
1%	5.6%			
10%	26.7%			
20%	24.3%			
30%	14.7%			
≥ 40%	28.7%			
Investment Grip (dummy)	0.4340029	0.4956279	0	1
Framing Gain	0.0686158	0.2528011	0	1
Framing Loss	0.334156	0.4716971	0	1
DFL	30.03989	4.693016	7	36
Male	0.6488814	0.4773225	0	1
Age	45.1985	12.29169	18	90
Age squared	2193.988	1158.423	324	8100
Marital Status	0.6717713	0.4695711	0	1
Children	1.139775	1.119885	0	12
Education	15.02066	2.091141	9	21
Full-time	0.7055565	0.4557946	0	1
Annual Income	7,749,892	4,250,053	1,000,000	20,000,000
Log of Household Income	15.70001	0.6078693	13.81551	16.81124

Household Assets	19,700,000	24,100,000	2,500,000	100,000,000
Log of Household Assets	16.18102	1.092191	14.7318	18.42068
Risk Aversion	0.532561	0.2361464	0	1
Myopic	2.42397	0.9650352	1	5
Observations	92,792			

2.4. Methods

This study examines the association between investors' investment grip and their susceptibility to framing effects using the empirical models specified in Equations (1) and (2) below.

$$\text{Investment Grip}_i = f(\text{Framing Gain}_i, X_i, \varepsilon_i), \quad (1)$$

$$\text{Investment Grip}_i = f(\text{Framing Loss}_i, X_i, \varepsilon_i), \quad (2)$$

As the main dependent variable in this study is ordinal, we used an ordered probit model for our analysis. This method is widely recognized in social science, economics, and behavioral finance research (Greene 2018; Wooldridge 2010; van Rooij et al. 2011). To assess the robustness of our findings, we additionally constructed an investment grip dummy variable and conducted a probit regression analysis. Many empirical studies have used probit models for robustness checks of ordered probit regressions (Delavande et al. 2008).

Model Specifications

We estimated four sequential model specifications to examine incremental explanatory power. Specifically, we added sociodemographic, economic, and psychological factors to the models sequentially as follows:

- Model 1: Framing variables only
- Model 2: Adds DFL and demographic characteristics
- Model 3: Adds employment status, household income, and financial assets.
- Model 4: Adds psychological variables (risk aversion and myopic view of the future)

Model 4 is treated as the preferred specification, but reporting all four models allows readers to assess whether the results are robust to alternative model compositions and not driven by omitted-variable bias.

The full set of estimated equations is presented in Equations (3) and (4). In these models, β_0 denotes the intercept, ε_i represents the error term, and β_1 – β_{13} are the estimated coefficients.

$$\begin{aligned} \text{Investment Grip}_i = & \beta_0 + \beta_1 \text{Framing Gain}_i + \beta_2 \text{DFL}_i + \beta_3 \text{Male}_i + \\ & \beta_4 \text{Age}_i + \beta_5 \text{Age square}_i + \beta_6 \text{Marital Status}_i + \beta_7 \text{Children}_i + \\ & \beta_8 \text{Education}_i + \beta_9 \text{Fulltime}_i + \beta_{10} \text{Log of Income}_i + \beta_{11} \text{Log of Assets}_i + \\ & \beta_{12} \text{Risk Aversion}_i + \beta_{13} \text{Myopic}_i + \varepsilon_i, \end{aligned} \quad (3)$$

$$\begin{aligned} \text{Investment Grip}_i = & \beta_0 + \beta_1 \text{Framing Loss}_i + \beta_2 \text{DFL}_i + \beta_3 \text{Male}_i + \\ & \beta_4 \text{Age}_i + \beta_5 \text{Age square}_i + \beta_6 \text{Marital Status}_i + \beta_7 \text{Children}_i + \\ & \beta_8 \text{Education}_i + \beta_9 \text{Fulltime}_i + \beta_{10} \text{Log of Income}_i + \beta_{11} \text{Log of Assets}_i + \\ & \beta_{12} \text{Risk Aversion}_i + \beta_{13} \text{Myopic}_i + \varepsilon_i \end{aligned} \quad (4)$$

All analyses were conducted using Stata 18. Multicollinearity was assessed using pairwise correlations and variance inflation factors (VIFs). All correlation coefficients were below conventional thresholds ($|r| < 0.6$), and all VIF values were below the conventional threshold of 10, indicating that multicollinearity is unlikely to bias the results. These diagnostic checks support the reliability and robustness of the empirical findings.

3. Empirical Results

In this section, we present results for two framing conditions across the four models. In all models, ordered probit regression results are presented to illustrate how different framing conditions shape investors' investment grip.

3.1. Loss-Framing Effects

Table 3 presents the results for the association between investment grip and loss framing (Framing_L). Our findings indicate a robust positive association between loss framing and investment grip across all model specifications. This stronger effect is consistent with prospect theory, which predicts that losses carry greater psychological weight than gains, leading individuals to respond more intensely to negatively framed information.

Table 3. Ordered probit regression results of Framing_L.

	(1)	Investment Grip (2)	(3)	(4)
	Model_1	Model_2	Model_3	Model_4
Framing_L	0.0659 *** (0.0073)	0.0431 *** (0.0074)	0.0385 *** (0.0075)	0.0371 *** (0.0075)
DFL_std		0.0381 *** (0.0007)	0.0329 *** (0.0007)	0.0324 *** (0.0007)
Male		0.3715 *** (0.0076)	0.3822 *** (0.0080)	0.3813 *** (0.0080)
Age		0.0343 *** (0.0019)	0.0243 *** (0.0020)	0.0243 *** (0.0020)
Age_sq		−0.0004 *** (0.0000)	−0.0004 *** (0.0000)	−0.0004 *** (0.0000)
Marital_status		−0.0402 *** (0.0089)	−0.0933 *** (0.0096)	−0.0943 *** (0.0096)
Children		−0.0245 *** (0.0039)	−0.0101 *** (0.0039)	−0.0113 *** (0.0039)
Education		0.0081 *** (0.0018)	−0.0171 *** (0.0018)	−0.0167 *** (0.0018)
Fulltime			−0.0040 (0.0094)	−0.0041 (0.0094)
Log_Hincome			−0.0032 (0.0079)	−0.0035 (0.0079)
Log_Hasset			0.2274 *** (0.0040)	0.2278 *** (0.0040)
Risk_Aversion				−0.0912 *** (0.0157)
Myopic				−0.0196 *** (0.0038)
/cut1	−1.5692 *** (0.0072)	−0.6930 *** (0.0530)	2.0940 *** (0.1128)	2.0078 *** (0.1136)
/cut2	−0.4371 *** (0.0050)	0.4957 *** (0.0529)	3.3086 *** (0.1129)	3.2227 *** (0.1137)
/cut3	0.1884 *** (0.0048)	1.1479 *** (0.0529)	3.9779 *** (0.1130)	3.8922 *** (0.1139)
/cut4	0.5857 *** (0.0050)	1.5629 *** (0.0529)	4.4029 *** (0.1131)	4.3174 *** (0.1139)

Observations	92,792	92,792	92,792	92,792
Pseudo R ²	0.0003	0.0266	0.0403	0.0405
Log likelihood	−138,960.0231	−135,297.2421	−133,400.7183	−133,370.8787

Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.2. Gain-Framing Effects

Table 4 reports the results for gain framing (Framing_G). The estimated coefficients are positive across all specifications; however, statistical significance is weak, with significance emerging only at the 10% level in models with full controls. In the first two models (Models 1 and 2) without full controls, the framing effect is not statistically significant. Once socioeconomic variables and psychological factors are included in Models 3 and 4, the effect becomes marginally significant at the 10% significance level. This suggests that gain framing has only a modest positive influence on investment grip, and that this relationship emerges only after accounting for other important factors.

Table 4. Ordered probit regression results of Framing_G.

	(1)	Investment Grip (2)	(3)	(4)
	Model_1	Model_2	Model_3	Model_4
Framing_G	0.0130 (0.0132)	0.0087 (0.0134)	0.0252 * (0.0134)	0.0245 * (0.0134)
DFL_std		0.0384 *** (0.0007)	0.0331 *** (0.0007)	0.0326 *** (0.0007)
Male		0.3695 *** (0.0076)	0.3804 *** (0.0080)	0.3795 *** (0.0080)
Age		0.0344 *** (0.0019)	0.0244 *** (0.0020)	0.0244 *** (0.0020)
Age_sq		−0.0004 *** (0.0000)	−0.0004 *** (0.0000)	−0.0004 *** (0.0000)
Marital_status		−0.0399 *** (0.0089)	−0.0931 *** (0.0096)	−0.0941 *** (0.0096)
Children		−0.0245 *** (0.0039)	−0.0101 *** (0.0039)	−0.0113 *** (0.0039)
Education		0.0084 *** (0.0018)	−0.0169 *** (0.0018)	−0.0165 *** (0.0018)
Fulltime			−0.0042 (0.0094)	−0.0043 (0.0094)
Log_Hincome			−0.0032 (0.0079)	−0.0034 (0.0079)
Log_Hasset			0.2277 *** (0.0040)	0.2281 *** (0.0040)
Risk_Aversion				−0.0916 *** (0.0157)
Myopic				−0.0201 *** (0.0038)
/cut1	−1.5894 *** (0.0068)	−0.7029 *** (0.0530)	2.0924 *** (0.1128)	2.0044 *** (0.1136)
/cut2	−0.4581 *** (0.0044)	0.4853 *** (0.0529)	3.3067 *** (0.1129)	3.2190 *** (0.1138)
/cut3	0.1671 *** (0.0043)	1.1374 *** (0.0529)	3.9759 *** (0.1130)	3.8885 *** (0.1139)
/cut4	0.5643 ***	1.5524 ***	4.4009 ***	4.3136 ***

	(0.0045)	(0.0529)	(0.1131)	(0.1139)
Observations	92,792	92,792	92,792	92,792
Pseudo R ²	0.0000	0.0265	0.0402	0.0404
Log likelihood	−138,999.0545	−135,313.6567	−133,412.2528	−133,381.5725

Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3. Control Variables

We employed several control variables as important predictors of investment grip. Digital financial literacy (DFL_std) shows a positive and highly significant result across all models, indicating that retail investors who are more proficient with digital financial tools and platforms are more likely to hold onto losing positions rather than selling them prematurely. Gender plays a substantial role, with males showing a positive and greater investment grip than females across all models. Moreover, age exhibits a non-linear relationship with investment grip, as evidenced by the positive coefficient of age and the negative coefficient of age squared, indicating that investment grip increases with age but at a diminishing rate. Furthermore, marital status shows a negative association with investment grip, with the effect becoming stronger when economic variables are added (Models 2 to 4). Having children also negatively predicts investment grip, though this effect weakens substantially when household assets are controlled for. On the contrary, education shows an interesting reversal, being positively associated with investment grip in Model 2 but turning negative once household assets are included, suggesting that the education effect operates through wealth accumulation. Household assets emerge as one of the strongest predictors, with positive and significant coefficients, indicating that wealthier households exhibit significantly greater investment grip. Employment status and household income, however, show no significant effects. In the final model, both risk aversion and myopic behavior demonstrate negative associations with investment grip, which aligns with theoretical expectations that more risk-averse and short-sighted individuals are less willing to tolerate losses.

The model fit improves as controls are added, with pseudo R-squared values increasing from approximately zero in Model 1 to around 0.04 in Model 4. The large sample size of 92,792 observations provides substantial statistical power for detecting even small effects. The Wald chi-square test (10,469.94, $p < 0.001$) indicates that the model is statistically significant overall.

3.4. Robustness Check

To assess the robustness of our findings, we re-estimated all models using a probit regression. We created a binary variable for both loss framing and gain framing using a 30% cut-off point, where 1 represents a tolerance of 30% or above, and 0 otherwise. The 30% threshold for the robustness check regarding investment grip has also been used in the existing literature (Kuramoto et al. 2025; Yamaguchi et al. 2025). The probit robustness check confirms the main pattern: loss framing remains positive and statistically significant, whereas the gain-framing association is not robust and becomes statistically insignificant. In particular, the loss-framing estimates (Table 5) demonstrate high robustness, maintaining consistent signs and significance levels across all specifications. While the gain-framing effect appeared positive and significant in the ordered probit specification (Models 3 & 4, $p < 0.1$), as shown in Table 6, these effects did not achieve statistical significance in the probit robustness check. This suggests that the influence of gain framing is fragile and potentially driven by threshold-specific responses rather than representing a generalizable behavioral pattern. These results confirm that our findings are robust to alternative model specifications and are not dependent on assumptions regarding the error term's underlying distribution (Greene 2018; Wooldridge 2010). The consistency across

both link functions indicates that the framing effects reflect stable underlying behavioral patterns rather than model-specific artifacts.

Table 5. Comparison of main (oprobit) results with robustness test (probit) results for loss-framing.

	Model 1		Model 2		Model 3		Model 4	
	Main	Probit	Main	Probit	Main	Probit	Main	Probit
Framing_L	0.066 *** (0.007)	0.049 *** (0.009)	0.043 *** (0.007)	0.027 *** (0.009)	0.039 *** (0.007)	0.022 ** (0.009)	0.037 *** (0.007)	0.020 ** (0.009)
DFL_std			0.038 *** (0.001)	0.039 *** (0.001)	0.033 *** (0.001)	0.033 *** (0.001)	0.032 *** (0.001)	0.032 *** (0.001)
Male			0.372 *** (0.008)	0.326 *** (0.009)	0.382 *** (0.008)	0.340 *** (0.010)	0.381 *** (0.008)	0.338 *** (0.010)
Age			0.034 *** (0.002)	0.041 *** (0.002)	0.024 *** (0.002)	0.031 *** (0.003)	0.024 *** (0.002)	0.032 *** (0.003)
Age_sq			−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)
Marital_status			−0.040 *** (0.009)	−0.055 *** (0.011)	−0.093 *** (0.010)	−0.098 *** (0.011)	−0.094 *** (0.010)	−0.099 *** (0.011)
Children			−0.024 *** (0.004)	−0.029 *** (0.005)	−0.010 *** (0.004)	−0.012 *** (0.005)	−0.011 *** (0.004)	−0.014 *** (0.005)
Education			0.008 *** (0.002)	0.001 (0.002)	−0.017 *** (0.002)	−0.024 *** (0.002)	−0.017 *** (0.002)	−0.024 *** (0.002)
Fulltime					−0.004 (0.009)	−0.012 (0.011)	−0.004 (0.009)	−0.013 (0.011)
Log_Hincome					−0.003 (0.008)	−0.030 *** (0.009)	−0.003 (0.008)	−0.030 *** (0.009)
Log_Hasset					0.227 *** (0.004)	0.240 *** (0.005)	0.228 *** (0.004)	0.240 *** (0.005)
Risk_Aversion							−0.091 *** (0.016)	−0.095 *** (0.018)
Myopic							−0.020 *** (0.004)	−0.026 *** (0.004)
_cons		−0.183 *** (0.005)		−1.118 *** (0.064)		−3.736 *** (0.134)		−3.629 *** (0.135)
/cut1	−1.569 *** (0.007)		−0.693 *** (0.053)		2.094 *** (0.113)		2.008 *** (0.114)	
/cut2	−0.437 *** (0.005)		0.496 *** (0.053)		3.309 *** (0.113)		3.223 *** (0.114)	
/cut3	0.188 *** (0.005)		1.148 *** (0.053)		3.978 *** (0.113)		3.892 *** (0.114)	
/cut4	0.586 *** (0.005)		1.563 *** (0.053)		4.403 *** (0.113)		4.317 *** (0.114)	
Observations	92,792	92,792	92,792	92,792	92,792	92,792	92,792	92,792
Pseudo R ²	0.000	0.000	0.027	0.038	0.040	0.061	0.040	0.061
Loglikelihood	−138,960.023	−63,492.070	−135,297.242	−61,068.784	−133,400.718	−59,632.571	−133,370.879	−59,604.490

Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Comparison of main (oprobit) results with robustness (probit) results for gain-framing.

	Model 1		Model 2		Model 3		Model 4	
	Main	Probit	Main	Probit	Main	Probit	Main	Probit
Framing_G	0.013 (0.013)	−0.010 (0.016)	0.009 (0.013)	−0.016 (0.017)	0.025 * (0.013)	0.002 (0.017)	0.024 * (0.013)	0.001 (0.017)

DFL_std		0.038 ***	0.039 ***	0.033 ***	0.033 ***	0.033 ***	0.032 ***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male		0.369 ***	0.325 ***	0.380 ***	0.339 ***	0.379 ***	0.337 ***
		(0.008)	(0.009)	(0.008)	(0.010)	(0.008)	(0.010)
Age		0.034 ***	0.041 ***	0.024 ***	0.031 ***	0.024 ***	0.032 ***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Age_sq		−0.000 ***	−0.000 ***	−0.000 ***	−0.000 ***	−0.000 ***	−0.000 ***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital_status		−0.040 ***	−0.055 ***	−0.093 ***	−0.098 ***	−0.094 ***	−0.099 ***
		(0.009)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Children		−0.024 ***	−0.029 ***	−0.010 ***	−0.012 ***	−0.011 ***	−0.014 ***
		(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Education		0.008 ***	0.002	−0.017 ***	−0.024 ***	−0.016 ***	−0.023 ***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fulltime				−0.004	−0.013	−0.004	−0.013
				(0.009)	(0.011)	(0.009)	(0.011)
Log_Hincome				−0.003	−0.030 ***	−0.003	−0.030 ***
				(0.008)	(0.009)	(0.008)	(0.009)
Log_Hasset				0.228 ***	0.240 ***	0.228 ***	0.240 ***
				(0.004)	(0.005)	(0.004)	(0.005)
Risk_Aversion						−0.092 ***	−0.095 ***
						(0.016)	(0.018)
Myopic						−0.020 ***	−0.026 ***
						(0.004)	(0.004)
_cons	−0.166 ***		−1.109 ***		−3.733 ***		−3.625 ***
	(0.004)		(0.064)		(0.134)		(0.135)
/cut1	−1.589 ***	−0.703 ***		2.092 ***		2.004 ***	
	(0.007)	(0.053)		(0.113)		(0.114)	
/cut2	−0.458 ***	0.485 ***		3.307 ***		3.219 ***	
	(0.004)	(0.053)		(0.113)		(0.114)	
/cut3	0.167 ***	1.137 ***		3.976 ***		3.888 ***	
	(0.004)	(0.053)		(0.113)		(0.114)	
/cut4	0.564 ***	1.552 ***		4.401 ***		4.314 ***	
	(0.004)	(0.053)		(0.113)		(0.114)	
Observations	92,792	92,792	92,792	92,792	92,792	92,792	92,792
Pseudo R ²	0.000	0.000	0.027	0.038	0.040	0.061	0.061
Loglikelihood	−138,999.054	−63,507.631	−135,313.657	−61,072.750	−133,412.253	−59,635.467	−133,381.572
	−59,606.966						

Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion

This study examined how informational framing is associated with investors' investment grip, using a large-scale survey of Japanese retail investors. Several important findings emerge. First, loss-framing is consistently associated with stronger investment grip: the coefficient remains positive and statistically significant across all ordered probit specifications, and the sign and significance are preserved in the probit robustness checks, although the magnitude is smaller. Even after controlling for a rich set of demographic, socioeconomic, and psychological factors, investors who exhibit loss-framing behavior demonstrate a higher tolerance for holding investments under adverse market conditions, although the magnitude of this association remains modest. In contrast, gain-framing effects are weak and fragile: while marginally significant in the ordered probit models with full controls, they disappear entirely in the probit robustness checks. This asymmetry underscores the dominant psychological role of losses, consistent with prospect theory's

prediction that losses exert a stronger motivational force than gains. Prior empirical studies on framing and retail investors in Japan have primarily focused on buy–sell decisions and short-term trading behavior. In contrast, our analysis shifts attention to investors' willingness to endure losses before acting, thereby complementing existing evidence on framing effects in Japanese financial markets.

4.1. Loss Framing and Commitment Under Threat

The positive association between loss framing and investment grip may appear counterintuitive at first glance, as negatively framed information is often linked to panic selling and excessive risk-taking. However, this finding can be interpreted through the lens of threat salience and defensive commitment. Loss-framed information heightens investors' attention to downside risk and potential regret (Loomes and Sugden 1982), which may paradoxically strengthen their resolve to maintain existing positions rather than realize losses (Shefrin and Statman 1985; Weber and Camerer 1998). In this sense, higher investment grip does not necessarily reflect rational patience, but rather a psychologically driven commitment to holding assets under perceived threat. This interpretation aligns with prior evidence that loss framing intensifies emotional engagement and prolongs decision inertia during market downturns (Odean 1998; Summers and Duxbury 2012).

Importantly, the present results suggest that framing effects operate not only at the level of buy–sell decisions, but also at a deeper level, influencing investors' willingness to endure losses before acting. By shaping how adverse information is perceived and processed, loss framing appears to influence the psychological threshold at which investors decide to exit the market.

4.2. Investment Grip and Loss Tolerance

While the underlying survey item used to measure investment grip is consistent with conventional measures of loss tolerance, the present study interprets this measure from a behavioral perspective, emphasizing investors' commitment to maintaining positions under psychologically stressful market conditions. To be explicit, we do not claim that investment grip is measured by a fundamentally new psychometric instrument. Rather, the present contribution is interpretive and contextual: we treat the conventional “maximum tolerable loss” item as a behavioral indicator of investors' ability to maintain commitment under stress in information-rich market environments. In our collaboration with an industry partner, we adopt the practitioner-facing label “investment grip” to communicate this behavioral perspective more intuitively, while keeping the underlying measurement comparable to the established loss-tolerance literature. Accordingly, throughout the paper, investment grip should be read as a behavioral operationalization of loss tolerance, with our novelty lying in linking this tolerance/commitment threshold to framing susceptibility. Accordingly, the reported relationships should be interpreted as correlational rather than causal. It is possible that more resilient investors self-select into particular framing-response patterns, which limits causal interpretation.

In this sense, investment grip should be understood as a behavioral operationalization of loss tolerance, rather than as an entirely separate psychological construct. This reframing highlights the dynamic and context-dependent nature of loss tolerance, particularly in information-rich financial environments, where investors are continuously exposed to emotionally charged news and market commentary.

By adopting the notion of investment grip, this study shifts the analytical focus from the static question of how much loss investors can tolerate to the behavioral question of how they respond to perceived threats while holding assets. This perspective complements existing research on loss tolerance by emphasizing the role of informational framing and emotional pressure in shaping holding behavior during periods of market stress.

4.3. Role of Financial Literacy, Wealth, and Psychological Traits

Beyond framing effects, several control variables exhibit economically and statistically meaningful associations with investment grip, suggesting that framing-related patterns differ systematically across investor characteristics such as age, asset levels, and digital financial literacy. DFL is positively related to investment grip, suggesting that investors who are more capable of navigating digital financial information are better equipped to withstand short-term losses (Lusardi and Mitchell 2014). Household financial assets also emerge as one of the strongest predictors of investment grip, indicating that greater financial buffers enhance investors' ability to remain committed during downturns (Guiso and Paiella 2008).

Conversely, risk aversion and myopic views of the future are negatively associated with investment grip, consistent with theoretical expectations (Benartzi and Thaler 1995; Kahneman and Tversky 1979b). Investors who are more sensitive to risk or focused on short-term outcomes appear less willing to tolerate losses before exiting the market (Barberis et al. 2001; Thaler et al. 1997). These findings reinforce the view that investment grip reflects an interaction between cognitive capacity, financial resources, and psychological orientation.

4.4. Practical Implications

From a practical standpoint, the findings have important implications for financial institutions and investor communication. The concept of investment grip offers an intuitive and behaviorally grounded framework for understanding client behavior during periods of market stress. Compared with the abstract notion of loss tolerance, investment grip may be more readily communicated to practitioners and investors, particularly when discussing holding decisions under adverse conditions. Importantly, stronger investment grip should not be interpreted unambiguously as welfare-improving behavior. While it may reflect healthy long-term investment persistence in some cases, it may also indicate loss-aversion-driven behavioral inertia that delays necessary portfolio adjustments.

Moreover, the strong association between loss framing and investment grip highlights the potential unintended consequences of negatively framed financial information. While loss framing may strengthen holding behavior in some contexts, it may also reflect emotionally driven inertia rather than informed long-term planning (Kahneman and Tversky 1984; Loewenstein et al. 2001). Financial institutions and regulators should therefore be mindful of how information is framed, especially in digital environments where investors are exposed to rapid and repeated loss-oriented messages (Bateman et al. 2014; Strömbäck et al. 2017).

4.5. Limitations and Future Research

This study has several limitations, most notably the reliance on a self-reported measure of maximum tolerable loss, which may differ from actual investor behavior under real market stress. Investment grip is measured using a self-reported maximum tolerable loss, which overlaps with traditional loss-tolerance measures. Accordingly, the results should be interpreted as reflecting a behavioral manifestation of loss tolerance rather than a fully distinct psychological construct. Future research could refine this concept by incorporating longitudinal data on actual holding behaviors or experimental designs that capture dynamic responses to market stress and information framing.

In addition, the analysis focuses on Japanese retail investors, and caution is warranted when generalizing the findings to other institutional or cultural contexts. Future cross-country studies could explore whether framing effects on investment grip vary across regulatory environments and financial cultures. In addition, the 2025 survey was conducted during a period of heightened geopolitical and economic uncertainty, which

may have influenced investors' perceptions and framing responses, thereby limiting the generalizability of the findings to more stable periods.

5. Conclusions

This study examines how informational framing is associated with investors' investment grip using a large-scale survey of Japanese retail investors. Drawing on more than 92,000 observations, we provide evidence that loss-framed information is robustly associated with a stronger investment grip, whereas gain-framed information exhibits weak and fragile effects that do not survive robustness checks. These findings underscore the asymmetric psychological role of losses and highlight the importance of framing in shaping investors' willingness to endure losses before exiting the market.

Conceptually, this study contributes to the literature by reframing loss tolerance from a behavioral perspective. While the underlying measure of investment grip is consistent with conventional loss-tolerance indicators, investment grip emphasizes investors' commitment to maintaining positions under psychologically stressful market conditions. By focusing on how investors respond to perceived threats while holding assets, rather than solely on the maximum loss they can tolerate, this study complements existing research on loss aversion and risk tolerance in behavioral finance.

From a behavioral standpoint, the results suggest that framing effects extend beyond buy–sell decisions and influence the psychological thresholds that govern holding behaviors. Loss framing appears to strengthen investment grip not necessarily through rational patience, but through defensive commitment and heightened emotional engagement. This finding helps reconcile seemingly contradictory behaviors observed during market downturns, where investors simultaneously exhibit panic selling and inertia in realizing losses.

The findings also carry practical implications. The concept of investment grip offers a behaviorally grounded and intuitive framework for understanding investor behavior during periods of market stress. Compared with the abstract notion of loss tolerance, investment grip may be more accessible to practitioners and financial institutions when assessing clients' reactions to adverse information. At the same time, the strong association between loss framing and investment grip highlights the potential unintended consequences of persistently negative financial communication, particularly in digital environments characterized by rapid information flows.

Several limitations should be noted. Investment Grip is measured using a self-reported maximum tolerable loss and therefore overlaps with traditional loss-tolerance measures. In addition, the analysis focuses on Japanese retail investors, which may limit the generalizability of the findings. Future research could extend this work by examining longitudinal holding behavior, employing experimental designs to isolate framing mechanisms, or conducting cross-country analyses to explore institutional and cultural heterogeneity.

Overall, this study advances the understanding of how informational framing shapes investors' loss-related behavior by highlighting the role of behavioral commitment under stress. By integrating framing effects with a behavioral interpretation of loss tolerance, the findings contribute to a more nuanced understanding of investor decision-making in contemporary, information-rich financial markets.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/risks14020040/s1>. Dataset S1: De-identified dataset containing the variables used in this study.

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Informed Consent Statement: We obtained written informed consent from all participants in this questionnaire survey under the guidance of the institutional compliance team.

Data Availability Statement: The de-identified dataset containing the variables used in this study is available in the Supplementary Materials (Dataset S1). Further inquiries can be directed to the corresponding author.

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Abbreviations

The following abbreviations are used in this manuscript:

VIF	Variance inflation factor
DFL	Digital financial literacy

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