

# Framing Effects in Investor Risk Profiling: Experimental Evidence from Brazil

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## Abstract

This paper investigates the causal effect of textual framing on risk classification in Investor Profile Analysis (IPA) questionnaires in Brazil. We tested whether the formulation of the questions systematically alters the classification of the investor's risk profile by conducting a randomized controlled trial (RCT) with 900 Brazilian adults, allocated to one of three versions of the questionnaire: Neutral (control), Positive (framing in gains), and Negative (framing in losses). The results reveal that negative framing increases the probability of classification as Conservative by 11 percentage points, while positive framing increases the classification as high-risk by 9 percentage points. The magnitude of the effect represents a change of approximately half a standard deviation in risk scores. Our results suggest that the presentation format of the suitability questionnaires can affect not only risk perception but also the consistency of investors' self-reported preferences.

**Keywords:** Behavioral Finance; Framing Effects; Investor Profile; Suitability; Financial Regulation; Prospect Theory

**JEL Classification:** D91, G41, C93, G11, D14

## 1. Introduction

The efficient allocation of financial products depends on instruments that accurately capture investors' risk profiles. In Brazil, this task is operationalized through the Investor Profile Analysis (API), a questionnaire that classifies clients into risk categories, serving as the basis for suitability assessment as required by CVM Resolution No. 30/2021 and ANBIMA (2021) guidelines.

This risk classification segments individuals from Conservative profiles (prioritizing safety as the decisive factor) and Moderate profiles (seeking to balance safety with long-term

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gains), to Bold and Aggressive profiles (with strong risk tolerance and focus on volatile markets). The API implicitly assumes that investor responses reflect neutral, rational choices free from contextual influences. However, this assumption is challenged by behavioral economics.

Building on Prospect Theory (Kahneman & Tversky, 1979), research documents that risk preferences are not stable but rather sensitive to how choices are presented. The central concept of framing (Tversky & Kahneman, 1981) demonstrates that logically equivalent formulations of a problem—whether emphasizing potential gains or potential losses—systematically lead to different decisions. This phenomenon, driven by loss aversion, has proven consistent, especially in financial contexts, where framing directly affects risk-taking, portfolio allocation, and savings decisions (Benartzi & Thaler, 1995; Barberis & Thaler, 2003).

Despite the extensive literature on framing and the regulatory role of API, little is known about how these biases affect the diagnostic instrument itself. If question formulation modifies an individual's risk classification, the neutrality and effectiveness of Brazil's suitability mechanism may be compromised.

This study fills this gap by investigating the following question: Does textual framing in API questionnaires causally influence investor risk classification? To test this hypothesis, we conducted a randomized controlled trial (RCT) with 900 participants. Participants were randomly assigned to one of three treatments: (i) a control group responding to a neutral API version; (ii) a positive framing group emphasizing "gains" and "opportunities"; or (iii) a negative framing group emphasizing "losses" and "risks." The intervention was constructed from an official API questionnaire used by a major Brazilian financial institution, ensuring practical applicability. Data analysis employs ordinal logistic and linear regression, appropriate for the categorical and ordered nature of the dependent variable (risk profiles).

Among the contributions of this study, we highlight its empirical contribution to the regulatory debate on the neutrality and effectiveness of suitability instruments used by financial institutions in Brazil. By employing an experimental design, we provide evidence useful for both academia and regulators such as CVM and ANBIMA. We also highlight the need to

consider psychological and communicational factors in questionnaire design, which may guide regulatory revisions and market best practices aimed at investor protection.

The article is organized as follows: Section 2 presents the theoretical framework underlying the research, highlighting key behavioral economics concepts. Section 3 describes the methodology adopted, including experimental design and analytical model. Section 4 presents results and discussion, and Section 5 concludes.

## **2. Literature Review**

This study is grounded in the intersection between financial regulation and behavioral economics. Suitability constitutes a central regulatory obligation in Brazil (CVM Resolution No. 30/2021), requiring financial intermediaries such as banks and brokerages to verify whether products are compatible with clients' objectives, financial situation, knowledge, and experience regarding the risks involved. This verification is operationalized through API, an instrument that assumes agent rationality. This article questions this assumption by investigating how cognitive biases may affect API effectiveness.

Responses to the Investor Profile Analysis (API) questionnaire guide client classification into different risk profiles, which serve as references for product suitability in financial institutions. In retail and high-income segments, these profiles are typically categorized as Conservative, Moderate, Bold, and Aggressive.

The behavioral critique of these traditional assessment instruments is supported by Prospect Theory (Kahneman & Tversky, 1979), which describes how individuals evaluate gains and losses asymmetrically relative to a reference point, with prevalence for loss aversion. The cumulative version of this theory (Tversky & Kahneman, 1992) incorporated nonlinear probability weighting, explaining people's tendency to overestimate rare events and underestimate common ones. Holt and Laury (2002) reinforce this framework by showing that risk aversion varies according to the magnitude of values involved.

Framing, a concept introduced by Tversky and Kahneman (1981), shows that the presentation format of a decision, emphasizing gains or losses, can alter choices even when

informational content remains identical. This effect is observed in financial contexts: positive framing tends to increase risk propensity, while negative framing intensifies loss aversion (Hillenbrand & Brooks, 2023). Similar evidence has been recorded in insurance (Barseghyan et al., 2013), in the realization of investment gains and losses (Weber & Camerer, 1998; Liu et al., 2014), and in sustainable financial products (Gutsche et al., 2023).

In the Brazilian context, recent findings confirm framing influence. Paiva and Silva (2023) show that information presentation format affects declared risk tolerance. Additionally, Monteiro and Bressan (2021) observed that fund performance presentation format, specifically comparing accumulated values versus monthly returns could alter investor risk perception. When past performance was presented in terms of monthly returns (bar format), investors perceived greater risk in variable income funds. The line format, focusing on accumulated fund value evolution, tended to reduce risk perception and increase return expectations, especially in fixed income products.

The influence of textual formulation has also been observed in different contexts and populations. For example, narrative structures were shown to affect entrepreneurs' risk perception (Massa et al., 2024), while small text changes on fintech digital platforms impacted user migration behavior (Karle et al., 2023). Collectively, these studies suggest that textual framing is associated with variations in risk perception and financial decisions in the country.

On the theoretical plane, behavioral financial economics incorporates contributions that question the full rationality assumed by traditional models. Thaler (1980, 1999) presented the concepts of mental accounting and self-control, showing that individuals treat resources in non-fungible and often non-optimized ways. These mechanisms help explain intertemporal inconsistencies, especially in savings and consumption decisions where they categorize resources and react differently to losses in distinct accounts.

Barberis et al. (2001) applied Prospect Theory elements to asset pricing models, explaining empirically observed price deviations. Ackert and Deaves (2009), Hirshleifer (2001), and Camerer and Loewenstein (2004) analyzed psychological mechanisms influencing risk and return evaluations that shape financial decisions, highlighting how cognitive heuristics, incidental emotions, and perception biases systematically affect risk and return

assessment. These studies consolidate the idea that agent rationality is limited and contextually shaped.

Specific contributions deepen this theoretical base. Laibson (1997) formulated the concept of hyperbolic discounting, evidencing the tendency to privilege immediate benefits over future gains, with direct impact on investment decisions. Barber and Odean (2001) empirically documented overconfidence among individual investors, associated with excessive trading patterns and inferior returns.

Rabin and Thaler (2001) complementarily show that the traditional explanation of risk aversion based solely on expected utility concavity is insufficient, as it would require implausible parameters for larger values. They argue that this limitation opens space for understanding risk aversion through mechanisms such as loss aversion and mental accounting. In this sense, small cognitive inconsistencies accumulate over time, affecting how investors perceive risks, evaluate alternatives, and consequently generate relevant distortions in financial markets.

The literature on bounded rationality (Kahneman, 2012) postulates that experience in the decision domain can attenuate cognitive biases such as the framing effect. The underlying mechanism involves interaction between two mental processing modes: System 1, which is fast, intuitive, and heuristic; and System 2, which is slow, analytical, and deliberative. In more experienced agents, although System 1 continues to generate automatic responses, System 2 is activated more effectively to supervise and correct potentially biased impulses. Familiarity with the subject therefore improves the ability to recognize contexts requiring greater cognitive scrutiny, reducing dependence on automatic responses that framing exploits.

This evidence strengthens the empirical motivation for this research and grounds the hypothesis that framing applied to API can significantly influence investor risk profile classification.

### 3. Methodology

#### 3.1 Data

This study uses primary data in a randomized controlled trial (RCT) design to identify the causal effect of textual framing on API questionnaire responses (Duflo, 2007; Angrist & Pischke, 2009; Bursztyn et al., 2017). The experiment was conducted in person in a major Brazilian city August and November 2025, using physical questionnaires (printed on paper). The experimental protocol was approved by the Research Ethics Committee (CEP-UNIEURO) under number CAAE 92370725.1.0000.5058, in compliance with CNS Resolutions 466/2012 and 510/2016.

The experiment manipulates textual framing of API questionnaire questions while keeping informational content constant. Three questionnaire versions were created and printed: (i) Neutral, the control group, with balanced formulation in the original API questions from the financial institution; (ii) Positive, emphasizing potential gains and opportunities; and (iii) Negative, emphasizing potential losses and risks. All three versions contain the same 11 questions from the standard API questionnaire used, as shown in Table 1, plus 3 control questions (gender, age range, and whether they have invested or regularly invest money in financial products), differing only in textual formulation. To avoid visual selection bias, all three versions were printed on identical paper (A4 format, Times New Roman 12pt font, standardized layout), with changes only in question text. Question adaptation followed established experimental practices in behavioral economics literature, respecting the principle of altering the decision frame without changing its substantive content (Tversky & Kahneman, 1981; Bursztyn et al., 2017).

**Table 1 – API Questions with Framing Treatments**

#	Neutral	Positive Framing	Negative Framing
1	Do you find it easy to invest?	Thinking about the opportunities the market offers, do you find it easy to invest?	Considering market uncertainties, do you find it easy to invest?

#	Neutral	Positive Framing	Negative Framing
2	Do you have any experience or training in finance?	To maximize your investment opportunities, have you acquired any experience or training in finance?	To minimize risks in investment decisions, have you acquired any experience or training in finance?
3	Before making any investment decision, what do you usually do?	To ensure your investment decisions are well-founded and strategic, what do you usually do before investing?	To avoid impulsive and risky decisions, what do you usually do before investing?
4	In which investment group do you have more familiarity and have frequently invested most of your resources in the last 12 months?	To boost your investment growth, in which group have you concentrated most of your resources?	To ensure greater financial security, in which group have you concentrated your investments recently?
5	When investing, what do you value most?	To ensure continuous growth of your wealth, what aspects do you value most when investing?	To reduce risks and negative impacts, what factors do you consider most important when investing?
6	If your investments varied between positive and negative returns, what would you do?	Recognizing that variations are a natural part of investment growth, how do you usually react to these fluctuations?	Given concerns about fluctuations that may impact your results, how do you usually react?
7	What is your main objective when investing?	To ensure you achieve your financial goals solidly and consistently, what is your main objective when investing?	Given possible instability scenarios, what is your main objective when investing?
8	According to your objectives and financial situation, when do you plan to use invested resources?	To make the most of future opportunities, when do you plan to use your invested resources?	Given the need to maintain liquidity for unexpected situations, when do you plan to use your investments?
9	What is your current monthly income?	Aiming to further expand your financial planning, what is your current monthly income?	Seeking to ensure your financial security, what is your current monthly income?

#	Neutral	Positive Framing	Negative Framing
10	What do you usually do when you receive extra resources?	When you receive additional resources, how do you usually maximize your financial reserves?	When you receive extra resources, how do you usually ensure protection of your wealth?
11	Considering only your financial investments in banks and brokerages, how much do you currently have invested?	To further strengthen your wealth, how much do you currently have in investments?	To ensure protection of your assets, how much do you currently have in investments?

*Source: Author's own elaboration based on the financial institution's retail API form (2025)*

Randomization was implemented at the individual level at the moment of contact with each participant. The field researcher carried stacks of the three questionnaire versions previously shuffled in random order. When approaching a potential participant, the researcher handed over the questionnaire from the top of the stack, ensuring random assignment without possibility of intentional selection. This procedure ensures that, in expectation, the three groups are identical in all pre-treatment characteristics, allowing causal attribution of observed differences in responses to textual framing.

The sample was recruited in person in São Paulo through approaches in multiple public and private locations: (i) subway stations and bus terminals; (ii) commercial centers and high-traffic areas; (iii) universities and educational institutions; (iv) finance and investment events; and (v) bank branches and brokerages (with prior authorization). Recruitment aimed to obtain a diversified sample in terms of gender, age, investment experience, and socioeconomic level, although it does not constitute a probabilistic sample of Brazilian investors.

Inclusion criteria were: (i) age 18 years or older; (ii) ability to read, understand, and respond to the questionnaire in Portuguese; and (iii) providing free and informed consent for research participation. There were no additional exclusion criteria.

The final sample consists of 900 participants, equally distributed among the three experimental groups (300 per group). This sample size was determined a priori through

statistical power analysis, aiming to detect a medium effect size (Cohen's  $d \approx 0.30$ ) with 80% power and 5% significance level in two-tailed tests.

The main dependent variable is the total API questionnaire score, obtained by summing points assigned to responses to the 11 questions. Each alternative has a predefined value, ranging from negative penalties to positive bonuses. This methodology follows the official scoring rule used by the studied financial institution for measuring investor risk profile.

Each participant's total score was calculated after collection, from digitizing responses in an electronic spreadsheet. The value was then mapped to one of four investor profiles according to the scoring rule: Conservative (-52 to 20 points), Moderate (21 to 60 points), Bold (61 to 80 points), and Aggressive (81 to 100 points).

The independent variables of interest correspond to textual framing experimental treatments, represented by two indicator variables: one assumes value 1 for participants who received the positive or negative questionnaire version (0 otherwise), with the neutral group used as the reference category.

Additionally, control variables were collected regarding demographic characteristics (gender and age range), financial experience (investment experience level and training or professional experience in finance), and socioeconomic profile (monthly income and investment wealth). These variables do not constitute the main focus of analysis but are employed to verify randomization balance, increase estimate precision, and explore possible heterogeneities in framing effects among different participant subgroups.

## **3.2 Regression Models**

To identify the effect of textual framing on API responses, linear regression (OLS) and ordinal logistic regression models were estimated.

### 3.2.1 Linear Regression (OLS)

To estimate the causal effect of framing on total API questionnaire score, we estimate the following linear regression model by ordinary least squares:

$$\text{Score}_i = \beta_0 + \beta_1 \text{Positive}_i + \beta_2 \text{Negative}_i + \mathbf{X}_i' \boldsymbol{\gamma} + \varepsilon_i \dots (1)$$

Where  $\text{Score}_i$  is participant  $i$ 's total score (-52 to +100 points);  $\text{Positive}_i$  and  $\text{Negative}_i$  are treatment dummies (reference: Neutral);  $\mathbf{X}_i$  is a vector of demographic controls (gender, age), financial experience (investments, training), and income; and  $\varepsilon_i$  is the error term. Coefficients  $\beta_1$  and  $\beta_2$  capture positive and negative framing effects relative to neutral. We estimate four specifications with progressive controls to assess robustness. All models use heteroskedasticity-robust standard errors (HC1, White 1980).

### 3.2.2 Ordinal Logistic Regression

As complementary analysis, we estimate ordinal logistic regression models (ordered logit) to evaluate framing effects on investor profile, treated as an ordinal variable (Conservative < Moderate < Bold < Aggressive). The model assumes proportional odds (Gemechu et al., 2023), according to which explanatory variable effects are constant across different cutpoints of the dependent variable. Formally, the model can be expressed as:

$$\log[\text{P}(\mathbf{Y}_i \leq j) / \text{P}(\mathbf{Y}_i > j)] = \alpha_j - \beta_1 \text{Pos}_i - \beta_2 \text{Neg}_i - \mathbf{X}_i' \boldsymbol{\gamma} \text{ for } j = 1, 2, 3 \dots (2)$$

Where  $\mathbf{Y}_i$  represents individual  $i$ 's risk profile;  $j$  corresponds to cutpoints between categories;  $\alpha_j$  are constants associated with each cutpoint;  $\text{Pos}_i$  and  $\text{Neg}_i$  are treatment dummies identifying whether the participant responded to the positive or negative questionnaire version (reference = neutral); and  $\mathbf{X}_i$  corresponds to the control variable vector.

Estimated coefficients ( $\beta$ ) are interpreted as log-odds ratios. Values of  $\exp(\beta)$  greater than 1 indicate increased odds of the participant being classified in higher risk categories compared to the reference group. The proportional odds assumption validity was tested using the Brant test (1990). To facilitate substantive interpretation, average marginal effects were also calculated, expressed as percentage point changes in allocation probability for each profile.

### 3.2.3 Robustness Tests

We conducted three robustness analyses: (i) Non-parametric permutation test with 10,000 random permutations of treatment assignment, calculating the p-value as the proportion of permutations generating an effect equal to or greater (in absolute value) than observed (Good, 2000); (ii) Sensitivity analysis to outliers, re-estimating models excluding observations in the extreme 5% of the score distribution (Huber, 1981; Hampel et al., 1986); and (iii) Pairwise comparisons between experimental groups through two-tailed t-tests, evaluating direct differences between Negative vs. Neutral, Positive vs. Neutral, and Positive vs. Negative (Imbens & Rubin, 2015).

## 4. Results

### 4.1 Sample Characteristics and Randomization Balance

Table 2 presents sample characteristics by experimental group. Chi-square tests confirm no statistically significant differences between groups for gender ( $\chi^2 = 0.51$ ,  $p = 0.775$ ), age range ( $\chi^2 = 2.39$ ,  $p = 0.664$ ), investment experience ( $\chi^2 = 0.40$ ,  $p = 0.983$ ), financial training ( $\chi^2 = 0.22$ ,  $p = 0.894$ ), and monthly income ( $\chi^2 = 0.45$ ,  $p = 0.978$ ). These results indicate successful randomization, ensuring internal validity and allowing causal attribution of observed effects to textual framing.

**Table 2 – Sample Characteristics by Experimental Group**

Characteristic	Negative	Neutral (Control)	Positive	$\chi^2$ Test	p- value
<b>Panel A: Demographics</b>					
Male (%)	45.7 (137/300)	48.3 (145/300)	46.0 (138/300)	0.51	0.775

<b>Characteristic</b>	<b>Negative</b>	<b>Neutral (Control)</b>	<b>Positive</b>	<b><math>\chi^2</math> Test</b>	<b>p- value</b>
Female (%)	54.3 (163/300)	51.7 (155/300)	54.0 (162/300)		
Age 18–34 (%)	36.7 (110/300)	32.0 (96/300)	36.3 (109/300)	2.39	0.664
Age 35–54 (%)	53.7 (161/300)	59.3 (178/300)	55.3 (166/300)		
Age 55+ (%)	9.7 (29/300)	8.7 (26/300)	8.3 (25/300)		
<b>Panel B: Financial Experience</b>					
Invests regularly (%)	51.0 (153/300)	53.3 (160/300)	51.7 (155/300)	0.40	0.983
Invests occasionally (%)	21.3 (64/300)	20.7 (62/300)	21.7 (65/300)		
Does not invest (%)	27.7 (83/300)	26.0 (78/300)	26.7 (80/300)		
Financial training (%)	45.0 (135/300)	45.0 (135/300)	46.7 (140/300)	0.22	0.894
<b>Panel C: Socioeconomic Profile</b>					
Income $\leq$ R\$4,000 (%)	29.3 (88/300)	30.0 (90/300)	30.3 (91/300)	0.45	0.978
Income R\$4,000–10,000 (%)	54.7 (164/300)	52.7 (158/300)	54.0 (162/300)		
Income $>$ R\$10,000 (%)	16.0 (48/300)	17.3 (52/300)	15.7 (47/300)		
<b>Panel D: Investor Profile</b>					

Characteristic	Negative	Neutral (Control)	Positive	$\chi^2$ Test	p- value
Conservative (%)	41.7 (125/300)	31.3 (94/300)	21.0 (63/300)	<b>46.61</b>	<b>&lt;0.001</b>
Moderate (%)	48.3 (145/300)	49.7 (149/300)	51.3 (154/300)		
Bold (%)	7.0 (21/300)	14.0 (42/300)	20.0 (60/300)		
Aggressive (%)	3.0 (9/300)	5.0 (15/300)	7.7 (23/300)		
<b>N (Total)</b>	300	300	300		

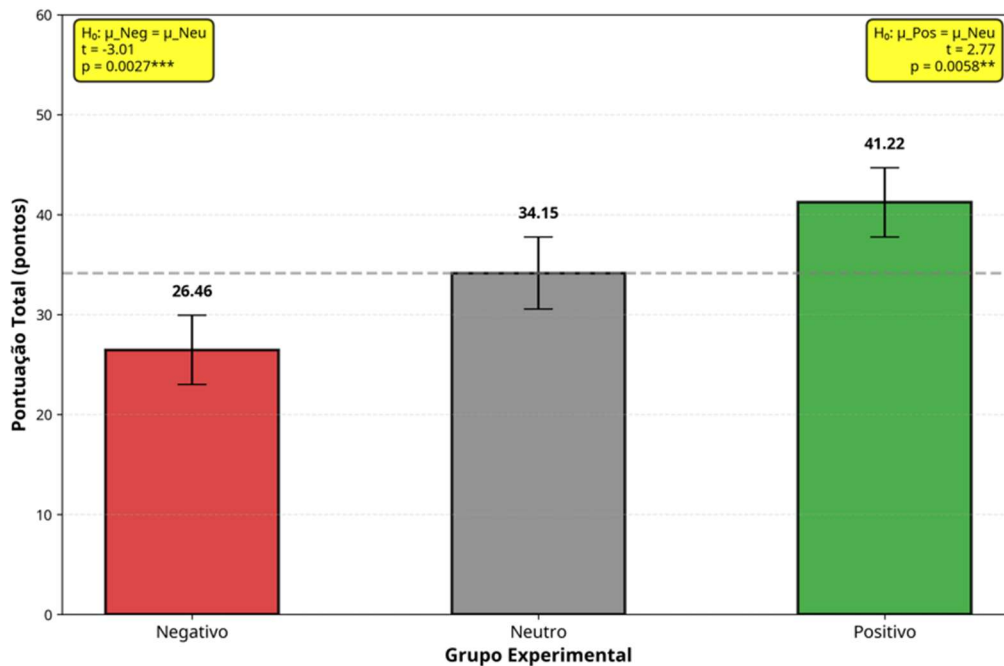
**Source:** Author's own elaboration (2025). **Notes:** Values represent percentages with absolute frequencies in parentheses. Pearson's  $\chi^2$  test and respective p-value are presented only in the aggregate row of each variable.

## 4.2 Main Effects of Framing

Regarding investor profile distribution, Panel D of Table 2 shows that negative framing led 41.7% of respondents to the Conservative profile, compared to only 21.0% in the positive group, a difference of 20.7 percentage points. The proportion of investors classified in high-risk profiles (Bold + Aggressive) was 10.0% in the Negative group and 27.7% in the Positive group, a difference of 17.7 percentage points. The Neutral group presented intermediate values (31.3% conservative and 19.0% high-risk). The chi-square test confirms that profile distribution differs significantly between groups ( $\chi^2(6) = 46.61, p < 0.001$ ).

Figure 1 illustrates mean total scores by experimental group. The positive group obtained a mean of 41.22 points, neutral 34.15 points, and negative 26.46 points. Two-tailed t-tests confirm that both the difference between Positive and Neutral ( $t = 2.77, p = 0.006$ ) and between Negative and Neutral ( $t = -3.01, p = 0.003$ ) are statistically significant. The net effect between Positive and Negative is 14.76 points, representing approximately 0.48 standard deviations of the total score distribution.

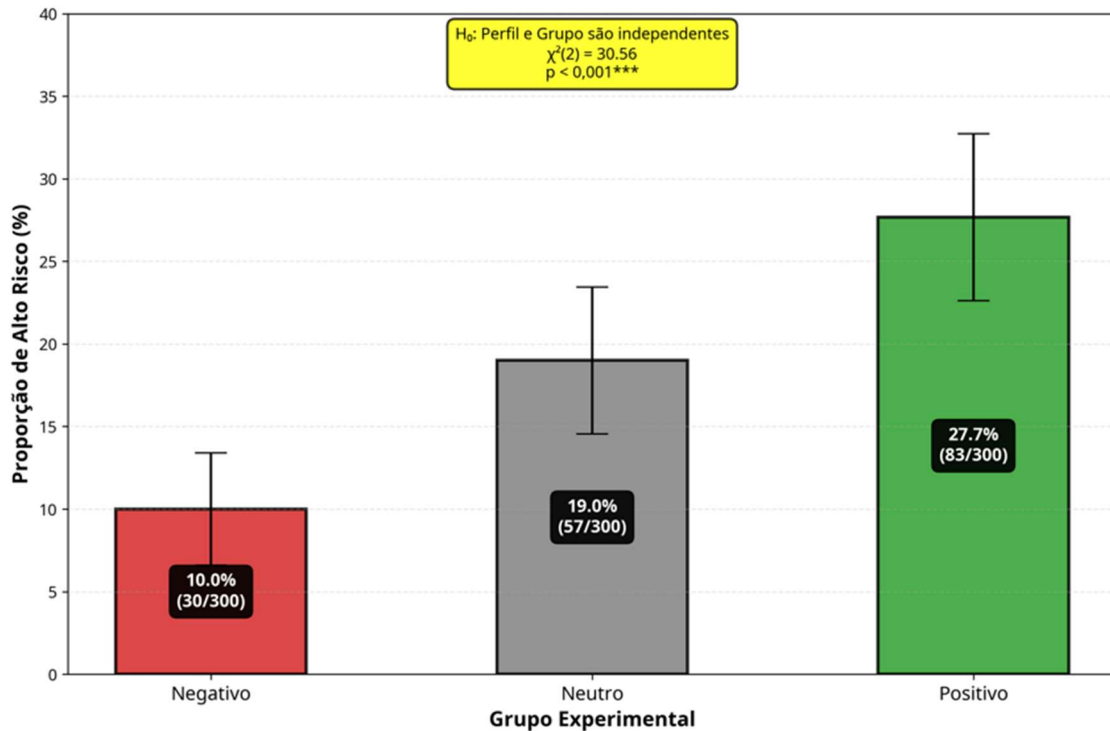
Figure 1 – Mean total API questionnaire score by experimental group



**Source:** Author's own elaboration (2025). **Notes:** Bars represent means with 95% confidence intervals. Dashed line indicates the baseline (Neutral/Control). Two-tailed *t*-tests.  $N = 300$  per group.  $p < 0.10$ ;  $p < 0.05$ ;  $p < 0.01$ .

Figure 2 shows that textual framing had significant impact on the proportion of investors classified in high-risk profiles (Bold + Aggressive). Only 10.0% of negative group participants were classified as high-risk, compared to 19.0% in the Neutral group and 27.7% in the Positive group. This means the probability of an investor being classified as higher risk in the positive group was almost three times higher than observed in the Negative group (difference of 17.7 percentage points). The chi-square test confirms this difference is statistically significant ( $\chi^2(2) = 30.56$ ,  $p < 0.001$ ), reinforcing evidence that question textual formulation directly influences risk profile categorization.

Figure 2 – Proportion of investors classified into high-risk profiles



**Source:** Author's own elaboration (2025). **Notes:** The chi-square test indicates a significant association between risk profile and experimental group ( $\chi^2(2) = 30.56$ ,  $p < 0.001$ ). Significance levels:  $p < 0.10$ ;  $p < 0.05$ ;  $p < 0.01$ .

Overall, these results reinforce the conclusion that textual framing materially affects investor risk classification outcomes. The magnitude of the observed differences across experimental groups suggests that framing is not a marginal artifact, but a substantive source of variation in suitability assessments. By systematically shifting the likelihood of classification into higher-risk profiles, question wording introduces non-neutrality into an instrument intended to capture stable risk preferences, raising concerns about the consistency and reliability of investor profiling mechanisms.

### 4.3 OLS Regression Results

Table 3 presents OLS regression results estimating framing effects on total API questionnaire score. Model (1), without control variables, indicates that positive framing increases the score by 7.07 points relative to neutral (SE = 2.56;  $p = 0.006$ ), while negative framing reduces the score by 7.69 points (SE = 2.56;  $p = 0.003$ ). The net effect between positive and negative is 14.76 points, equivalent to approximately 0.48 standard deviations of total score distribution.

Model (2), with gender variable addition, shows that framing coefficients remain virtually unchanged: +7.09 points for positive ( $p = 0.006$ ) and -7.67 points for negative ( $p = 0.003$ ).  $R^2$  shows minimal increase (from 0.036 to 0.036), suggesting gender explains little additional variation in score.

In Model (3), incorporating financial experience and training variables,  $R^2$  increases substantially to 0.228, evidencing that these characteristics are relevant score predictors. The framing effect remains robust and significant (+6.85 points,  $p = 0.003$ ; -7.42 points,  $p = 0.001$ ). Investing regularly adds on average 15.43 points ( $p < 0.001$ ) and having financial training adds 20.08 points ( $p < 0.001$ ).

Model (4), with high income variable inclusion, does not alter coefficients or  $R^2$  relative to Model (3), indicating income does not contribute to explaining additional variation beyond financial experience.

**Table 3 – Effect of Framing on Total Score (OLS)**

<b>Variable</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
Positive	7.070**	7.085**	6.846***	6.846***
	(2.556)	(2.554)	(2.270)	(2.270)
	[0.006]	[0.006]	[0.003]	[0.003]
Negative	-7.690***	-7.673***	-7.424***	-7.424***
	(2.556)	(2.554)	(2.303)	(2.303)
	[0.003]	[0.003]	[0.001]	[0.001]
Female	—	-0.634	-0.330	-0.330

Variable	(1)	(2)	(3)	(4)
		(2.076)	(1.868)	(1.868)
Invests	—	—	15.431***	15.431***
			(2.150)	(2.150)
Financial Training	—	—	20.077***	20.077***
			(2.026)	(2.026)
Constant	34.173***	34.490***	18.854***	18.854***
	(1.808)	(2.393)	(2.395)	(2.395)
Observations	900	900	900	900
R <sup>2</sup>	0.036	0.036	0.228	0.228
Adjusted R <sup>2</sup>	0.034	0.033	0.224	0.223
F-statistic	16.88***	11.29***	52.95***	42.36***

**Notes:** Dependent variable: Total Score (ranging from -52 to 100). Heteroskedasticity-robust standard errors (HCl) in parentheses. P-values in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Reference group: Neutral.

The stability of framing coefficients across all specifications (variation less than 4% between models) reinforces result robustness and confirms that effects are not explained by observable participant characteristics, consistent with successful randomization.

#### 4.4 Robustness: Financially Sophisticated Subsample

To deepen analysis and test finding robustness, we investigated whether the framing effect would persist in a participant subgroup with greater financial knowledge. A plausible argument would be that experience or training in the area could mitigate or eliminate susceptibility to this cognitive bias, more consistently activating System 2 analytical processing (Kahneman, 2012).

To test this hypothesis, a subsample (N = 661) was created comprising all participants who declared prior investment experience ("Invests regularly" or "Invests occasionally") or financial training. The OLS regression model was then re-estimated for this qualified group.

**Table 4 – Framing Effect – Subsample with Financial Experience or Training**

Variable	Coefficient	Std. Error (HC1)	t-statistic	p-value
Positive Treatment	6.85***	(1.058)	6.48	<0.001
Negative Treatment	-7.83***	(1.011)	-7.74	<0.001
Constant	45.16***	(0.778)	58.05	<0.001

*Notes: Dependent variable: Total Score. Heteroskedasticity-robust standard errors (HC1). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .*

Results demonstrate that the causal framing effect remains robust and statistically significant even among more experienced participants. Coefficient magnitudes are consistent with complete sample results: Positive framing raises risk score by 6.85 points and Negative reduces it by 7.83 points, both with high statistical significance ( $p < 0.001$ ).

This robustness test therefore offers strong evidence against the hypothesis that experience neutralizes the bias. Susceptibility to framing appears to be a deeper phenomenon affecting decision-making even in more financially literate individuals, reinforcing the validity and practical relevance of this study's conclusions.

## 4.5 Ordinal Logistic Regression Results

Table 5 presents ordinal logistic regression results, modeling the probability of belonging to higher risk profile categories (Conservative < Moderate < Bold < Aggressive), respecting the ordinal nature of the dependent variable. Model (1), without controls, establishes the causal effect: positive framing significantly increases the probability of classification in higher profiles ( $\beta = 0.465$ ;  $p = 0.003$ ), while negative framing reduces it ( $\beta = -0.594$ ;  $p < 0.001$ ).

**Table 5 – Effect of Framing on Investor Profile (Ordered Logit)**

Variable	(1) No controls	(2) + Gender	(3) + Exp/Training
Positive	0.465***	0.465***	0.527***
	(0.156)	(0.156)	(0.158)
Negative	-0.594***	-0.594***	-0.619***
	(0.156)	(0.156)	(0.163)
Female	—	-0.074	-0.080
		(0.127)	(0.131)
Invests	—	—	1.871***
			(0.147)
N	900	900	900
Pseudo R <sup>2</sup>	0.022	0.022	0.112

*Notes: Standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Reference group: Neutral.*

### **Odds Ratios (Model 3):**

- Positive: OR = 1.694 ( $p = 0.001$ ) — 69.4% higher odds of higher profile
- Negative: OR = 0.538 ( $p < 0.001$ ) — 46.2% lower odds of higher profile

Treatment framing coefficients remain stable and statistically significant after including demographic controls (Model 2) and financial experience (Model 3). In the complete specification (Model 3), Positive framing ( $\beta = 0.527$ ;  $p = 0.001$ ) and Negative ( $\beta = -0.619$ ;  $p < 0.001$ ) maintain their magnitude. Controls reveal that, although gender is not a significant predictor (Model 2), practical investment experience has a positive and expressive effect on risk propensity ( $\beta = 1.871$ ;  $p < 0.001$ ).

In terms of practical relevance, odds ratio analysis from Model 3 is conclusive. Positive framing increases by 69.4% the odds of an individual being classified in a higher risk profile (OR = 1.694;  $p < 0.001$ ), while negative framing reduces these odds by 46.2% (OR = 0.538;  $p < 0.001$ ), both relative to the Neutral control group.

The Brant test ( $\chi^2(4) = 0.81$ ,  $p = 0.937$ ) does not reject the null hypothesis of proportional odds, validating the fundamental assumption of the ordinal logistic model. This result indicates coefficients are statistically indistinguishable between different cutpoints (Conservative | Moderate, Moderate | Bold, Bold | Aggressive), justifying use of a single coefficient per variable.

Pseudo  $R^2$  increases from 2.2% (Model 1) to 11.2% (Model 3), indicating investment experience explains a relevant portion of variance in profile classification. However, even after controlling for experience, training, gender, and income, the framing effect remains robust and significant, confirming its causal relevance.

## **4.6 Additional Robustness Tests**

Framing effect robustness is validated by a set of specification tests. First, treatment statistical significance is confirmed by a non-parametric permutation test, which with 10,000 permutations returns  $p < 0.001$  for both framings. Second, sensitivity analysis to outliers,

excluding the extreme 5% of score distribution, shows framing coefficients vary less than 8% and maintain significance at the 1% level.

Finally, risk score analysis (via t-tests) confirms means differ significantly in all pairwise comparisons: Negative vs. Neutral ( $\Delta = -7.69$ ;  $p = 0.003$ ), Positive vs. Neutral ( $\Delta = +7.07$ ;  $p = 0.006$ ), and the largest difference between Positive vs. Negative ( $\Delta = +14.76$ ;  $p < 0.001$ ). Together, these tests demonstrate the identified causal effect is robust to different statistical specifications.

## 5. Discussion

The results of this study provide robust experimental evidence that textual framing in API questionnaires significantly affects investor risk profile classification. The findings are consistent with Prospect Theory (Kahneman & Tversky, 1979, 1981), which postulates that individuals are more sensitive to losses than equivalent gains (loss aversion) and that how options are presented systematically affects choices (framing effect).

Our findings extend this literature by demonstrating that framing not only affects hypothetical decisions in classic experimental contexts (Tversky & Kahneman, 1981) but also influences responses to regulatory assessment instruments used in financial markets. The observed effect size (Cohen's  $d = 0.48$ ) places it at the upper limit of the typical range reported in framing study meta-analyses (Levin et al., 1998), suggesting the Brazilian financial context may be particularly susceptible to formulation effects.

From a theoretical standpoint, this study contributes to behavioral finance literature by identifying a source of systematic bias in suitability instruments. While previous studies documented biases in individual investment decisions (Benartzi & Thaler, 1995; Thaler et al., 1997), this study experimentally demonstrates that the profile assessment instrument itself can introduce formulation-dependent bias.

The practical implications are substantial. CVM Instruction 539/2013 requires financial institutions to assess investors' risk profiles before recommending products but does not specify question formulation. Results suggest this regulatory gap allows systematic variation in profile

classifications, potentially compromising investor protection. If approximately 1 million investors respond to API questionnaires annually in Brazil (B3, 2023), and framing could alter classification for up to 20% of them, this represents 200,000 investors potentially classified inconsistently.

The finding that framing effects persist even among financially sophisticated participants (Table 4) is particularly noteworthy. This contradicts the intuition that financial literacy would protect against cognitive biases and suggests that susceptibility to framing is a deeper phenomenon affecting decision-making regardless of expertise level. This result has important implications for the design of financial education programs and regulatory instruments.

## 6. Conclusion

This study provides experimental evidence that textual framing in API questionnaires significantly affects investor risk profile classification. Using a randomized controlled trial with 900 participants in São Paulo, we demonstrated that question formulation, emphasizing potential gains versus potential losses, systematically alters investor responses, even when informational content is equivalent.

Key findings include:

- 1 Negative framing increases the probability of Conservative classification by 11 percentage points (41.7% vs. 31.3% in neutral), representing a 33% relative increase.
- 2 Positive framing increases high-risk profile classification (Bold + Aggressive) by 9 percentage points (27.7% vs. 19.0% in neutral), representing a 46% relative increase.
- 3 The net effect between positive and negative framing is 14.76 points (Cohen's  $d = 0.48$ ), representing approximately half a standard deviation shift in risk scores.
- 4 Effects are robust to multiple statistical specifications, remain significant after controlling for demographics and financial experience, and are homogeneous across genders.

- 5 Framing effects persist even among financially sophisticated participants, contradicting the hypothesis that experience neutralizes cognitive biases.

These results are consistent with Prospect Theory and extend behavioral finance literature by demonstrating that framing effects manifest in regulatory instruments currently used in financial markets.

The findings have direct implications for financial regulation, suitability practices, and investor protection. From a regulatory perspective, the results suggest that supervisory bodies such as CVM and ANBIMA could consider providing guidance on neutral question formulation in API questionnaires, with the aim of reducing the potential influence of framing effects. At the institutional level, financial intermediaries may benefit from periodically reviewing their suitability instruments to identify formulations that could unintentionally affect investor classification. More broadly, the results underscore the value of incorporating discussions of cognitive biases into financial education initiatives, helping investors better understand how question wording and presentation may shape self-reported risk preferences.

This study has limitations suggesting directions for future research. First, the experiment was conducted in a controlled environment without real money at stake, which may underestimate or overestimate effects observed in real investment decisions. Future approaches could examine whether framing in API questionnaires affects not only classification but also subsequent portfolio allocation decisions.

Second, we tested only one API questionnaire model (based on a Brazilian financial institution); effect amplitude may vary in other instruments. Third, we did not investigate psychological mechanisms underlying beyond Prospect Theory, lacking exploration of the role of factors such as financial skills, prior investment experience, and personality characteristics in framing susceptibility.

Despite these limitations, this study provides robust causal evidence that textual framing in API questionnaires significantly affects investor risk profile classification in Brazil. Findings have direct implications for financial regulation, suitability practices, and investor protection, and suggest the need for greater attention to risk assessment instrument formulation.

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### **Declaration of Competing Interest**

The authors declare no conflicts of interest.

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## **Appendix: Ethics Statement**

This study was approved by the Research Ethics Committee of Instituto Brasileiro de Ensino, Desenvolvimento e Pesquisa (CEP-IDP) under protocol CAAE 92370725.1.0000.5058, in compliance with Brazilian National Health Council Resolutions 466/2012 and 510/2016. All participants provided written informed consent prior to participation. The study involved minimal risk, and participant anonymity was preserved throughout data collection and analysis.