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The impact of behavioural biases on the decision-making of individual investors:
An empirical study of the French market

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GLOSSARY

OECD (Organisation for Economic Co-operation and Development) : International organisation made up of 38 member countries, aiming to promote policies that improve the economic and social well-being of populations. It produces analyses, statistics and recommendations on subjects such as the economy, finance, education and the environment.

AMF (Autorité des Marchés Financiers): Independent public body responsible for protecting savings invested in financial products, ensuring the smooth operation of financial markets and providing information to investors. It supervises and regulates financial market participants in France, such as management companies, brokers and listed companies.

Retail investor: Individuals who invest in the financial markets on their own behalf, generally in a less informed manner and for smaller amounts than institutional investors.

Interaction Effect: In statistical analysis, this refers to the combined effect of two or more independent variables on a dependent variable, indicating how their joint influence differs from their individual effects.

Multiple Linear Regression: A statistical technique used to model the relationship between a dependent variable and multiple independent variables, allowing the analysis of how each predictor contributes to the outcome.

Hypothetical Scenarios: Constructed examples or case studies used in surveys to gauge respondents' reactions and predict their likely behaviour in similar real-life situations.

Likert Scale: A psychometric scale commonly used in questionnaires to measure respondents' attitudes or perceptions, typically ranging from 'Strongly Disagree' to 'Strongly Agree'.

Plan d'Épargne en Actions (PEA): A French tax-advantaged investment account designed to encourage individuals to invest in European stocks and ETFs, providing certain tax benefits after a holding period.

Confidence level : Probability that the estimated interval contains the true value of the population. In other words, it is the statistical certainty that the results of the sample reflect those of the population.

Margin of error : indicator of the precision of the results obtained from the sample in relation to the target population. It reflects the amount whereby the sample findings may diverge from the population's real parameters. A lower margin of error indicates greater precision in the results, while a higher margin means greater uncertainty. Using a wider margin of error also makes the study more feasible, both in terms of time and cost (Lohr, 2010).

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INTRODUCTION

In the 21st century, the impact of behavioural biases on financial decisions has become a critical issue for individuals, companies, and the economy as a whole. Financial decisions, whether made by individual investors or institutions, shape markets and directly influence economic stability. When biased by psychological distortions, these decisions can lead to sub-optimal outcomes, exacerbate market fluctuations and compromise risk management (Shefrin, 2000*)*. Traditional finance theories, such as the Efficient Market Hypothesis (Fama, 1970) and Modern Portfolio Theory (Markowitz, 1952), have long posited that investors act rationally, basing decisions on available information to maximize utility and optimize risk-return trade-offs. These models assume efficient markets where asset prices reflect all relevant information, and rational behaviour governs investment decisions.

However, real-world financial phenomena often deviate from these assumptions. Events such as the 2008 financial crisis, speculative bubbles, and market crashes have exposed significant limitations of traditional frameworks. Behavioural anomalies, including irrational reactions to uncertainty, overconfidence during market booms, and herd behaviour in trends, suggest that psychological and emotional factors play a far more significant role in decision-making than previously acknowledged.

Behavioural finance offers an alternative lens to understand these deviations, challenging the rationality of traditional finance. It demonstrates that biases such as overconfidence, loss aversion, and many other distort risk perception and influence both individual and collective market behaviour. These biases interact, creating complex dynamics that affect not only personal investment outcomes but also broader financial stability.

In the French context, specific cultural and economic characteristics further highlight the relevance of studying these biases. This market offers a compelling case for analysis due to its unique combination of investor preferences for guaranteed financial products, a pronounced home bias, and the significant role of social and cultural factors on investment behaviors.

By combining theoretical analysis with empirical validation, this study seeks to answer key questions: *How do these biases disrupt the decisions of French investors? Which biases are most predominant? And what strategies can mitigate their negative effects on financial behaviour?*

Ultimately, this research aspires to contribute to the growing field of behavioural finance while offering practical insights for investors, financial institutions, and regulators. A deeper understanding of behavioural biases is essential for promoting more rational investment practices and strengthening the resilience of financial markets against future uncertainties.

CHAPTER 1 : LITERATURE REVIEW

Among the many biases identified in behavioural finance, four stand out as particularly relevant to understanding the challenges faced by French investors: overconfidence, loss aversion, herding bias, and home bias. These biases were chosen due to their prevalence in empirical studies and their significant impact on investment strategies and market dynamics. This literature review explores these biases, their implications for investor behaviour, and their interactions. By focusing on the French market, it aims to provide insights into how these biases have a role in the decision-making process. Understanding these behavioural tendencies is essential for developing strategies to mitigate their negative effects and improve investment outcomes.

1.a. The Overconfidence Bias and Its Effects on Risk-Taking

Overconfidence bias refers to the tendency of investors to overestimate their skills, knowledge, or ability to predict financial markets. This behaviour leads to excessive risk-taking, driven by an inflated sense of confidence in decision-making abilities. According to Daniel and Hirshleifer (2015), overconfident investors frequently trade in the belief that they can capitalize on short-term market fluctuations. However, such frequent trading often results in poor outcomes, largely due to high transaction costs, poor market timing, and flawed data interpretation (Barber and Odean, 2001). On the French market, the overconfidence bias became particularly apparent with the influx of new retail investors between 2020 and 2022 (AMF, 2024). These investors engaged in active trading, significantly increasing transaction costs and eroding their net returns (AMF, 2021). Furthermore, overconfidence often causes investors to disregard publicly available information in favour of their own judgment, amplifying risks in complex financial products such as crypto-assets (AMF, 2024).

A comparative analysis of Indian investors reveals a similar pattern. Jain and Kesari (2022) found that overconfident Indian investors exhibit a higher trading frequency and greater portfolio turnover, often misattributing their successes to personal skill rather than favourable market conditions. This similarity underscores the global prevalence of overconfidence bias and its consistent influence on trading behaviour. Overconfidence frequently interacts with herding behaviour, especially during periods of market volatility. While overconfident investors perceive themselves as independent decision-makers, their actions often align with prevailing market trends, contributing to speculative bubbles. An example is the tech bubble of the early 2000s, many investors believed they could outperformed the market, however they face significant losses during the correction.

In conclusion, addressing overconfidence bias is crucial for reducing unnecessary risk-taking and preventing costly errors. Though it drives risky behaviours, its interplay with loss aversion may paradoxically push investors towards more conservative strategies when faced with potential losses, further complicating their decision-making processes.

1.b. The Loss Aversion Bias and Conservative Investment Behaviour

Loss aversion, introduced by Kahneman and Tversky (1979) through prospect theory, reflects a stronger aversion to losses than the desire for equivalent gains. This bias influences investors in several ways, such as holding onto losing positions for too long in hopes of recovery or prematurely selling profitable assets to secure gains. On the French market, loss aversion is a driving factor behind the conservative investment behaviours observed among retail investors. French investors demonstrate a marked preference for low-risk financial products like Euro funds, which guarantee capital preservation but limit long-term returns. According to Morningstar's Global Investor Portfolio Study (2022), this tendency is consistent with a desire to avoid volatility, even at the cost of missed opportunities on international markets offering potentially higher returns. The AMF's 2022 barometer reinforces this observation, showing that 42% of French investors are risk-averse—a figure that has remained stable over time. Additionally, the share of French households willing to invest in equities has dropped to 25%, reflecting a growing reluctance to engage in riskier assets amid economic uncertainty. The interaction between loss aversion and other biases further complicates investment decisions. For instance, overconfidence may lead some investors to take excessive risks and loss aversion may cause the same individuals to retreat into overly conservative strategies when faced with potential losses. This paradox creates a behavioural push-and-pull that can hinder adaptability and long-term performance, especially in volatile market conditions.
In summary, loss aversion plays a significant role in shaping the investment behaviour of French investors, fostering a preference for safety at the expense of growth. Addressing this bias through targeted education on the benefits of risk-adjusted returns and diversification could help mitigate its negative impact and promote more balanced investment strategies.

1.c. The Herding Bias and Collective Investor Behaviour

Thirdly, herding bias manifests itself in the bent of investors to follow the behaviour of other market participants rather than basing their own rational analysis (Baddeley 2017, Keynes 1930). Even in the presence of private or contradictory information, individuals prefer to align themselves with the majority, often for fear of missing an opportunity or disagreeing with the market (Banerjee, 1992). This phenomenon is particularly exacerbated during periods of uncertainty or high market volatility. In the French market, herding bias has been amplified by the rise of social networks and online trading platforms, particularly among younger investors. According to the AMF (2023), many of these investors entered the market during the COVID-19 pandemic, relying heavily on collective advice shared in online communities. This behaviour contributed to speculative bubbles and heightened price volatility, as seen in the overvaluation of certain stocks during the 2020-2021 period. Historical examples illustrate the dangers of herding bias. During the dot-com bubble of the early 2000s, French investors, like their global counterparts, rushed to invest in technology stocks, driven by widespread optimism. The CAC 40 index saw significant gains, fueled by inflated valuations of tech companies, before suffering a sharp correction. According to Euronext (2003), French technology companies lost an average of 70% of their market capitalisation following the

bubble's collapse. More recently, herding has influenced investments in renewable energy stocks, driven by societal trends and policy incentives (Banque de France, 2024). Such thematic investments align with broader trends, but they also risk overvaluation when driven primarily by collective sentiment. Different studies tried to quantify this bias, for example, a study from India highlights that during periods of market stress, Indian investors tend to replicate the trading strategies of institutional players, exacerbating volatility and deepening market corrections. This dynamic mirrors the behaviour of French investors during past speculative episodes, underscoring the universal nature of herding bias. The interplay between herding and other biases, such as overconfidence, further amplifies market instability.
To conclude, herding bias plays a significant role in shaping market dynamics, particularly during periods of collective euphoria or panic. Mitigating its effects requires fostering financial literacy, promoting critical analysis, and encouraging investors to evaluate their decisions independently of market trends.

1.d. The Home bias and Lack of International Diversification

Fourthly, home bias refers to the habit of investors to favour investment choices with which they are familiar, often to the detriment of optimal diversification. This bias leads investors to concentrate on shares in domestic companies or sectors they know, while neglecting international or diversified opportunities. It is linked to the feeling of perceived competence (Heath and Tversky 1991). In France, this bias is expressed in a strong preference for domestic assets, to the detriment of foreign investments. According to the European Central Bank (2024), French households show a high concentration in domestic funds, with around 50.7% of investment funds held by French investors invested in domestic funds (*Figure 2*). This preference is also reflected in excessive cash deposits and insurance products with capital guarantees, such as Euro funds (Morningstar, 2022). These choices reveal an aversion to risk and a reluctance to invest internationally, reducing portfolio diversification and limiting exposure to growth opportunities abroad. Compared with other European countries, French investors seem more attached to this familiarity (*Figure 2*). Home bias often interacts with overconfidence and loss aversion, reinforcing risk-averse behaviours. Simultaneously, fear of potential losses in foreign markets discourages further diversification. This results in under-diversified portfolios, missing out on the benefits of global market opportunities, and limiting long-term returns. As well as restricting the geographical diversification of portfolios, the home bias hinders French investors' participation in international markets, preventing them from taking advantage of growth opportunities in other markets.

Behavioural biases do not operate in isolation, they interact in complex ways, complicating investment decisions and hindering portfolio performance. Understanding these biases is crucial to anticipating investor behaviour and developing strategies that can help to mitigate their negative effects on financial decision-making. The next chapter will explore how these biases will be tested empirically to assess their specific impacts on French investors' decisions.

CHAPTER 2 : THEORETICAL FRAMEWORK AND HYPOTHESIS

Behavioural biases play an essential role in the way investors make decisions in the financial market. A fundamental question that this study seeks to explore is: *how do these biases influence the investment decisions of individual investors in the French market ?*

2.a. Research Objectives

The objective of this research is to measure how behavioural biases—namely overconfidence, loss aversion, herding bias, and home bias—influence individual French investors' decision-making processes. The study will quantify the extent to which these biases lead investors to deviate from rational decision-making. For instance, overconfidence may result in excessive trading or taking higher risks without proper analysis, particularly in bullish markets. Similarly, the herding bias can lead investors to follow market trends blindly, amplifying price volatility and contributing to the formation of speculative. By identifying the dominant biases that emerge in the decision-making processes of French investors, this study will provide insights into how these psychological factors disrupt rational investment strategies and highlight the most impactful biases within this market context.

2.b. Research Design

This research will adopt an explanatory approach, aiming to identify and understand the causal relationships between behavioural biases and the investment decisions of French individual investors. The explanatory approach will allow for a deeper understanding of both the manifestations of these biases and their underlying mechanisms, as well as their specific impacts on the decision-making process. Explanatory research is essential to go beyond simple description and will explore the underlying causes and mechanisms that influence investor behaviour. Following this logic, the aim of this study will be to identify causal relationships between behavioural biases and investment choices. Rather than merely observing investor behaviour, the goal will be to understand how these biases influence decisions (Creswell, 2014).

2.c. Hypothesis

Each hypothesis is grounded in both established behavioural finance theory and empirical evidence from the French market.

H1: Overconfidence bias leads French individual investors to trade more frequently and take higher risks, believing they can outperform the market.

Source: Barber and Odean (2001) – AMF (2024) - OCDE (2023)

H2: Loss aversion bias causes French individual investors to prioritize avoiding losses, influencing their investment choices and risk preferences.

Source: Kahneman and Tversky's (1979) – Boolell-Gunesh, Broihanne, and Merli (2008) – AMF (2022)

H3: Herding bias leads French individual investors to engage in more frequent trading as they follow the observed actions of other market participants.

Source: Baddeley (2017), Keynes (1930) - Euronext (2003) - Banque de France (2024)

H4: The home bias leads French individual investors to underestimate the benefits of international diversification, thereby increasing the likelihood of a high domestic allocation.

Source: Heath and Tversky (1991) - European Central Bank (2024) – Morningstar (2022)

H5: Behavioural biases interact dynamically to amplify suboptimal investment decisions among French individual investors.

Source: AMF (2021)

CHAPTER 3 : METHODOLOGICAL APPROACH

3.a. Nature of the Study: A Quantitative approach

This study will employ a quantitative methodology to empirically test the formulated hypothesis. A structured questionnaire will be used to collect data from individual investors, measuring the extent to which these biases influence their decision-making processes. The questionnaire will be distributed electronically to ensure a representative and diversified sample of French investors. Data collected will be analyzed objectively, allowing for quantification of investor behaviour and biases, making the quantitative methodology particularly suitable for exploring causal relationships between variables (Creswell, 2014).

3.b. Sample Design and Size

To ensure generalizability, a representative sample was determined based on statistical parameters including confidence level and margin of error. The target population comprises individual investors active in the French financial markets. According to AMF (2023), this population is estimated at 1.43 million investors (*Figure 3*) . Using Cochran's formula[1], a sample of 96 respondents was selected, with a 95%[2] confidence level and a ±10%[3] margin of error. Although the sample represents approximately 0.0067% of the total population, it is sufficient to capture key demographic characteristics and the diversity of investor behaviours (Cochran, 1977).

3.c. Targeted Population

The target population for this study is individual investors active on French financial markets. These investors are defined as individuals who make investment decisions independently, without the direct intervention of a professional fund manager. They actively participate in the market by buying and selling shares, bonds, derivatives, or other financial assets.

Characteristics of the target population :

- Recent market activity: Participants are required to have completed financial transactions on French markets within the last 12 months.
- Diverse Experience Levels: The population includes both novice investors (less than 3 years' experience) and experienced investors (more than 3 years' experience).
- Access to Financial Information: Investors have regular access to economic and financial news via online platforms or other information channels, which can influence their investment decisions and reactions to market trends.

[1] Calculations in Appendix
[2] Common standard in quantitative research (Creswell, 2014)
[3] 10% allow flexibility in sample size, maintaining a certain level of statistical validity. This decision made it possible to reduce the sample size while maintaining acceptable precision (Cochran, 1977).

- Variety of Assets: The target investors hold a diverse portfolio that may include equities, bonds, ETFs, and crypto-assets, reflecting a range of investment strategies and risk appetites.
- French Market Focus: Although individual investors can access international markets, this study focuses on their behaviour within the French financial markets, allowing a detailed analysis of domestic investment patterns and biases.

Studying active individual investors is crucial as they are directly responsible for their investment choices and are more susceptible to behavioural biases compared to institutional investors. Given the increased market participation of French individual investors post-COVID-19 (AMF, 2021), this group offers valuable insights into the impact of biases on decision-making in a volatile and evolving financial environment.

3.d. Questionary Design

The questionnaire will be structured to collect quantitative data on the behavioural biases of individual investors active in the French financial markets. It will consist of several sections to capture the impact of biases, such as overconfidence, loss aversion, herding, and home bias (see Appendix). The questionnaire will also include hypothetical scenarios to assess how investors react to market fluctuations. The data collected via this questionnaire will enable the formulated hypothesis to be tested directly by examining how each behavioural bias influences investment decisions.

3.e. Hypothesis-Data Mapping

The responses collected via the Likert scale in Section 3 (see Appendix) will be used to quantitatively measure the degree to which individual investors exhibit behavioural biases. Each statement within the Likert scale is designed to capture the intensity of a particular bias based on the respondent's self-assessment. The responses will be aggregated by assigning numerical values to each Likert point to create composite scores for each bias. The data will be tested for correlations using Pearson coefficients, and multiple regression analyses will be performed to identify significant relationships between biases and investment behaviours. Interaction effects between biases will also be explored to assess their combined influence on decision-making. For instance, the relationship between overconfidence and trading frequency will be examined using regression analysis, where "trading frequency" is the dependent variable and "overconfidence bias" is an independent variable. The significance of regression coefficients (p-values) and adjusted R^2 values will be used to evaluate the strength of these relationships.

CHAPTER 4 : DATA COLLECTION AND ANALYSIS

To answer the research question, empirical data were collected using a structured questionnaire. Access to a targeted sample of active French individual investors was facilitated by leveraging professional networks within a private bank. Furthermore, an academic network from a French business school provided additional participants, including friends, colleagues, and acquaintances fitting the study's target criteria. This approach ensured a broader yet focused sample aligned with the study's objectives, capturing a diverse set of investor profiles. The statistical analysis that follows, using tools such as regressions and Cronbach's alpha, will make it possible not only to identify the presence of these biases, but also to quantify their influence on specific behaviours such as trading frequency or domestic asset allocation.

4.a. Demographic Profile of the Sample

A total of 100 questionnaires was distributed via email. Out of the total distributed, 68 responses were received and collected for analysis. *Table 1* provides a summary and analysis of the respondents' demographic profile, including factors such as gender, age, and other relevant aspects. The demographic analysis shows a predominance of male respondents (78%), with females making up the remaining 22%. Age distribution highlights a young cohort, with 37% under 25 years old and 25% aged between 25 and 34 years, indicating a majority of younger investors actively participating in the market. Educational level is high within the sample: 73% of respondents hold a Master's degree, while only a small fraction (3%) have a doctorate. This suggests a well-educated investor base, likely to have better access to financial information. Professional status varies, with managers forming the largest group (31%), followed by employees (28%) and students (28%). Income levels show significant heterogeneity. The largest segment (35%) earns over €80,000 annually, 26% have an income below €20,000. This diversity allows the study to explore how different financial circumstances influence biases and investment decisions. In summary, the sample composition indicates a diverse and well-educated group of investors, predominantly young and with varied income levels. These characteristics provide a solid foundation for examining the influence of behavioural biases on investment decisions, particularly given the increase in market participation among younger and highly educated investors following the COVID-19 pandemic (AMF, 2021).

4.b. Investor Behaviour Analysis

This section analyzes the investment habits and behaviours of the sample, considering factors such as investment duration, motivations for investing, frequency of transactions, and performance monitoring, the *Table 2* exposes the results. The majority of respondents (30.9%) have invested for 1 to 3 years, reflecting significant interest among younger, newer investors. In contrast, 28% of participants have over 10 years of experience, suggesting a solid base of seasoned investors. Investment motivations are primarily centered on capital growth (66.2%),

indicating a focus on wealth accumulation. Secondary reasons include retirement preparation (16.2%) and generating additional income (10.3%). Regarding trading frequency, daily and weekly trading, combined, account for 52.9%, showing an important segment of highly active investors. 26.5% of respondents trade monthly, reflecting moderate engagement, while 20.6% trade less than once a month, indicating a more passive approach. When it comes to monitoring investment performance, 29.4% of respondents review their portfolios daily, demonstrating a high level of engagement, while monthly monitoring is preferred by 25%. Notably, 17.7% of investors review their performance less than once a month, highlighting a group of less active participants. The data expresses a diverse range of investor behaviours, from highly engaged individuals who frequently trade and monitor their portfolios, to more passive investors who prefer less frequent involvement.

4.b.a. Portfolio Allocation Analysis

The questionnaire also provided insights into the asset allocation of investors' portfolios, showed on the *Table 3*. French and international equities are moderately represented, with most investors (36 out of 68 for French equities and 27 for international equities) allocating between 0 and 25% of their portfolios to these assets. Larger allocations are uncommon. Bonds are also predominantly allocated in small proportions (0-25%) by 27 investors, suggesting they are not the core asset in portfolios. Conversely, ETFs show diverse usage; 23 investors allocate 0-25% to ETFs, while 7 allocate 76-100%, highlighting their popularity for some investors. Cryptocurrencies remain a cautious choice, with 21 investors allocating between 0-25%. Finally, derivatives are seldom used, with 55 investors having none in their portfolios, indicating an aversion to these complex instruments. In summary, investor portfolios tend to be moderately diversified, with a cautious use of riskier assets.

4.b.b. Financial Knowledge Assessment

This section evaluates investors' level of financial knowledge across different types of assets (equities, bonds, derivatives, cryptocurrencies, and ETFs) using a Likert scale ranging from 1 (very low knowledge) to 5 (very high knowledge). For equities, a majority of investors exhibit high proficiency: 28 out of 68 rate themselves at level 5, and 22 at level 4. In contrast, only 1 and 5 investors are at levels 1 and 2, respectively, indicating that few participants have low knowledge in this area. For bonds, the distribution is more varied. While 16 investors rank at level 5 and 18 at level 4, a similiar proportion (15) are at the intermediate level (3), and 12 are at level 1, suggesting a more heterogeneous understanding of this asset. Derivatives reveal generally lower levels of mastery: 17 investors are at level 1, and 19 at level 2, indicating unfamiliarity or aversion. Knowledge of cryptocurrencies also appears limited, with 17 participants at level 1 and 19 at level 2. Only 12 investors rate at level 5, and 9 are at level 4, reflecting limited confidence in this volatile asset. ETFs, however, show a higher level of understanding: 19 respondents rank at levels 5 and 22 at level 4, suggesting greater familiarity and mastery of this instrument.

4.b.c. Information Sources Analysis

The *Table 5* shows the information sources investors use to make investment decisions. The most popular sources are financial websites and specialist journals, consulted by 90% of participants, indicating a reliance on reputable, up-to-date information. Financial advisors are the second most common source, used by 44.1% of respondents, highlighting the value of professional expertise. Social networks (25%) and friends, family, or colleagues (29.4%) are also frequently consulted, showing the role of social interactions in investment decisions. Bloomberg is the least used, with 1.5% of respondents, suggesting limited accessibility or familiarity among the sample.

4.c. Statistic Bias Identification

4.c.a. Statistics Related to the Overconfidence Bias

The results on *Table 6* on overconfidence bias demonstrate that investors' levels of overconfidence vary, with Likert scale ratings ranging from 1 (low overconfidence) to 5 (high overconfidence). The majority of respondents, 47% for level 4 and 5, have high levels of overconfidence, reflecting a positive assessment of their investment abilities. In contrast, 16% of respondents are at level 1 and 24% at level 2, indicating modest overconfidence and a cautious assessment of their talents. These data indicate that, a large number of investors demonstrate moderate to high overconfidence but a sizable proportion remain cautious in assessing their talents.

4.c.b. Statistics Related to the Loss Aversion Bias

The results in *Table 7* indicate a diverse range of loss aversion among investor. A significant 40% of respondents are classified at level 4, indicating a substantial concern about losses, thus reflecting higher aversion. Meanwhile, 21% are at level 2, showing moderate resistance to losses, and 13% scored at level 1, demonstrating low loss aversion. These results suggest that a considerable portion of investors exhibit heightened sensitivity to potential losses but as well a significant number maintain a more tolerant stance.

4.c.c Statistics Related to the Herding Bias

The results in *Table 8* on herding bias reveal a distinct distribution of tendencies among investors. 29% of respondents are at level 4, displaying a strong inclination to follow market trends and the decisions of others, indicating pronounced herding behaviour. Nevertheless, 53% of respondents are at level 1 and 2, indicating a low inclination to follow the decisions of others. It highlight a divide between investors who rely on independent decision-making and those influenced by collective behaviours.

4.c.d. Statistics Related to the Home Bias

The results in *Table 9* related to the home bias indicate a significant preference among investors for domestic investments. The highest proportion, 33% of respondents, are at level 4, indicating a strong preference for familiar, local investments. In contrast, 42% of participants fall at level 2 and 1, showing a moderate inclination towards home bias and indicating a greater openness to foreign assets. A significant proportion of investors exhibit strong home bias, and as well a significant segment remains relatively open to international diversification.

4.d. Validation of Bias Measurement Scales: Cronbach's Alpha & Composite Reliability

In order to make the study as accurate as possible, it is important to assess the internal consistency of the scales used to measure behavioural bias. To do this, two main indicators are used: Cronbach's Alpha[4] and Composite Reliability (CR)[5]. For the Cronbach Alpha, a coefficient greater than 0.7 is generally considered acceptable (Nunnally & Bernstein, 1994). In this analysis, the results[6] in *Table 10* show good internal consistency for the overconfidence (0.873) and loss aversion (0.759) biases, with values exceeding the 0.7 threshold. However, the herding bias has a slightly lower value (0.650), it may indicate heterogeneity in the responses or question wording that needs to be improved. The CR results[7] (*Table 10*) confirm those of Cronbach's Alpha, with good internal consistency for the overconfidence and loss aversion biases. The herding bias (CR = 0.658) is slightly below the threshold of 0.7, but this can be justified by the complexity of the concept measured and the size of the sample. Overall, these results indicate that the measurement scales are sufficiently reliable to be used in the analysis of behavioural biases.

[4] Cronbach's Alpha is a measure commonly used to evaluate the internal consistency of scale items (Cronbach, 1951).
[5] Composite Reliability (Fornell and Larcker, 1981) is an alternative, more robust measure of internal consistency that takes into account the factor loadings of the items.
[6] Calculation in the Appendix
[7] Formula in the Appendix

4.e. Validity tests (KMO and Bartlett's Test)

The validity tests undertaken to assess the adequacy of the data as part of the analysis of behavioural biases include the Kaiser-Meyer-Olkin (KMO) test[8] and Bartlett's test of sphericity[9]. First of all, for KMO test, generally, a value greater than 0.6 is considered acceptable to indicate that the sample is adequate (Hair et al., 2014). The results[10] obtained in *Table 11* reveal that the overconfidence, loss aversion and home bias display respective KMO scores of 0.796, 0.726 and 0.715, reflecting a good adequacy of the sample for in-depth analysis. On the other hand, the KMO score of 0.534 obtained for the herding bias is slightly below the recommended threshold, suggesting less relevance for this specific bias.
Secondly, for Bartlett's sphericity test. A p-value of less than 0.05 indicates that the correlations observed between items are statistically significant (Hair et al., 2014). The results[11] of Bartlett's test for all the biases studied show p-values equal to 0.000 (*Table 11*), confirming the statistical significance of the correlations and the relevance of the data.

4.f. Correlation matrix (Pearson coefficient)

The correlation matrix obtained (*Table 12*) for the analysis of behavioural biases presents interesting results on the relationship between the various biases measured. Correlations are assessed using Pearson's correlation coefficient, a widely used metric for detecting linear relationships between continuous variables (Cohen, 1988). Pearson's coefficient is calculated as:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

The values observed in the matrix indicate that most of the biases have moderate correlations, particularly between the herding bias and the home bias (r= 0.41), it could suggest a potential common influence. Similarly, there is a positive correlation between overconfidence and herding (r= 0.38), although it remains within a moderate range. In contrast, the correlations between loss aversion and the other biases are low to moderate, ranging from -0.016 to 0.36, indicating a limited relationship with the other factors studied. The correlation matrix does not display high enough relationships (above 0.6) to indicate problematic multicollinearity in subsequent data analysis, it is essential to ensure the validity of future regressions (Hair et al., 2014). These results provide an initial assessment of the potential interactions between the biases, providing a basis for further quantitative analysis.

[8] KMO test (Kaiser, 1974) is used to estimate the relevance of the sample by measuring the degree of correlation between the observed variables.
[9] Bartlett's sphericity test (Bartlett, 1950) examines whether the variables are sufficiently correlated to justify a multivariate analysis.
[10] Formula in the Appendix
[11] Formula in the Appendix

4.g. Multiple Linear regression

4.g.a. Key Findings of models

Then, a multiple linear regression was carried out. *Table 13* presents the regression results for the determinants of trading frequency across three models. The models incrementally introduce additional variables and interaction terms to refine the understanding of the relationship between behavioural biases, demographic factors, and trading activity.

Model 1 establishes a baseline relationship between behavioural biases and trading frequency:

$$Trading_{Frequency} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Herding\ bias) + \beta 4(Home\ bias) + \varepsilon$$

Among these, overconfidence bias shows a positive and highly significant association with trading frequency (β= 0.4577, p < 0.01). However, other biases, such as loss aversion bias (β2= −0.070, p= 0.626) and herding bias (β3= −0.156, p= 0.389) are not statistically significant.

Model 2 incorporates demographic controls into the regression:

$$Trading_{Frequency} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Herding\ bias) + \beta 4(Home\ bias) + \beta 5\,(Age) + \beta 6\,(Years\ of\ experience) + \beta 7\,(Income\ Level) + \beta 8(Gender) + \varepsilon$$

In this model, overconfidence bias (β1=0.463, p <0.001) remains significant and positive, although the effect size is slightly reduced compared to Model 1. Gender (β8=0.574, p <0.05) emerges as significant, suggesting that males may exhibit higher trading activity. However, other demographic variables, including age (β5=−0.165, p=0.196) and income level (β7= −0.003, p = 0.963) do not have a significant impact.

Model 3 introduces interaction terms to capture potential moderating effects, and with only significative variables:

$$Trading_{Frequency} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Overconfidence\ bias\ and\ age) + \beta 4(Loss\ Aversion\ bias\ and\ Gender) + \varepsilon$$

The results indicate that overconfidence bias (β1=0.680, p <0.001) continues to significantly predict trading frequency, maintaining its robustness across specifications. Additionally, the interaction term Overconfidence × Age (β3=−0.115, p <0.001) suggests that the positive effect of overconfidence on trading frequency diminishes with age. Contrary to previous results, the model also highlights the significant impact of loss aversion bias on trading frequency. The coefficient associated with this bias (β2= −0.2489, p= 0.03) indicates that loss aversion reduces trading frequency as it is negative. Furthermore, the interaction term Loss Aversion × Gender (β4= 0.153, p <0.05) reveals that this bias is moderated by gender, making the impact of loss aversion less pronounced for a specific group. This suggests that demographic differences may influence how this bias affects investment behaviour.

4.g.b. Robustness Diagnostics

The robustness diagnostics for the three models are summarized in *Table 16*. Across all models, the number of observations remains consistent at 68, ensuring comparability. The explanatory power of the models increases from Model 1 (R^2= 0.227) to Model 2 (R^2= 0.557) with Model 3 slightly reducing it to (R^2= 0.522) due to the inclusion of interaction terms. The F-statistic values across models confirm the overall significance of the models, particularly for Model 3 (F= 17.23), highlighting its robustness in explaining the variance in trading frequency. Additionally, multicollinearity checks conducted through Variance Inflation Factors (VIFs) in *Table 15* indicate no significant multicollinearity concerns, meaning that the variables included in the models contribute unique explanatory power without redundancy. This supports the validity and reliability of the regression estimates. To finish, the results of the Breusch-Pagan test for Model 2 in *Table 14*, evaluated as the most complex model, indicate no evidence of heteroskedasticity (p= 0.398). The residuals exhibit constant variance, validating the assumption of homoscedasticity.

4.h. Logistic Analysis of Hypothetical Scenarios

Then, a logistic regression was carried out to analyze the influence of behavioural biases on three dependent variables**:** LVMH response**,** Investment response, and Energy response. *Table 17* summarizes the regression coefficients (β) and p-values for each model.
The Model 1 for LVMH response is specified as:

$$LVMH_{response} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Herding\ bias) + \beta 4(Home\ bias) + \varepsilon$$

The results show that the constant term (β0= −13.203, p= 0.006) is significant, indicating a baseline adjustment in the absence of the biases. None of the behavioural biases included in the model demonstrate statistical significance at the 5% level. However, Home Bias (β4= 1.479, p= 0.094) approaches significance, suggesting a potential effect on the likelihood of LVMH response, although further validation is required.

The Model 2 for Investment response follows the equation:

$$Invest_{response} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Herding\ bias) + \beta 4(Home\ bias) + \varepsilon$$

In this model, Loss Aversion Bias (β2= −0.902, p= 0.024) is significant and negatively associated with the likelihood of investment response, indicating that higher levels of loss aversion reduce the probability of engagement. Other biases, including Herding Bias (β3= 0.856, p= 0.082), show marginal significance, suggesting a potential positive influence, but these results are not definitive.

The Model 3 for Energy response is :

$$Energy_{response} = \beta 0 + \beta 1\,(Overconfidence\ bias) + \beta 2\,(Loss\ Aversion\ bias) + \beta 3(Herding\ bias) + \beta 4(Home\ bias) + \varepsilon$$

The results indicate that none of the behavioural biases reach statistical significance at the 5% level, although Overconfidence Bias (β1= 0.385, p= 0.412) and Home Bias (β4= 0.685, p= 0.256) suggest positive associations that are not statistically robust.

CHAPTER 5 : DISCUSSION AND INTERPRETATION OF THE RESULTS

5.a. Hypothesis Interpretation

H1: Overconfidence bias leads French individual investors to trade more frequently and take higher risks, believing they can outperform the market. – Supported

Source: Barber and Odean (2001) – AMF (2024) - OCDE (2023)

The results obtained support hypothesis 1. Firstly, Descriptive statistics indicate that 34% of respondents scored level 4 on the Likert scale for overconfidence, while 13% scored level 5, underscoring its prevalence. Then, the multiple regression analysis carried out on trading frequency reveals that the overconfidence bias has a significant positive association with trading frequency in all three model. This supports the strong role of overconfidence in trading activity. The inclusion of demographic variables in Model 2 slightly reduces the effect size of overconfidence bias, but the association remains robust. Gender also emerges as a significant factor, suggesting that it may moderate the relationship between overconfidence and trading frequency. Model 3, which includes interaction terms, reveals that the effect of overconfidence diminishes with age, suggesting that older investors are less influenced by overconfidence bias. This interaction highlights how demographic factors moderate the impact of this bias. Overall, the findings are consistent with the literature, it emphasizes the tendency of overconfident investors to overtrade, driven by their overestimation of their skills (Barber and Odean (2001)).

H2: Loss aversion bias causes French individual investors to prioritize avoiding losses, influencing their investment choices and risk preferences. – Supported

Source: Kahneman and Tversky's (1979) – Boolell-Gunesh, Broihanne, and Merli (2008) – AMF (2022)

The results obtained validate H2 in certain configurations. Descriptive statistics show that 40% of respondents scored level 4 on the loss aversion scale, while 13 percent reached level 5, indicating strong sensitivity to losses. However, this bias is not statistically significant in model 1 of the multiple linear regression. This suggests that, when isolated from the other variables, the direct impact of loss aversion on trading frequency remains limited in this sample. On the other hand, in model 3, where interaction terms are included, loss aversion becomes significant. These results show that, under specific conditions, increased loss aversion leads to a decrease in trading frequency. This finding is reinforced by the significant interaction between loss aversion and gender indicating that the impact of this bias is attenuated for certain demographic groups. In addition, the logistic regression results in Model 2 (Investment Response) further validate this, identifying loss aversion as statistically significant influencing investment choices, particularly in preferring less risky assets over equities to minimize potential losses. These results demonstrate the irrational influence of loss aversion in decision-making under uncertainty, in line with Kahneman and Tversky's (1979) prospect theory.

H3: Herding bias leads French individual investors to engage in more frequent trading as they follow the observed actions of other market participants. – Not supported

Source: Baddeley (2017), Keynes (1930) - Euronext (2003) - Banque de France (2024)

The results do not support H3. Across all regression models, herding bias fails to demonstrate a statistically significant relationship with trading frequency or investment behaviour. The data implies that herding behaviour does not play a prominent role in influencing the trading frequency of French individual investors within the studied sample. It contrasts with certain literature on behavioural finance, which often identifies herding as a significant driver of market dynamics and it contrasts as well contrasts with the observations of the AMF (2023). The lack of statistical significance may reflect either the diversity of trading strategies among individual investors or their limited exposure to peer-driven market influences. Further research may be needed to explore herding behaviour in different contexts or subgroups.

H4: Home bias leads French individual investors to underestimate the benefits of international diversification, thereby increasing the likelihood of a high domestic allocation. - Supported

Source: Heath and Tversky (1991) - European Central Bank (2024) – Morningstar (2022)

Analysis of hypothesis H4 reveals conclusive results. A multiple linear regression (*Table 18*) was run using domestic allocation as the dependent variable and the home bias score as the main explanatory variable, adding age as control variable. Model 1, focusing solely on Home Bias, reveals a significant positive relationship with domestic allocation (β=0.5180, p=0.000), explaining 23.2% of the variance (R^2 = 0.232). Moreover, Model 2 shows a marginal effect of age (β=0.1324, p =0.073) while maintaining the strong significance of home bias (β= 0.4857, p= 0.000). This model slightly improves explanatory power (R^2 = 0.269). A higher home bias leads to increased domestic allocation, with demographic factors like age potentially playing a secondary role. Furthermore, descriptive statistics further corroborate, with 33% of respondents displaying a high familiarity bias (level 4), while only 16% reported openness to international investments (level 1). This supports the notion that familiarity strongly influences investment decisions.

H5: Behavioural biases interact dynamically to amplify suboptimal investment decisions among French individual investors. - Supported

Source: AMF (2021)

The analysis of H5 reveals significant evidence supporting the hypothesis. The regression models and the correlation matrix collectively illustrate how biases interconnect, creating a feedback loop that exacerbates irrational behaviour in investment decision-making. The regression models highlight the distinct but intertwined effects of behavioural biases. Overconfidence consistently emerges as a significant factor across the models, encouraging excessive trading and risk-taking. The addition of demographic controls in the models further underscores the complexity of these interactions, as biases often vary with age and gender. The correlation matrix provides further evidence of these dynamic interactions. Herding bias and

home bias exhibit the strongest correlation as mentionned, suggesting that investors who follow market trends are also inclined toward domestic investments, possibly due to perceived safety or familiarity. Additionally, overconfidence correlates moderately with herding bias, meaning that overconfident investors are more likely to align their actions with market movements while believing in their independent decision-making abilities. Loss aversion also correlates with home bias, reinforcing the preference for perceived safer domestic assets among risk-averse individuals. These data demonstrate how biases, rather than operating in isolation, amplify each other. For instance, overconfidence may drive excessive trading during periods of market optimism, but loss aversion could lead to conservative reactions during downturns, resulting in inconsistent and suboptimal strategies. Herding bias, in turn, reinforces these behaviours by aligning individual decisions with collective market movements, amplifying volatility and reducing diversification. To conclude, the dynamic interplay between behavioural biases compounds the challenges faced by French individual investors, leading to suboptimal investment decisions such as excessive trading, limited diversification, and increased market exposure. Addressing these biases requires a comprehensive understanding of their interconnected effects and tailored strategies to mitigate their influence on investment performance.

5.b. Theoretical, practical and regulatory implications

From a theoretical perspective, these findings highlight the complexity of behavioural biases, suggesting the need for more sophisticated models to capture dynamics. The results support the idea that traditional investment models need to incorporate these biases in order to better reflect the reality of individual investors' decisions. In particular, the significant impact of the interaction between overconfidence and home bias indicates that investor behaviour is influenced by a combination of biases, rather than by isolated biases, which requires an integrated approach in models of financial behaviour. For individual investors, these results highlight the importance of strategies aimed at minimising the impact of behavioural biases. Better financial education and the adoption of automated tools could mitigate these biases, encouraging more rational decision-making and optimal diversification to improve long-term performance. As far as financial institutions are concerned, banks and financial advisers should set up awareness-raising programmes for their customers. For example, when an investor opens a Plan d'Épargne en Actions (PEA), they could be offered a self-assessment test to identify their potential biases, such as overconfidence or loss aversion. These assessments would not only help customers to better understand their own behaviour, but would also enable financial advisers to adapt their recommendations accordingly.

Finally, financial regulation could play a key role in mitigating the effects of behavioural biases. Regulatory authorities, such as the AMF, could impose mandatory training programmes for investment professionals to enhance their knowledge of behavioural biases and mitigation strategies. In addition, nationwide financial education campaigns could raise public awareness of the impact of emotions on their investment decisions, promoting a more disciplined and diversified approach to portfolio management. These initiatives aim to protect investors against impulsive decisions and improve their resilience to market fluctuations, thereby contributing to greater stability in the financial system as a whole.

5.c. Limitations and Suggestions for Future Research

Despite the results obtained, this study has certain limitations. One of the main limitations concerns the size of the sample, which, although adequate for an initial exploration, could be considered insufficient to exhaustively represent all French individual investors. A larger and more diversified sample would strengthen the validity of the conclusions and improve the representativeness of the results. In addition, the biases studied were measured mainly using self-reported scores, which may introduce response biases, particularly due to the tendency of participants to underestimate or overestimate their biased behaviour. A complementary approach using real behavioural data, such as transaction histories, would provide a more objective and nuanced assessment of behavioural biases. Furthermore, the study focused on a limited selection of behavioural biases and only partially explored the complex interactions between these biases. Future research could incorporate other psychological dimensions, such as risk tolerance, which could modulate the impact of biases on decision-making. For example, an in-depth analysis of risk tolerance as a moderator of biased behaviour would provide a better understanding of how investors adjust their strategies according to their appetite for risk. Finally, the development of dynamic models integrating the evolution of behavioural biases over time and according to market cycles could refine bias management strategies and offer new perspectives for financial education and market regulation.

CONCLUSION

In a period where financial markets are increasingly influenced by both individual behaviours and global uncertainties, this study highlights the role of behavioural biases in shaping the investment decisions of French individual investors. By exploring overconfidence, loss aversion, herding, and home bias, this research provides a nuanced understanding of how these cognitive distortions disrupt rationality, leading to suboptimal decisions that ultimately impact market efficiency and individual wealth accumulation.

The findings reveal not only the prevalence of these biases among French investors but also their intricate interactions, highlighting how overconfidence amplifies risk-taking, how loss aversion fosters conservatism, and how home bias limits diversification. While herding bias showed limited statistical significance, its potential influence during periods of market euphoria or panic cannot be ignored. These insights underscore the importance of addressing these biases to promote more rational investment behaviours and improve financial outcomes.

Beyond academic contribution, this study carries significant practical and regulatory implications. It calls for enhanced financial education and tailored advisory services to help investors recognize and mitigate their biases. Regulatory bodies, such as the AMF, have an essential role to play in fostering awareness and resilience, ensuring that both individual investors and the financial system are better equipped to face future challenges.

However, the journey towards understanding and managing behavioural biases is far from complete. This research opens avenues for future studies to delve deeper into the dynamics of biases, their evolution over time, and their impact across diverse investor profiles. By building on these findings, future work can pave the way for more adaptive and bias-aware financial ecosystems. Indeeed, within the context of digital transformation, the increasing reliance on automated trading systems and artificial intelligence in investment decisions raises important questions about how these technologies interact with human biases. For instance, automation could potentially mitigate certain biases, but it may also create new challenges, such as over-reliance on algorithmic outputs or a diminished understanding of underlying market dynamics. Technology will continue to reshape the investment landscape. Moreover, recent market phenomena highlight the urgency of understanding the broader implications of behavioural biases. The volatility of cryptocurrencies and the speculative bubbles observed during the COVID-19 pandemic underscore how biases can drive extreme market behaviours. For example, overconfidence and fear of missing out have likely played roles in the meteoric rise, and subsequent correction, of certain digital assets. These episodes call for a deeper investigation into how biases amplify market fluctuations, particularly in emerging asset classes where regulatory oversight and investor understanding remain limited.

Ultimately, this thesis reinforces a fundamental truth: while behavioural biases are deeply ingrained in human psychology, their effects are not immutable. Through education, regulation, and innovation, there exists an opportunity to transform these limitations into levers for more informed, balanced, and sustainable investment strategies. By addressing these biases head-on, we take a critical step toward building not only better investors but also a more resilient financial future.

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APPENDIX

CHAPTER 1 : LITERATURE REVIEW

Figure 1 : CAC 40 Performance
Source : Yahoo Finance

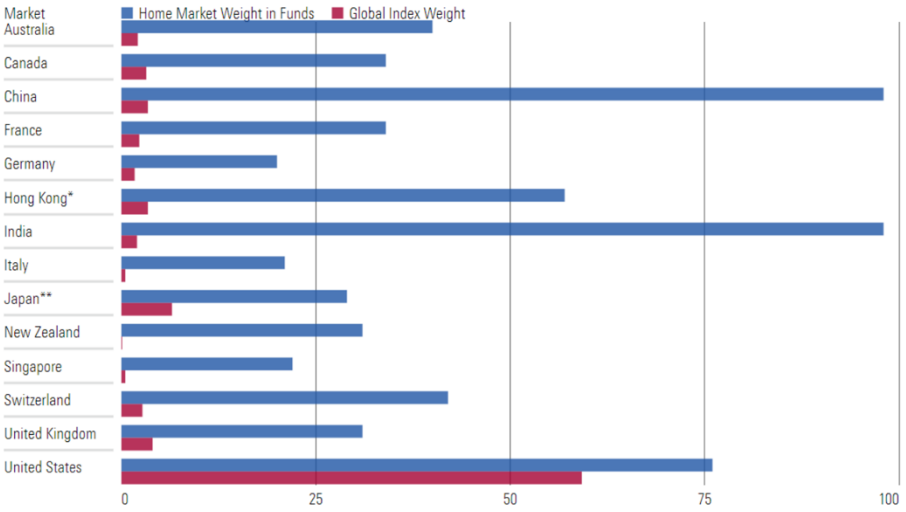
(domestic funds), (ii) funds investing in equity that are domiciled in non-domestic funds incorporated in financial centers, and (iii) other non-domestic funds investing in equity (in percent of the investor country's total investment in funds that invest in equity), based on 2021 data (see Columns 2 to 4). Column 1 shows the country. AT stands for Austria, BE for Belgium, DE for Germany, EE for Estonia, ES for Spain, FI for Finland, FR for France, GR for Greece, IE for Ireland, IT for Italy, LT for Lithuania, MT for Malta, LU for Luxembourg, LV for Latvia, NL for the Netherlands, PT for Portugal and EA for euro area. In line with Chan et al. (2005), the financial centers are: the United States, the United Kingdom, Luxembourg, Switzerland, Ireland, Japan, Hong Kong, and Singapore. The last row shows the euro area average.

	Domestic funds	Financial centres	Other funds
AT	46.8	41.1	12.1
BE	29.9	66.7	3.4
DE	40.9	56.2	2.9
EE	1.9	86.3	11.8
ES	12.9	81.6	5.5
FI	61.4	33.7	4.9
FR	50.7	47.9	1.3
GR	1.1	94.7	4.2
IE	30.4	67.1	2.5
IT	15.9	80.4	3.6
LT	1.3	95.9	2.8
LU	57.0	23.8	19.2
LV	4.6	87.5	7.9
MT	1.0	95.5	3.5
NL	50.9	47.8	1.2
PT	37.0	60.6	2.3
EA	27.7	66.7	5.6

Figure 2 : Fund Investment Allocation of Domestic Investors

Source: European Central Bank (2024) : Is home bias biased ?

Exhibit 5 Home-Market Weight in Equity Open-End Funds and ETFs by Domicile, Compared With Index



Source: Morningstar Direct. Data as of 30 September 2022. *Hong Kong includes Chinese stocks listed in Hong Kong. **Japan does not include ETFs as these flows are strongly driven by the central bank. Index used is Morningstar Global Equity Index.

Source: Morningstar, "Global Investor Portfolio Study 2022".

CHAPTER 3 : METHODOLOGICAL APPROACH

3.b. Sample Design and Size

Statistical parameters (Cochran, 1977)

The basic formula used to determine the sample size is : $$n = \frac{Z^2 \times P \times (1-P)}{E^2}$$

Where:
n = Sample size
Z = Z-score corresponding to the confidence level (1.96 for a 95% confidence level)
P = Estimated proportion (generally 0.5 if no specific data is available)
E = Margin of error

$$n = \frac{1.96^2 \times 0.5 \times (1-0.5)}{0.10^2} = 96,04$$

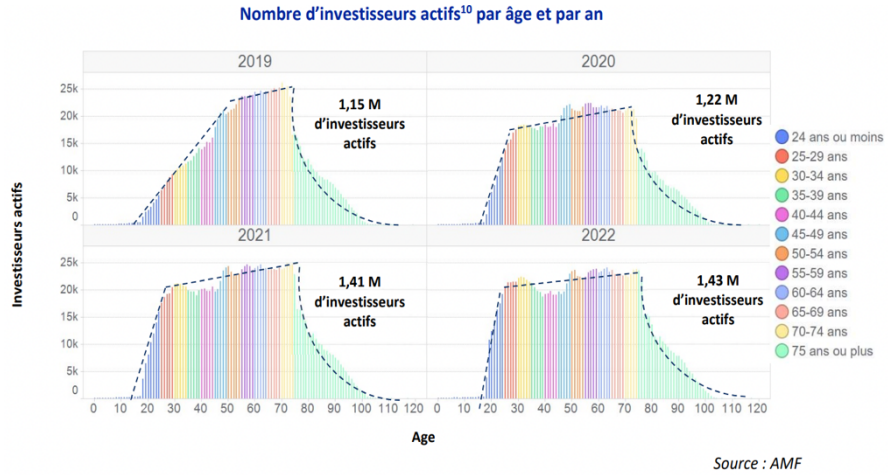


Figure 3 : Numbers of actifs investors in France

3.d. Questionary Design

SECTION 1: DEMOGRAPHIC INFORMATION

The purpose of this section is to gather key demographic information about respondents, including their age, gender, level of education, annual income… This information is important as it allows respondents to be segmented according to different criteria, facilitating further analysis of behavioural biases.

1. **What is your age?**

- Under 25 years
- 25-34 years
- 35-44 years
- 45-54 years
- 55 years and older

2. **What is your gender?**

- Male
- Female

3. **What is your level of education?**

- High School Diploma
- BTS, DUT
- Bachelor's Degree
- Master's Degree
- Doctorate

4. **What is your professional status?**

- Worker
- Employee
- Manager
- Business Owner
- Artisan, Merchant
- Retired
- Other: _____

5. **What is your annual income?**

- Less than €20,000
- €20,000 - €40,000
- €40,001 - €60,000
- €60,001 - €80,000
- More than €80,000

Source : Survio. (n.d.). *Sondage démographique*. Survio. https://www.survio.com/exemple-questionnaire/sondage-demographique

SECTION 2: INVESTOR BEHAVIOUR

This section focuses on participants' investment behaviour. Questions about the frequency of transactions, the types of assets invested, etc. offer insights into investors' strategies and habits. By asking questions about portfolio management behaviour, this section allows us to begin to understand the psychological dynamics underlying investment decisions.

1. **How many years of experience do you have in investment?**

- Less than 1 year
- 1-3 years
- 3-5 years
- 6-10 years
- More than 10 years

2. **What is your primary motivation for investing in financial markets? (Select the option that best represents your current goal)**

- Grow my capital
- Prepare for retirement
- Obtain supplementary income
- Finance a project
- Other: _____

3. **How frequently do you buy or sell financial assets (stocks, bonds, ETFs) in the financial markets?**

- Daily
- Weekly
- Monthly
- Less than once a month

4. **Estimate the percentage of your investment portfolio allocated to the following asset categories. If unsure, provide your best estimate.**

Items	0-25%	26-50%	51-75%	76-100%
Local Stocks:				
International Stocks:				
Bonds:				
Derivatives (options, futures, etc.):				
Cryptocurrencies:				
Other:				

5. **How often do you track the performance of your investments?**

- Daily
- Weekly
- Monthly
- Rarely

6. **How would you rate your knowledge of the following investment products? (Rate each product on a scale of 1 to 5, where 1 = No knowledge, and 5 = Expert knowledge).**

Investment Product	1	2	3	4	5
Stocks					
Bonds					
Exchange-Traded Funds (ETFs)					
Cryptocurrencies					
Options					

7. **Which sources of information do you primarily rely on when making investment decisions? (Select up to 2 options that you use most frequently).**

- Financial websites & journals
- Financial advisors
- Social networks
- Friends or family
- Other: _____

Source : Autorité des Marchés Financiers (2020). *Étude sur les investisseurs particuliers, leurs motivations et leurs pratiques d'investissement*.

Source : Quintet (2024). *Questionnaire Investisseurs et Pratiques*

SECTION 3: ANALYSIS OF BIASES

Section 3 is devoted to an in-depth analysis of specific behavioural biases using a Likert scale. Each bias (overconfidence, loss aversion, herding bias, and home bias) is assessed through targeted statements that measure the intensity with which respondents identify with these biases. These questions are essential for establishing quantitative links between biases and investment behaviour. For each statement below, please indicate how much you agree with the following on a scale from 1 to 5, where 1 means 'Strongly Disagree' and 5 means 'Strongly Agree'. Please try to avoid selecting 'Neutral' unless absolutely necessary.

	ITEMS	1	2	3	4	5
OVERCONFIDENCE	I think that I can beat the market thanks to my skills.					
	I believe that my investment decisions are better than those of the majority of investors.					
	I tend to underestimate the risks associated with my investments.					
	When I make an investment mistake, I am convinced I will do better next time.					
LOSS AVERSION	I avoid selling losing stocks in the hope that they will recover.					
	I prefer safe investments, even if that means smaller gains.					
	When I suffer a loss, I feel intense emotional pain.					
	I hesitate to invest in risky assets because of the fear of losing money.					
	I am more inclined to sell a winning stock to make a profit, even if it means missing out on future gains.					
HERDING BIAS	I am influenced by the investment decisions of my friends and family.					
	I am often inclined to follow market trends.					
	When I see other investors buying an asset, I'm more inclined to buy it too.					
	I often consult the recommendations of analysts or experts before making a decision.					
	I tend to change my investments to mimic those I see on social networks.					
HOME BIAS	I prefer to invest in French companies rather than foreign ones.					
	I feel more comfortable investing in products I know well, even if they are less profitable.					
	I tend to keep my investments in companies that I have followed for a long time.					
	I often choose assets that are linked to brands or products that I know.					
	I avoid investing in sectors that I don't understand well, even if they have potential.					

Sources :

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SECTION 4 : HYPOTHETICAL SCENARIOS

This last section uses scenarios to assess how investors react to market events, such as price falls or fluctuations due to external factors. These scenarios allow us to observe the decisions taken and identify behavioural biases, such as loss aversion or overconfidence. By understanding investors' choices in realistic contexts, we can better grasp the psychological dynamics that influence their financial decisions.

8. You have recently invested in LVMH shares, but following disappointing financial results, the stock drops by 15% in one day.

- I sell immediately to avoid further losses because I am sure the downward trend will continue.
- I wait a few days to see if the price rebounds.
- I buy more shares at a reduced price because I believe the drop is a long-term buying opportunity.

9. **An unexpected announcement regarding trade sanctions has led to significant volatility in the energy sector, causing the price of oil to drop. You hold shares in oil companies like TotalEnergies.**

- I sell all my shares in oil companies to limit losses.
- I analyze the long-term impacts and maintain my investment, convinced that oil prices will recover.
- I reallocate part of my portfolio towards renewable energies.
- I buy more shares.

10. **You have a significant amount to invest, and you are hesitant between buying shares of large stable companies or long-term bonds.**

- I invest everything in stocks, convinced that long-term returns will exceed those of bonds.
- I invest only in bonds, preferring safety and fixed income, even if the return is lower.
- I create a mixed portfolio, spreading my investment between stocks and bonds.

CHAPTER 4 : DATA COLLECTION AND ANALYSIS

4.a. Demographic Profile of the Sample

Demographics Factors	Categories	Participants	%
AGE	Less than 25 years	25	36,76%
	25 - 34 years	17	25,00%
	35 - 44 years	7	10,29%
	45 - 54 years	11	16,18%
	55 ans and more	8	11,76%
	TOTAL	**68**	**100,00%**
GENDER	Female	15	22,06%
	Male	53	77,94%
	TOTAL	**68**	**100,00%**
DEGREE	CAP	1	1,47%
	High School Diploma	4	5,88%
	BTS, DUT	3	4,41%
	Bachelor's Degree	8	11,76%
	Master's Degree	50	73,53%
	Doctorate	2	2,94%
	TOTAL	**68**	**100,00%**
PROFESIONAL STATUTE	Student	19	27,94%
	Worker	3	4,41%
	Employee	19	27,94%
	Entrepreneur	4	5,88%
	Manager	21	30,88%
	Retired	2	2,94%
	TOTAL	**68**	100,00%
INCOME	Less than 20 000 €	18	26,47%
	20 000 - 40 000 €	11	16,18%
	40 001 - 60 000 €	8	11,76%
	60 001 - 80 000 €	7	10,29%
	More than 80 000 €	24	35,29%
	TOTAL	**68**	**136,00%**

Table 1 : Demographics Profiles

4.b. Investor Behaviour Analysis

Investment Behavior	Categories	Participants	%
YEARS OF INVESTMENT	Less than a year	10	14,71%
	1-3 years	21	30,88%
	3-5 years	13	19,12%
	6-10 years	5	7,35%
	More than 10 years	19	27,94%
	TOTAL	**68**	**100,00%**
MOTIVATION TO INVEST	Grow my capital	45	66,18%
	Finance a project	4	5,88%
	Obtain additional income	7	10,29%
	Pleasure	1	1,47%
	Prepare for retirement	11	16,18%
	TOTAL	**68**	**100,00%**
FREQUENCY OF BUYING & SELLING	Daily	15	22,06%
	Weekly	21	30,88%
	Monthly	18	26,47%
	Less than once a month	14	20,59%
	TOTAL	**68**	**100,00%**
FREQUENCY OF LOOKING PERFORMANCE	Daily	20	29,41%
	Weekly	19	27,94%
	Monthly	17	25,00%
	Less than once a month	12	17,65%
	TOTAL	**68**	**100,00%**

Table 2 : Investors Behaviours

4.b.a. Portfolio Allocation Analysis

Investment Type	Categories	French Stocks	International Stocks	Bonds	ETF	Cryptocurrency	Derivatives
PORTFOLIO ALLOCATION	N/A	8	12	47	21	31	55
	0-25%	36	27	18	23	21	11
	26% - 50%	15	19	1	8	12	1
	51% - 75%	6	6	1	9	4	1
	76% - 100%	3	4	1	7	0	0
	TOTAL	68	68	68	68	68	68

Table 3 : Portfolio Allocation

4.b.b. Financial Knowledge Assessment

Investment Type	Categories (Linkert-Scale)	Stocks	Bonds	Derivatives	Cryptocurrency	ETF
FINANCIAL KNOWLEDGES	1	1	12	17	14	9
	2	5	7	19	19	4
	3	12	15	11	17	14
	4	22	18	9	14	22
	5	28	16	12	4	19
	TOTAL	**68**	**68**	**68**	**68**	**68**

Table 4 : Financial Knowledge

4.b.c. Information Sources Analysis

Investment Type	Categories	Participants	%
Informations Sources to make the choice to invest	Financial websites & Journals	61	89,7%
	Financial advisors	30	44,1%
	Social networks	17	25,0%
	Friends or family or colleagues	20	29,4%
	Bloomberg	1	1,5%
	Total	**68**	**100,0%**

Table 5 : Informations Sources

4.c. Statistic Bias Identification

4.c.a. Statistics Related to the Overconfidence Bias

Biases	Categories (Linkert-Scale)	Question 1	Question 2	Question 3	Question 4	%
OVERCONFIDENCE BIAS	1	15	11	14	4	16%
	2	14	21	19	11	24%
	3	4	9	7	15	13%
	4	26	22	20	24	34%
	5	9	5	8	14	13%
	Total	68	68	68	68	100%

Table 6 : Statistics Overconfidence Bias

4.c.b. Statistics Related to the Loss Aversion Bias

Biases	Categories (Linkert-Scale)	Question 1	Question 2	Question 3	Question 4	Question 5	%
LOSS AVERSION BIAS	1	4	11	6	13	10	13%
	2	11	13	9	19	21	21%
	3	5	11	13	9	6	13%
	4	30	25	33	23	25	40%
	5	18	8	7	4	6	13%
	Total	68	68	68	68	68	100%

Table 7 : Statistics Loss Aversion

4.c.c Statistics Related to the Herding Bias

Biases	Question 1	Question 2	Question 3	Question 4	Question 5	%
HERDING BIAS	17	6	15	6	50	28%
	22	16	13	19	14	25%
	8	11	13	3	0	10%
	19	27	23	25	4	29%
	2	8	4	15	0	9%
	68	68	68	68	68	100%

Table 8 : Statistics Herding Bias

4.c.d. Statistics Related to the Home Bias

Biases	Categories (Linkert-Scale)	Question 1	Question 2	Question 3	Question 4	Question 5	%
HOME BIAS	1	24	6	7	9	7	16%
	2	24	17	10	20	17	26%
	3	7	5	5	8	8	10%
	4	6	27	34	21	23	33%
	5	7	13	12	10	13	16%
	Total	68	68	68	68	68	100%

Table 9 : Statistics Home Bias

4.d. Validation of Bias Measurement Scales: Cronbach's Alpha & Composite Reliability

Formula for Cronbach's Alpha

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$$

Where :
N: Number of items
$\bar{c}$: Average covariance between items (off-diagonal).
$\bar{v}$: Average variance of the items.

Calculation Cronbach for Overconfidence Bias

$$N = 4$$

$$\bar{c} = \begin{bmatrix} 2.03 & 1.42 & 1.09 & 1.10 \\ 1.42 & 1.57 & 0.93 & 1.01 \\ 1.09 & 0.93 & 1.87 & 0.95 \\ 1.10 & 1.01 & 0.95 & 1.36 \end{bmatrix} = 1.0818$$

$$\bar{v} = \frac{2.03 + 1.57 + 1.87 + 1.36}{4} = 1.7075$$

$$\alpha = \frac{4 \cdot 1.0818}{1.7075 + (4-1) \cdot 1.0818} = \mathbf{0.873}$$

Formula for Composite Reliability (CR)

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \theta_i}$$

Where:
λi : Standardized factor loading for item i
θi : Error variance for item i

To ensure accuracy and streamline the calculations, metrics, including Cronbach's Alpha and Composite Reliability, were computed using Python.

Biases	Cronbach Alpha	Composite Reliability
Overconfidence bias	0.873	0.880
Loss aversion bias	0.759	0.774
Herding bias	0.650	0.658
Home bias	0.730	0.739

Table 10 : Cronbach Alpha & Composite Reliability

4.e. Validity tests (KMO and Bartlett's Test)

Formula for Kaiser-Meyer-Olkin (KMO) Test

$$KMO = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} u_{ij}^2}$$

Where :
rij : Correlation coefficient between variables i and j
uij : Partial correlation coefficient between variables i and j

Formula for Bartlett's Test of Sphericity

$$\chi^2 = -\left(n - 1 - \frac{2p + 5}{6}\right) \cdot \ln \det(R)$$

Where :
n : Sample size,
p : Number of variables,
R : Correlation matrix.

To ensure accuracy and streamline the calculations, metrics, including KMO test and Barlett's Test, were computed using Python.

Biases	KMO	Chi-square	p-value
Overconfidence bias	0.796	150.243	0.000
Loss aversion bias	0.726	96.359	0.000
Herding bias	0.534	84.563	0.000
Home bias	0.715	83.771	0.000

Table 11 : KMO, Chi Square & P-value

4.f. Correlation matrix (Pearson coefficient)

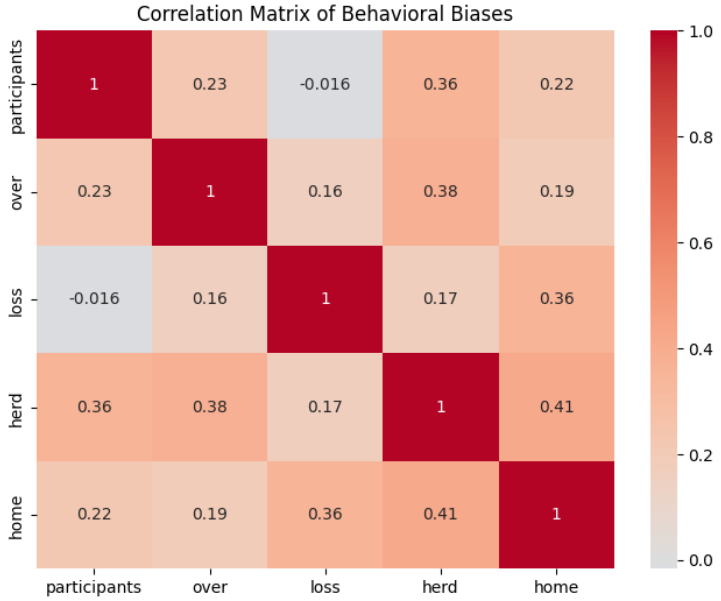


Table 12 : Correlation Matrix of Behavioural Biases

4.g. Multiple Linear regression

OLS Regression Results

Dep. Variable:	trading_frequency	R-squared:	0.227
Model:	OLS	Adj. R-squared:	0.178
Method:	Least Squares	F-statistic:	4.628
Date:	Wed, 20 Nov 2024	Prob (F-statistic):	0.00244
Time:	13:13:08	Log-Likelihood:	-91.001
No. Observations:	68	AIC:	192.0
Df Residuals:	63	BIC:	203.1
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.4808	0.592	4.191	0.000	1.298	3.664
overconfidence_bias	0.4577	0.114	4.002	0.000	0.229	0.686
loss_aversion_bias	-0.0701	0.143	-0.490	0.626	-0.356	0.216
herding_bias	-0.1563	0.180	-0.867	0.389	-0.516	0.204
home_bias	-0.2240	0.151	-1.481	0.144	-0.526	0.078

Omnibus:	3.304	Durbin-Watson:	1.634
Prob(Omnibus):	0.192	Jarque-Bera (JB):	1.779
Skew:	-0.038	Prob(JB):	0.411
Kurtosis:	2.211	Cond. No.	32.0

MODEL 1

OLS Regression Results

Dep. Variable:	trading_frequency	R-squared:	0.557
Model:	OLS	Adj. R-squared:	0.497
Method:	Least Squares	F-statistic:	9.282
Date:	Wed, 20 Nov 2024	Prob (F-statistic):	3.55e-08
Time:	13:13:29	Log-Likelihood:	-72.058
No. Observations:	68	AIC:	162.1
Df Residuals:	59	BIC:	182.1
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.6756	0.552	4.851	0.000	1.572	3.779
overconfidence_bias	0.4632	0.092	5.053	0.000	0.280	0.647
loss_aversion_bias	-0.0910	0.113	-0.805	0.424	-0.317	0.135
herding_bias	-0.2691	0.146	-1.837	0.071	-0.562	0.024
home_bias	-0.0494	0.124	-0.399	0.691	-0.297	0.198
age	-0.1652	0.126	-1.308	0.196	-0.418	0.087
years_experience	-0.0858	0.051	-1.683	0.098	-0.188	0.016
income level	-0.0033	0.071	-0.047	0.963	-0.145	0.139
Gender	0.5743	0.246	2.331	0.023	0.081	1.067

Omnibus:	0.049	Durbin-Watson:	1.680
Prob(Omnibus):	0.976	Jarque-Bera (JB):	0.093
Skew:	-0.055	Prob(JB):	0.955
Kurtosis:	2.857	Cond. No.	58.0

MODEL 2

OLS Regression Results

Dep. Variable:	trading_frequency	R-squared:	0.522
Model:	OLS	Adj. R-squared:	0.492
Method:	Least Squares	F-statistic:	17.23
Date:	Wed, 20 Nov 2024	Prob (F-statistic):	1.35e-09
Time:	15:05:53	Log-Likelihood:	-74.632
No. Observations:	68	AIC:	159.3
Df Residuals:	63	BIC:	170.4
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.7571	0.399	4.404	0.000	0.960	2.554
overconfidence_bias	0.6800	0.106	6.436	0.000	0.469	0.891
loss_aversion_bias	-0.2489	0.113	-2.210	0.031	-0.474	-0.024
overconfidence_age	-0.1149	0.021	-5.606	0.000	-0.156	-0.074
loss_aversion_gender	0.1526	0.068	2.237	0.029	0.016	0.289

Omnibus:	1.601	Durbin-Watson:	1.607
Prob(Omnibus):	0.449	Jarque-Bera (JB):	1.226
Skew:	0.086	Prob(JB):	0.542
Kurtosis:	2.365	Cond. No.	46.5

MODEL 3

4.g.a. Key Findings of models

	Model 1			Model 2			Model 3		
Variable	**Coefficient β**	**SE**	**p-value**	**Coefficient β**	**SE**	**p-value**	**Coefficient β**	**SE**	**p-value**
Constante	2.4808	0.592	0.000 ***	2.6756	0.552	0.000 ***	1.7571	0.339	0.000 ***
Overconfidence Bias	0.4577	0.114	0.000 ***	0.4632	0.092	0.000 ***	0.6800	0.106	0.000 ***
Loss Aversion Bias	-0.0701	0.143	0.626	-0.0910	0.113	0.424	-0.2489	0.113	0.031**
Herding Bias	-0.1563	0.180	0.389	-0.2691	0.146	0.071	N/A	N/A	N/A
Home Bias	-0.2240	0.151	0.144	-0.0494	0.124	0.691	N/A	N/A	N/A
Age	N/A	N/A	N/A	-0.1652	0.126	0.196	N/A	N/A	N/A
Years of Experience	N/A	N/A	N/A	-0.0858	0.051	0.098	N/A	N/A	N/A
Income Level	N/A	N/A	N/A	-0.0033	0.071	0.963	N/A	N/A	N/A
Gender	N/A	N/A	N/A	0.5743	0.246	0.023 **	N/A	N/A	N/A
Overconfidence × Age	N/A	N/A	N/A	N/A	N/A	N/A	-0.1149	0.021	0.000 ***
Loss Aversion × Gender	N/A	N/A	N/A	N/A	N/A	N/A	0.1526	0.068	0.029**

Table 13 : Results of Models

4.g.b. Robustness Diagnostics

Variable	VIF	Multicollinearity
Constante	38.45	N/A
Overconfidence Bias	1.26	No
Loss Aversion Bias	1.22	No
Herding Bias	1.63	No
Home Bias	1.47	No
Age	3.94	No
Years of Experience	4.10	No
Income Level	1.78	No
Gender	1.31	No
Overconfidence × Age	N/A	N/A
Herding × Gender	N/A	N/A
Loss Aversion × Gender	N/A	N/A

Table 15 : Test VIF

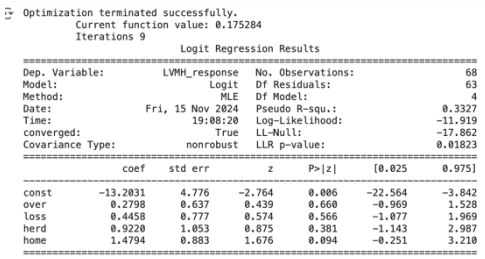
Robustness Diagnostics	Model 1	Model 2	Model 3
Observations	68	68	68
R^2	0.227	0.557	0.522
R^2 Ajusted	0.178	0.497	0.492
F-statistic	4.628	9.282	17.23

Table 16 : Results Robustness Diagnostics

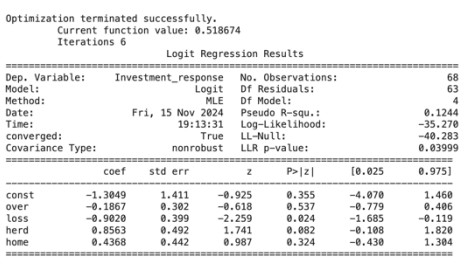
Test Heteroskedasticity (Breusch-Pagan)	Model 2
p-value	0.398
Heteroskedasticity	Tested - result ok

Table 14: Test Heteroskedasticity

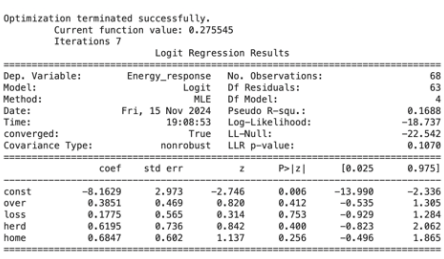
4.h. Logistic Analysis of Hypothetical Scenarios



```
Optimization terminated successfully.
         Current function value: 0.175284
         Iterations 9
                           Logit Regression Results
==============================================================================
Dep. Variable:          LVMH_response   No. Observations:                   68
Model:                          Logit   Df Residuals:                       63
Method:                           MLE   Df Model:                            4
Date:                Fri, 15 Nov 2024   Pseudo R-squ.:                 0.3327
Time:                        19:08:20   Log-Likelihood:                -11.919
converged:                       True   LL-Null:                       -17.862
Covariance Type:            nonrobust   LLR p-value:                  0.01823
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -13.2031      4.776     -2.764      0.006     -22.564      -3.842
over           0.2798      0.637      0.439      0.660      -0.969       1.528
loss           0.4458      0.777      0.574      0.566      -1.077       1.969
herd           0.9220      1.053      0.875      0.381      -1.143       2.987
home           1.4794      0.883      1.676      0.094      -0.251       3.210
==============================================================================
```



```
Optimization terminated successfully.
         Current function value: 0.518674
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:     Investment_response   No. Observations:                   68
Model:                          Logit   Df Residuals:                       63
Method:                           MLE   Df Model:                            4
Date:                Fri, 15 Nov 2024   Pseudo R-squ.:                 0.1244
Time:                        19:13:31   Log-Likelihood:                -35.270
converged:                       True   LL-Null:                       -40.283
Covariance Type:            nonrobust   LLR p-value:                  0.03999
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -1.3049      1.411     -0.925      0.355      -4.070       1.460
over         -0.1867      0.302     -0.618      0.537      -0.779       0.406
loss         -0.9020      0.399     -2.259      0.024      -1.685      -0.119
herd          0.8563      0.492      1.741      0.082      -0.108       1.820
home          0.4368      0.442      0.987      0.324      -0.430       1.304
==============================================================================
```



```
Optimization terminated successfully.
         Current function value: 0.275545
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:      Energy_response   No. Observations:                   68
Model:                          Logit   Df Residuals:                       63
Method:                           MLE   Df Model:                            4
Date:                Fri, 15 Nov 2024   Pseudo R-squ.:                 0.1688
Time:                        19:08:53   Log-Likelihood:                -18.737
converged:                       True   LL-Null:                       -22.542
Covariance Type:            nonrobust   LLR p-value:                   0.1070
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -8.1629      2.973     -2.746      0.006     -13.990      -2.336
over          0.3851      0.469      0.820      0.412      -0.535       1.305
loss          0.1775      0.565      0.314      0.753      -0.929       1.284
herd          0.6195      0.736      0.842      0.400      -0.823       2.062
home          0.6847      0.602      1.137      0.256      -0.496       1.865
==============================================================================
```

MODEL 1 MODEL 2 MODEL 3

	Model 1 : LVMH_response		Model 2 : Investment_response		Model 3 : Energy_response	
Variable	**Coefficient β**	**p-value**	**Coefficient β**	**p-value**	**Coefficient β**	**p-value**
Constante	-13.2031	0.006	-1.3049	0.355	-8.1629	0.006
Overconfidence Bias	0.2798	0.660	-0.1867	0.537	0.3851	0.412
Loss Aversion Bias	0.4458	0.574	-0.9020	0.024	0.1775	0.753
Herding Bias	0.9220	0.875	0.8563	0.082	0.6195	0.400
Home Bias	1.4794	0.094	0.4368	0.324	0.6847	0.256

Table 17 : Results Logistic Analysis

CHAPTER 5 : DISCUSSION AND INTERPRETATION OF THE RESULTS

H4: Home bias leads French individual investors to underestimate the benefits of international diversification, thereby increasing the likelihood of a high domestic allocation. - Supported

OLS Regression Results

Dep. Variable:	allocation_domestic	R-squared:	0.232
Model:	OLS	Adj. R-squared:	0.220
Method:	Least Squares	F-statistic:	19.93
Date:	Sun, 17 Nov 2024	Prob (F-statistic):	3.21e-05
Time:	11:33:35	Log-Likelihood:	-84.631
No. Observations:	68	AIC:	173.3
Df Residuals:	66	BIC:	177.7
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.1833	0.372	-0.493	0.624	-0.926	0.559
home	0.5180	0.116	4.465	0.000	0.286	0.750

Omnibus:	7.469	Durbin-Watson:	1.731
Prob(Omnibus):	0.024	Jarque-Bera (JB):	7.184
Skew:	0.790	Prob(JB):	0.0275
Kurtosis:	3.196	Cond. No.	12.6

MODEL 1

OLS Regression Results

Dep. Variable:	allocation_domestic	R-squared:	0.269
Model:	OLS	Adj. R-squared:	0.247
Method:	Least Squares	F-statistic:	11.98
Date:	Thu, 21 Nov 2024	Prob (F-statistic):	3.72e-05
Time:	09:15:47	Log-Likelihood:	-82.933
No. Observations:	68	AIC:	171.9
Df Residuals:	65	BIC:	178.5
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.4032	0.385	-1.048	0.299	-1.172	0.366
home	0.4857	0.115	4.209	0.000	0.255	0.716
age	0.1324	0.073	1.824	0.073	-0.013	0.277

Omnibus:	6.766	Durbin-Watson:	1.860
Prob(Omnibus):	0.034	Jarque-Bera (JB):	6.502
Skew:	0.756	Prob(JB):	0.0387
Kurtosis:	3.104	Cond. No.	16.5

MODEL 2

	Model 1			Model 2		
Variable	**Coefficient β**	**SE**	**p-value**	**Coefficient β**	**SE**	**p-value**
Constante	-0.1833	0.372	0.624	-0.4032	0.385	0.299
Home Bias	0.5180	0.116	0.000	0.4857	0.115	0.000
Age	N/A	N/A	N/A	0.1324	0.073	0.073

Table 18 : Resultats Multiple Regression H4