Research-Thesis: Are finance professionals immune to gender stereotypes when it comes to investing?

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Diplôme : Master en sciences de gestion, à finalité spécialisée en Banking and Asset Management
Année académique : 2025-2026
URI/URL : http://hdl.handle.net/2268.2/25181

ARE FINANCE PROFESSIONALS IMMUNE TO GENDER STEREOTYPES WHEN IT COMES TO INVESTING?

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Master thesis presented by
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To obtain the degree of
MASTER IN MANAGEMENT
with a specialization in
Banking and Asset Management

Academic year 2025/2026

Ecole de Gestion de l'Université de Liège

ACKNOWLEDGMENTS

I would first like to express my sincere gratitude to Mr. Hübner, my thesis supervisor, for his guidance from the very early stages of this research. His advice was instrumental in refining the research topic and in defining a clear direction for this thesis. I am also grateful for his availability and for the valuable feedback he provided whenever needed.

I would also like to thank HEC Liège and the entire faculty. Over the course of these three years, I have developed solid theoretical and practical skills, which I was able to mobilise in the context of this thesis and beyond my academic journey.

I am equally grateful to Ms. Mertens de Wilmars, my reader, for the time she devoted to reviewing this work, as well as for her critical perspective and valuable comments.

I would like to extend my sincere thanks to all the individuals who participated in my survey. Their availability, expertise, and the quality of their responses made the empirical dimension of this research possible. In particular, I am grateful to the professionals met during events I attended, to former colleagues from BGL, where I completed an internship, and to the individuals encountered throughout my academic path. Each of them contributed, in their own way, to enriching my reflection.

I wish to express special gratitude to my uncle, Thierry Badot, and my aunt, Virginie Determermann, for their kind support, insightful advice, and careful reviews throughout the writing process. Their constant support was invaluable, both from a methodological and a personal perspective. I would also like to thank Eric Bernagou for his insightful advice and for taking the time to review this thesis.

Finally, I would like to warmly thank my family and close friends for their unwavering support, patience, and encouragement. Their presence and confidence in me were a true source of motivation in the completion of this thesis and throughout my academic journey.

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1 GLOSSARY AND ABBREVIATIONS

1.1 ABBREVIATIONS

BH	Benjamini-Hochberg procedure
CAPM	Capital Asset Pricing Model
CFA	Chartered Financial Analyst
CI	Confidence Interval
CSSF	Commission de Surveillance du Secteur Financier (Luxembourg financial supervisory authority)
EUT	Expected Utility Theory
EM	Emerging Markets
EMH	Efficient Market Hypothesis
ESG	Environmental, Social, and Governance
ETF	Exchange-Traded Fund
FDR	False Discovery Rate
GDPR	General Data Protection Regulation
GICS	Global Industry Classification Standard
IAT	Implicit Association Test
IQ	Intelligence Quotient
IQR	Interquartile Range
LOGIT	Logistic regression model
MANOVA	Multivariate Analysis of Variance
MiFID II	Markets in Financial Instruments Directive II
MPT	Modern Portfolio Theory
OLS	Ordinary Least Squares
PaRA	Payoff Risk Aversion
PrRA	Price Risk Aversion
SMB	Small Minus Big
HML	High Minus Low
UBS	Union Bank of Switzerland
US	United States

1.2 GLOSSARY OF KEY CONCEPTS

Ambiguity Aversion: Preference for known risks over situations with unknown probabilities.

Behavioural Finance: Study of psychological, cognitive, and social factors into the analysis of financial decision-making.

Big Five: In psychology, the “Big Five” is a model that describes five broad dimensions of personality (openness, conscientiousness, extraversion, agreeableness, neuroticism).

Diversification: Risk management strategy involving the allocation of investments across various assets to reduce idiosyncratic risk.

Efficient Frontier: Set of optimal portfolios offering the highest expected return for a given level of risk.

Factor Investing: Investment approach targeting specific characteristics of securities, called factors (eg. value, size, momentum, or quality).

Grit: In psychology, grit is a personality trait characterised by perseverance and passion for achieving long-term goals.

Herding Behaviour: Tendency of investors to mimic the actions of others rather than rely on independent analysis.

Implicit Association Test (IAT): A test that measures unconscious biases by observing how quickly people associate different concepts.

Investment Horizon: The length of time an investor expects to hold a financial product.

Loss Aversion: Behavioural bias whereby losses are perceived as more painful than equivalent gains.

Overconfidence: Cognitive bias involving an exaggerated belief in one’s own knowledge or predictive abilities.

Risk Aversion: Preference for certainty over risky alternatives with the same expected value.

Strategic Asset Allocation: Long-term portfolio strategy based on the needs and preferences of an individual's goals.

Sustainable Finance: Financial practices that integrate environmental, social, and governance considerations into investment decisions.

Trading Frequency: The number of transactions executed by an individual over a given period, reflecting how often the individual buys or sells financial assets.

2 INTRODUCTION

For decades, financial decision-making was modelled under the assumption of rational agents making investment choices through rational optimisation. However, behavioural finance research highlights the role of cognitive, emotional, and contextual factors that are imperfectly reflected in conventional models. Within this broader behavioural framework, gender has gradually been recognised as a relevant dimension for understanding heterogeneity in investment behaviour.

A large body of literature highlights the existence of difference between investment behaviours of men and women. Men are generally characterised as more risk-tolerant, more prone to overconfidence and more inclined to engage in frequent trading, whereas women are, on average, more cautious, more averse to uncertainty and less confident in their investment decisions. These empirical findings have gradually contributed to the formation of stereotypical representations of male and female investors.

Nevertheless, these findings raise a question that has not been explicitly explored: do these differences still exist when investment decisions are made in a professional context? In other words, do the gendered behaviours patterns observed among individual investors persists among professionals, who are trained in financial decision-making, have technical expertise and market experience and work within highly regulated institutional structures in which decision-making processes, risk management frameworks and performance constraints play a central role?

This thesis seeks to address this question by shifting the focus from individual investors with heterogeneous profiles to finance professionals, and more specifically to investment professionals, who, beyond their technical expertise, directly or indirectly influence their client's financial decisions. The objective is not only to highlight potential differences between men and women, but also to examine whether, where and to what extent gender stereotypes continue to manifest in investment decisions and preferences.

This thesis follows a progressive line of reasoning. It opens with a theoretical framework, outlining the foundations of classical finance before discussing the main contributions of behavioural finance. It then reviews the literature on gender differences in finance, which provides the basis for the formulation of the research hypotheses tested empirically. The second part outlines the methodology used, based on a survey of investment professionals, and details the choices made regarding questionnaire design and the analytical tools employed. The third part is devoted to the analysis of results, with the composition of the sample, strategic asset allocation, factor preferences and several key behavioural dimensions, including risk tolerance, overconfidence, diversification, investment horizon and interest in ESG (Environmental, Social, and Governance) criteria. Finally, the empirical analysis is complemented by multivariate regression models designed to assess the robustness of the observed patterns while jointly controlling for demographic and professional characteristics.

Finally, the results are discussed in light of the existing literature to assess whether the observed differences reflect genuinely gendered behaviours or are better explained by variations in professional background, experience, and expertise. By questioning the extent to which gender stereotypes persist within a supposedly rational and standardised environment, this thesis offers a nuanced examination of the role of gender in professional financial decision-making.

3 LITERATURE REVIEW

3.1 "CLASSICAL" THEORETICAL FRAMEWORKS

3.1.1 Core assumptions and models

Traditional finance is grounded in the assumption of rational agents, maximising a stable utility function under constraints, operating in competitive markets where prices efficiently aggregate information. This vision is built upon three core pillars: Expected Utility Theory (EUT) (Von Neumann & Morgenstern, 1944), Modern Portfolio Theory (MPT) (Markowitz, 1952) and its extensions, and the efficient market hypothesis (EMH) (Fama, 1970). Together, these frameworks offer a micro-foundation for decision-making under risk, a normative rule for portfolio construction, and a theoretical characterisation of equilibrium asset prices.

At the individual level, the foundations of expected utility theory (EUT) date back to Daniel Bernoulli's resolution of the St. Petersburg paradox Daniel Bernoulli (1954[1938]), which introduced the concepts of diminishing marginal utility and risk aversion. This intuition was then formalised by von Neumann and Morgenstern (1944), who modelled individual choice under uncertainty as the maximisation of expected utility. In this framework, risk-averse investors may prefer certainty to risky prospects offering a higher expected monetary value.

Extending this logic from individual choice to portfolio construction, Markowitz (1952) developed the mean-variance framework underlying Modern Portfolio Theory (MPT). In this approach, investment decisions are modelled as a trade-off between expected return and risk, measured by the variance or standard deviation of portfolio returns. A key contribution of this framework lies in the recognition that diversification benefits arise from imperfect correlations between asset returns, allowing investors to reduce portfolio risk without necessarily lowering expected returns. Rational investors are thus assumed to select portfolios located on the efficient frontier, which offers the highest attainable expected return for a given level of risk.

On this basis, these insights constitute the foundation of the Capital Asset Pricing Model, independently developed by Sharpe (1964), Lintner (1965), and Mossin (1966), which posits a linear relationship between expected returns and systematic market risk. Extensions of the CAPM, notably the multifactor models proposed by Fama and French (1993, 1996), introduce additional sources of systematic risk, such as firm size and value characteristics, while preserving the equilibrium logic of classical finance.

Finaly, Efficient Market Hypothesis (EMH), formalised by Fama (1970), constitutes a natural complement to Modern Portfolio Theory and the CAPM. If investors are rational and asset prices correctly aggregate available information, then the financial market should fully reflect this information at all times. Under this assumption, prices instantaneously adjust to new information, leaving no systematic opportunities for abnormal risk-adjusted returns. The EMH distinguishes three forms of efficiency depending on the information set reflected in prices: the weak form, based on historical market data; the semi-strong form, which incorporates all publicly available information; and the strong form, which assumes that even private information is fully reflected in prices.

3.1.2 Scope and limitations of “classical” models

Modern portfolio theory, the CAPM and the efficient market hypothesis provide a consistent and homogeneous framework for analysing financial markets. However, a growing body of research has highlighted significant limitations in their ability to accurately describe the actual dynamics of markets.

As Shiller (2003) points out, market efficiency should not be understood as implying that prices are always correct or that there can be no major misinterpretations of economic events. In particular, market efficiency theory can lead to misleading interpretations of phenomena such as speculative bubbles, excessive volatility, and major stock market booms and crashes, which seem difficult to reconcile with fully rational pricing.

The development of behavioural finance has emerged precisely in response to these shortcomings. As noted by Barberis (2018), the field has grown out of the discovery of empirical anomalies that challenge the traditional paradigm, alongside the incorporation of insights from psychology into economic modelling. Rather than claiming that markets are systematically exploitable or that inefficiencies generate easy profits, behavioural finance recognises that deviations from efficiency may arise in subtle and time-varying ways, consistent with observed patterns of underreaction, overreaction, and instability in asset prices (Shiller, 2003).

A central contribution of behavioural finance is its reassessment of the role of arbitrage and investor behaviour. Shleifer (2000) shows that even in the absence of extreme assumptions about investor irrationality, arbitrage is subject to important limits, implying that mispricing can persist rather than being immediately corrected. This perspective challenges the presumption that financial markets necessarily function as efficient mechanisms that always reflect fundamental information. Finally, as emphasised by Statman (2020), the behavioural approach does not merely focus on cognitive errors, but instead broadens the analysis to account for investors’ normal wants, including utilitarian, expressive and emotional motives, which play a central role in shaping saving, portfolio choice, asset pricing and market efficiency.

3.2 FROM TRADITIONAL FINANCE TO BEHAVIOURAL FINANCE

3.2.1 Origins and context

The 1970s marked a major turning point in financial thought. Although models grounded in rationality and market efficiency still dominated theoretical finance, an increasing body of empirical and experimental evidence began to challenge their assumptions. Research in cognitive psychology demonstrated that individuals do not evaluate probabilities and gains in an objective manner (Barberis et al. 1998), but instead rely on heuristics, i.e. mental shortcuts that can bias judgment and decision-making (Tversky & Kahneman, 1974).

At the same time, financial markets exhibited phenomena that are difficult to explain using traditional models: speculative bubbles, sudden crashes, persistent anomalies (e.g. the January effect, momentum, underreaction to earnings announcements) (De Long et al., 1990; Ramiah, Xu & Moosa, 2015). These observations have led to the emergence of a new paradigm: behavioural finance, a discipline at the crossroads of psychology, experimental economics and empirical finance, which aims to understand how cognitive, emotional and social biases influence financial decisions.

3.2.2 Prospect Theory

There is no single unified theory in behavioural finance; however, among the theories that challenge the strictly rational model outlined above, Prospect Theory, proposed by Kahneman and Tversky (1979), constitutes one of its cornerstones. This theory provides an alternative to Expected Utility Theory by aiming to explain how individuals really make decisions under conditions of risk, rather than assuming perfect rationality. In contrast with classical models, in which choices are based on the maximisation of expected utility, Prospect Theory proposes that individuals evaluate outcomes relative to a reference point, often their status quo or expectations.

Kahneman and Tversky demonstrate that the psychological value attributed to gains and losses is not symmetric. In particular, losses exert a stronger emotional impact than equivalent gains, a phenomenon known as loss aversion. This asymmetry leads individuals to avoid situations involving potential losses, even when the expected outcome is favourable.

The theory also emphasises that individuals tend to overestimate unlikely events and underestimate highly probable events. This bias explains certain paradoxical behaviours, such as the attraction of games of chance despite negative expected returns or, conversely, underinsurance against highly probable risks.

Overall, prospect theory has profoundly transformed the understanding of economic and financial behaviour. It demonstrates that decision-making is not solely guided by calculative rationality, but is also influenced by psychological factors, emotions and subjective perceptions of risk and value. These contributions have paved the way for extensive research in behavioural economics and finance, providing valuable insights into many deviations from neoclassical models, particularly in the areas of portfolio management and investment decision-making.

3.2.3 Cognitive and emotional biases

In this thesis, the analysis of cognitive and emotional biases is deliberately limited to the mechanisms explicitly discussed in the literature on gender differences in financial behaviour, as summarised in section 3.3. The aim is not to provide an exhaustive review of behavioural finance, but to identify biases that appear in studies comparing the investment decisions of men and women.

3.2.3.1 Overconfidence bias

Overconfidence bias is defined as the tendency of individuals to overestimate the accuracy of their knowledge and the soundness of their judgements (Corbellini, 2021; Lichtenstein, Slovic & Fischhoff, 1977). When decisions have to be made, overconfidence leads actors to place excessive confidence in their intuitions, estimates and ability to anticipate future events. In finance, this bias translates into an overestimation of forecasting skills and an underestimation of uncertainty. Individuals believe they can predict market movements more accurately than they actually can (Barber & Odean, 2001). This illusion of control manifests itself in particular through excessive trading activity, portfolio concentration and low diversification.

3.2.3.2 Anchoring bias

Anchoring bias occurs when individuals rely disproportionately on an initial piece of information they receive (the "anchor") when forming a judgement, and subsequently adjust their estimate from that point, even when that first piece of information is arbitrary or irrelevant (Epley & Gilovich, 2006). In financial decision-making, anchors often take the form of past prices, purchase prices, historical returns or previously stated forecasts (Andini & Asiri, 2016; Tversky & Kahneman, 1974). As a result, investors may exhibit inertia in their decisions, maintaining positions despite changes in market conditions or new information. This phenomenon is not limited to retail investors: Bouteska and Regaieg (2020) and Cen, Hilary and Wei (2013) demonstrate that financial analysts remain strongly anchored to past performance, slowing the collective incorporation of new information.

3.2.3.3 Framing effect

The framing effect refers to the tendency of individuals to respond differently to equivalent decision problems depending on how they are presented (Diacon & Hasseldine (2007); Tversky & Kahneman, 1981). Rather than evaluating choices solely on their objective outcomes, individuals are influenced by whether options are framed in terms of gains or losses, security or performance, opportunity or risk. In finance, framing effects arise in the presentation of investment products, risk disclosures, performance reports and advisory communication.

3.2.3.4 Herding behaviour (mimicry bias)

Herding behaviour refers to the tendency of individuals to imitate the actions of others rather than relying on their own information or analysis (Banerjee, 1992; Devenow & Welch, 1996). While such imitation may be rational in situations characterised by uncertainty or information asymmetry, it becomes biased when collective behaviour substitutes for independent judgement. In financial markets, herding manifests itself through synchronised buying or selling, excessive reliance on market sentiment and heightened sensitivity to social or informational signals.

3.2.3.5 Ambiguity aversion bias

Ambiguity aversion, first described by Ellsberg (1961), refers to a preference for situations in which probabilities are known rather than uncertain. Individuals tend to avoid decisions involving ill-defined or imprecise parameters, even when these choices may be rationally advantageous. In the financial context, this bias leads to a preference for familiar assets and domestic markets, a phenomenon commonly referred to as "home bias" (French & Poterba, 1991).

3.2.4 Toward an integrated approach: psychology, social context and gender

Beyond individual traits, other factors may contribute to explaining differences between men and women in financial behaviour. In contexts characterised by formal rules, hierarchical structures and performance constraints, behaviour is not solely the product of individual psychology, but also reflects social roles, identity dynamics and organisational norms. These perspectives provide a relevant analytical framework for examining how gendered behaviours may emerge, evolve or be attenuated within professional financial environments.

3.2.4.1 Social and gender theories

The behavioural differences observed between women and men in various areas, particularly financial and professional, cannot be explained solely by biological factors. According to Eagly's social role theory (1987), these differences are primarily the result of social structure, which assigns distinct roles to each gender and expects specific behaviours from them. Individuals, evolving in these differentiated contexts, develop skills and attitudes in line with these social expectations. In addition, the gender socialisation theory proposed by Bussey and Bandura (1999) emphasises that individuals learn from an early age to internalise gender roles through processes of observation, imitation and social reinforcement. As a result, gender norms are continuously reproduced and become deeply embedded in individual practices and expectations.

In the same vein, Tajfel and Turner's (1979) social identity theory highlights individuals’ tendency to adjust their behaviour in order to maintain a self-concept that is consistent with their group membership. Gender, as a salient social category, is therefore a central identity marker: women and men are inclined to behave in ways that conform to the expectations associated with their respective groups, particularly in contexts where gender stereotypes are salient.

These dynamics of socialisation and identity provide an initial key to understanding the differences in behaviour between men and women. However, their concrete translation into the professional sphere depends heavily on the institutional and organisational framework, which are examined in the following section.

3.2.4.2 Institutional and organisational factors

Professional standards and organisational cultures play a decisive role in constructing and reproducing gender differences in behaviour, particularly in terms of decision-making, leadership and risk management. According to DiMaggio and Powell's institutional theory (1983), organisations tend to become similar due to coercive, mimetic and normative pressures that homogenise their structures and practices. By extension, these institutional dynamics also influence the behaviours expected of individuals within these organisations, imposing implicit and explicit standards of performance, conformity and competition.

The concept of the ‘glass ceiling’ proposed by Morrison et al. (1987) further illustrates the existence of invisible yet powerful barriers that limit women’s access to senior decision-making positions. This phenomenon, fuelled by structural and cultural biases, perpetuates the under-representation of women in positions of power, which can indirectly influence their relationship to risk, performance and decision-making.

Finally, the role congruence theory developed by Eagly and Karau (2002) highlights the tension between gender stereotypes and expectations related to leadership roles. Women who display behaviours traditionally coded as masculine, such as assertiveness, ambition or risk-taking, are often perceived as less likeable or less legitimate, creating a “double bind” between conformity to gender norms and professional effectiveness. This perceived incongruity between gender and leadership roles contributes to the persistence of organisational inequalities and reinforces existing norms within professional environments.

3.2.5 Summary: towards a broader view of rationality

The following table summarises the main conceptual differences between classical finance and behavioural finance, highlighting the shift from a purely rational framework to an approach that incorporates cognitive, emotional and social dimensions of decision-making.

Table 1: Comparison between Classical Finance and Behavioural Finance

Dimensions	Classical Finance	Behavioural Finance
Assumptions	Perfect rationality, complete information	Bounded rationality, cognitive and emotional biases
Decision-Making	Expected utility maximisation	Relative evaluation, loss aversion, heuristics
Market	Price efficiency, perfect arbitrage	Influenced by emotions, limits to arbitrage
Social factors	Exogenous/absent	Endogenous: social roles, norms, identity
Risk perception	Measurable, objective	Perceived, psychological, contextual

Source: author's own elaboration based on the theoretical framework developed in Sections 3.1 and 3.2

Behavioural finance does not replace classical finance; rather, it complements it. By incorporating human, social and institutional factors into financial analysis, it provides a more nuanced understanding of real-world economic decision-making. As such, it serves as a bridge between economics and psychology, and more recently between economics and the sociology of gender, paving the way for a multidisciplinary approach to financial rationality.

This synthesis provides the conceptual foundation for the literature reviewed in the next section, where gender differences in financial behaviour are examined in light of the behavioural, social and institutional mechanisms outlined above.

3.3 Gender stereotypes in economics and behavioural finance

3.3.1 Stylised results from experimental literature and limitations

This section begins with a set of widely cited experimental studies that provide the foundational stylised facts structuring the debate on gender differences in risk-taking. These contributions synthesise a large number of experimental results and establish benchmark findings that subsequent work either refines, qualifies, or challenges. Starting from these sources allows us to identify both the dominant empirical patterns and their methodological limitations before turning to more context-specific analyses.

The literature on gender differences in risk-taking converges toward a general but nuanced conclusion: on average, women choose safer options than men, but the extent of this difference depends largely on experimental design, framing, and contextual factors.

Eckel and Grossman (2008) conduct a series of laboratory experiments to study gender differences in risk attitudes and show that women are, on average, more risk averse than men across a range of experimental settings. Although the broader literature highlights some sensitivity of results to experimental design and measurement, their findings suggest that gender differences in risk aversion are relatively robust within their framework.

Adopting a broader perspective, Croson and Gneezy (2009) revisit a body of empirical studies (conducted primarily with student samples) and examine whether women are, on average, more risk-averse than men, as well as the mechanisms underlying this difference. In particular, they emphasise affective responses to risk: men and women differ in their emotional reactions to situations of uncertainty, and these emotions play a key role in shaping decision-making. Men also tend to exhibit greater confidence, leading to different perceptions of risk. However, the authors stress that these differences are context-dependent and tend to be mitigated by experience and professional background.

Moving beyond standard measures of risk aversion, Borghans et al. (2009) distinguish between decision-making under risk (known probabilities) and decision-making under ambiguity (unknown probabilities) using an Ellsberg-type lottery protocol, in which ambiguity is increased gradually. Their results show, on the one hand, that women are on average more risk-averse than men. On the other hand, when faced with a low level of ambiguity, women do not demand an additional premium, whereas men already reduce their valuation of the bet (they are more “ambiguity-averse” from the outset). When ambiguity becomes high, both sexes react in the same way to an additional increase in ambiguity (similar marginal aversion). Finally, while psychological traits (IQ, Big Five, grit, etc.) explain some of the variations in risk aversion between individuals, they do not explain the differences in ambiguity aversion, suggesting that risk and ambiguity reflect distinct preference dimensions.

Using a single investment task, Charness and Gneezy (2012), provide a more focused summary: they group together 15 datasets using the same investment game (participants receive an endowment and choose how much to invest in a risky asset). The samples are diverse (students, professionals, rural populations; in the lab and online) and the variants numerous (framing, feedback, ambiguity, illusion of control). This homogeneity of method allows for a clear comparison: in almost all cases, women invest less than men and appear to be more financially risk-averse than men. The evidence is therefore strong, but within this specific paradigm.

Despite the apparent robustness of these results within specific experimental paradigms, Nelson (2016) critically reviews a broad body of experimental evidence, including the findings synthesised by Charness and Gneezy (2012), and shows that gender differences in risk aversion, when they appear, are typically modest differences in means at the aggregate level. Given the high intra-gender variability and significant overlap in distributions, these differences do not allow for valid inferences at the individual level. In several studies, the difference is not statistically significant, or even reversed. Finally, Nelson points out that framing effects and stereotypes activated by experimental designs may contribute to these results. She therefore recommends paying greater attention to variability and overlap between genders in order to avoid hasty generalisations and potentially discriminatory uses of the results.

Overall, this first set of studies highlights an average gap in favour of greater caution among women, but this gap appears to be highly dependent on the framing, protocols and context of analysis. In line with Nelson (2016), it is important to emphasise that these differences are often modest, unstable and largely overlapping, which limits the scope of conclusions at the individual level. The challenge is therefore not to categorise women as more cautious overall, but to identify the circumstances that bring these differences to light or, conversely, render them invisible. This critical reading avoids any essentialisation of behaviour and paves the way for the examination of studies focusing on more specific contexts.

3.3.2 Individual investors: European evidence

This section focuses on European evidence in order to examine gender differences in financial behaviour in contexts characterised by relatively homogeneous access to financial markets and institutional frameworks.

A first strand of the literature focuses on gender differences in market participation. An initial set of studies highlights that women participate less frequently in financial markets. This phenomenon does not reflect a lack of interest in investment, but rather stems from differences in life trajectories and social constraints. Family responsibilities, career interruptions, and lower wealth accumulation limit women's exposure to risky assets and opportunities for financial learning. Ohlund (2017) shows that female participation follows an arc-shaped life-cycle pattern: increasing until the age of 30, declining during the years associated with family responsibilities, and rising again with greater economic stability later in life. Similar results are reported by Halko et al. (2012), who observe a U-shaped relationship between age and risk tolerance, suggesting that financial behaviour evolves over the life cycle and is strongly conditioned by socio-economic circumstances rather than fixed preferences.

Beyond participation, studies also examine gender differences in the composition of financial portfolios. Women's preference for safer and capital-preserving financial instruments (savings products, life insurance, pension funds, etc.) is a recurring finding in the literature (Halko et al., 2012; Mikelionytė & Lezgovko, 2021; Powell & Ansic, 1997). This caution is mainly due to a fear of losing money in an economic situation that is considered more precarious, rather than a general aversion to risk. Even after controlling for wealth, financial knowledge and family situation, women remain less inclined to hold risky assets (Halko et al., 2012; Marinelli et al., 2017). Marinelli et al. (2017) point out that men are characterised by greater risk tolerance and a more optimistic attitude, contributing to increased exposure to risky assets.

The literature also highlights the central role of financial literacy and perceived confidence as joint determinants of financial participation. Bannier and Schwarz (2018) show that actual financial knowledge increases wealth for both genders, but that highly educated women benefit disproportionately. Conversely, self-confidence has a stronger effect on men, encouraging greater risk exposure. Almenberg and Dreber (2015) show, based on a representative sample of the Swedish population, that women have on average a lower level of financial literacy than men and that this gap explains a significant part of women's lower participation in the stock market. However, even after controlling for literacy, a risk-taking gap remains, suggesting that other factors also contribute to the gender gap. Mikelionytė and Lezgovko (2021) shed further light on this issue by showing that women, on average, lack knowledge and understanding of financial products, which contributes to limiting their exposure to risky assets. This perceived cognitive deficit fuels under-confidence and reinforces cautious decision-making, even at comparable levels of education.

These mechanisms are further corroborated by the Swiss study by Bucher-Koenen et al. (2021), conducted among investors and individuals with an explicit background in finance or experience with financial products. The authors introduce an innovative method for assessing risk tolerance using the Implicit Association Test (IAT), which they compare to risk tolerance questionnaires and the analysis of actual portfolios. The results show no significant difference between men and women, either consciously or implicitly, in their attitudes towards risk. It is experience and financial literacy, not gender, that explain the variations observed. This result suggests that technical competence tends to neutralise gender behavioural differences, but does not erase imbalances in access and recognition. This dynamic is reinforced by the work of Marconi et al. (2025), which shows that behavioural differences are largely mitigated when differences in income, education and confidence are taken into account. The effect of gender thus largely disappears once these variables are controlled for.

In addition to these individual-level mechanisms, there is a more structural channel operating through the financial advisory relationship. The study by Brooks et al. (2019), based on more than 500,000 interactions between advisers and clients in the United Kingdom, shows that investment experience is the most important factor explaining differences in risk tolerance, outweighing the explanatory power of age, employment status, or marital status. On average, however, women exhibit lower levels of investment experience. The authors also observe that advisers make greater adjustments to female clients' portfolios, particularly when they are investing as a couple, which tends to shift the final choices away from their initial preferences. This finding highlights that financial literacy and confidence are not solely determined at the individual level: they also interact with the social and professional dynamics of the advisory relationship, indirectly contributing to maintaining the gender gap.

Gender gaps in financial behaviour can also be explained by differences in self-confidence. The study by Cupák et al. (2021) shows that differences in investment behaviour are explained more by levels of self-confidence than by financial literacy. Women's lower participation in financial markets can be explained by the fact that they perceive themselves as less capable of managing financial investments. Marinelli et al. (2017) show that men exhibit marked overconfidence, correlated with higher optimism and a biased perception of their own financial abilities. This overconfidence leads to greater risk tolerance and more active behaviour in the markets. This conclusion is consistent with the analyses of Wu and Westerholm (2021), who attribute part of the observed performance differences not to competence but to male overconfidence and investment frequency. This result contradicts the idea, often put forward in the literature, that overconfidence systematically leads to underperformance.

Gender differences also emerge in investment horizons. Men tend to exhibit longer investment horizons, reflecting their greater tolerance for volatility and confidence in future asset returns (Marinelli et al., 2017). Conversely, women favour more liquid and secure investments, often due to more discontinuous career paths or the need to maintain a financial safety net (Halko et al., 2012; Ohlund, 2017). These differences in investment time horizons reflect adaptive strategies: women's caution is a response to income constraints and perceived stability.

Relatedly, the literature documents differences in trading frequency and speculative behaviour. Men tend to trade more frequently and engage in more speculative behaviour (Marinelli et al., 2017; Mikelionytė and Lezgovko, 2021). They often favour individual stocks and bonds, while women tend to opt for collective products and more stable savings solutions. Mikelionytė and Lezgovko (2021) confirm that men invest more often and engage in more active market behaviour, even when wealth and income are comparable.

Finally, portfolio diversification provides an important perspective on gender differences in outcomes. Marinelli et al. (2017) further show that while men and women may rely on different investment processes and decision-making strategies, the authors find that their portfolios do not significantly differ in terms of overall diversification outcomes. This suggests that heterogeneous behavioural pathways can lead to comparable financial results. Consistent with this finding, Wu and Westerholm (2021) show that women initially diversify less than men, but that this gap narrows with experience and skill accumulation. As women gain financial knowledge and market exposure, their investment behaviour progressively converges toward that of men. This learning process highlights the dynamic nature of the gender gap: differences in investment behaviour are not fixed, but evolve as women accumulate informational capital and develop a stronger perception of their own financial legitimacy.

In reviewing this literature, we note above all that women are not “less rational” or less capable of managing investments: they simply operate in an environment where caution is often the most reasonable strategy. Gender differences in investment seem to stem from a combination of economic constraints, social norms, differences in confidence, in financial knowledge and institutional practices, rather than an innate preference for security. Recent studies converge on the idea that gender largely loses its explanatory power once income, experience and confidence are controlled for, showing that the problem is less individual than structural. To reduce these inequalities in the long term, Bannier and Schwarz (2018), Cupák et al. (2021) and Marconi et al. (2025) emphasise that improving technical literacy is not enough: we must also work on confidence, self-representation and the gendered norms that still frame risk-taking.

3.3.3 Individual investors: International evidence

As the empirical analysis of this study focuses on Belgian and Luxembourg respondents, the literature review first examines evidence from European countries, where financial institutions, market access and regulatory frameworks are relatively comparable. However, restricting the analysis to the European context alone would limit the ability to assess whether the observed gender differences reflect context-specific mechanisms or more general patterns. For this reason, a complementary body of international research is also reviewed. Studies conducted outside Europe make it possible to examine whether similar gender-related patterns in financial behaviour emerge across heterogeneous economic, institutional and cultural environments.

In Canada, Robson and Peetz (2020) analyse financial literacy and financial capability using data that combine socio-economic characteristics (including income and education) with psychological traits. They show that although women score lower on average than men, a large share of this gap can be explained by observable individual differences, such as income, education level, responsibility for financial decision-making, and certain personality traits. Once these factors are taken into account, gender itself becomes a much weaker predictor of financial capability. However, some disparities persist, particularly in the choice of financial products and the ability to remain informed, suggesting that gender gaps are not solely driven by individual characteristics, but are also shaped by the structure of financial markets and the way financial information is produced and disseminated.

Research conducted in Asia and the Middle East extends these findings by emphasising the role of behavioural biases and emotions in financial decision-making. Several studies (Adil et al., 2022; Siraji et al., 2021) show that women tend to be more influenced by risk aversion, herding behaviour, and anchoring, whereas men are more frequently characterised by overconfidence and a lower perception of risk. Importantly, these studies also highlight that financial literacy can play a moderating role, reducing the influence of emotional and cognitive biases and thereby narrowing observed gender differences in investment behaviour.

Focus on investment decisions, Kumari (2023) examines the relationship between financial literacy and investment outcomes and finds that women with higher levels of financial literacy tend to adopt more effective investment strategies. These results underline the role of knowledge acquisition in narrowing observed gender differences. Finally, Chaitra and Madhavi (2025) examine overconfidence among women, a bias often considered to be a male bias, and demonstrate that this bias also affects some high-income female investors. However, financial literacy acts as a moderating factor: better-educated women are less prone to overconfidence and more rational in their decisions.

Across all Asian studies considered (Adil et al. (2022); Chaitra & Madhavi (2025); Gupta & Goyal (2024); Holden & Tilahun (2022); Jaiswal & Kamil (2012) and Kumari (2023)) and a similar pattern emerges: women tend to participate less frequently in financial markets, favour safer assets, display higher sensitivity to potential losses, and show a lower propensity to engage in speculative investment strategies. Men, by contrast, invest more actively, often driven by higher levels of overconfidence and, in some cases, excessive optimism. However, these differences in behaviour tend to diminish among Millennials (Gupta & Goyal, 2024), where men and women display limited but comparable rationality, reflecting a shift towards behavioural homogenisation.

In the United States, the pioneering studies by Barber and Odean (2001) and Dwyer, Gilkeson and List (2002) have durably shaped research on gender and investment behaviour. Using data from more than 35,000 brokerage accounts, Barber and Odean show that men trade 45% more frequently than women, due to excessive overconfidence in their ability to outperform the market, which reduces their net returns by 2.65% per year. Women, by contrast, adopt a more disciplined, long-term approach and achieve better risk-adjusted performance. Dwyer et al. (2002) confirm these findings by showing that women hold less risky portfolios than men, but that these differences become insignificant once income, education, and experience are taken into account. Eckel and Grossman (2008) consistently confirm higher risk aversion among women across different experimental settings and also show that participants correctly perceive this difference, revealing the existence of a stable gender stereotype in risk assessment. Finally, a more recent study by Zeytoon-Nejad (2025) nuances this consensus: while women remain more averse to payoff risk (Payoff Risk Aversion, PaRA), they are paradoxically less averse to price risk (Price Risk Aversion, PrRA) than men, and exhibit a smaller PaRA-PrRA gap, suggesting greater decision-making consistency.

Studies based on the U.S. Survey of Consumer Finances (Jianakoplos & Bernasek, 1998; Fisher & Yao, 2017) reach similar conclusions. Women appear more cautious, not because of an irrational aversion to risk, but because they face more uncertain income and greater wealth precariousness. Fisher and Yao (2017) show that income uncertainty reduces risk tolerance among women, while it increases it among men; conversely, higher wealth raises the propensity to invest for both genders, but more strongly for men.

Overall, international evidence shows that gender differences in investment behaviour are widespread but largely context-dependent. While women appear, on average, more cautious, less confident and less active in financial markets, these differences are substantially reduced once income, wealth, financial literacy, experience, and confidence are taken into account. Gender thus has limited explanatory power on its own: observed gaps are better understood as the outcome of structural constraints, social norms, and unequal exposure to financial risk rather than intrinsic preferences.

3.3.4 Finance professionals

Empirical studies focusing on finance professionals remain relatively scarce compared with those examining individual investors. Yet, they provide a particularly valuable setting for assessing the persistence of gender differences in a context where training, experience, and economic rationality should, in theory, neutralise behavioural biases.

The Spanish study by Gonzalez-Iguala et al. (2021) examines how education, age, and gender influence behavioural biases among professional advisors and investors. Women perceive themselves as more cautious and less prone to irrational biases, whereas men and younger professionals appear more sensitive to emotions and impulsive behaviour. CFA (Chartered Financial Analyst) holders display a better theoretical understanding of behavioural finance, but this is not sufficient to eliminate biased behaviour. The study highlights a lack of structured behavioural training in financial professions, which is particularly crucial for aligning advisors' attitudes with those of their clients, but also for correcting stereotypes of excessive caution often attributed to women.

Research on fund managers confirms this apparent performance neutrality while emphasising pronounced differences in perception and visibility. The study by Atkinson et al. (2003) shows that women manage their funds in a manner similar to men, with comparable returns and risk levels. However, funds managed by women systematically attract less capital, especially during their first year of operation, revealing a confidence bias on the part of investors. This phenomenon, interpreted as a form of structural discrimination, helps explain the low proportion of female asset managers in a sector that is nonetheless based on measurable performance.

The study by Babalos et al. (2015) reinforces this conclusion using a large sample of European funds, finding no significant differences in performance or risk between male and female managers. The authors nonetheless document differences in investment style. Female managers exhibit slightly higher alphas and a preference for growth-oriented strategies, but display weaker market-timing abilities. Male managers, by contrast, tend to favour small-cap stocks and show modestly positive timing indices with respect to size and growth factors.

Similar results are found in the hedge fund segment examined by Aggarwal and Boyson (2016). Female-only-managed hedge funds display performance and risk profiles comparable to those of male-managed funds, while mixed-gender teams tend to underperform both groups and take less risk, resulting in similar Sharpe ratios. Despite this equivalence in skill, female-managed funds remain rare and systematically attract lower assets under management, even when performance is strong, suggesting persistent barriers in capital allocation rather than differences in managerial ability.

Finally, Sehrish et al. (2024) focus on liquidity management in mutual fund portfolios. Female managers favour more liquid assets and transparent strategies, which reduce risk at the cost of slightly lower returns, but enhance fund stability and resilience, particularly during periods of crisis. This cautious approach, interpreted not as a weakness but as contextualised rationality, illustrates the added value of gender diversity in asset management: the complementarity of styles improves the overall robustness of the financial system.

Taken as a whole, these studies lead to a clear conclusion: gender differences do not translate into gaps in competence or performance, but rather into a persistent undervaluation and underrepresentation of women in professional finance. Despite comparable performance, women remain a minority in management and advisory positions due to perceptual biases, structural career barriers, and a lack of visible role models. This scarcity therefore does not reflect lower ability, but rather the product of an institutional environment that valorises male risk-taking while interpreting female caution as a lack of ambition. Consequently, the analysis of gender in financial professions cannot be limited to performance measurement alone; it must also examine the social mechanisms of recognition and legitimacy that perpetuate structural imbalance within the expert spheres of finance.

3.3.5 Sustainable finance, ESG, and gendered investment motivations

Recent research highlights that the issue of gender in finance is no longer limited to differences in performance or risk tolerance; it now extends to the way men and women conceive the very purpose of investment. The emergence of sustainable finance and responsible investment (Environmental, Social and Governance, ESG) has brought to light an essential dimension: ethical and prosocial motivations.

Empirical studies confirm a marked female preference for responsible and impact investing, regardless of financial literacy or experience. The study by Grumann et al. (2024), conducted in Portugal, shows that women favour sustainable investments more than men, even after controlling for income, education and stock market experience. This preference is therefore not due to a lack of competence, but rather to a motivation based on ethical values and the search for meaning, rather than on maximising performance. These results corroborate those of Riedl and Smeets (2017) and Bauer et al. (2023), cited by Gutsche et al. (2023), who emphasise that women associate investing with social contribution before seeing it as a strategy for return.

The German study by Bauer et al. (2023) specifies that gender differences in sustainable investment are mediated by psychological factors: women exhibit more “warm-glow motives”, i.e. the positive feeling of acting in a fair or useful way, and are more sensitive to the emotional and identity aspects of responsible finance. On the other hand, their slightly lower financial literacy tends to limit the proportion of actual ESG investments, showing that moral motivation sometimes precedes technical competence. In other words, the gender difference in sustainable investing is indirect: it is mediated by values, trust and perception of impact.

In terms of behaviour, Assaf et al. (2025) demonstrate that while men and women adopt similar investment behaviours with regard to ESG, their motivations differ profoundly: women act primarily out of ethical, social or environmental concerns, while men favour performance or reputation. The study concludes that parity in behaviour does not mean parity in values: women embody a 'value-driven' approach, in which sustainability is an end in itself, rather than simply a means to achieve returns.

Beyond the academic literature, several financial institutions corroborate these trends through their reports and surveys.

The EY report (2023) identifies three key patterns among women: a strong demand for transparency, a preference for investments with positive impact, and a responsible approach to wealth planning that prioritises sustainability and lifestyle coherence over pure performance. The global UBS Women on Purpose survey (2022) shows that nearly 80% of female investors ensure that their investments reflect their personal values and beliefs, viewing money as a lever for social and environmental change. Similarly, Amundi (2023) finds that one in two women report deliberately investing in companies that meet ESG criteria, compared with one in three men, confirming the leading role of women in the diffusion of responsible investment practices. Finally, BNY Mellon (2022) highlights that women's persistent mistrust of financial markets, driven by lower confidence and higher perceived risk, represents a systemic opportunity cost: if women's investment participation matched that of men, this would amount to more than £3.2 trillion in additional capital, largely directed toward sustainable projects.

Taken together, these academic and institutional studies converge on a common conclusion: the feminisation of finance is accompanied by a redefinition of economic motivations. Women tend to invest not to "beat the market," but to give meaning to value creation by reconciling returns, responsibility, and ethical consistency. Such an approach not only contributes to more sustainable participation in financial markets, but may also help reduce persistent inequalities in access to traditional financial institutions.

3.3.6 Summary of the literature regarding gender stereotypes and research positioning

The literature review highlights a now well-established but deeply nuanced finding: differences in financial behaviour between men and women do exist, but they are highly contextual, heterogeneous and largely mediated by structural factors. Foundational experimental work shows that, on average, women adopt more cautious behaviours than men in risk-taking situations. However, these differences appear to be sensitive to experimental protocols, decision framing and stereotypes activated by the devices themselves. They most often translate into small differences in means, accompanied by high intra-gender variability and a large overlap in distributions, which limits the scope of conclusions at the individual level.

Empirical studies of individual investors, both in Europe and internationally, confirm this diagnosis and reinforce it. The differences observed in terms of market participation, portfolio composition, trading frequency and investment horizon do not seem to be due to intrinsic risk aversion, but rather to a combination of economic constraints (income, wealth, career paths), differences in financial socialisation, and psychological factors, foremost among which are self-confidence and perceived competence. A recurring conclusion in this literature is that gender loses most of its explanatory power when controlling for experience, financial literacy and confidence, suggesting that the observed differences are more a product of different environments than of fundamental preferences.

Research on finance professionals reinforces this interpretation. In contexts characterised by a high level of training and expertise, differences in performance and competence largely disappear, both among fund managers and in alternative management. The remaining differences mainly relate to investment styles, strategic choices or preferences in terms of liquidity, without ever calling into question equality of ability. On the other hand, these studies repeatedly highlight the persistence of perceptual biases, statistical discrimination mechanisms and structural barriers, which contribute to the under-representation of women in decision-making roles and their lower visibility, regardless of their actual performance.

Finally, the rise of sustainable finance adds an extra dimension to gender analysis in finance. The differences observed no longer relate solely to risk-taking or performance, but to the very purpose of investment. Women appear more inclined to incorporate ethical, social and environmental considerations into their decisions, not because they lack rationality, but rather because they embrace a broader rationality focused on meaning, consistency and sustainability in value creation.

Therefore, the empirical challenge is not so much to measure a hypothetical "female risk aversion", but to examine whether, and to what extent, these differences persist when observing an expert population that is homogeneous in terms of skills and directly involved in financial decision-making. It is precisely this perspective that informs the present study. By focusing on practising investment professionals, it aims to test the robustness of the findings from the literature on individuals, while helping to fill a blind spot in empirical research: the detailed analysis of gender-based behaviours, preferences and potential biases in an environment where financial expertise is high and shared. This approach thus makes it possible to move from a debate on observed average differences to a more structural analysis of the mechanisms that shape, neutralise or perpetuate behavioural differences in expert financial circles.

Building on the literature reviewed above, this study formulates a set of hypotheses aimed at assessing whether gender-related differences documented among individual investors persist within a professional investment context. Rather than assuming intrinsic behavioural differences, the analysis focuses on dimensions that the literature identifies as potentially gender-sensitive, while acknowledging their strong contextual and structural determinants.

Specifically, the hypotheses are structured as follows. The analysis first examines whether female professionals exhibit lower risk tolerance than male professionals (H1), and whether they display lower levels of financial overconfidence (H2). It then investigates whether these differences translate into behavioural outcomes, namely lower trading frequency (H3) and shorter investment horizons (H4) among female professionals. The study further tests whether female professionals report higher levels of portfolio diversification (H5) and favour more defensive or conservative investment styles (H6). Finally, in line with recent research on sustainable finance, the analysis examines whether female professionals attach greater importance to ESG criteria in their investment decisions (H7).

Table 2 summarises the main findings from the literature, highlights their key limitations, and maps each dimension of financial behaviour to the corresponding research hypothesis. Together, these hypotheses provide a coherent empirical framework for identifying which aspects of financial behaviour remain gender-sensitive once financial expertise, market exposure, and professional norms are largely shared.

Table 2: Summary of the literature and research hypotheses

Dimensions	Main findings from the literature	Key limitations and nuances	Sources (indicatives)	Hypotheses
Risk tolerance	Lower risk tolerance among women	Strong context and framing effects; large intra-gender variability; effect weakens with controls	Almenberg & Dreber (2015); Croson & Gneezy (2009); Eckel & Grossman (2008)	H1
Overconfidence	Higher financial overconfidence among men	Gap reduced by experience and education	Barber & Odean (2001); Marinelli et al. (2017); Wu & Westerholm (2021)	H2
Trading frequency	Higher trading activity among men	Largely mediated by confidence and experience	Barber & Odean (2001); Marinelli et al. (2017); Mikelionytė & Lezgovko (2021)	H3
Investment horizon	Longer horizons among men; higher liquidity preference among women	Adaptive response to income uncertainty and career paths	Halko et al. (2012); Marinelli et al. (2017); Ohlund (2017)	H4
Diversification	More diversified portfolios or greater use of collective vehicles among women	Convergence with experience; similar efficiency outcomes	Marinelli et al. (2017); Wu & Westerholm (2021)	H5
Investment styles	More defensive and liquidity-oriented styles among women	No systematic performance differences	Babalos et al. (2015); Powell & Ansic (1997)	H6
ESG preferences	Stronger ESG and responsible investment orientation among women	Differences driven by values and motivations rather than skills	Grumann et al. (2024); Riedl & Smeets (2017)	H7

Notes: Empirical tests assess the rejection of the null hypothesis of no gender difference, while hypotheses H1–H7 correspond to literature-based alternative research hypotheses used as the reference framework for interpretation.

Source: author's own elaboration based on the literature on gender differences in financial behaviour.

4 METHODOLOGY

4.1 RESEARCH DESIGN

This study adopts a quantitative approach based on the analysis of primary data collected from investment professionals using a structured questionnaire. This methodological choice directly addresses the research objective: to determine whether gender differences in behaviour persist in a professional environment characterised by a high level of financial expertise. Rather than replicating existing performance-based studies on professionals, this research shifts the focus toward the underlying behavioural dimensions of investment decision-making, allowing for an assessment of whether gender differences persist beyond observable outcomes.

The literature on individual investors documents differences between men and women, particularly with respect to risk tolerance, trading frequency, and overconfidence. However, these studies typically rely on ex post statistical controls for knowledge or experience, rather than directly observing a population that is genuinely homogeneous along these dimensions.

The originality of this study lies precisely in this approach: interviewing practising professionals with high and comparable financial skills in order to examine whether the differences documented among individuals persist when looking at an expert population. This approach reduces the need for corrective statistical adjustments and allows for a more direct observation of behaviour.

Although some research has been conducted among professionals, it remains limited and often focuses on specific segments (e.g., fund managers). By positioning itself in a real-world operational context, this study favours observation in natural conditions, gathering preferences and attitudes as they actually manifest themselves in daily practice, thus complementing the data obtained in controlled experimental contexts.

Finally, the use of a multidimensional questionnaire makes it possible to capture several dimensions of investment behaviour simultaneously: risk tolerance, overconfidence, factor preferences, investment horizon, trading frequency, ESG integration, etc.

4.2 SAMPLING AND DATA COLLECTION PROCEDURE

The study targets investment professionals working in asset management, multi-asset management, trading desks, or related functions.

Respondents were recruited through several complementary channels:

- Internal dissemination within the BNP Paribas Group, via professional and personal networks.
- Direct contact with professionals from other financial institutions (asset management firms, banks, etc.), by email or via LinkedIn.
- Snowball sampling, whereby some respondents voluntarily forwarded the questionnaire to colleagues or team members.

Participation was entirely voluntary and anonymous. No exclusion criteria were applied, except for the requirement that respondents currently hold a position related to investment. Data collection was conducted using an online questionnaire, accessible via a link circulated between October 22, 2025, and November 25, 2025.

4.3 DATA COLLECTION TOOLS AND DATA PROCESSING

The questionnaire was administered via LimeSurvey, an open-source platform widely used in academic research for the design and dissemination of quantitative surveys. This choice was motivated by its ability to efficiently structure a questionnaire composed of multiple thematic blocks and standardised response scales, which precisely matched the requirements of this study.

LimeSurvey made it possible to clearly organise the 27 items into thematic blocks (asset allocation, factor preferences, risk tolerance, overconfidence, investment horizon, trading behaviour, ESG), ensuring a smooth and consistent response process for participants.

The use of LimeSurvey is also consistent with the institutional practices of HEC Liège, where this tool is the preferred solution for quantitative research conducted by students and researchers. Its accessibility, compliance with GDPR (General Data Protection Regulation) requirements, and operational reliability explain its frequent adoption in management science research projects.

Statistical data analysis was conducted using the R software through the RStudio environment, in line with the practices taught at HEC Liège as part of the Quantitative Method Management course. This choice ensures consistency between the methods taught and the techniques actually applied in this thesis.

R is now recognised as one of the reference software tools for quantitative analysis in management sciences. The book R for Data Science (Wickham & Grolemund, 2023) highlights its ability to transform raw data into actionable insights, as well as the coherence of the tools it provides for importing, organising, analysing, and visualising data. This academic recognition reinforces the relevance of using R in research requiring transparency, reproducibility, and methodological rigor.

The RStudio environment, combined with the several packages, enables a clear and reproducible structure for the analyses. All statistical processing was carried out using scripts, ensuring full traceability of the analytical workflow. In this context, R and RStudio constitute a robust, transparent, and methodologically appropriate environment for conducting the statistical analyses required for this research.

4.4 QUESTIONNAIRE DESIGN

The questionnaire administered (Appendix 1) consists of 27 items and was designed to cover key dimensions of investment behaviour in a professional context. It is structured around thematic blocks, directly inspired by the behavioural finance literature and explicitly aligned with the hypotheses formulated in the previous section.

The objective is not to measure abstract psychological traits, but rather to capture self-reported preferences and behaviours that are closely related to actual professional practice, in line with the empirical positioning of the study.

4.4.1 Strategic portfolio allocation

Respondents are first asked to report their average “strategic” allocation across four broad asset classes: equities, bonds, cash, and alternative assets. This allocation constitutes a central entry point for the analysis, as it directly reflects the effective structure of portfolios managed or recommended by professionals.

4.4.2 Factor preferences and investment styles

A second block composed of fifteen items assesses preferences for different factor styles (Size, Value/Growth, Quality, Conservative/Aggressive, Momentum) across three geographical areas (Europe, United States, Emerging Markets). This battery enables a detailed analysis of preferred investment styles and provides a higher level of granularity than asset-class allocation alone.

4.4.3 Risk tolerance

Risk tolerance is measured through several complementary dimensions: general risk tolerance, tolerance under extreme scenarios, and maximum acceptable annual loss. These items capture both the subjective perception of risk and its translation into explicit financial constraints, offering a more robust assessment than one-dimensional risk measure.

4.4.4 Overconfidence

A specific perceptual item measures respondents' relative confidence in their ability to achieve higher performance than their peers. This measure captures overconfidence, a bias widely documented in the literature as a driver of excessive trading.

4.4.5 Investment horizon and trading frequency

The questionnaire then collects information on the preferred investment horizon and the frequency of portfolio rebalancing or trading activity. These two dimensions inform the temporal structure of decision-making and the intensity of transactional behaviour, both of which have been shown to differ by gender in studies of individual investors but remain underexplored among professionals.

4.4.6 ESG preferences

Finally, three items explore sensitivity to extra-financial criteria through: the share of ESG investments in portfolios, the preferred ESG approach (own approach, institutional approach, both, or exclusion), and expectations regarding the relative performance of sustainable assets. This block is designed to test whether gender differences documented in the literature on responsible investment persist within a professional context.

4.5 STATISTICAL APPROACH

This section describes the statistical methodology employed to test the research hypotheses and to assess gender differences across behavioural and investment-related dimensions. The choice of statistical tests follows a structured decision framework based on the nature of the variable, its measurement scale, and distributional properties or sample size constraints (Rudas, 2018, Nayak & Hazra, 2011).

4.5.1 Decision framework for the selection of statistical tests

Table 3 summarizes the decision rules guiding the selection of statistical tests applied in the empirical analysis.

Table 3: Decision framework for the selection of statistical tests

Nature of the variables	Measurement scale	Distribution / sample considerations	Inference approach	Statistical test
Categorical	Nominal	Sufficient expected cell frequencies	Parametric (asymptotic)	χ^2 test of independence
Categorical	Nominal	Small expected cell frequencies	Exact	Fisher's exact test
Numerical	Continuous	Normal distribution	Parametric	Student's t-test
Numerical	Continuous	Non-normal distribution or small sample size	Non-parametric	Mann-Whitney U test
Categorical	Ordinal	Ordered but non-cardinal data	Rank-based	Mann-Whitney U test

Source: author's synthesis based on standard statistical decision rules

For ordinal variables measured on Likert-type scales (e.g. risk tolerance, overconfidence), the Mann-Whitney U test is used to compare the distributions between female and male respondents. This test is recommended when the normality assumption is violated and when the data are ordinal rather than interval-scaled (de Winter & Dodou, 2010). Methodological discussions in the statistical literature highlight that treating Likert-type data as continuous and analysing them using parametric tests may lead to biased statistical inference, particularly when sample sizes are small or when distributions are asymmetric (Jamieson, 2004).

For nominal categorical variables, the χ^2 test of independence is applied when expected cell frequencies satisfy asymptotic conditions. Methodological literature recommends that no more than 20% of cells have an expected frequency below 5 and that no cell have an expected frequency below 1 (Bewick et al., 2004; McHugh, 2013). When these conditions are violated, Fisher's exact test is preferred due to its exact nature and superior performance in small samples (Agresti, 2007; Fisher, 1922).

When numerical variables deviate from normality, non-parametric tests based on ranks are preferred, as they are less sensitive to extreme values and do not rely on distributional assumptions (Conover, 1999).

The significance threshold is set at $\alpha = 5\%$, in line with standard practice in the social sciences (Cohen, 1994), and two-sided tests are systematically applied.

4.5.2 From univariate tests to multivariate robustness checks

While the univariate tests provide initial evidence of gender differences across individual indicators, they do not account for the potential influence of demographic and professional characteristics. To address this limitation, the analysis is subsequently extended through multivariate regression models, which allow for the simultaneous inclusion of control variables. This approach is standard in applied empirical research, as it enables a more rigorous assessment of associations by accounting for observable heterogeneity across individuals (Angrist & Pischke, 2009; Wooldridge, 2010).

These multivariate robustness checks are presented in Section 5.5. Ordinary least squares (OLS) regressions are employed when the dependent variable is continuous, while logit models are used for binary outcomes, in line with standard econometric practice (Greene, 2018). The results from these models are not interpreted as establishing causal relationships, but rather as robustness analyses aimed at verifying whether the univariate findings persist once relevant control variables are taken into account.

4.6 METHODOLOGICAL LIMITATIONS

Like any empirical research, this study is subject to a number of methodological limitations that must be taken into account when interpreting the results.

First, the sample is characterised by a strong institutional concentration, with a large proportion of respondents affiliated with the same banking group (BNP Paribas). While this reflects the professional and personal networks through which the survey was distributed, it may restrict the external validity of the findings and limit their generalisability to the broader financial industry.

Second, the relatively modest sample size (N = 79), combined with an uneven gender distribution, constitutes a major constraint for statistical inference. These characteristics reduce statistical power and increase the risk of type II errors, particularly in multivariate settings. As a result, the estimates derived from regression models must be interpreted with caution, especially when coefficients fail to reach conventional significance levels. In this context, regression analyses were primarily used as exploratory tools to assess the direction and relative magnitude of gender effects while controlling for selected professional characteristics. Given the limited sample size, the models were intentionally kept parsimonious, and interaction terms or highly disaggregated controls were avoided in order to preserve estimation stability.

Third, the strong concentration of respondents within specific age groups, experience levels and professional roles further limits the feasibility of detailed subgroup analyses. Several categories are represented by very few observations, rendering stratified or function-level comparisons statistically unreliable and preventing more granular modelling strategies.

Finally, the study relies on self-reported data collected through a questionnaire. Such data may be subject to social desirability bias or discrepancies between stated preferences and actual professional behaviour. In the absence of experimental designs or observed trading data, the analysis captures declared attitudes and self-perceived behaviours rather than realised investment decisions.

Taken together, these limitations do not invalidate the results but clearly delineate the scope within which they should be interpreted. The findings should therefore be viewed as indicative rather than definitive. They nonetheless provide valuable insights and open promising avenues for future research, particularly studies based on larger and more diversified professional samples or on behavioural data drawn from real investment activity.

5 RESULTS

5.1 REPRESENTATIVENESS AND STRUCTURE OF THE SAMPLE

5.1.1 General description and gender distribution

The sample consists of 79 respondents working in investment-related roles (private bankers, portfolio managers, product specialists, etc.), mainly in Belgium (and a few in Luxembourg). It includes 51 men (65%) and 28 women (35%). The initial objective was to achieve gender parity; however, despite targeted follow-ups with female professionals, this could not be achieved. This imbalance reflects the reality of the investment sector, which remains predominantly male.

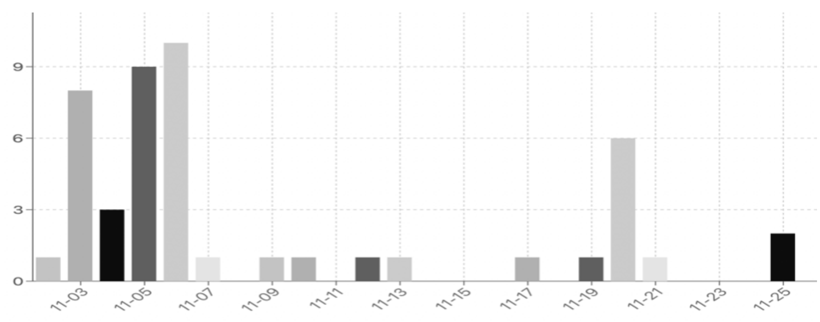
While the Belgian financial sector now appears broadly gender-balanced overall, with approximately 50.6% women in 2024 according to the "Human Resources 2024" report published by Febelfin, this apparent parity masks substantial internal disparities across hierarchical levels and functions. According to the Wo.Men in Finance Belgium report (Annual Report, 2024-2025), women account for 47.4% of middle management positions and just over 35% of senior management roles in the Belgian financial sector.

In Luxembourg, sectoral statistics also indicate near parity in total employment: in 2024, women represented 46.8% of employees in the financial sector, according to data reported by Paperjam (August 2025). However, representation declines sharply when focusing on senior decision-making positions. Based on the assessment conducted by the CSSF (Commission de Surveillance du Secteur Financier) following its data collection exercise in 2023, women occupy on average only 16.3% of management positions within credit institutions, investment firms, and payment or electronic money institutions. As of 31 December 2021, women accounted for only 23.8% of non-executive directors and 16.3% of executive directors, with some institutions having no women represented at all in their governing bodies.

This imbalance is even more pronounced in asset management roles. According to the Alpha Female Report 2024 published by Citywire, an international media outlet specialising in asset management, women represent only 18% of portfolio managers in Belgium and just 14% in Luxembourg.

The response rate was 72%. Data collection took place between 22 October and 25 November, a deliberately limited period designed to avoid biases related to rapid fluctuations in market conditions. Figure 1 illustrates the temporal distribution of responses over the data collection period, showing how participation evolved over time:

Figure 1: Temporal distribution of responses

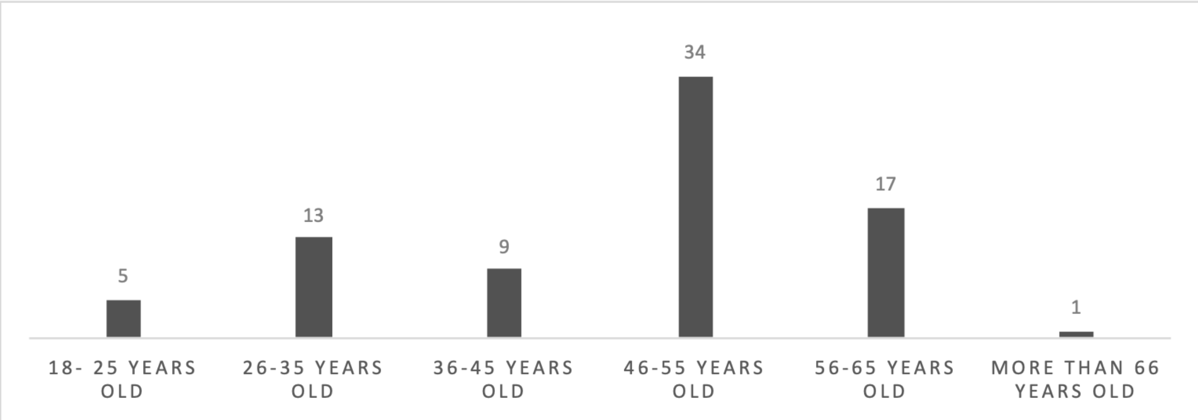


Source: survey data, processed using Excel

5.1.2 Age group distribution

Figure 2 presents the age group distribution of respondents in the sample.

Figure 2: Age group distribution



Source: survey data, processed using Excel

The age distribution shows a strong presence of experienced professionals within the sample. The 46-55 age group is by far the most represented, with 34 respondents, accounting for approximately 43% of the total sample. This overrepresentation is consistent with the age structure observed in investment-related professions, where advisory, portfolio management, and client relationship roles are predominantly held by senior profiles with several years of experience.

The 56-65 age group (17 respondents, 22%), as well as the 26-35 (13 respondents, 16%) and 36-45 (9 respondents, 11%) age groups, constitute the other most represented categories. This distribution suggests a combination of established professionals and mid-career profiles, which is typical of investment teams.

The 18-25 age group (5 respondents, 6%) and the over-66 age group (1 respondent) are marginal. This can be explained by the structure of the sector: entry into investment professions generally requires specialised training and initial professional experience, while very senior profiles are rare due to retirement.

Overall, this distribution reflects an age pyramid characteristic of financial professions, dominated by intermediate to advanced age groups, thereby reinforcing the relevance of the sample for the study of professional investment behaviour.

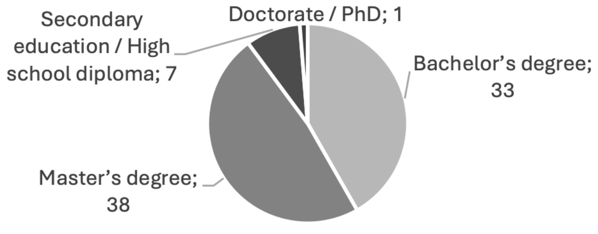
These results are consistent with the age structure observed in the financial and insurance activities sector at the European level. According to the most recent data published by Eurostat for 2024 (Appendix 2), employment in the Belgian financial sector is largely concentrated in the 25-49 age group (89.2 thousand) and the 50-64 age group (55.4 thousand), while the 15-24 age group represents only a marginal share (2.8 thousand).

In Luxembourg, a comparable structure is observed, with a dominant concentration in the 25-49 age group (29.6 thousand) and a smaller presence in the 50-64 age group (9.9 thousand). Younger cohorts are also marginally represented. These data confirm that financial professions rely primarily on intermediate to advanced age profiles, which empirically validates the strong representation of the 46-55 and 56-65 age groups observed in the sample.

5.1.3 Education level and professional experience

This section describes the educational background and professional experience of respondents, two key dimensions for assessing the relevance and expertise of the sample in the context of investment behaviour. Figure 3 first illustrates the educational attainment of respondents.

Figure 3: Distribution by education level



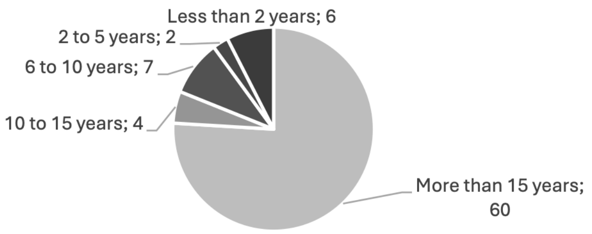
Source: survey data, processed using Excel

The distribution by education level shows a high degree of academic qualification among respondents, which is consistent with the requirements of the financial sector, particularly in investment-related professions. The majority of participants hold a Master's degree (38 respondents, 48%) or a Bachelor's degree (33 respondents, 42%), together accounting for approximately 90% of the sample. The marginal presence of PhD holders (1 respondent) as well as profiles with secondary education (7 respondents) reflects some diversity in educational backgrounds, but confirms that access to investment roles primarily relies on higher and specialised education.

This distribution reinforces the relevance of the sample for the study of financial behaviour, as the vast majority of respondents possess a theoretical foundation enabling them to understand and apply asset management principles.

Beyond formal education, professional experience provides an additional indicator of respondents' expertise and exposure to financial markets. Figure 4 displays respondents' professional experience.

Figure 4: Distribution by experience



Source: survey data, processed using Excel

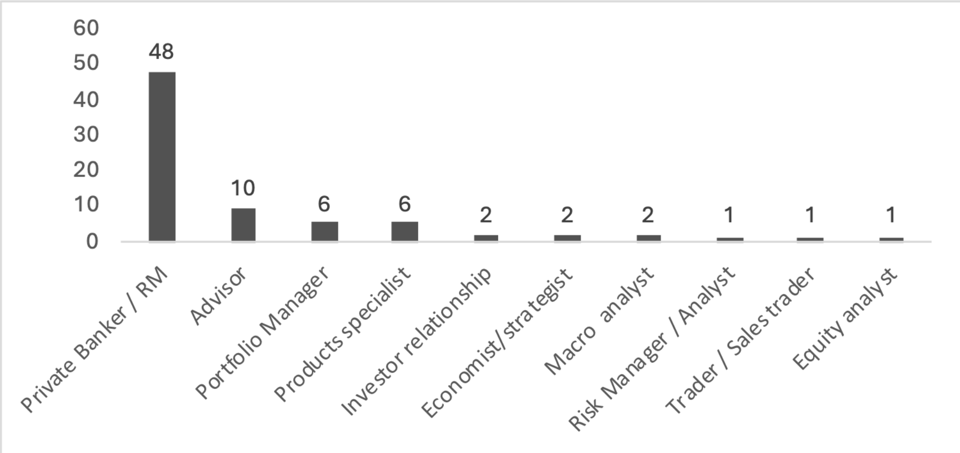
The distribution of professional experience highlights a population largely composed of senior professionals. The category with more than 15 years of experience includes 60 respondents, representing nearly three-quarters of the sample. Intermediate categories, 10 to 15 years (7 respondents), 6 to 10 years (6 respondents), and 2 to 5 years (4 respondents), are far less represented, while professionals with less than two years of experience remain marginal.

This structure confirms that the sample consists of respondents with a high level of expertise, which is particularly relevant for a study focusing on investment behaviour: their responses reflect established practices shaped by years of exposure to financial markets and investment decision-making.

5.1.4 Position

Figure 5 illustrates the professional positions held by respondents, providing insight into their functional roles within financial institutions.

Figure 5: Distribution by position



Source: survey data, processed using Excel

The distribution of respondents by position shows a predominance of roles oriented toward client relations and financial advisory. Private bankers and relationship managers account for 48 respondents, representing more than 60% of the sample. This overrepresentation is consistent with the staff structure of large banking institutions, where these functions constitute a substantial share of professionals in direct contact with end investors.

Investment advisors and wealth advisors form the second most represented group with 10 respondents, followed by portfolio managers and product specialists, each comprising 6 respondents. These two categories include more technical profiles involved in portfolio construction or financial engineering.

More specialised roles, such as economists, macro analysts, equity analysts, risk managers, and traders, are marginally represented (between 1 and 2 respondents each). This distribution reflects the organisational reality of the sector: these roles are structurally less numerous within commercial and wealth management teams.

5.1.5 Institution

The vast majority of respondents (68 out of 79, representing 86% of the sample) come from the BNP Group. This concentration is explained by the researcher's professional and personal network being largely embedded within BNP Paribas and its entities in Belgium and Luxembourg. The other institutions represented include ING (5 respondents), Degroof Petercam (3 respondents), as well as a small number of respondents from Nagelmackers, Crédit Agricole Indosuez Wealth Management, and KBC.

This concentration constitutes a methodological limitation that should be acknowledged: the sample is largely drawn from a single organisational culture, which may influence certain observed behaviours. As a result, the findings should not be interpreted as fully generalisable beyond similar institutional contexts.

5.1.6 Client contact

Finally, 67 out of 79 respondents report being in direct contact with clients, representing approximately 85% of the sample. This characteristic is not trivial in a study focusing on cognitive biases and investment behaviour. Advisory professionals are not merely technical executors: their own beliefs, preferences, and biases may influence the way they guide or support their clients' investment decisions.

The fact that the majority of respondents are engaged in advisory relationships therefore strengthens the relevance of the sample for analysing "real-world" behaviours, but also implies that the results should be interpreted in light of this dimension. The observed biases may reflect not only individual preferences, but also potential influence effects inherent to the professional advisory role.

5.1.7 Structural tests

Before comparing investment behaviours between men and women, we examine whether the sample exhibits structural imbalances along key sociodemographic and professional dimensions that could confound gender-based comparisons. A structural bias would arise if men and women were unevenly distributed across characteristics such as age, professional experience, or job roles, which are themselves likely to influence investment behaviour.

Given the categorical nature of the variables, tests of independence were conducted using contingency tables. Chi squared test of independence (χ^2) test was applied whenever standard assumptions regarding expected cell frequencies were satisfied. When these conditions were not met due to sparse cells, Fisher's exact test was used instead.

To ensure reliable inference, several variables were recoded into broader, substantively meaningful categories. Age was grouped into three career-stage classes (≤35, 36–55, and 56+), professional experience into junior, intermediate, and senior levels, and job functions into three broad professional families (client-facing, investment & research, and support/product/risk roles).

The results, reported in Table 4, indicate no statistically significant association between gender and age, education level, professional experience, or employer. A marginal association is observed for job function, suggesting limited functional segmentation. A significant association is found for client contact. However, this variable closely overlaps with job-function orientation and is therefore interpreted as a descriptive feature of task allocation rather than as an independent structural bias.

Table 4: Structural tests

Dimensions	Statistical test	p-value	Conclusion
Gender × Age	χ^2	0.575	No association
Gender × Education	χ^2	0.391	No association
Gender × Job function	Fisher exact	0.088	No association
Gender × Institution	Fisher exact	0.507	No association
Gender × Experience	Fisher exact	0.615	No association
Gender × Client contact	Fisher exact	0.021	Significant association

Source: survey data, processed using R

Overall, these findings suggest that the sample does not exhibit major structural imbalances between men and women along the dimensions considered.

5.2 STRATEGIC ASSET ALLOCATION

5.2.1 Overall distribution of allocation by asset class

Respondents were asked to indicate the strategic allocation they would recommend for a typical portfolio, by allocating 100% across the main asset classes (equities, bonds, cash, and alternative assets).

The average allocation (available in Appendix 3) is clearly equity-oriented, with equities accounting for an average of 60.57% of the portfolio (median: 60%), reflecting an overall dynamic positioning of the sample. Bonds constitute the second largest asset class (22.53%), while cash holdings remain marginal (7.27%), confirming a low preference for defensive strategies. Alternative assets represent an average of 9.63% of the allocation.

The high standard deviations observed across all asset classes indicate substantial heterogeneity in strategies, with portfolios ranging from very conservative to highly risk-exposed profiles. This diversity is methodologically important, as it ensures that any subsequent absence of gender differences cannot be attributed to an artificial uniformity in allocations.

This overall overview makes it possible to situate the general level of risk-taking within the sample and justifies, in the following section, the use of a classification of portfolios into strategic allocation profiles based on equity exposure.

5.2.2 Average portfolios by gender

To examine potential differences in portfolio construction between men and women, two average portfolios were constructed by computing the mean allocation to each asset class and sub-asset class for both groups. Median allocations were also examined to ensure that results were not driven by extreme values. The resulting average portfolios are reported in Table 5.

Table 5: Average portfolios

Asset classes	Sub asset classes	Men	Women
EQUITIES	Equities US	29,11%	23,40%
	Equities Europe	16,38%	23,01%
	Equities Japan	3,43%	3,84%
	Equities Dev. Asia	5,65%	4,28%
	Equities EM	5,44%	7,07%
BONDS	Sovereign bonds US	2,38%	2,84%
	Sovereign bonds EUR	3,97%	4,00%
	Corporate bonds US	4,38%	3,47%
	Corporate bonds EUR	7,77%	6,26%
	EM bonds	2,24%	4,40%
	Global Aggregate bonds	2,16%	0,89%
ALTERNATIVE ASSETS	Gold/Precious Metals	3,20%	1,88%
	Real Estate	1,43%	1,36%
	Commodities	1,19%	1,58%
	Hedge Funds	0,93%	1,18%
	Private Markets	2,53%	1,42%
	Digital Assets	0,95%	1,11%
CASH	Cash	6,86%	8,00%

Source: survey data, processed using Excel

At first glance, differences between average portfolios appear modest, although several descriptive patterns can be observed. In terms of equity exposure, men hold portfolios that are relatively more exposed to U.S. equities and developed Asian markets, whereas women allocate a larger share to European equities and emerging markets. Bond allocations are broadly similar across genders; however, women exhibit higher exposure to emerging market debt, while men maintain slightly greater allocations to Global Aggregate bonds and euro-denominated corporate bonds. Allocations to alternative assets remain marginal for both groups, men show somewhat higher exposure to gold and precious metals as well as to private markets. Finally, women hold a slightly higher share of cash on average, suggesting a more liquid portfolio structure.

These observations are purely descriptive and do not, at this stage, imply statistically significant differences. To formally assess whether observed allocation differences are statistically meaningful, non-parametric Mann–Whitney tests were conducted for each asset class, as allocation variables are non-normal, bounded, and skewed (see Appendix 4). The results show that allocation differences between the two groups are generally limited. After adjusting p-values using the Benjamini-Hochberg (1995) procedure to control for the false discovery rate, only the allocation to European equities remains statistically significant at the 5% level ($p = 0.016$), with women allocating a higher proportion than men. For all other asset classes, adjusted p-values remain well above conventional significance thresholds, indicating that the overall portfolio structure is largely similar across genders.

This convergence is consistent with the literature on finance professionals. While studies on individual investors typically document higher risk aversion among women and lower exposure to risky assets (Barber & Odean, 2001; Cupák et al., 2021; Marinelli et al., 2017) research on fund managers instead shows a high degree of homogeneity in allocations and risk levels. Atkinson et al. (2003) and Babalos et al. (2015) find no significant differences in performance or volatility between male- and female-managed funds; Aggarwal and Boyson (2016) and Sehrish et al. (2024) reach similar conclusions for hedge funds and mutual funds. The average portfolios observed here therefore align with this finding of a neutralisation of gender differences when portfolios are constructed within a professional framework.

5.2.3 Strategic allocation profiles and risk classification

In order to analyse differences in strategic positioning among respondents, portfolios were classified into allocation profiles based on their total exposure to equities. This classification allows for a clearer and more synthetic comparison of strategic positioning than analyses based on detailed portfolio compositions. This choice is grounded in standard multi-asset management practices, in which the share invested in equities constitutes the primary determinant of a portfolio's overall risk level, while bonds mainly play a stabilising role.

The profiles used in this study are based on international strategic asset allocation conventions commonly observed among major asset managers, who structure their model portfolios around benchmarks such as 20/80 (or 30/70), 40/60, 60/40, and 80/20 (equities/bonds), corresponding respectively to defensive, moderate, balanced, and dynamic profiles. These orders of magnitude are widely employed in multi-asset profile funds offered by major international institutions such as Vanguard (LifeStrategy Funds) or BlackRock (iShares Core Allocation Funds) and are consistent with the risk-profiling framework arising from MiFID II regulation.

Given that the statistical objective is not to replicate specific regulatory mandates exactly, but rather to compare relative levels of risk-taking, these references profiles were transformed into continuous equity exposure bands, allowing each respondent to be assigned to a unique category. Each individual portfolio was thus assigned to a unique strategic allocation profile based on its total equity exposure, as presented in table 6.

Table 6: Allocation profiles

Equity exposures	Profiles	Men	Women
Below 30%	**Conservative**	0,00%	3,57%
Between 30% and 50%	**Moderate**	15,69%	14,29%
Between 50% and 70%	**Balanced**	49,02%	42,86%
Above 70%	**Dynamic**	35,29%	39,29%

Source: survey data, processed using Excel

For both genders, the dominant profiles are the balanced and dynamic profiles, which together account for nearly 84% of men and more than 82% of women. The conservative profile is almost absent from the sample, while the moderate profile concerns a comparable proportion of men and women.

The construction of strategic allocation profiles transforms the original numerical allocation variables into categorical variables, making the use of a chi-square test of independence appropriate. To ensure compliance with the test's assumptions, the "conservative" and "moderate" profiles were therefore grouped into a single "low-risk" category. After this regrouping, the conditions for applying the chi-square test are satisfied.

The chi-square test performed does not reveal any statistically significant relationship between gender and strategic allocation profile ($p = 0.871$). This result indicates that the distribution of risk profiles is statistically similar between men and women within the sample.

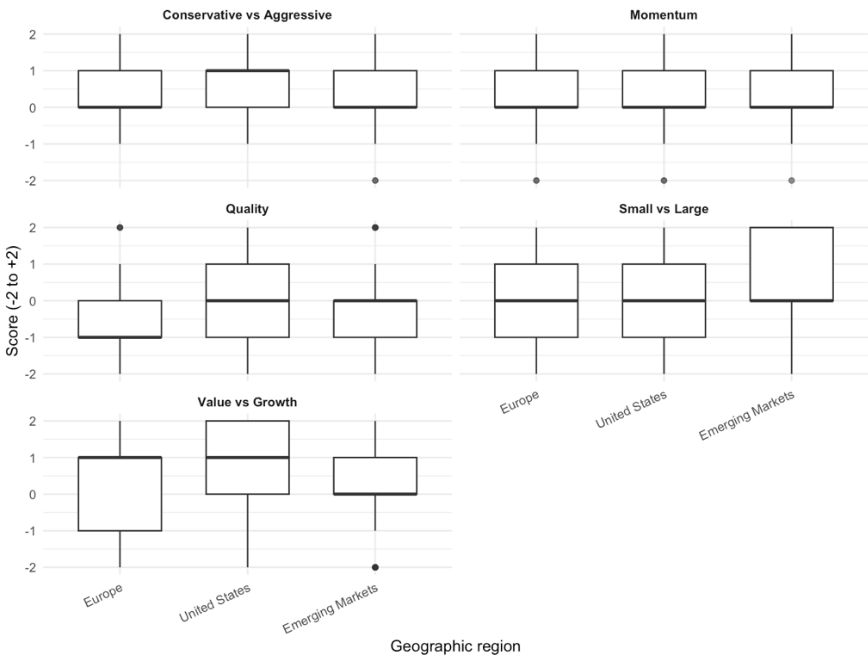
From an economic and behavioural perspective, this finding suggests that, in a professional context, strategic allocation structures are largely homogenised, regardless of gender. While the analysis of strategic allocation highlights a strong convergence of risk profiles between men and women in a professional setting, it does not allow conclusions to be drawn regarding potential differences in individual risk tolerance as measured through self-reported attitudes. It is therefore necessary to examine whether the convergence observed at the portfolio level is also reflected in respondents' expressed attitudes toward risk. This is the focus of Section 5.4.1, which is devoted to testing Hypothesis H1 related to risk tolerance.

5.3 FACTOR PREFERENCES

5.3.1 Overall description of factors

The analysis of factor exposures makes it possible to examine the extent to which respondents express stylistic preferences (Value, Growth, Momentum, Quality, or Small/Large Caps). The scores range from −2 (strong preference for the left-hand side of the axis) to +2 (preference for the right-hand side), providing a standardised measure of declared sensitivities. In order to visualise these preferences in a synthetic manner, boxplots were produced (Figure 6). The interpretation of the boxplot follows the classical definition proposed by Tukey (1977) and widely adopted in the statistical literature (McGill et al., 1978). The median corresponds to the central line, the box represents the interquartile range (IQR), the whiskers delimit the range of non-extreme values, and isolated points identify outlying observations.

Figure 6: Boxplots: Factors preferences



Source: survey data, processed using R

The examination of the distributions of factor scores reveals a set of preferences that are generally centred and weakly differentiated. In most cases, medians located close to zero indicate that respondents do not exhibit systematic stylistic biases toward one side of a factor axis (e.g., Value vs. Growth, Small vs. Large, Conservative vs. Aggressive). The moderate width of the boxes suggests limited intra-group variability, reflecting a relative convergence of declared preferences. The whiskers remain contained, indicating an absence of extreme dispersion, with the exception of a few isolated observations that reflect more pronounced stylistic positioning. Finally, the structure of the distributions remains broadly comparable across geographic regions, suggesting that declared factor preferences are relatively stable and only weakly influenced by specific market contexts. Taken together, these elements highlight predominantly neutral and weakly polarised stylistic profiles within the sample.

5.3.2 Factors and genders

Building on the factor preferences described in the previous section, this subsection examines whether these investment styles differ systematically between men and women within the professional sample. Table 7 reports the statistical analysis of factor preferences by gender.

Table 7: Factors and gender analysis

Regions	Styles	Δ (H-F)	p-value	p-adj BH
Europe	Conservative ←→ Aggressive	0.074	0.948	0.948
	Weak Momentum ←→ Strong Momentum	0.385	0.190	0.568
	High Quality ←→ Low	0.042	0.775	0.948
	Small Caps ←→ Large Caps	**0.633**	**0.0166**	0.234
	Value ←→ Growth	0.276	0.227	0.568
United States	Conservative ←→ Aggressive	0.050	0.752	0.948
	Weak Momentum ←→ Strong Momentum	0.006	0.678	0.948
	High Quality ←→ Low	0.013	0.937	0.948
	Small Caps ←→ Large Caps	0.451	0.143	0.535
	Value ←→ Growth	0.129	0.467	0.778
Emerging Markets	Conservative ←→ Aggressive	−0.154	0.393	0.778
	Weak Momentum ←→ Strong Momentum	−0.024	0.868	0.948
	High Quality ←→ Low	0.268	0.419	0.778
	Small Caps ←→ Large Caps	0.492	0.0648	0.324
	Value ←→ Growth	**0.633**	**0.0312**	0.234

Source: survey data, processed using R

The Mann-Whitney tests highlight a few isolated differences between men and women for certain factors (notably Small vs. Large in Europe and Value vs. Growth in emerging markets), with mean differences of around 0.6 points on a scale ranging from −2 to +2 (detailed means and medians are presented in Appendix 5). However, none of these differences remains statistically significant after applying the Benjamini-Hochberg correction for multiple testing (adjusted p-values ≥ 0.23). Overall, these results suggest that gender is not a robust determinant of factor preferences within this sample of professionals.

5.4 HYPOTHESIS TESTING

To preserve clarity and conciseness, the presentation of results for the seven hypotheses focuses primarily on hypothesis testing. Descriptive statistics are reported in Appendix 6, while the main body of the text is devoted to inferential analysis and economic interpretation. When relevant, descriptive patterns are briefly illustrated through graphical representations, in order to support interpretation without overloading the main body. All R codes used in the empirical analysis are also provided in Appendix 8.

When nonparametric tests are employed, the estimated location difference corresponds to the Hodges-Lehmann estimator. Confidence intervals and location estimates are reported only for statistically significant results, so as to avoid presenting uninformative statistics.

The hypotheses are presented following a consistent analytical order reflecting the main dimensions of investment behaviour examined in the behavioural finance literature. The analysis begins with individual attitudes and behavioural traits: risk aversion (H1), overconfidence (H2), and trading frequency (H3), and then proceeds to investment horizon (H4), diversification (H5), sector and style preferences (H6), and ESG-related investment choices (H7).

5.4.1 H1: Risk Aversion / Risk Tolerance

H1: Female professionals exhibit significantly higher risk aversion than men.

While strategic allocation analysis captures revealed risk-taking through portfolio structure, it does not directly measure individual risk preferences or attitudes. To assess whether this convergence in portfolio construction is also reflected at the attitudinal level, the following section turns to self-reported and behavioural measures of risk tolerance. This hypothesis, widely documented in the literature on individual investors (Barber & Odean, 2001; Croson & Gneezy, 2009; Halko et al., 2012, etc.), is tested here in a professional context using three complementary indicators: a self-reported measure of “normal” risk tolerance, a self-reported measure of “extreme” risk tolerance, an operational measure based on the maximum acceptable loss. Table 8 summarises the results of the univariate tests conducted for each indicator.

Table 8: Gender differences in risk aversion

Indicators	Scale	Test	p-value	Estimated location difference	95% CI	Conclusion
Normal risk tolerance	Ordinal (Likert 1-5)	Mann-Whitney	0.197	-	-	No significant difference
Extreme risk tolerance	Ordinal (Likert 1-6)	Mann-Whitney	0.153	-	-	No significant difference
Maximum acceptable loss (%)	Continuous (non-normal)	Mann-Whitney	0.0057	~10	~ [0;10]	Men > Women

Source: survey data, processed using R

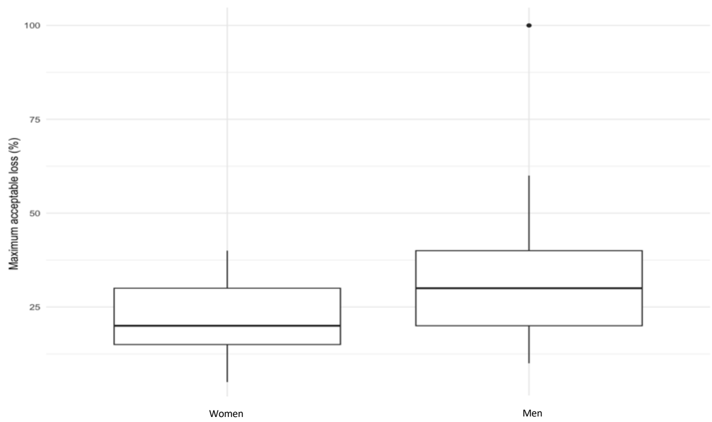
The results provide mixed evidence regarding gender differences in risk aversion. No statistically significant difference is observed for declarative measures of risk tolerance, whether in normal or extreme situations. By contrast, a strong and statistically robust difference emerges when risk aversion is measured through the behavioural indicator of maximum acceptable loss.

Prior to hypothesis testing, the normality of the maximum acceptable loss variable was assessed using the Shapiro-Wilk test. The null hypothesis of normality is clearly rejected for men ($p < 0.001$), while it cannot be rejected for women ($p = 0.13$), indicating asymmetric distributional properties across genders. As at least one group exhibits a non-normal distribution, the Student's t-test is inappropriate. Accordingly, gender differences were assessed using the nonparametric Mann-Whitney U test.

The test reveals a highly significant difference between men and women ($p = 0.0057$). The Hodges-Lehmann estimator indicates that men report a median maximum acceptable loss approximately ten percentage points higher than women. The 95% confidence interval is strictly positive, confirming that this difference is both statistically robust and economically meaningful.

As a visual complement, Figure 7 illustrates the distribution of maximum acceptable losses by gender. The male distribution appears more dispersed and right-skewed, with a higher median, visually corroborating the inferential results and highlighting the behavioural nature of the observed gender gap.

Figure 7 : Distribution of maximum acceptable loss by gender



Source: survey data, processed using R

This divergence between declared risk attitudes and effective loss tolerance is consistent with previous findings highlighting the limits of self-reported measures of risk preferences. Some studies highlight a gap between declared risk tolerance and risk tolerance actually revealed through behaviour. Grable and Lytton (1999) show that "most people misstate their risk tolerance" and that individuals tend to "overestimate their actual level of risk tolerance" due to social desirability. Moreover, Weber et al. (2002) demonstrate that self-reported risk attitudes are only moderately correlated with actual decision-making behaviour. It suggests that gender differences in risk-taking may not be expressed at the level of discourse, but rather in concrete exposure to financial losses.

Overall, Hypothesis H1 is partially supported: while no gender difference appears in declared risk tolerance, a substantial gap is observed when risk aversion is captured through a behavioural measure.

5.4.2 H2: Overconfidence

H2: Female professionals exhibit a lower level of financial confidence than men.

Overconfidence, often described in the literature as being more pronounced among men (Barber & Odean, 2001; Marinelli et al., 2017; Wu & Westerholm, 2021; etc.), was measured using a three-level ordinal scale, in which respondents indicated whether they considered themselves less performant, similar, or more performant than their peers.

As for other dimensions measured with Likert-scale, differences between men and women are assessed using the Mann-Whitney test. The test results indicate no statistically significant difference between the two groups ($p = 0.995$). The response distributions therefore appear very similar for men and women, with no systematic shift toward higher self-assessment levels for either group. In other words, no significant gender-based difference in declared overconfidence is identified within this sample of finance professionals.

It should be noted that the indicator used captures perceived relative performance rather than objective miscalibration or excessive trading behaviour. In a professional setting, such self-assessments may be shaped by institutional norms, peer benchmarking, and shared performance metrics, which could attenuate gender differences documented among retail investors.

These results suggest that, in an expert setting, overconfidence, often documented in the literature on individual investors, does not manifest differently between men and women. This finding supports the idea of a convergence of cognitive behaviours when financial decision-making takes place in a professional context. As a result, Hypothesis H2 is rejected.

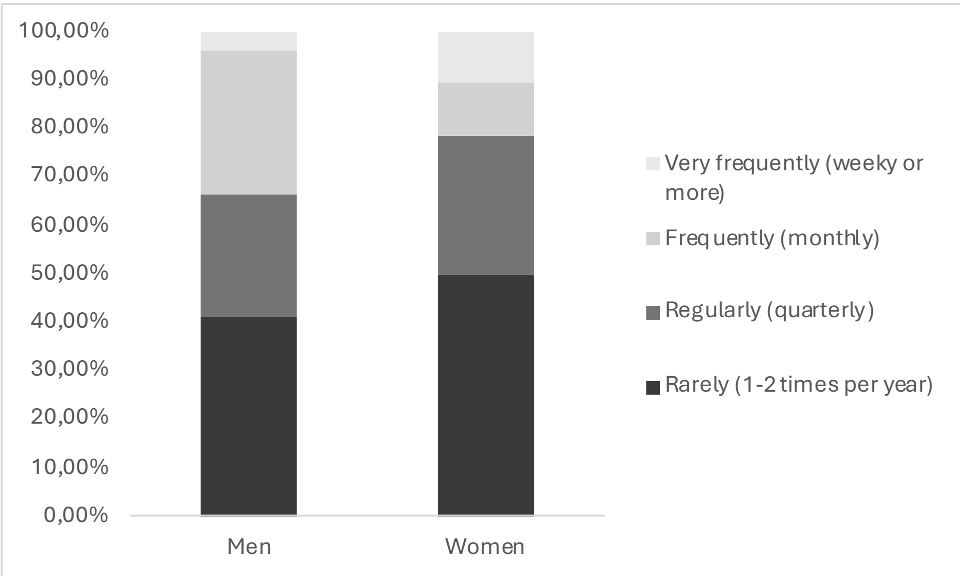
5.4.3 H3: Trading frequency

H3: Female professionals report less intensive trading activity than male professionals.

Trading frequency, or portfolio adjustment frequency, is frequently discussed in the literature as a behavioural outcome linked to overconfidence and investment horizon, and is often analysed through a gender lens, with several studies suggesting higher trading intensity among male investors (Marinelli et al., 2017; Mikelionytė and Lezgovko, 2021). In this study, trading frequency is measured using an ordered categorical variable with four levels: rarely (1-2 times per year), regularly (quarterly), frequently (monthly), and very frequently (weekly or more).

Figure 8 displays the distribution of trading frequencies by gender using 100% stacked bars. While men appear slightly more represented among higher trading frequencies, the overall distributions remain close across genders.

Figure 8: Distribution of trading frequencies by gender



Source: survey data, processed using Excel

From a statistical perspective, a Mann-Whitney test was performed to examine whether trading frequency differs by gender. This non-parametric test is appropriate for ordered categorical variables, as it takes into account the natural ranking of trading frequencies without requiring distributional assumptions.

The results ($p = 0.4321$) indicate that no statistically significant difference can be established between men and women in terms of trading frequency. While descriptive patterns suggest that men may be slightly more represented among higher trading frequencies, these differences remain limited and do not reflect a systematic shift in trading behaviour across genders.

Consistent with the absence of significant gender differences in declared overconfidence (H2), trading frequency does not appear to depend on gender in this professional sample. This finding nuances claims in the literature that women are systematically less active traders. Consequently, H3 is rejected.

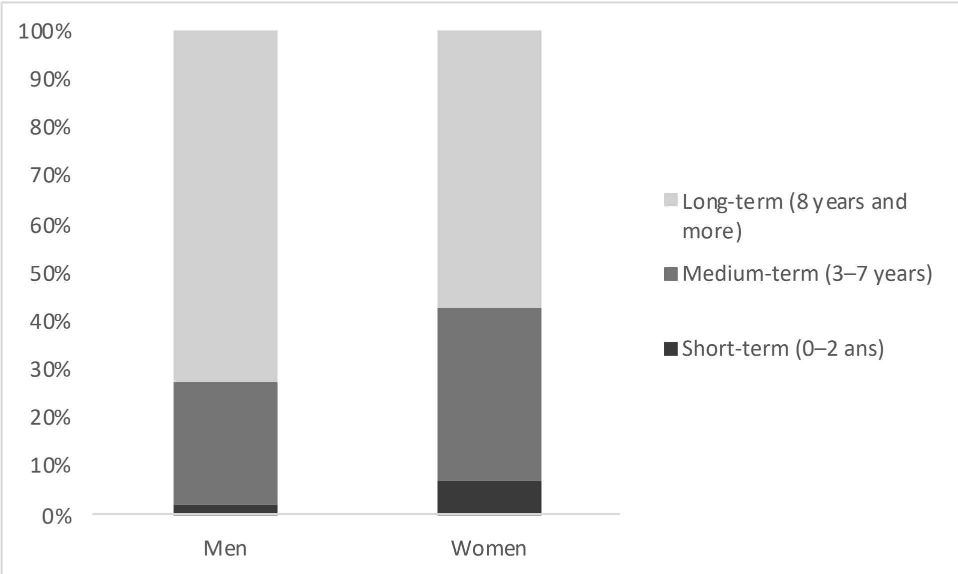
5.4.4 H4: Investment horizon

H4: Investment horizon: Female professionals adopt a shorter investment horizon than male professionals.

According to the literature, men are more likely to adopt long investment horizons, while women tend to favour shorter horizons and greater liquidity (Halko et al., 2012; Marinelli et al., 2017; etc.). To assess this hypothesis, respondents were asked whether they primarily favoured a short (0-2 years), medium (3-7 years), or long (8 years and more) investment horizon.

Figure 9 presents the distribution of investment horizons by gender. While women appear slightly more represented in short- and medium-term horizons and men in long-term horizons, these differences remain limited.

Figure 9: Distribution of investment horizons by gender



Source: survey data, processed using Excel

From a statistical perspective, a Mann-Whitney test was performed to examine whether investment horizon differs by gender. This non-parametric test is appropriate for ordered categorical variables, as it accounts for the natural ranking of investment horizons (short, medium, long) without requiring distributional assumptions.

The results ($p = 0.1422$) indicate that no statistically significant difference can be established between men and women with respect to their chosen investment horizon.

Although descriptive patterns suggest minor differences in the distribution of horizons across genders, these differences do not translate into a systematic shift toward shorter or longer horizons for either group. In this professional sample, investment horizon therefore does not appear to depend on gender. Consequently, H4 is rejected.

5.4.5 H5: Diversification

H5: Female professionals report more diversified portfolios than male professionals.

The analysis in Section 5.2 showed that overall allocations across asset classes are very similar between men and women. However, diversification does not depend solely on allocation: the choice of investment vehicles (ETFs, active funds, direct holdings) has a strong influence on the effective level of portfolio diversification. Indeed, the literature emphasises that the use of collective investment instruments, such as ETFs or mutual funds, reduces idiosyncratic risk and provides access to broader diversification than portfolios composed of individual securities (Goetzmann & Kumar, 2008; Polkovnichenko, 2005).

In this context, it is relevant to examine whether declared preferences regarding investment vehicles differ by gender. To statistically assess the possible existence of a gender effect, appropriate tests were applied depending on the normality observed in each group.

Table 9: Shapiro-Wilk Test (Normality) - Investment vehicles

Variables	p-value Men	p-value Women	Interpretations
Exchange-Traded-Funds (ETFs)	0,140	0,383	⇨ Approximately normal distribution in both groups → t-test and Mann-Whitney possible
Active funds	0,001	0,128	⇨ Normality not satisfied for men → Mann-Whitney
Direct holdings	0,00038	0,00004	⇨ Non-normal distribution in both groups → Mann-Whitney

Source: survey data, processed using R

Normality tests indicate that only the ETF share can reasonably be subjected to a t-test; for the other two vehicles, a nonparametric test is required.

The t-test does not indicate any significant difference between men and women ($p = 0.3941$; $t = -0.8578$). The mean difference (approximately +4.3 percentage points in favour of women) is not statistically robust, and the confidence interval [-14.16; +5.65] includes zero, confirming the absence of an effect.

Table 10: Mann-Whitney Test - Investment vehicles

Vehicles	p-value	Interpretations
Exchange-Traded-Funds (ETFs)	0,300	No significant difference
Active funds	0,796	No significant difference
Direct holdings	0,154	No significant difference

Source: survey data, processed using R

No statistical test indicates a significant difference between men and women in the choice of investment vehicles. The three categories, ETFs, funds, and individual securities, exhibit similar distributions and small, non-significant location differences.

H5 is therefore rejected, in this professional sample, the choice of investment vehicles is homogeneous between men and women, suggesting a comparable level of structural diversification.

5.4.6 H6: Sector Preferences and Investment Styles

H6: Female professionals favour more defensive or conservative sector allocations than men.

In Section 5.3, the analysis of investment styles did not reveal any significant differences between genders. This section extends that analysis by examining sector preferences, which may reflect more or less defensive allocation choices. To this end, respondents were asked to allocate their portfolios across the eleven sectors defined by the GICS (Global Industry Classification Standard), jointly developed by MSCI (Morgan Stanley Capital International) and S&P Dow Jones Indices.

Table 11 presents the average sector allocations reported by men and women, together with the results of Mann-Whitney tests, adjusted for multiple testing using the Benjamini-Hochberg procedure.

Table 11: Descriptive and statistical analysis of sector allocations

Sectors	Δ (H-F)	p-value	Adj p-value (BH)
Energy	-1,69%	0,226	0,643
Materials	-1,90%	0,316	0,643
Industrials	-0,26%	0,875	0,962
Consumer Discretionary	-0,57%	0,351	0,643
Consumer Staples	1,38%	0,329	0,643
Health Care	-1,20%	0,689	0,938
Financials	0,06%	0,767	0,938
Information Technology	6,52%	0,173	0,643
Communication Services	-2,44%	0,043	0,469
Utilities	0,10%	0,969	0,969
Real Estate	-0,01%	0,643	0,938

Source: survey data, processed using R

A reading of the table does not reveal any marked differences between male and female portfolios. Some descriptive divergences can nevertheless be observed for specific sectors. In particular, the information technology sector shows an average gap of approximately 6.5 percentage points, with a higher allocation among men, while communication services appear slightly more represented in female portfolios.

However, these descriptive differences do not translate into statistically robust results. Although a p-value below the 5% threshold is observed for the communication services sector in the unadjusted analysis, no sectoral difference remains significant after applying the Benjamini-Hochberg correction. Overall, these results indicate that, among finance professionals, gender does not constitute a major determinant of sector preferences. This absence of sectoral differentiation reinforces the idea of a convergence in investment practices within an expert setting, already highlighted in the analysis of investment styles. As a result, Hypothesis H6 is rejected.

5.4.7 H7: ESG preferences

H7: Female professionals assign greater importance to ESG criteria than male professionals.

In a context where extra-financial dimensions are taking on increasing importance in investment decisions, it appears relevant to examine the role attributed to so-called ESG investments (environmental, social, and governance). This hypothesis examines whether men and women differ in the importance they attribute to those criteria. Three complementary dimensions are considered: (i) the proportion of ESG assets included in portfolios, (ii) the approach adopted toward ESG integration, and (iii) perceptions of ESG performance. Table 12 presents the results obtained throughout the tests, and those results are discussed below.

Table 12: Gender differences in ESG-related preferences

Dimensions	Scale	Test	p-value	Estimated location difference	95% CI	Conclusion
ESG allocation	Continuous (non-normal)	Mann-Whitney	0,00197	~ -15	~ [-25;-5]	Women > Man
ESG approach	Categorical	Fisher's exact	0.0244	-	-	Women > Men
Expected ESG performance	Ordinal (Likert 1-5)	Mann-Whitney	0.27	-	-	No significant difference

Source: survey data, processed using R

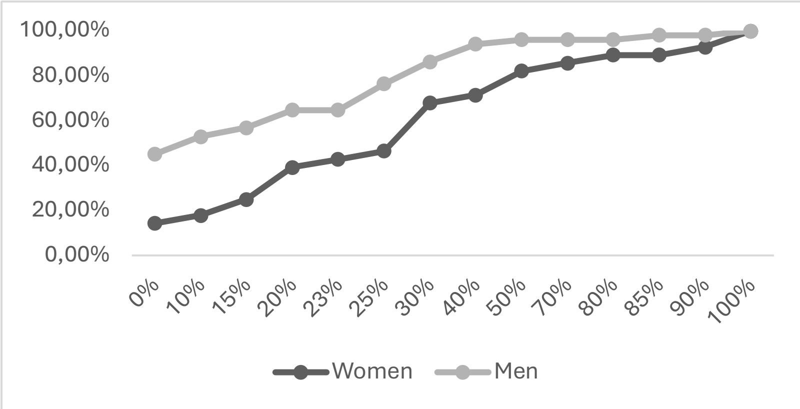
ESG allocation

Gender differences in ESG allocation are first assessed by comparing the share of ESG assets reported in respondents' portfolios. Given that ESG allocation percentages are discrete, bounded, and highly skewed, a nonparametric Mann-Whitney U test is applied.

The test reveals a strong and statistically significant difference between men and women ($p = 0.002$). The Hodges-Lehmann estimator indicates that women allocate, on average, approximately 15 percentage points more to ESG assets than men. The 95% confidence interval is strictly negative, confirming that this difference is both statistically robust and economically meaningful.

Figure 10 shows that the cumulative distribution for men lies above that of women across most allocation thresholds, indicating a higher concentration of low or zero ESG allocations among men. The rightward shift of the female distribution reflects stronger ESG integration.

Figure 10: Cumulative distribution of ESG allocations



Source: survey data, processed using Excel

ESG integration approach

After establishing that women allocate a significantly higher share of their portfolios to ESG, it is relevant to examine how these criteria are incorporated into the investment process. Respondents were offered four possible approaches: investing according to personal convictions, following institutional ESG policy, combining personal convictions and institutional policy, not taking ESG criteria into account.

To assess the statistical significance of this difference, Fisher's exact test was applied, given the contingency table structure and modest cell counts in some categories. The test yields p = 0.0244, indicating that the distribution of ESG approaches differs significantly by gender at the 5% level. The declared choices of men and women therefore do not stem from the same distribution: ESG approach is indeed conditioned by gender in this professional sample.

It should nevertheless be noted that interpretation of the test relies on a distribution including a highly asymmetric category, namely respondents who do not take ESG into account. This imbalance mechanically amplifies the detection of statistical dependence. In other words, while the test does reveal an association, this association largely reflects the fact that a substantial subgroup (men) simply reports ignoring ESG, thereby making other categories comparatively less represented.

In summary, while the previous section showed that women allocate more to ESG in quantitative terms, this analysis further reveals that they also adopt more systematic and institutionally aligned ESG approaches, whereas men are characterised by a greater propensity to exclude these criteria.

Expected ESG performance

Before closing this section on responsible investment, an essential question arises: do men exclude ESG criteria more often because they perceive these investments as less performant? To shed light on this issue, respondents evaluated the expected performance of ESG investments using a five-point Likert scale ranging from "significantly lower" to "significantly higher."

As the variable is ordinal and characterised by tied values, a nonparametric Mann-Whitney test was applied. The test does not reveal any statistically significant difference between men and women ($p = 0.27$). Although women appear slightly more optimistic in descriptive terms, this difference remains small and statistically unstable. Perceptions of ESG performance are therefore broadly similar across genders in this professional sample.

These results indicate that, despite some minor descriptive differences, men and women do not differ significantly in their assessment of the expected performance of ESG investments. The absence of a statistically significant difference calls for caution in interpretation and suggests that men's lower propensity to integrate ESG criteria into their portfolios is unlikely to stem from more pessimistic performance expectations. Rather, other factors, whether institutional, behavioural, or related to individual preference, may better account for these choices and warrant further investigation in future research.

The objective of this analysis was to test whether men and women differ in their assessment of ESG investments and in the importance they attribute to ESG criteria. While a significant gender difference is observed in terms of ESG integration, the precise mechanisms underlying this preference cannot be identified within the scope of the present study. Indeed, no statistically significant difference emerges with respect to expected ESG performance, suggesting that the stronger ESG integration observed among women is not driven by more optimistic performance expectations. The exact reasons for this preference therefore remain unknown. Nevertheless, based on this specific professional sample, we can conclude that female respondents do assign greater importance to ESG criteria in their investment decisions, H7 is therefore accepted.

5.4.8 Summary of the results obtained throughout hypothesis testing

Table 13 provides a synthetic overview of the results obtained from the hypothesis testing conducted in Section 5.4.

Table 13: Results obtained throughout hypothesis testing

Dimensions/ Hypothesis	Indicator	Scale	Test	p-value
H1- RISK TOLERANCE	Normal risk tolerance	Ordinal (Likert 1-5)	Mann-Whitney	0.197
	Extreme risk tolerance	Ordinal (Likert 1-6)	Mann-Whitney	0.153
	Maximum acceptable loss (%)	Continuous (non-normal)	Mann-Whitney	**0.0057**
H2 - OVERCONFIDENCE	Overconfidence	Ordinal (Likert 1-3)	Mann-Whitney	0,995
H3 - TRADING FREQUENCY	Trading frequency	Categorical (ordinal)	Mann-Whitney	0,429
H4 - INVESTMENT HORIZON	Investment horizon	Categorical (ordinal)	Mann-Whitney	0,141
H5 - DIVERSIFICATION	Strategic allocation	Numerical (non normal)	Mann-Whitney	≥ 0,21[a]
	Vehicles	Numerical (non normal)	Mann-Whitney	≥ 0,299
H6 - SECTOR PREFERENCES AND INVESTMENT STYLES	Factor preferences	5-point bipolar scale (-2;+2)	Mann-Whitney + BH	≥ 0.23
	Sector preferences	Numerical	Mann-Whitney + BH	≥ 0.46
H7 - ESG	ESG Allocation	Continuous (non-normal)	Mann-Whitney	**0,001975**
	ESG Approach	Categorical (nominal)	Fisher	**0,0244**
	ESG Perf	Ordinal (Likert 1-5)	Mann-Whitney	0,27

Notes: [a] For strategic asset allocation, all asset class comparisons between men and women are statistically non-significant at the 5% level, with the exception of European equities, for which a significant difference is observed (p = 0.0158).
Source: author's own elaboration based on the empirical analyses and results in Section 6.4.

Overall, the evidence points to limited gender differences across most behavioural dimensions. In particular, no statistically significant differences are observed in overconfidence, trading frequency, investment horizon, diversification proxies, or investment style preferences once appropriate non-parametric tests are applied.

By contrast, two dimensions stand out. First, women report a significantly lower maximum acceptable loss than men, indicating a lower tolerance for extreme downside risk. Second, ESG-related outcomes display consistent gender differences: women allocate a higher share of their portfolios according to ESG criteria and are more likely to adopt ESG-oriented investment approaches. These results are robust across different indicators and statistical tests.

Taken together, the findings suggest that gender differences among financial professionals are selective rather than systematic, primarily emerging in dimensions related to downside risk exposure and sustainability preferences, while remaining absent in trading behaviour, overconfidence, and investment style choices. This summary provides the foundation for the multivariate robustness checks presented in Section 6.5.

5.5 MULTIVARIATE ROBUSTNESS CHECKS

This section presents a series of multivariate regression analyses designed to complement the hypotheses evaluated in the previous section by assessing the robustness of the previously identified patterns. Specifically, the objective is to examine whether the observed differences persist once demographic and professional characteristics are jointly taken into account. The empirical strategy follows a unified framework across all outcomes, with the choice of the econometric model being determined by the measurement scale of the dependent variable.

Continuous behavioural outcomes (e.g. risk tolerance, diversification intensity, ESG allocation) are analysed using ordinary least squares (OLS) regressions, while binary outcomes (e.g. overconfidence, trading frequency, investment horizon) are examined using logit models (Greene, 2018; Wooldridge, 2010). For binary outcomes, logit models are estimated and results are reported in terms of average marginal effects (AME), which facilitate interpretation and comparison across model specifications in non-linear models (Cameron & Trivedi, 2005), AMEs measure the average change in predicted probabilities associated with a one-unit change in each explanatory variable. Expressing results in this way allows for a direct and intuitive interpretation of the estimated effects and facilitates comparisons across model specifications.

For the OLS specifications, the normality was imposed. While alternative modelling strategies tailored to non-normal outcomes could in principle be considered, these approaches typically rely on larger samples to yield stable and interpretable estimates.

Given the relatively limited sample size and the behavioural nature of the survey data, the multivariate analyses are therefore interpreted as identifying conditional associations rather than causal effects. Accordingly, emphasis is placed on the direction, stability, and economic magnitude of the estimated coefficients across alternative specifications, rather than on statistical significance alone.

To preserve parsimony and limit the risk of overfitting, control variables are introduced sequentially and retained in the final specifications in line with a parsimonious modelling strategy. For OLS models, only control variables that improve the explanatory power of the model are retained in the final specification, in other words, the selection is guided by improvements in the adjusted R^2, while for logit models robustness is assessed through the stability of the estimated average marginal effects across specifications. Extended model specifications, including additional controls that were ultimately excluded from the baseline analysis, are reported in Appendix 7 for transparency and robustness purposes.

Throughout this section, statistical significance is indicated using the conventional notation:
*** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. Estimated coefficients should therefore be interpreted as statistically meaningful only when meeting these thresholds.

5.5.1 Risk tolerance - maximum acceptable loss

Risk tolerance is assessed using the maximum acceptable loss over a one-year horizon. As this variable is quantitative and continuous, the analysis relies on ordinary least squares (OLS) linear regressions. Table 14 presents the results of ordinary least squares (OLS) regressions:

Table 14: Linear regression results: Determinants of maximum acceptable loss

Dependent variable: Maximum acceptable loss (%)

Independent variables	Model 1	Model 4	Model 5	Model 6 (Full model)
Intercept	30.980*** (1.928)	35.945*** (3.395)	24.868*** (4.529)	28.575*** (4.637)
Female	−9.302** (3.238)	−9.745** (3.204)	−7.927* (3.343)	−7.791* (3.237)
Senior experience	-	−6.330 (3.586)	-	−9.114* (3.702)
Client-facing role	-	-	6.633 (4.455)	10.367* (4.572)
R^2	0.097	0.132	0.122	0.188
Adjusted R^2	0.085	0.110	0.099	0.156
*** p<0.001, ** p < 0.01, * p<0.05				

Notes: Standard errors are reported in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. Models 2 and 3, which introduce age and education respectively, do not improve the adjusted R^2 and are therefore not retained in the main analysis; the corresponding results are reported in Appendix 7.1.
Source: survey data, processed using R

The baseline specification (Model 1) estimates the unconditional effect of gender on risk tolerance. The coefficient associated with being a female is negative and statistically significant at the 1% level. Relative to men, women report a maximum acceptable loss that is approximately 9 percentage points lower, indicating a substantially lower tolerance for risk. Despite its parsimony, this model explains 8.5% of the variation in individual risk tolerance, which is meaningful for a behavioural outcome.

Building on this baseline, the next model introduces professional experience. While the coefficient is negative, suggesting that more experienced professionals tend to be more risk-averse, it does not reach conventional significance levels. In a similar vein, the next model incorporates a variable capturing direct client contact. This variable is positively associated with risk tolerance, but remains below standard significance thresholds.

The full specification combines professional experience and client contact and yields the highest explanatory power among the retained models (15,6%). In this specification, seniority becomes statistically significant, and client-facing roles are associated with a significantly higher tolerance for risk. Importantly, the coefficient on female remains negative, statistically significant, and very similar in magnitude to that observed in the previous models.

Overall, the results point to a robust and economically meaningful gender effect on risk tolerance, which persists across alternative specifications and is not explained by professional experience or job characteristics.

5.5.2 Overconfidence

Overconfidence is measured using a binary indicator, taking the value of one when respondents exhibit overconfident behaviour and zero otherwise. Given the dichotomous nature of the dependent variable, the analysis relies on logistic regression models, and the results are reported in terms of average marginal effects (AMEs) to facilitate interpretation. Table 15 reports the results of the logit regression models:

Table 15: Logit regression results (average marginal effects): Determinants of overconfidence

Dependent variable: Overconfidence (binary indicator)

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Female	−0.012 (0.111)	−0.003 (0.111)	−0.006 (0.111)	−0.011 (0.111)	−0.036 (0.115)
Age 36-55	-	0.050 (0.136)	-	-	-
Age 56+	-	0.110 (0.156)	-	-	-
Higher education	-	-	0.058 (0.105)	-	-
Senior experience	-	-	-	0.017 (0.125)	-
Client-facing role	-	-	-	-	−0.112 (0.145)
*** p<0.001, ** p < 0.01, * p<0.05					

Notes: Average marginal effects are reported with standard errors in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. The full specification model (reported in Appendix 7.2) exhibits implausible marginal effects and inflated standard errors, indicating estimation instability; it is therefore not retained for interpretation.
Source: survey data, processed using R

Across all model specifications, the average marginal effect associated with being a female is small in magnitude and statistically insignificant. Importantly, the estimated standard errors are substantially larger than the corresponding coefficients, indicating a lack of statistical precision and placing the estimates far from conventional significance thresholds.

Overall, these results provide no empirical evidence of a gender difference in overconfidence within the sample. The absence of statistical significance is not borderline but rather reflects coefficients that are small relative to their standard errors, reinforcing the conclusion that gender does not meaningfully affect the probability of being overconfident. These findings are consistent with the descriptive and non-parametric results.

5.5.3 Trading frequency

Trading frequency is measured using a binary indicator equal to one when respondents report trading frequently or very frequently, and zero otherwise. Given the dichotomous nature of the dependent variable, the analysis relies on logistic regression models. Results are reported in terms of average marginal effects (AMEs), which capture the change in the predicted probability of frequent trading associated with a one-unit change in each explanatory variable. Table 16 reports the results of the logit regression models for trading frequency.

Table 16: Logit regression results (average marginal effects): Determinants of trading frequency

	Dependent variable: Frequent trading (binary indicator)				
Independent variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Female	−0.123 (0.109)	−0.139 (0.108)	−0.116 (0.109)	−0.131 (0.108)	−0.200 (0.115)
Age 36-55	-	−0.114 (0.117)	-	-	-
Age 56+	-	−0.185 (0.147)	-	-	-
Higher education	-	-	0.073 (0.101)	-	-
Senior experience	-	-	-	−0.108 (0.112)	-
Client-facing role	-	-	-	-	−0.292* (0.126)
*** p<0.001, ** p < 0.01, * p<0.05					

Notes: Average marginal effects are reported with standard errors in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. The full specification model (reported in Appendix 7.3) exhibits implausible marginal effects and inflated standard errors, indicating estimation instability; it is therefore not retained for interpretation.
Source: survey data, processed using R

Across all specifications, the estimated marginal effect associated with gender is consistently negative. However, these effects are not statistically significant, indicating that no robust gender difference in trading frequency can be identified once controls are taken into account.

The inclusion of demographic controls (age, education) and professional characteristics (seniority, client contact) does not materially alter the estimated gender effect.

An exception arises in Model 5, where client-facing roles are associated with a significantly lower probability of frequent trading. This result may reflect a more advisory or long-term oriented investment approach among professionals in direct contact with clients.

Overall, the multivariate analysis does not provide conclusive evidence of a gender difference in trading frequency. These findings are consistent with the descriptive and non-parametric results reported earlier.

5.5.4 Investment horizon

Investment horizon is measured using a binary indicator equal to one when respondents report a long-term investment horizon, and zero otherwise. Given the dichotomous nature of the dependent variable, the analysis relies on logistic regression models. Results are reported in terms of average marginal effects (AMEs), which capture the change in the predicted probability of adopting a long-term investment horizon associated with a one-unit change in each explanatory variable. Table 17 reports the results of the logit regression models for investment horizon:

Table 17: Logit regression results (average marginal effects): Determinants of investment horizon

Dependent variable: Long-term investment horizon (binary indicator)

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Female	−0.147 (0.102)	−0.130 (0.101)	−0.155 (0.102)	−0.135 (0.101)	−0.096 (0.106)
Age 36-55	-	0.189 (0.115)	-	-	-
Age 56+	-	0.181 (0.144)	-	-	-
Higher education	-	-	−0.074 (0.104)	-	-
Senior experience	-	-	-	0.164 (0.109)	-
Client-facing role	-	-	-	-	0.229 (0.129)
*** p<0.001, ** p < 0.01, * p<0.05					

Notes: Average marginal effects are reported with standard errors in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. The full specification model (reported in Appendix 7.4) exhibits implausible marginal effects and inflated standard errors, indicating estimation instability; it is therefore not retained for interpretation.
Source: survey data, processed using R

Across all model specifications, no statistically significant gender differences are observed. The estimated marginal effects associated with gender are small in magnitude and remain far from conventional significance thresholds, even after controlling for demographic and professional characteristics.

None of the control variables exhibit robust associations with investment horizon, and the inclusion of additional covariates does not reveal any latent gender effect. Overall, the multivariate analysis does not support the existence of a systematic gender difference in investment horizon, in line with the descriptive and non-parametric evidence presented earlier.

5.5.5 Diversification

Portfolio diversification is proxied by the proportion of the portfolio invested in collective investment vehicles, namely funds and exchange-traded funds (ETFs). This measure captures the extent to which respondents rely on pooled investment instruments rather than direct holdings.

By construction, higher values indicate a greater reliance on funds and ETFs, which are commonly associated with broader diversification through exposure to a large number of underlying securities. Direct holdings are excluded from this measure, as they do not provide the same degree of automatic diversification.

Given the quantitative nature of the dependent variable, the analysis relies on ordinary least squares (OLS) regressions. Several model specifications are estimated in order to assess the robustness of the results to the inclusion of demographic and professional controls.

Table 18 presents the results of the OLS regressions analysing the determinants of portfolio diversification, proxied by the use of funds and ETFs:

Table: 18: Linear regression results: Determinants of diversification (Funds / ETFs)

Dependent variable: Portfolio share invested in funds and ETFs (%)

Independent variables	Model 1	Model 3	Model 5	Model 6
Intercept	74.118*** (3.142)	79.040*** (4.608)	61.019*** (7.303)	67.583*** (8.864)
Female	5.525 (5.277)	4.588 (5.219)	8.471 (5.390)	7.119 (5.467)
Higher education	-	−9.298 (4.993)	-	−6.795 (5.248)
Client-facing role	-	-	14.213* (7.183)	10.994 (7.571
R^2	0.014	0.057	0.062	0.083
Adjusted R^2	0.001	0.032	0.038	0.046
*** p<0.001, ** p < 0.01, * p<0.05				

Notes: Standard errors are reported in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. Models 2 and 4, which introduce age and experience respectively, do not improve the adjusted R^2 and are therefore not retained in the main analysis; the corresponding results are reported in Appendix 7.5.
Source: survey data, processed using R

Across all reported specifications, the estimated coefficient associated with gender is positive but statistically insignificant, indicating no robust difference between female and male professionals in the proportion of the portfolio invested in funds and ETFs. The lack of statistical significance, combined with relatively large standard errors and low explanatory power, prevents any meaningful economic interpretation of the estimated gender effect.

Model 3 shows a negative (but non-significant) association between higher education and the share invested in funds and ETFs. This effect remains negative in the full specification, although it does not reach conventional significance levels. By contrast, Model 5 indicates that client-facing roles are associated with a significantly higher proportion invested in funds and ETFs. This result suggests that professionals in direct contact with clients may rely more strongly on pooled investment instruments, potentially reflecting suitability considerations, institutional practices, or a preference for diversified "off-the-shelf" solutions. However, this effect becomes statistically insignificant once education is included in the full model, indicating that it should be interpreted with caution.

Overall, the multivariate analysis does not provide evidence of a robust gender difference in portfolio diversification when diversification is proxied by the proportion invested in funds and ETFs. These results are consistent with earlier descriptive and non-parametric findings and do not support the hypothesis that female professionals hold systematically more diversified portfolios (H5), at least within the scope of this proxy.

5.5.6 Investment style

Investment style preferences, including factor- and sector-based strategies, differ from the other behavioural outcomes examined in this section in that they are inherently multidimensional. Respondents may simultaneously adopt several investment styles or sector exposures, which are not mutually exclusive and cannot be meaningfully ordered along a single continuous or binary scale.

Given the limited sample size and the large number of potential style and sector categories, conducting multivariate regression analyses would require estimating a high number of parameters relative to the available observations. Such an approach would substantially increase the risk of overfitting and yield unstable estimates with limited interpretability.

In line with the parsimonious modelling strategy adopted throughout this section, and to preserve interpretability, investment style differences are therefore analysed using descriptive statistics and non-parametric tests, as presented in Section 5.4. These methods are better suited to capture gender-based differences in stylistic preferences without imposing restrictive parametric assumptions or generating misleading inference.

Accordingly, no multivariate robustness checks are reported for investment style preferences.

5.5.7 ESG preferences

The importance attached to ESG considerations is measured using the percentage of the portfolio invested according to ESG criteria. Given the continuous nature of the dependent variable, the analysis relies on ordinary least squares (OLS) regressions. Table 19 presents the results of the OLS regressions analysing the determinants of ESG investment intensity:

Table 19: Linear regression results: Determinants of ESG investment intensity

Dependent variable: ESG investment intensity (% of portfolio)

Independent variables	Model 1	Model 2	Model 4	Model 6 (Full model)
Intercept	16.569*** (3.418)	10.992* (6.275)	10.625* (6.086)	11.129* (6.304)
Female	18.360** (5.741)	19.392** (5.758)	18.891** (5.744)	19.085** (5.802)
Age 36-55	—	4.220 (6.847)	—	−11.129 (25.209)
Age 56+	—	12.788 (8.160)	—	−2.947 (26.179)
Senior experience	—	—	7.578 (6.429)	15.684 (24.783)
R^2	0.117	0.147	0.133	0.152
Adjusted R^2	0.106	0.113	0.110	0.106
*** p<0.001, ** p < 0.01, * p<0.05				

Notes: Standard errors are reported in parentheses. A dash (-) indicates that the variable is not included in the corresponding specification. Models 3 and 5, which introduce education and contact with clients respectively, do not improve the adjusted R² and are therefore not retained in the main analysis; the corresponding results are reported in Appendix 7.6.
Source: survey data, processed using R

Across all model specifications, the coefficient associated with gender is positive, large in magnitude, and statistically significant at the 1% level. Female professionals allocate, on average, approximately 18 to 19 percentage points more of their portfolios to ESG investments than their male counterparts. This effect is economically meaningful and remains remarkably stable across alternative specifications.

The inclusion of demographic controls such as age does not materially affect the estimated gender coefficient, and none of the age categories are robustly associated with ESG investment intensity. Similarly, senior professional experience is not statistically significant once included in the models.

While the full specification yields the highest R^2, the adjusted R^2 (0,106) does not improve relative to simpler models, suggesting that the additional controls do not substantially enhance explanatory power. Consistent with a parsimonious modelling strategy, the gender coefficient remains the primary driver of variation in ESG investment intensity.

Overall, the results provide strong and robust evidence of a gender difference in ESG preferences, with female professionals displaying a significantly higher propensity to allocate assets according to ESG criteria. These findings are consistent with the descriptive and non-parametric results presented earlier.

5.5.8 Summary of the results obtained throughout multivariate checks

This section has examined whether the gender differences identified in the descriptive and non-parametric analyses remain robust once demographic and professional characteristics are jointly taken into account. Depending on the nature of the dependent variables, OLS or logit models were estimated, with results interpreted cautiously in light of the relatively limited sample size and the behavioural nature of the outcomes.

Overall, the multivariate analyses confirm a heterogeneous pattern of gender effects across behavioural dimensions.

First, risk tolerance emerges as one of the most robust findings. Across all model specifications, female professionals report a significantly lower maximum acceptable loss than male professionals. This gender effect remains economically meaningful and statistically significant even after controlling for senior experience and client-facing roles, suggesting that differences in risk tolerance are not merely driven by these professional characteristics.

Second, ESG investment intensity also exhibits a strong and stable gender effect. Female professionals consistently allocate a substantially higher share of their portfolios to ESG investments than their male counterparts. This effect is large in magnitude, statistically significant across all specifications, and largely unaffected by the inclusion of demographic or professional controls. Among all outcomes examined, ESG preferences display the clearest and most robust gender-related difference.

By contrast, no robust gender effects are identified for overconfidence, trading frequency, investment horizon, or portfolio diversification once controls are introduced. In these cases, estimated gender coefficients are generally small relative to their standard errors and remain far from conventional significance thresholds. Importantly, the absence of significance reflects a lack of statistical precision rather than borderline effects, reinforcing the conclusion that gender does not play a meaningful role for these dimensions within the sample.

Some control variables display occasional associations, most notably client-facing roles in certain specifications, but these effects are not consistently robust across models and should therefore be interpreted with caution.

Taken together, the multivariate robustness checks largely corroborate the earlier findings. Gender differences among our sample of financial professionals appear selective rather than pervasive, being concentrated primarily in risk tolerance and ESG-related investment behaviour, while other behavioural outcomes show no systematic gender patterns once observable characteristics are accounted for. These results highlight the importance of distinguishing between behavioural dimensions when assessing gender effects, rather than assuming uniform differences across all aspects of investment decision-making.

6 IMPLICATIONS AND DISCUSSION

This thesis tested seven hypotheses related to gender differences in investment behaviour among finance professionals. The empirical results indicate that only one hypothesis is clearly validated, one is partially supported, while the remaining hypotheses are not supported by the data. Rather than leading to a definitive conclusion, these findings invite a broader discussion on the role of professional context, institutional constraints, and individual heterogeneity in shaping investment behaviour.

Overall, the results suggest that gender-based differences in investment behaviour are substantially attenuated in a professional setting. With the notable exceptions of maximum acceptable loss and ESG investment intensity, the analyses do not reveal robust gender differences in portfolio composition, investment styles, diversification strategies, overconfidence, trading frequency, or investment horizon. This pattern contrasts with a large body of literature documenting pronounced gender effects among individual investors and supports the idea that professionalisation acts as a powerful homogenising force.

Several mechanisms may explain this attenuation. Professional investors operate within institutional frameworks characterised by formal risk controls, investment committees, regulatory constraints, and performance benchmarks. These elements limit the scope for idiosyncratic behaviour and reduce the expression of individual behavioural biases, regardless of gender. The acquisition of similar technical skills, common analytical frameworks, and exposure to comparable market information may further contribute to the convergence of decision-making practices.

At the same time, the persistence of gender differences in risk tolerance and ESG preferences suggests that professionalisation does not entirely erase behavioural heterogeneity. Female professionals report a lower maximum acceptable loss, even after controlling for experience and job characteristics, indicating a more cautious approach to downside risk. Similarly, the higher allocation to ESG investments among women appears robust and economically meaningful. These findings are consistent with prior research linking gender to attitudes toward risk and sustainability, while showing that such differences manifest selectively rather than uniformly.

Importantly, these remaining differences should not be interpreted in normative or hierarchical terms. A slightly higher risk tolerance among men and a stronger emphasis on ESG considerations among women may reflect complementary perspectives rather than opposing investment philosophies. In contexts such as asset management teams or financial advisory services, this diversity of approaches can enhance decision-making quality by balancing risk-taking with long-term responsibility and sustainability considerations.

However, the interpretation of these results must remain cautious. The relatively small sample size and its specific composition limit the external validity of the findings. Moreover, the cross-sectional nature of the data precludes any causal interpretation of the observed associations. The absence of statistically significant gender effects for several behavioural dimensions should therefore not be interpreted as definitive evidence of equality in all professional contexts, but rather as an indication that such differences are not detectable within the scope of this study.

From a broader perspective, these findings contribute to the ongoing debate on gender and finance by suggesting that observed gender gaps in investment behaviour may be context-dependent. While gender appears to play a meaningful role among retail investors, its explanatory power diminishes in professional environments shaped by strong institutional and organisational constraints.

Ultimately, these results invite a shift in perspective, from gender-based explanations toward an analysis of the institutional conditions that shape individual behaviour. Rather than asking whether men or women invest "better," the relevant question becomes how professional environments can harness diverse perspectives to improve risk management, sustainability integration, and long-term investment outcomes.

7 CONCLUSION

This thesis set out to examine whether the gender differences in investment behaviour extensively documented in the behavioural finance literature persist when financial decisions are made in a professional context. While traditional finance models assume rational decision-making based on quantitative information, behavioural finance has shown that investment choices are often shaped by cognitive biases, emotions, and social factors. Gender has been repeatedly identified as a key dimension influencing these behaviours, contributing to persistent stereotypes opposing risk-seeking, overconfident male investors to more cautious female investors. This study questioned the relevance of such representations within the context of professional investment decision-making, where expertise, institutional constraints, and regulatory frameworks play a central role.

To address the research question, this thesis followed a structured approach. It first established the theoretical and empirical background by reviewing the literature on traditional and behavioural finance, with particular emphasis on gender-related investment behaviour and the role of institutional and organisational factors. It then presented the research design, data collection process, and statistical methodology underlying the empirical analysis. The results section reported hypothesis testing, and multivariate robustness checks based on original survey data collected from investment professionals. Finally, the discussion section interpreted these findings in light of existing literature, highlighting their implications as well as the main limitations of the study.

The empirical analysis, based on original survey data collected from investment professionals, provides a nuanced answer to this question. Across most behavioural and investment-related dimensions examined (risk tolerance, overconfidence, trading frequency, investment horizon, diversification, investment style and ESG considerations), gender differences appear substantially reduced or statistically insignificant once the professional context is taken into account. While some descriptive differences emerge, they generally do not persist once formal statistical tests and robustness checks are applied. These findings suggest that institutional norms, formalised decision-making processes, and performance constraints significantly limit the expression of individual behavioural biases.

Beyond the interpretation of results, this research also calls for a critical reflection on its own methodological choices. The concentration of the sample within a limited number of institutions, and in particular within a dominant organisational culture, constitutes a genuine limitation that may influence observed behaviours. While structural tests and control variables were used to assess and partially mitigate this effect, the external validity of the findings remains constrained. With hindsight, a broader and more balanced institutional sampling strategy would have strengthened the representativeness of the study. Similarly, complementing self-reported survey data with observed behavioural or transactional data would have further enhanced the robustness of the conclusions.

Despite these limitations, the study highlights an important insight: behavioural patterns commonly attributed to gender may be highly context-dependent rather than intrinsic. In professional environments characterised by standardisation, oversight and accountability, individual differences appear less salient than the institutional structures within which decisions are made.

Looking ahead, future research could build on this work by using larger and more diverse samples, adopting longitudinal approaches, and integrating organisational and team-level dynamics. Such extensions would help further disentangle the respective roles of gender, professional socialisation and institutional context in shaping investment behaviour. By shifting the focus from individual traits to structural environments, this line of research offers promising avenues for a more nuanced understanding of behaviour in professional finance.

8 APPENDIXES

8.1 APPENDIX 1 : THE QUESTIONNAIRE (EN VERSION)

Stereotypes and Financial Decisions: Clichés or Reality Among Experts?

Hello,

My name is Camille, and I am currently in my final year of a Master's degree in **Banking & Asset Management** at **HEC Liège**.

The last step before fully entering my professional career is the writing of my master's thesis, which focuses on:
"Investment Behaviors Among Finance Professionals."

Your participation in this questionnaire is extremely valuable — and even essential — to the success of this research project.

I would like to warmly thank you in advance for the time you will dedicate to it 🙏

A few important details:

- The questionnaire is **completely anonymous** — no personal data is collected.
- The responses will be used **solely for academic purposes** within the framework of my master's thesis.
- The estimated completion time is **about 10 minutes**.

Thank you once again for your help and contribution to this project.

Camille

There are 27 questions in this survey.

THIS SURVEY IS ANONYMOUS.
The record of your survey responses does not contain any identifying information about you, unless a specific survey question explicitly asked for it.
If you used an identifying access code to access this survey, please rest assured that this code will not be stored together with your responses. It is managed in a separate database and will only be updated to indicate whether you did (or did not) complete this survey. There is no way of matching identification access codes with survey responses.

Next

Made in LimeSurvey

Part 1: Demographic Information

* 1
What is your gender?

Choose one of the following answers

- ○ Female
- ○ Male
- ○ Prefer not to answer

* 2
What is your age group?

Choose one of the following answers

- ○ 18–25 years old
- ○ 26–35 years old
- ○ 36–45 years old
- ○ 46–55 years old
- ○ 56–65 years old
- ○ Over 66 years old

* 3
What is your level of education?

Choose one of the following answers

- ○ Secondary education / High school diploma
- ○ Bachelor’s degree
- ○ Master’s degree
- ○ Doctorate / PhD

* 4

What is your current position?

Please select the option that best matches your main role:

Choose one of the following answers

Please choose...

* 5

Which financial institution do you currently work for?

Choose one of the following answers

Please choose...

* 6

How long have you been working in the financial sector?

Choose one of the following answers

- ○ Less than 2 years
- ○ 2–5 years
- ○ 6–10 years
- ○ 10–15 years
- ○ More than 15 years

* 7

Are you in direct contact with clients?

Yes No

Part 2: Investment Budget Allocation

8

Global Allocation

If you had to define a strategic allocation for a hypothetical portfolio of €1,000,000, how would you currently distribute this amount among the following major asset classes?

Only numbers may be entered in these fields.

The total must equal 100% (currently 0%).

Equities	
Bonds	
Cash	
Alternatives	

9

Equity Allocation by Region

How would you currently allocate the equity portion of your portfolio by geographic region?

The total must equal 0% or 100% (currently 0%).

	%
United States	
Europe	
Japan	
Developed Asia ex-Japan	
Emerging Markets	

10

Equity Allocation by Sector

How would you currently allocate the equity portion of your portfolio by sector?

The total must equal 0% or 100% (currently 0%).

	%
Energy	
Materials	
Industrials	
Consumer Discretionary	
Consumer Staples	
Healthcare	
Financials	
Information Technology	
Communication Services	
Utilities	
Real Estate	

11
Bond Allocation
How would you currently allocate the bond portion of your portfolio?

The total must equal 0% or 100% (currently 0%).

	%
Sovereign Bonds (USD)	
Sovereign Bonds (EUR)	
Corporate Bonds (USD)	
Corporate Bonds (EUR)	
Emerging Market Bonds	
Global Aggregate Bonds	

12
Alternatives Allocation
How would you currently allocate the "Alternative Assets" portion of your portfolio?

The total must equal 0% or 100% (currently 0%).

	%
Gold / Precious Metals	
Real Estate	
Commodities	
Hedge Funds	
Private Markets	
Digital Assets	

13
Allocation by Investment Vehicle
What proportion of your portfolio would you currently invest through each type of vehicle?

The total must equal 100% (currently 0%).

	%
Index Funds / ETFs	
Active Funds	
Individual Securities	

∗ 14

Factor Preferences (Europe)

Indicate your current allocation preference using a scale from **−2 to +2**:
−2 = Strong preference for the left-hand pole
−1 = Moderate preference for the left-hand pole
0 = No preference (neutral)
+1 = Moderate preference for the right-hand pole
+2 = Strong preference for the right-hand pole

	-2	-1	0	+1	+2
Small Caps ←→ Large Caps	○	○	○	○	○
Value ←→ Growth	○	○	○	○	○
High Quality / Profitability ←→ Low	○	○	○	○	○
Conservative Companies ←→ Aggressive	○	○	○	○	○
Weak Momentum (Mean Reversion) ←→ Strong Momentum (Trend Following)	○	○	○	○	○

∗ 15

Factor Preferences (United States)

Indicate your current allocation preference using a scale from **−2 to +2**:
−2 = Strong preference for the left-hand pole
−1 = Moderate preference for the left-hand pole
0 = No preference (neutral)
+1 = Moderate preference for the right-hand pole
+2 = Strong preference for the right-hand pole

	-2	-1	0	+1	+2
Small Caps ←→ Large Caps	○	○	○	○	○
Value ←→ Growth	○	○	○	○	○
High Quality / Profitability ←→ Low	○	○	○	○	○
Conservative Companies ←→ Aggressive	○	○	○	○	○
Weak Momentum (Mean Reversion) ←→ Strong Momentum (Trend Following)	○	○	○	○	○

∗ 16

Factor Preferences (Emerging Markets)

Indicate your current allocation preference using a scale from **−2 to +2**:
−2 = Strong preference for the left-hand pole
−1 = Moderate preference for the left-hand pole
0 = No preference (neutral)
+1 = Moderate preference for the right-hand pole
+2 = Strong preference for the right-hand pole

	-2	-1	0	+1	+2
Small Caps ←→ Large Caps	○	○	○	○	○
Value ←→ Growth	○	○	○	○	○
High Quality / Profitability ←→ Low	○	○	○	○	○
Conservative Companies ←→ Aggressive	○	○	○	○	○
Weak Momentum (Mean Reversion) ←→ Strong Momentum (Trend Following)	○	○	○	○	○

Part 3: Behavioral Dimensions

* 17

General Risk Tolerance
What level of risk would you be willing to accept in managing your portfolio?

Choose one of the following answers

○ 1 – Very conservative: you prioritize maximum safety, with low returns and virtually no capital loss.

○ 2 – Rather conservative: you accept small fluctuations and limited losses for slightly higher returns.

○ 3 – Balanced: you are comfortable with moderate volatility and temporary losses in exchange for reasonable potential returns.

○ 4 – Dynamic: you accept significant volatility and short-term losses to seek higher long-term returns.

○ 5 – Very aggressive: you aim for maximum return, even if it involves high volatility and a significant risk of loss.

* 18

Sensitivity to Extreme Risks
On a scale of 1 to 6, indicate your tolerance toward extreme losses (low-probability but high-impact scenarios):

Choose one of the following answers

○ 1 – Zero tolerance: I refuse any extreme loss risk, even rare.

○ 2 – Very low tolerance: I only accept minimal exceptional losses.

○ 3 – Low tolerance: I accept rare but moderate losses.

○ 4 – Medium tolerance: I accept that an extreme scenario could have a significant temporary impact.

○ 5 – High tolerance: I accept potential extreme losses if they increase my chance of high returns.

○ 6 – Maximum tolerance: I fully accept the risk of extreme losses in exchange for maximum potential gains.

* 19

Maximum Acceptable Loss
What maximum loss (in %) would you be willing to accept over a one-year horizon?

Only numbers may be entered in this field.

* 20

Reaction to Shocks — Scenario 1
Equity markets fall by 20% in 3 months. What would be your investment reaction?

Choose one of the following answers

○ Significant reduction in equity exposure (≥ −20%)

○ Minor adjustment in exposure (−5% to −10%)

○ Maintain current allocation

○ Increase exposure

∗ 21

Reaction to Shocks — Scenario 2

Interest rates rise by +150 basis points in 6 months, causing a decline of about 8% in long-term bonds. What would be your reaction?

Choose one of the following answers

- ◯ Significant reduction in bond duration (sell long-term bonds in favor of shorter maturities)
- ◯ Maintain current duration (you consider the increase temporary)
- ◯ Gradually increase bond exposure to benefit from higher yields

∗ 22

Investment Horizon

What is your average investment horizon?

Choose one of the following answers

- ◯ Short-term (0–2 years)
- ◯ Medium-term (3–7 years)
- ◯ Long-term (8+ years)

∗ 23

Self-Confidence

Compared to your peers, your investment decisions are on average:

Choose one of the following answers

- ◯ Less performant (1)
- ◯ Similar (2)
- ◯ More performant (3)

∗ 24

ESG

What proportion of your portfolio would you allocate to ESG investments? (in %)

Only numbers may be entered in this field.

∗ 25

ESG

When integrating ESG criteria into your investment decisions, what is your main approach?

Choose one of the following answers

○ I follow my institution's ESG policy

○ I apply ESG criteria according to my personal convictions

○ I combine both approaches

○ I do not consider ESG criteria

∗ 26

ESG

Compared to traditional investments, what financial performance do you expect from ESG investments?

Choose one of the following answers

○ 1 – Significantly lower

○ 2 – Slightly lower

○ 3 – Comparable

○ 4 – Slightly higher

○ 5 – Significantly higher

∗ 27

Active Trading Frequency

How often do you adjust your portfolios?

Choose one of the following answers

○ Rarely (1–2 times per year)

○ Regularly (each quarter)

○ Frequently (each month)

○ Very frequently (weekly or more)

Thanks to your participation, I am advancing toward the final stage of my academic journey and will be able to conduct a more precise analysis of investment behaviors in the financial sector.

All collected data will, of course, remain 100% anonymous and confidential.

Once again, a huge thank-you for the time and attention you have devoted to this questionnaire.

Camille

8.2 Appendix 2: Age repartition in the financial and insurance activities sector (Eurostat)

Appendix table 1: Age repartition finance and insurance sectors

GEO	AGE	2024
Belgium	From 15 to 24 years	2.8 (u)
Belgium	From 25 to 49 years	89.2
Belgium	From 50 to 64 years	55.4
Belgium	65 years or over	: (u)
Luxembourg	From 15 to 24 years	: (u)
Luxembourg	From 25 to 49 years	29.6
Luxembourg	From 50 to 64 years	9.9
Luxembourg	65 years or over	: (u)

Source: Eurostat, Data Browser

8.3 APPENDIX 3: OVERALL DISTRIBUTION OF ALLOCATION BY ASSET CLASS

Appendix table 2: Overall distribution of allocation by asset class

STRATEGIC ALLOCATION BY ASSET CLASS	MEAN	MEDIAN	MINIMUM	MAXIMUM	STAND. DEV.
EQUITIES	**60,57%**	**60,00%**	**25,00%**	**100,00%**	**14,41%**
BONDS	**22,53%**	**25,00%**	**0,00%**	**50,00%**	**12,27%**
CASH	**7,27%**	**5,00%**	**0,00%**	**25,00%**	**5,71%**
ALTERNATIVE ASSETS	**9,63%**	**10,00%**	**0,00%**	**38,00%**	**7,63%**
Equities US	44,22%	45,00%	0,00%	80,00%	13,26%
Equities Europe	30,87%	30,00%	0,00%	70,00%	10,04%
Equities Japan	5,94%	5,00%	0,00%	25,00%	5,14%
Equities Dev. Asia	8,87%	10,00%	0,00%	30,00%	6,16%
Equities EM	10,09%	10,00%	0,00%	30,00%	6,48%
Sovereign bonds US	11,24%	10,00%	0,00%	50,00%	10,89%
Sovereign bonds EUR	16,11%	10,00%	0,00%	70,00%	15,29%
Corporate bonds US	16,85%	20,00%	0,00%	60,00%	13,79%
Corporate bonds EUR	29,73%	30,00%	0,00%	100,00%	19,35%
EM bonds	11,90%	10,00%	0,00%	100,00%	13,29%
Global Aggregate bonds	7,84%	5,00%	0,00%	100,00%	13,51%
Gold/Precious Metals	28,23%	25,00%	0,00%	100,00%	24,25%
Real Estate	12,96%	10,00%	0,00%	50,00%	13,38%
Commodities	13,66%	15,00%	0,00%	50,00%	11,90%
Hedge Funds	8,42%	0,00%	0,00%	40,00%	10,80%
Private Markets	20,91%	20,00%	0,00%	100,00%	21,76%
Digital Assets	8,23%	0,00%	0,00%	100,00%	14,83%

Source: survey data, processed using R

8.4 APPENDIX 4: MANN-WHITNEY TEST ON AVERAGE PORTFOLIOS

Appendix table 3: Mann Whitney test on average portfolios

Asset classes	Median Men	Median Women	p-value	p-value BH
Equities US	0.29	0.23	0.044404	0.266422
Equities Europe	0.16	0.21	0.000876	0.015759
Equities Japan	0.03	0.03	0.613155	0.702321
Equities Dev. Asia	0.05	0.04	0.131428	0.394283
Equities EM	0.05	0.06	0.102666	0.369596
Sovereign bonds US	0.02	0.02	0.702321	0.702321
Sovereign bonds EUR	0.03	0.03	0.633278	0.702321
Corporate bonds US	0.03	0.03	0.414985	0.634389
Corporate bonds EUR	0.07	0.06	0.422926	0.634389
EM bonds	0.02	0.02	0.282692	0.565384
Global Aggregate bonds	0.01	0.00	0.169516	0.435898
Gold/Precious Metals	0.03	0.01	0.023730	0.213573
Real Estate	0.01	0.01	0.519292	0.676762
Commodities	0.01	0.02	0.224110	0.504247
Hedge Funds	0.00	0.01	0.076042	0.342189
Private Markets	0.01	0.01	0.526370	0.676762
Digital Assets	0.00	0.00	0.676588	0.702321
Cash	0.05	0.09	0.314470	0.566046

Source: survey data, processed using R

8.5 APPENDIX 5: FACTOR PREFERENCES: MEANS AND MEDIANS

Appendix table 4: Factor preferences: means and medians

Region	Style	Mean H	Mean F	Med H	Med F
Europe	Conservative ←→ Aggressive	0.431	0.357	0	1
	Weak Momentum ←→ Strong Momentum	0.314	−0.071	0	0
	High Quality ←→ Low	−0.529	−0.571	−1	−1
	Small Caps ←→ Large Caps	0.490	−0.143	1	0
	Value ←→ Growth	0.490	0.214	1	0.5
United States	Conservative ←→ Aggressive	0.765	0.714	1	1
	Weak Momentum ←→ Strong Momentum	0.471	0.464	0	0.5
	High Quality ←→ Low	−0.059	−0.071	0	0
	Small Caps ←→ Large Caps	0.451	0	0	0
	Value ←→ Growth	0.843	0.714	1	1
Emerging Markets	Conservative ←→ Aggressive	0.275	0.429	0	0
	Weak Momentum ←→ Strong Momentum	0.333	0.357	0	0
	High Quality ←→ Low	−0.196	−0.464	0	−0.5
	Small Caps ←→ Large Caps	0.706	0.214	1	0
	Value ←→ Growth	0.490	−0.143	1	0

Source: survey data, processed using R

8.6 APPENDIX 6: DESCRIPTIVE STATISTICS

8.6.1 Risk tolerance

"Normal" Risk Tolerance

Appendix table 5: Observed Distributions - "Normal" Risk

Risk tolerance profiles	Men	Women
1 - Very conservative	0%	0%
2 - Rather conservative	1,96%	3,57%
3 - Balanced	13,73%	21,43%
4 - Dynamic	64,71%	64,29%
5 - Very aggressive	19,61%	10,71%

Source: survey data, processed using Excel

Extreme Risk Tolerance

Appendix table 6: Observed Distributions - Extreme Risk

Risk tolerance profiles (extreme risk)	Men	Women
1 - No tolerance	0%	10,71%
2 - Very low tolerance	3,92%	0%
3 - Balanced tolerance	5,88%	7,14%
4 - Medium tolerance	33,33%	39,29%
5 - High tolerance	49,02%	39,29%
6 - Maximum tolerance	7,84%	3,57%

Source: survey data, processed using Excel

Maximum Acceptable Loss

Appendix table 7: Distribution of Maximum Acceptable Losses

Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
5	20	30	27,68	30	100

Source: survey data, processed using R

Appendix table 8: Observed Distributions - Maximum Acceptable Losses

Loss acceptable	Men	Women
5%	0,00%	3,57%
7%	0,00%	3,57%
10%	5,88%	14,29%
15%	11,76%	10,71%
20%	15,69%	21,43%
25%	5,88%	10,71%
30%	27,45%	28,57%
35%	1,96%	3,57%
40%	19,61%	3,57%
50%	5,88%	0,00%
60%	3,92%	0,00%
100%	1,96%	0,00%

Source: survey data, processed using Excel

8.6.2 Overconfidence

Appendix table 9: Observed Distributions - Overconfidence

Level of confidence	Men	Women
1 - Less performant	1,96%	0%
2 - Similar	64,71%	67,86%
3 - More performant	33,33%	32,14%

Source: survey data, processed using Excel

8.6.3 Trading frequency

Appendix table 10: Observed Distributions - Trading Frequency

Frequency	Men	Women
Rarely (1-2/year)	41,18%	50,00%
Regularly (quarterly)	25,49%	28,57%
Frequently (monthly)	29,41%	10,71%
Very frequently (weekly or more)	3,92%	10,71%

Source: survey data, processed using Excel

8.6.4 Investment horizon

Appendix table 11: Observed Distributions - Investment Horizon

Gender	Short (0-2years)	Medium (3-7years)	Long (years and more)
Men	2%	25%	73%
Women	7%	36%	57%

Source: survey data, processed using Excel

8.6.5 Diversification

Appendix table 12: Observed Distributions - Investment vehicles

Vehicles	Men	Women
ETF vehicles	48,14%	52,39%
Fund vehicles	25,98%	27,25%
Direct holdings	25,88%	20,36%

Source: survey data, processed using Excel

8.6.6 Sector preferences

Appendix table 13: Observed Distributions - Sectors allocation

Sectors	Men Mean (%)	Women Mean (%)
Energy	9,66	11,36
Materials	7,39	9,29
Industrials	8,96	9,21
Consumer Discretionary	6,07	6,64
Consumer Staples	6,49	5,11
Health Care	11,00	12,20
Financials	11,10	11,00
Information Technology	23,70	17,20
Communication Services	5,92	8,36
Utilities	4,03	3,93
Real Estate	5,74	5,75

Source: survey data, processed using Excel

Appendix table 14: Observed Distributions - Defensive vs Cyclical

Sectors	Men	Women
Defensive (Energy, Consumer staples, Healthcare and Utilities)	31,16%	32,57%
Cyclical (Materials, Industrials, Consumer discretionary, Financials, Information technology, Consumer services, real estate)	68,84%	67,43%

Source: survey data, processed using Excel
According to MSCI classification

8.6.7 ESG

Appendix table 15: Observed Distributions - ESG Allocation

ESG proportion	Women	Men
0%	14,29%	45,10%
10%	3,57%	7,84%
15%	7,14%	3,92%
20%	14,29%	7,84%
23%	3,57%	0,00%
25%	3,57%	11,76%
30%	21,43%	9,80%
40%	3,57%	7,84%
50%	10,71%	1,96%
70%	3,57%	0,00%
80%	3,57%	0,00%
85%	0,00%	1,96%
90%	3,57%	0,00%
100%	7,14%	1,96%

Source: survey data, processed using Excel

Appendix table 16: Observed Distributions - ESG Approach

Preferred approach	Men	Women
Personal convictions	5,88%	0,00%
Following institutional ESG policy	31,37%	50,00%
Combining both	9,80%	25,00%
Not taking ESG criteria into account	52,94%	25,00%

Source: survey data, processed using Excel

Appendix table 17: Observed Distributions - Expected ESG Performance

Expected performance	Men	Women
1 - Significantly lower	19,61%	7,14%
2 - Slightly lower	29,41%	35,71%
3 - Comparable	43,14%	42,86%
4 - Slightly higher	7,84%	10,71%
5 - Significantly higher	0,00%	3,57%

Source: survey data, processed using Excel

8.7 APPENDIX 7: PREVIOUS MODEL SPECIFICATIONS (MULTIVARIATE CHECKS)

8.7.1 Appendix 7.1: Risk tolerance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	30.980 ***	32.332 ***	30.699 ***	35.945 ***	24.868 ***	28.575 ***
	(1.928)	(3.577)	(2.552)	(3.395)	(4.529)	(4.637)
gender_female	-9.302 **	-9.622 **	-9.248 **	-9.745 **	-7.927 *	-7.791 *
	(3.238)	(3.282)	(3.274)	(3.204)	(3.343)	(3.237)
age_36_55		-0.557				
		(3.902)				
age_56_more		-4.104				
		(4.651)				
edu_high			0.531			
			(3.132)			
exp_senior				-6.330		-9.114 *
				(3.586)		(3.702)
contact_clients					6.633	10.367 *
					(4.455)	(4.572)
R^2	0.097	0.109	0.097	0.132	0.122	0.188
Adj. R^2	0.085	0.073	0.073	0.110	0.099	0.156
Num. obs.	79	79	79	79	79	79

*** p < 0.001; ** p < 0.01; * p < 0.05

8.7.2 Appendix 7.2: Overconfidence

	AME (1)	AME (2)	AME (3)	AME (4)	AME (5)	AME (6)
gender_female	-0.012	-0.003	-0.006	-0.011	-0.036	-0.011
	(0.111)	(0.111)	(0.111)	(0.111)	(0.115)	(0.115)
age_36_55		0.050				3.521
		(0.136)				(305.812)
age_56_more		0.110				3.602
		(0.156)				(305.812)
edu_high			0.058			0.040
			(0.105)			(0.113)
exp_senior				0.017		-3.427
				(0.125)		(305.812)
contact_clients					-0.112	-0.147
					(0.145)	(0.156)

*** p < 0.001; ** p < 0.01; * p < 0.05

8.7.3 Appendix 7.3: Trading frequency

	AME (1)	AME (2)	AME (3)	AME (4)	AME (5)	AME (6)
gender_female	-0.123	-0.139	-0.116	-0.131	-0.200	-0.208
	(0.109)	(0.108)	(0.109)	(0.108)	(0.115)	(0.116)
age_36_55		-0.114				-2.834
		(0.117)				(274.670)
age_56_more		-0.185				-2.910
		(0.147)				(274.673)
edu_high			0.073			-0.000
			(0.101)			(0.108)
exp_senior				-0.108		2.801
				(0.112)		(274.672)
contact_clients					-0.292 *	-0.264
					(0.126)	(0.140)

*** p < 0.001; ** p < 0.01; * p < 0.05

Appendix 7.4: Investment horizon

	AME (1)	AME (2)	AME (3)	AME (4)	AME (5)	AME (6)
gender_female	-0.147	-0.130	-0.155	-0.135	-0.096	-0.090
	(0.102)	(0.101)	(0.102)	(0.101)	(0.106)	(0.108)
age_36_55		0.189				3.053
		(0.115)				(295.516)
age_56_more		0.181				3.045
		(0.144)				(295.518)
edu_high			-0.074			0.005
			(0.104)			(0.112)
exp_senior				0.164		-2.918
				(0.109)		(295.517)
contact_clients					0.229	0.173
					(0.129)	(0.145)

*** p < 0.001; ** p < 0.01; * p < 0.05

8.7.4 Appendix 7.5: Diversification

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	74.118 ***	75.341 ***	79.040 ***	73.984 ***	61.019 ***	67.583 ***
	(3.142)	(5.862)	(4.068)	(5.646)	(7.303)	(8.864)
gender_female	5.525	5.482	4.588	5.537	8.471	7.119
	(5.277)	(5.379)	(5.219)	(5.328)	(5.390)	(5.467)
age_36_55		-2.137				
		(6.396)				
age_56_more		-0.197				
		(7.623)				
edu_high			-9.298			-6.795
			(4.993)			(5.248)
exp_senior				0.170		
				(5.963)		
contact_clients					14.213	10.994
					(7.183)	(7.571)
R^2	0.014	0.016	0.057	0.014	0.062	0.083
Adj. R^2	0.001	-0.023	0.032	-0.012	0.038	0.046
Num. obs.	79	79	79	79	79	79

*** p < 0.001; ** p < 0.01; * p < 0.05

8.7.5 Appendix 7.6: ESG

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	16.569 ***	10.992	17.421 ***	10.625	10.618	10.035
	(3.418)	(6.275)	(4.523)	(6.086)	(8.111)	(7.893)
gender_female	18.360 **	19.392 **	18.198 **	18.891 **	19.698 **	18.981 **
	(5.741)	(5.758)	(5.802)	(5.744)	(5.987)	(5.831)
age_36_55		4.220				
		(6.847)				
age_56_more		12.788				
		(8.160)				
edu_high			-1.610			0.699
			(5.551)			(5.898)
exp_senior				7.578		7.858
				(6.429)		(6.889)
contact_clients					6.457	
					(7.978)	
R^2	0.117	0.147	0.118	0.133	0.125	0.133
Adj. R^2	0.106	0.113	0.095	0.110	0.102	0.099
Num. obs.	79	79	79	79	79	79

*** p < 0.001; ** p < 0.01; * p < 0.05

8.8 APPENDIX 8 : R CODES

8.8.1 Structural tests (5.1.7)

```
> library(readxl)
> library(dplyr)
> library(janitor)
> library(stringr)
> library(purrr)
> library(tibble)
> library(writexl)
>
>
> df <- read_excel("structural_tests.xlsx", sheet = "sheet1") %>%
+   clean_names() %>%
+   mutate(across(everything(), ~ str_squish(as.character(.)))) %>%
+   filter(!is.na(genre), genre != "") %>%
+   mutate(
+     genre = case_when(
+       str_to_lower(genre) %in% c("femme", "female", "f") ~ "Femme",
+       str_to_lower(genre) %in% c("homme", "male", "m") ~ "Homme",
+       TRUE ~ genre
+     ),
+     genre = factor(genre)
+   )
New names:
• `` -> `...8`
• `` -> `...9`
• `` -> `...10`
>
> vars_to_test <- c("age", "etudes", "fonction", "institution", "experience", "contact_clients")
> vars_to_test <- vars_to_test[vars_to_test %in% names(df)]
> if (length(vars_to_test) == 0) stop("Aucune variable à tester ne correspond aux noms de colonnes après clean_names().")
>
> chi2_ok <- function(expected) {
+   v <- as.vector(expected)
+   all(v >= 1) && mean(v >= 5) >= 0.80
+ }
>
> run_test <- function(data, var_name) {
+   tmp <- data %>% filter(!is.na(.data[[var_name]]), .data[[var_name]] != "")
+   tab <- table(tmp$genre, tmp[[var_name]])
+
+   chi <- suppressWarnings(chisq.test(tab, correct = FALSE))
+   if (chi2_ok(chi$expected)) {
+     tibble(variable = var_name, test = "Chi-square (Pearson)", p_value = unname(chi$p.value))
+   } else {
+     tibble(variable = var_name, test = "Fisher exact", p_value = unname(fisher.test(tab)$p.value))
+   }
+ }
>
> results <- map_dfr(vars_to_test, ~ run_test(df, .x)) %>%
+   mutate(
+     p_value_fmt = format.pval(p_value, digits = 3, eps = 0.001),
+     conclusion = ifelse(p_value < 0.05, "Association significative", "Pas d'association")
+   )
>
```

```
> table4 <- results %>%
+   transmute(
+     Test = paste("Genre x", str_replace_all(variable, "_", " ")),
+     `Test statistique` = test,
+     `p-value` = p_value_fmt,
+     Conclusion = conclusion
+   )
>
> print(table4)
# A tibble: 6 x 4
  Test                     `Test statistique`   `p-value` Conclusion
  <chr>                    <chr>                <chr>     <chr>
1 Genre x age              Chi-square (Pearson) 0.5754    Pas d'association
2 Genre x etudes           Chi-square (Pearson) 0.3912    Pas d'association
3 Genre x fonction         Fisher exact         0.0884    Pas d'association
4 Genre x institution      Fisher exact         0.5069    Pas d'association
5 Genre x experience       Fisher exact         0.6147    Pas d'association
6 Genre x contact clients  Fisher exact         0.0214    Association significative
>
> write_xlsx(list(Table4 = table4), path = "structural_tests_results.xlsx")
> 
```

8.8.2 Global allocation (5.2.2)

```
> # Chargement des packages
> library(readxl)
> library(dplyr)
> library(purrr)
>
> # Import des données
> survey_calc <- read_excel("Survey_Calculs.xlsx") %>%
+     mutate(genre = factor(genre))
>
> # Liste des classes d'actifs (allocations en % du portefeuille)
> vars_alloc <- c(
+     "actions_us",
+     "actions_europe",
+     "actions_japon",
+     "actions_asie_dev",
+     "actions_emergents",
+     "obl_sov_usd",
+     "obl_sov_eur",
+     "obl_corp_usd",
+     "obl_corp_eur",
+     "obl_emerg",
+     "obl_global_agg",
+     "alt_or_metaux_precieux",
+     "alt_immobilier",
+     "alt_matieres_premieres",
+     "alt_hedge_funds",
+     "alt_private",
+     "alt_actifs_numeriques",
+     "CASH"
+ )
>
> # On restreint aux variables réellement présentes dans la base
> vars_alloc_ok <- intersect(vars_alloc, names(survey_calc))
>
> # Fonction qui applique le test de Wilcoxon pour une classe d'actifs donnée
> test_alloc <- function(data, var) {
+     df_var <- data %>%
+         select(genre, all_of(var)) %>%
+         rename(val = !!var) %>%
+         filter(!is.na(genre), !is.na(val))
+
+     # Test de Wilcoxon (Mann-Whitney) non paramétrique
+     w <- wilcox.test(val ~ genre, data = df_var, exact = FALSE)
+
+     data.frame(
+         variable = var,
+         median_H = median(df_var$val[df_var$genre == "Homme"], na.rm = TRUE),
+         median_F = median(df_var$val[df_var$genre == "Femme"], na.rm = TRUE),
+         p_value  = w$p.value,
+         stringsAsFactors = FALSE
+     )
+ }
>
```

```
> # Application du test à l'ensemble des classes d'actifs
> res_alloc <- map_dfr(vars_alloc_ok, ~ test_alloc(survey_calc, .x)) %>%
+     mutate(
+         # Correction du risque d'erreur de type I (multiplicité) par Benjamini-Hochberg
+         p_adj_BH = p.adjust(p_value, method = "BH"),
+         # Mise en forme pour le tableau (p-values à 6 décimales, médianes arrondies)
+         p_value  = sprintf("%.6f", p_value),
+         p_adj_BH = sprintf("%.6f", p_adj_BH),
+         median_H = round(median_H, 2),
+         median_F = round(median_F, 2)
+     )
> res_alloc
                 variable median_H median_F  p_value p_adj_BH
1              actions_us     0.29     0.23 0.044404 0.266422
2          actions_europe     0.16     0.21 0.000876 0.015759
3           actions_japon     0.03     0.03 0.613155 0.702321
4         actions_asie_dev     0.05     0.04 0.131428 0.394283
5        actions_emergents     0.05     0.06 0.102666 0.369596
6             obl_sov_usd     0.02     0.02 0.702321 0.702321
7             obl_sov_eur     0.03     0.03 0.633278 0.702321
8            obl_corp_usd     0.03     0.03 0.414985 0.634389
9            obl_corp_eur     0.07     0.06 0.422926 0.634389
10              obl_emerg     0.02     0.02 0.282692 0.565384
11         obl_global_agg     0.01     0.00 0.169516 0.435898
12 alt_or_metaux_precieux     0.03     0.01 0.023730 0.213573
13         alt_immobilier     0.01     0.01 0.519292 0.676762
14 alt_matieres_premieres     0.01     0.02 0.224110 0.504247
15         alt_hedge_funds     0.00     0.01 0.076042 0.342189
16            alt_private     0.01     0.01 0.526370 0.676762
17  alt_actifs_numeriques     0.00     0.00 0.676588 0.702321
18                   CASH     0.05     0.09 0.314470 0.566046
```

➢ Strategic allocation profiles (5.2.3)

```
> profils_h <- c(
+     Conservative = 0,
+     Moderate     = 8,
+     Balanced     = 25,
+     Aggressive   = 18
+ )
>
> profils_f <- c(
+     Conservative = 1,
+     Moderate     = 4,
+     Balanced     = 12,
+     Aggressive   = 11
+ )
>
> tab_init <- rbind(
+     Homme = profils_h,
+     Femme = profils_f
+ )
>
> tab_init              # tableau de contingence brut
      Conservative Moderate Balanced Aggressive
Homme            0        8       25         18
Femme            1        4       12         11
```

```
> ## 2. Regroupement des profils peu représentés ---------------------------
>
> # Création d'une nouvelle catégorie "Peu_risque" = Conservative + Moderate
>
> tab_regroupe <- cbind(
+     Peu_risque = tab_init[, "Conservative"] + tab_init[, "Moderate"],
+     Balanced   = tab_init[, "Balanced"],
+     Aggressive = tab_init[, "Aggressive"]
+ )
>
> tab_regroupe
      Peu_risque Balanced Aggressive
Homme          8       25         18
Femme          5       12         11
```

```
> ## 3. Test du Khi-deux d'indépendance -----------------------------------
>
> # Test du χ² sans correction de continuité
> test_chi2 <- chisq.test(tab_regroupe, correct = FALSE)
Warning message:
In chisq.test(tab_regroupe, correct = FALSE) :
  Chi-squared approximation may be incorrect
> test_chi2

	Pearson's Chi-squared test

data:  tab_regroupe
X-squared = 0.27679, df = 2, p-value = 0.8708

>
> # Effectifs théoriques (vérification des conditions d'application)
> test_chi2$expected
      Peu_risque Balanced Aggressive
Homme   8.392405 23.88608   18.72152
Femme   4.607595 13.11392   10.27848
>
>
> ## 4. Test exact de Fisher (contrôle de robustesse) ---------------------
>
> test_fisher <- fisher.test(tab_regroupe)
> test_fisher

	Fisher's Exact Test for Count Data

data:  tab_regroupe
p-value = 0.8586
alternative hypothesis: two.sided
```

8.8.3 Factors preferences (5.3)

```
> library(readxl)
> library(dplyr)
> library(tidyr)
> library(ggplot2)
> library(effsize)
>
> # Données
> fichier <- "/Users/camm/Desktop/Survey_Fact.xlsx"
> feuille <- excel_sheets(fichier)[1]
> Survey_Fact <- read_excel(fichier, sheet = feuille) |>
+     filter(!is.na(genre)) |>
+     mutate(
+         genre = factor(genre, levels = c("Homme", "Femme")),
+         across(starts_with("fact_"), as.numeric)
+     )
>
> # Long format + région + style
> sf_long <- Survey_Fact |>
+     pivot_longer(
+         cols = starts_with("fact_"),
+         names_to  = "facteur",
+         values_to = "score"
+     ) |>
+     mutate(
+         region = case_when(
+             grepl("^fact_eu_", facteur) ~ "Europe",
+             grepl("^fact_us_", facteur) ~ "États-Unis",
+             grepl("^fact_em_", facteur) ~ "Marchés émergents",
+             TRUE ~ NA_character_
+         ),
+         style = case_when(
+             grepl("conserv_aggressive", facteur) ~ "Conservateur vs Agressif",
+             grepl("momentum",          facteur) ~ "Momentum",
+             grepl("quality",           facteur) ~ "Quality",
+             grepl("small_large",       facteur) ~ "Small vs Large",
+             grepl("value_growth",      facteur) ~ "Value vs Growth",
+             TRUE ~ NA_character_
+         ),
+         region = factor(region,
+                         levels = c("Europe", "États-Unis", "Marchés émergents")),
+         style  = factor(style,
+                         levels = c("Conservateur vs Agressif",
+                                    "Momentum",
+                                    "Quality",
+                                    "Small vs Large",
+                                    "Value vs Growth"))
+     ) |>
+     filter(!is.na(region), !is.na(style))
>
```

```
> # Boxplots globaux (tous répondants)
> p_facteurs_global <- ggplot(sf_long, aes(x = region, y = score)) +
+     geom_boxplot(fill = "lightblue", alpha = 0.7, outlier.alpha = 0.7) +
+     facet_wrap(~ style, ncol = 2) +
+     scale_y_continuous(breaks = -2:2, limits = c(-2.1, 2.1)) +
+     labs(x = "Zone géographique", y = "Score (-2 à +2)",
+          title = "Expositions factorielles par style et par zone") +
+     theme_minimal() +
+     theme(
+         strip.text = element_text(face = "bold"),
+         axis.text.x = element_text(angle = 30, hjust = 1)
+     )
>
> # print(p_facteurs_global)
>
> # Tests Mann-Whitney par facteur
> fact_cols <- names(Survey_Fact)[grepl("^fact_", names(Survey_Fact))]
>
> analyse_facteur <- function(var) {
+     x_F <- Survey_Fact |>
+         filter(genre == "Femme") |>
+         pull(var)
+     y_H <- Survey_Fact |>
+         filter(genre == "Homme") |>
+         pull(var)
+
+     test <- wilcox.test(y_H, x_F, exact = FALSE)
+     cd   <- cliff.delta(y_H, x_F)$estimate
+
+     reg <- case_when(
+         grepl("^fact_eu_", var) ~ "Europe",
+         grepl("^fact_us_", var) ~ "États-Unis",
+         grepl("^fact_em_", var) ~ "Marchés émergents",
+         TRUE ~ NA_character_
+     )
+
+     style <- case_when(
+         grepl("conserv_aggressive", var) ~ "Conservateur vs Agressif",
+         grepl("momentum",          var) ~ "Momentum",
+         grepl("quality",           var) ~ "Quality",
+         grepl("small_large",       var) ~ "Small vs Large",
+         grepl("value_growth",      var) ~ "Value vs Growth",
+         TRUE ~ NA_character_
+     )
+
+     tibble(
+         facteur      = var,
+         region       = reg,
+         style        = style,
+         mean_H       = mean(y_H, na.rm = TRUE),
+         mean_F       = mean(x_F, na.rm = TRUE),
+         median_H     = median(y_H, na.rm = TRUE),
+         median_F     = median(x_F, na.rm = TRUE),
+         delta_mean   = mean(y_H, na.rm = TRUE) - mean(x_F, na.rm = TRUE),
+         p_value      = test$p.value,
+         cliffs_delta = cd
+     )
+ }
>
```

```
> resultats_facteurs <- bind_rows(lapply(fact_cols, analyse_facteur)) |>
+     filter(!is.na(style)) |>
+     mutate(p_adj_BH = p.adjust(p_value, method = "BH")) |>
+     arrange(style, region)
>
> resultats_facteurs
# A tibble: 15 × 11
   facteur                     region            style             mean_H  mean_F median_H median_F delta_mean p_value cliffs_delta p_adj_BH
   <chr>                       <chr>             <chr>              <dbl>   <dbl>    <dbl>    <dbl>      <dbl>   <dbl>        <dbl>    <dbl>
 1 fact_eu_conserv_aggressive Europe            Conservateur v…   0.431   0.357        0      1       0.0742  0.948       0.00910   0.948
 2 fact_em_conserv_aggressive Marchés émergents Conservateur v…   0.275   0.429        0      0      -0.154   0.393      -0.110     0.778
 3 fact_us_conserv_aggressive États-Unis        Conservateur v…   0.765   0.714        1      1       0.0504  0.752       0.0399    0.948
 4 fact_eu_momentum            Europe            Momentum          0.314  -0.0714       0      0       0.385   0.190       0.167     0.568
 5 fact_em_momentum            Marchés émergents Momentum          0.333   0.357        0      0      -0.0238  0.868      -0.0210    0.948
 6 fact_us_momentum            États-Unis        Momentum          0.471   0.464        0      0.5     0.00630 0.678      -0.0532    0.948
 7 fact_eu_quality             Europe            Quality          -0.529  -0.571       -1     -1       0.0420  0.775      -0.0385    0.948
 8 fact_em_quality             Marchés émergents Quality          -0.196  -0.464        0     -0.5     0.268   0.419       0.107     0.778
 9 fact_us_quality             États-Unis        Quality          -0.0588 -0.0714       0      0       0.0126  0.937      -0.0112    0.948
10 fact_eu_small_large         Europe            Small vs Large    0.490  -0.143        1      0       0.633   0.0166      0.319     0.234
11 fact_em_small_large         Marchés émergents Small vs Large    0.706   0.214        1      0       0.492   0.0648      0.244     0.324
12 fact_us_small_large         États-Unis        Small vs Large    0.451   0            0      0       0.451   0.143       0.196     0.535
13 fact_eu_value_growth        Europe            Value vs Growth   0.490   0.214        1      0.5     0.276   0.227       0.157     0.568
14 fact_em_value_growth        Marchés émergents Value vs Growth   0.490  -0.143        1      0       0.633   0.0312      0.286     0.234
15 fact_us_value_growth        États-Unis        Value vs Growth   0.843   0.714        1      1       0.129   0.467       0.0952    0.778
>
>
```

8.8.4 Risk tolerance (5.4.1)

```
> Survey_final$risk_tolerance_num <- as.numeric(
+     gsub("[^0-9]", "", Survey_final$risk_tolerance)
+ )
>
> Survey_final$extreme_risk_tolerance_num <- as.numeric(
+     gsub("[^0-9]", "", Survey_final$extreme_risk_tolerance)
+ )
>
>
> ############################################################
> # 1. Tolérance au risque « normal »
> ############################################################
>
> ## 1.1. Distributions observées par genre (effectifs et pourcentages)
>
> tab_risque_normal <- table(Survey_final$genre, Survey_final$risk_tolerance_num)
> tab_risque_normal

         2  3  4  5
  Femme  1  6 18  3
  Homme  1  7 33 10
> addmargins(tab_risque_normal)

         2  3  4  5 Sum
  Femme  1  6 18  3  28
  Homme  1  7 33 10  51
  Sum    2 13 51 13  79
>
> prop_risque_normal <- prop.table(tab_risque_normal, margin = 1) * 100
> round(prop_risque_normal, 2)

            2     3     4     5
  Femme  3.57 21.43 64.29 10.71
  Homme  1.96 13.73 64.71 19.61
>
>
> ## 1.2. Test de Mann-Whitney (Wilcoxon rank-sum)
>
> test_risque_normal <- wilcox.test(
+     risk_tolerance_num ~ genre,
+     data       = Survey_final,
+     exact      = FALSE,       # approximation normale (n > 50)
+     conf.int   = TRUE,
+     conf.level = 0.95
+ )
>
> test_risque_normal

	Wilcoxon rank sum test with continuity correction

data:  risk_tolerance_num by genre
W = 606.5, p-value = 0.1969
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -9.453283e-06  4.415219e-05
sample estimates:
difference in location
         -2.748966e-06
```

```
> ##############################################################
> # 2. Tolérance au risque « extrême »
> ##############################################################
>
> ## 2.1. Distributions observées par genre
>
> tab_risque_extreme <- table(Survey_final$genre, Survey_final$extreme_risk_tolerance_num)
> tab_risque_extreme

         1  2  3  4  5  6
  Femme  3  0  2 11 11  1
  Homme  0  2  3 17 25  4
> addmargins(tab_risque_extreme)

         1  2  3  4  5  6 Sum
  Femme  3  0  2 11 11  1  28
  Homme  0  2  3 17 25  4  51
  Sum    3  2  5 28 36  5  79
>
> prop_risque_extreme <- prop.table(tab_risque_extreme, margin = 1) * 100
> round(prop_risque_extreme, 2)

            1     2     3     4     5     6
  Femme 10.71  0.00  7.14 39.29 39.29  3.57
  Homme  0.00  3.92  5.88 33.33 49.02  7.84
>
>
> ## 2.2. Test de Mann-Whitney
>
> test_risque_extreme <- wilcox.test(
+     extreme_risk_tolerance_num ~ genre,
+     data       = Survey_final,
+     exact      = FALSE,
+     conf.int   = TRUE,
+     conf.level = 0.95
+ )
>
> test_risque_extreme

        Wilcoxon rank sum test with continuity correction

data:  extreme_risk_tolerance_num by genre
W = 584, p-value = 0.1525
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -9.999519e-01  2.522251e-05
sample estimates:
difference in location
         -2.639761e-05
```

```
> ############################################################
> # 3. Pertes maximales annuelles acceptées (max_loss_1y)
> ############################################################
>
> ## 3.1. Statistiques descriptives globales
>
> summary(Survey_final$max_loss_1y)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   5.00   20.00   30.00   27.68   30.00  100.00
> quantile(Survey_final$max_loss_1y, probs = c(0.25, 0.5, 0.75))
25% 50% 75%
 20  30  30
>
>
> ## 3.2. Distributions observées par genre
>
> tab_maxloss <- table(Survey_final$genre, Survey_final$max_loss_1y)
> tab_maxloss

         5  7 10 15 20 25 30 35 40 50 60 100
  Femme  1  1  4  3  6  3  8  1  1  0  0   0
  Homme  0  0  3  6  8  3 14  1 10  3  2   1
> addmargins(tab_maxloss)

         5  7 10 15 20 25 30 35 40 50 60 100 Sum
  Femme  1  1  4  3  6  3  8  1  1  0  0   0  28
  Homme  0  0  3  6  8  3 14  1 10  3  2   1  51
  Sum    1  1  7  9 14  6 22  2 11  3  2   1  79
>
> prop_maxloss <- prop.table(tab_maxloss, margin = 1) * 100
> round(prop_maxloss, 2)

            5     7    10    15    20    25    30    35    40    50    60   100
  Femme  3.57  3.57 14.29 10.71 21.43 10.71 28.57  3.57  3.57  0.00  0.00  0.00
  Homme  0.00  0.00  5.88 11.76 15.69  5.88 27.45  1.96 19.61  5.88  3.92  1.96
>
>
> ## 3.3. Test de normalité de Shapiro-Wilk par genre
>
> shapiro_h <- shapiro.test(Survey_final$max_loss_1y[Survey_final$genre == "Homme"])
> shapiro_f <- shapiro.test(Survey_final$max_loss_1y[Survey_final$genre == "Femme"])
>
> shapiro_h

	Shapiro-Wilk normality test

data:  Survey_final$max_loss_1y[Survey_final$genre == "Homme"]
W = 0.85074, p-value = 1.37e-05

> shapiro_f

	Shapiro-Wilk normality test

data:  Survey_final$max_loss_1y[Survey_final$genre == "Femme"]
W = 0.94312, p-value = 0.1327
```

```
> ## 3.4. Test de Mann–Whitney sur la perte maximale acceptée
>
> test_maxloss <- wilcox.test(
+     max_loss_1y ~ genre,
+     data       = Survey_final,
+     exact      = FALSE,
+     conf.int   = TRUE,
+     conf.level = 0.95
+ )
>
> test_maxloss

	Wilcoxon rank sum test with continuity correction

data:  max_loss_1y by genre
W = 448, p-value = 0.005669
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -1.000007e+01 -3.785943e-05
sample estimates:
difference in location
             -9.999932
```

8.8.5 Overconfidence (5.4.2)

```
> suppressPackageStartupMessages(library(dplyr))
>
> df_overconf <- Survey_final %>%
+     mutate(
+         genre = factor(genre),
+         overconfidence = as.character(overconfidence),
+         # extrait le chiffre dans "(1)" "(2)" "(3)"
+         overconfidence = sub(".*\\(([1-3])\\).*", "\\1", overconfidence),
+         overconfidence = suppressWarnings(as.numeric(overconfidence))
+     ) %>%
+     filter(
+         genre %in% c("Homme", "Femme"),
+         !is.na(overconfidence),
+         overconfidence %in% 1:3
+     ) %>%
+     droplevels()
>
> ## Descriptifs
> df_overconf %>%
+     group_by(genre) %>%
+     summarise(
+         n = n(),
+         moyenne = mean(overconfidence),
+         mediane = median(overconfidence),
+         .groups = "drop"
+     )
# A tibble: 2 × 4
  genre       n moyenne mediane
  <fct>  <int>   <dbl>   <dbl>
1 Homme     51    2.31       2
2 Femme     28    2.32       2
>
> ## Test Wilcoxon / Mann-Whitney (ordinal)
> wilcox.test(overconfidence ~ genre, data = df_overconf, exact = FALSE)

	Wilcoxon rank sum test with continuity correction

data:  overconfidence by genre
W = 713, p-value = 0.995
alternative hypothesis: true location shift is not equal to 0
```

8.8.6 Trading frequency and investment horizon (5.4.3 and 5.4.4)

```
> library(dplyr)
>
>   Survey_final <- Survey_final %>%
+     mutate(
+       horizon_ord = case_when(
+         horizon == "Court terme (0–2 ans)" ~ 1,
+         horizon == "Moyen terme (3–7 ans)" ~ 2,
+         horizon == "Long terme (8 ans et +)" ~ 3,
+         TRUE ~ NA_real_
+       )
+     )
```

```
> df_kw <- Survey_final %>%
+   filter(!is.na(horizon_ord), !is.na(genre)) %>%
+   mutate(genre = factor(genre))
> wilcox.test(horizon_ord ~ genre, data = df_kw, exact = FALSE)

        Wilcoxon rank sum test with continuity correction

data:  horizon_ord by genre
W = 832, p-value = 0.1422
alternative hypothesis: true location shift is not equal to 0
```

```
> Survey_final <- Survey_final %>%
+   mutate(
+     trading_ord = case_when(
+       trading_frequence == "Rarement (1–2 fois / an)" ~ 1,
+       trading_frequence == "Régulièrement (chaque trimestre)" ~ 2,
+       trading_frequence == "Fréquemment (chaque mois)" ~ 3,
+       trading_frequence == "Très fréquemment (hebdo ou +)" ~ 4,
+       TRUE ~ NA_real_
+     )
+   )
```

```
> df_kw <- Survey_final %>%
+   filter(!is.na(trading_ord), !is.na(genre)) %>%
+   mutate(genre = as.factor(genre))
> wilcox.test(trading_ord ~ genre, data = df_kw, exact = FALSE)

        Wilcoxon rank sum test with continuity correction

data:  trading_ord by genre
W = 786.5, p-value = 0.4321
alternative hypothesis: true location shift is not equal to 0
```

8.8.7 Diversification (5.4.5)

```
> table20 <- df %>%
+     group_by(gender) %>%
+     summarise(
+         ETF = mean(ETF, na.rm = TRUE),
+         Funds = mean(Funds, na.rm = TRUE),
+         Direct = mean(Direct, na.rm = TRUE),
+         .groups = "drop"
+     ) %>%
+     pivot_longer(cols = c(ETF, Funds, Direct),
+                  names_to = "Vehicle",
+                  values_to = "Mean_share") %>%
+     mutate(Mean_share = round(Mean_share, 2)) %>%
+     pivot_wider(names_from = gender, values_from = Mean_share)
>
> table20
# A tibble: 3 × 3
  Vehicle Femme Homme
  <chr>   <dbl> <dbl>
1 ETF      52.4  48.1
2 Funds    27.2  26.0
3 Direct   20.4  25.9
>
```

```
> shapiro_by_gender <- function(data, var){
+     data %>%
+         group_by(gender) %>%
+         summarise(
+             n = sum(!is.na(.data[[var]])),
+             p_value = ifelse(n >= 3,
+                              shapiro.test(.data[[var]][!is.na(.data[[var]])])$p.value,
+                              NA_real_),
+             .groups = "drop"
+         ) %>%
+         mutate(Variable = var) %>%
+         select(Variable, gender, p_value)
+ }
>
> table21 <- bind_rows(
+     shapiro_by_gender(df, "ETF"),
+     shapiro_by_gender(df, "Funds"),
+     shapiro_by_gender(df, "Direct")
+ ) %>%
+     mutate(p_value = signif(p_value, 4)) %>%
+     pivot_wider(names_from = gender, values_from = p_value)
>
> table21
# A tibble: 3 × 3
  Variable      Femme    Homme
  <chr>         <dbl>    <dbl>
1 ETF       0.383     0.140
2 Funds     0.128     0.00134
3 Direct    0.0000447 0.000381
```

```
> tt_etf <- t.test(ETF ~ gender, data = df, var.equal = FALSE)
> tt_etf

        Welch Two Sample t-test

data:  ETF by gender
t = 0.85784, df = 64.786, p-value = 0.3941
alternative hypothesis: true difference in means between group Femme and group Homme is not equal to 0
95 percent confidence interval:
 -5.652513 14.163717
sample estimates:
mean in group Femme mean in group Homme
           52.39286            48.13725
```

```
> mw_test <- function(data, var){
+     x <- data %>% filter(!is.na(.data[[var]]), !is.na(gender))
+     if(length(unique(x$gender)) != 2) stop("gender must have exactly 2 groups")
+
+     res <- wilcox.test(x[[var]] ~ x$gender,
+                        conf.int = TRUE,
+                        exact = FALSE)  # avoids issues with ties / larger N
+
+     tibble(
+         Vehicle = var,
+         p_value = res$p.value,
+         conf_low = as.numeric(res$conf.int[1]),
+         conf_high = as.numeric(res$conf.int[2]),
+         est_location_diff = as.numeric(res$estimate)  # Hodges-Lehmann
+     )
+ }
>
> table22 <- bind_rows(
+     mw_test(df, "ETF"),
+     mw_test(df, "Funds"),
+     mw_test(df, "Direct")
+ ) %>%
+     mutate(
+         p_value = signif(p_value, 4),
+         conf_low = round(conf_low, 6),
+         conf_high = round(conf_high, 6),
+         est_location_diff = round(est_location_diff, 6)
+     )
>
> table22
# A tibble: 3 × 5
  Vehicle p_value conf_low conf_high est_location_diff
  <chr>     <dbl>    <dbl>     <dbl>             <dbl>
1 ETF       0.300    -3.00 10.0                   5.00
2 Funds     0.796   -10.00 10.0                   0.000055
3 Direct    0.154   -15.0   0.000005             -5.00
>
```

8.8.8 Sectorial preferences (5.4.6)

```
> suppressPackageStartupMessages({
+   library(readxl)
+   library(dplyr)
+   library(purrr)
+ })
>
> ## 1. Charger Excel Secteurs
> Survey_Sect <- read_excel("Survey_Sect.xlsx", sheet = 1)
>
> ## 2. Colonnes secteurs
> sect_cols <- c(
+   "actions_energie",
+   "actions_matieres_premieres",
+   "actions_industrie",
+   "actions_consommation_discretionnaire",
+   "actions_consommation_base",
+   "actions_sante",
+   "actions_finance",
+   "actions_technologie_information",
+   "actions_service_communication",
+   "actions_utilities",
+   "actions_immobilier"
+ )
>
> df <- Survey_Sect %>%
+   mutate(
+     genre = as.factor(.data[[genre_col]])
+   ) %>%
+   select(genre, all_of(sect_cols)) %>%
+   ## conversion robuste en numérique (%, virgules, etc.)
+   mutate(across(all_of(sect_cols), ~ {
+     x <- gsub("%", "", as.character(.x))
+     x <- gsub(",", ".", x)
+     suppressWarnings(as.numeric(x))
+   })) %>%
+   filter(genre %in% c("Homme", "Femme")) %>%
+   droplevels()
>
> ##4. controle
> df <- df %>%
+   mutate(total_secteurs = rowSums(across(all_of(sect_cols)), na.rm = TRUE))
>
> controle_total <- df %>%
+   group_by(genre) %>%
+   summarise(
+     n = n(),
+     mean_total   = mean(total_secteurs),
+     median_total = median(total_secteurs),
+     sd_total     = sd(total_secteurs),
+     .groups = "drop"
+   )
>
> ## 6. Tests
> resultats_secteurs <- map_dfr(sect_cols, function(col) {
+
+   xH <- df %>% filter(genre == "Homme") %>% pull(.data[[col]])
+   xF <- df %>% filter(genre == "Femme") %>% pull(.data[[col]])
+
+   wt <- wilcox.test(df[[col]] ~ df$genre, exact = FALSE)
```

```
+
+   tibble(
+     secteur = col,
+     mean_H  = mean(xH, na.rm = TRUE),
+     mean_F  = mean(xF, na.rm = TRUE),
+     median_H = median(xH, na.rm = TRUE),
+     median_F = median(xF, na.rm = TRUE),
+     delta_mean = mean_F - mean_H,
+     W = unname(wt$statistic),
+     p_value = wt$p.value,
+     cliffs_delta = cliffs_delta(xH, xF)
+   )
+ }) %>%
+   mutate(
+     p_adj_BH = p.adjust(p_value, method = "BH"),
+     significatif_BH = if_else(p_adj_BH < 0.05, "Oui", "Non")
+   ) %>%
+   arrange(p_adj_BH)
>
> ## 7. Résultats
> controle_total
# A tibble: 2 × 5
  genre      n mean_total median_total sd_total
  <fct> <int>      <dbl>        <dbl>    <dbl>
1 Femme    28      1                1 1.07e-16
2 Homme    51      0.961            1 1.96e- 1
> test_total_HF

        Wilcoxon rank sum test with continuity correction

data:  total_secteurs by genre
W = 698, p-value = 0.835
alternative hypothesis: true location shift is not equal to 0

> resultats_secteurs
# A tibble: 11 × 11
   secteur                             mean_H mean_F median_H median_F delta_mean     W p_value cliffs_delta p_adj_BH significatif_BH
   <chr>                                <dbl>  <dbl>    <dbl>    <dbl>      <dbl> <dbl>   <dbl>        <dbl>    <dbl> <chr>
 1 actions_service_communication       0.0592 0.0836     0.05    0.1     0.0244     871  0.0427      -0.270     0.469 Non
 2 actions_energie                     0.0966 0.114      0.1     0.1     0.0169     798. 0.226       -0.164     0.643 Non
 3 actions_matieres_premieres          0.0739 0.0929     0.08    0.1     0.0190     779  0.316       -0.136     0.643 Non
 4 actions_consommation_discretionnaire 0.0607 0.0664    0.05    0.085   0.00571    772  0.351       -0.125     0.643 Non
 5 actions_consommation_base           0.0649 0.0511     0.05    0.05   -0.0138     596  0.329        0.131     0.643 Non
 6 actions_technologie_information     0.237  0.172      0.2     0.15   -0.0652     558  0.173        0.187     0.643 Non
 7 actions_sante                       0.110  0.122      0.1     0.1     0.0120     722. 0.689       -0.0532    0.938 Non
 8 actions_finance                     0.111  0.11       0.1     0.1    -0.000612   658. 0.767        0.0401    0.938 Non
 9 actions_immobilier                  0.0574 0.0575     0.05    0.05    0.0000510  730. 0.643       -0.0634    0.938 Non
10 actions_industrie                   0.0896 0.0921     0.1     0.1     0.00255    700. 0.875       -0.0211    0.962 Non
11 actions_utilities                   0.0403 0.0393     0.05    0.05   -0.00102    682  0.969        0.00583   0.969 Non
>
> ## 8.Tableau
> # write.csv(resultats_secteurs,
> #           "resultats_allocations_sectorielles_HF.xlsx",
> #           row.names = FALSE)
>
```

8.8.9 ESG preferences (5.4.6)

```
> df_esg <- Survey_final %>%
+     select(genre, esg_proportion, esg_approche, esg_perf_expectation) %>%
+     filter(!is.na(genre))
>
> df_esg <- df_esg %>%
+     mutate(
+         genre = factor(genre, levels = c("Femme", "Homme")),
+
+         # ESG proportion: gère "30%", "30", "30,0", etc.
+         esg_prop_num = as.character(esg_proportion) %>%
+             str_trim() %>%
+             str_replace_all("%", "") %>%
+             str_replace_all(",", ".") %>%
+             as.numeric()
+     )
>
> tab_esg_prop <- df_esg %>%
+     filter(!is.na(esg_prop_num)) %>%
+     mutate(esg_prop_cat = paste0(esg_prop_num, "%")) %>%
+     count(esg_prop_cat, genre) %>%
+     group_by(genre) %>%
+     mutate(pct = 100 * n / sum(n)) %>%
+     ungroup() %>%
+     select(esg_prop_cat, genre, pct) %>%
+     tidyr::pivot_wider(names_from = genre, values_from = pct, values_fill = 0) %>%
+     # tri numérique des pourcentages (0,10,15,...)
+     mutate(esg_prop_sort = as.numeric(str_replace(esg_prop_cat, "%", ""))) %>%
+     arrange(esg_prop_sort) %>%
+     select(-esg_prop_sort)
>
> tab_esg_prop
# A tibble: 14 × 3
   esg_prop_cat Femme Homme
   <chr>        <dbl> <dbl>
 1 0%           14.3  45.1
 2 10%           3.57  7.84
 3 15%           7.14  3.92
 4 20%          14.3   7.84
 5 23%           3.57  0
 6 25%           3.57 11.8
 7 30%          21.4   9.80
 8 40%           3.57  7.84
 9 50%          10.7   1.96
10 70%           3.57  0
11 80%           3.57  0
12 85%           0     1.96
13 90%           3.57  0
14 100%          7.14  1.96
>
```

```
> mw_esg_alloc <- wilcox.test(
+     esg_prop_num ~ genre,
+     data = df_esg %>% filter(!is.na(esg_prop_num)),
+     conf.int = TRUE,
+     conf.level = 0.95,
+     exact = FALSE
+ )
>
> mw_esg_alloc

	Wilcoxon rank sum test with continuity correction

data:  esg_prop_num by genre
W = 1009.5, p-value = 0.001975
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
  4.999989 25.000046
sample estimates:
difference in location
              15.00002
```

```
> tab_esg_app <- df_esg %>%
+     filter(!is.na(esg_approche)) %>%
+     count(genre, esg_approche) %>%
+     group_by(genre) %>%
+     mutate(pct = 100 * n / sum(n)) %>%
+     ungroup() %>%
+     select(esg_approche, genre, pct) %>%
+     tidyr::pivot_wider(names_from = genre, values_from = pct, values_fill = 0)
>
> tab_esg_app
# A tibble: 4 × 3
  esg_approche                                                          Femme Homme
  <chr>                                                                 <dbl> <dbl>
1 Je combine les deux approches                                            25  9.80
2 Je me conforme à la politique ESG de mon institution                     50 31.4
3 Je ne tiens pas compte des critères ESG                                  25 52.9
4 J'intègre les critères ESG selon mes propres convictions et critères personnels     0  5.88
>
> mat_esg_app <- table(df_esg$genre, df_esg$esg_approche)
> fisher.test(mat_esg_app)

	Fisher's Exact Test for Count Data

data:  mat_esg_app
p-value = 0.0244
alternative hypothesis: two.sided
```

```
> df_esg <- df_esg %>%
+     mutate(
+         perf_raw = str_squish(as.character(esg_perf_expectation)),
+         perf_raw = str_replace_all(perf_raw, "-|-", "-"),
+
+         # extrait le chiffre 1..5 s'il existe
+         esg_perf_num = as.numeric(str_extract(perf_raw, "[1-5]")),
+
+         # sinon, mapping via le texte (au cas où)
+         esg_perf_num = case_when(
+             !is.na(esg_perf_num) ~ esg_perf_num,
+             str_detect(perf_raw, regex("nettement\\s*inf", ignore_case = TRUE)) ~ 1,
+             str_detect(perf_raw, regex("l[eé]g[eè]rement\\s*inf", ignore_case = TRUE)) ~ 2,
+             str_detect(perf_raw, regex("compar", ignore_case = TRUE)) ~ 3,
+             str_detect(perf_raw, regex("l[eé]g[eè]rement\\s*sup", ignore_case = TRUE)) ~ 4,
+             str_detect(perf_raw, regex("nettement\\s*sup", ignore_case = TRUE)) ~ 5,
+             TRUE ~ NA_real_
+         )
+     )
>
>
> library(dplyr)
> library(tidyr)
>
> tab_esg_perf <- df_esg %>%
+     filter(!is.na(genre), !is.na(esg_perf_num), genre %in% c("Femme", "Homme")) %>%
+     count(genre, esg_perf_num) %>%
+     group_by(genre) %>%
+     mutate(pct = 100 * n / sum(n)) %>%
+     ungroup() %>%
+     select(esg_perf_num, genre, pct) %>%
+     pivot_wider(
+         names_from = genre,
+         values_from = pct,
+         values_fill = 0
+     ) %>%
+     arrange(esg_perf_num)
>
> tab_esg_perf
# A tibble: 5 × 3
  esg_perf_num Femme Homme
         <dbl> <dbl> <dbl>
1            1  7.14 19.6
2            2 35.7  29.4
3            3 42.9  43.1
4            4 10.7   7.84
5            5  3.57  0
>
> wilcox.test(esg_perf_num ~ genre, data = df_perf, exact = FALSE)

        Wilcoxon rank sum test with continuity correction

data:  esg_perf_num by genre
W = 815, p-value = 0.2734
alternative hypothesis: true location shift is not equal to 0
```

8.8.10 Multivariate robustness checks

This appendix reports the R codes used to estimate the multivariate regression models presented in the main analysis. All specifications follow a consistent modelling framework across outcomes, with results reported in terms of estimated coefficients for OLS models and average marginal effects for logit models.

8.8.11 Linear regression models

```
Regression_1 <- lm(dependent_variable ~ main_independent_variable, data = dataset)
Regression_2 <- lm(dependent_variable ~ main_independent_variable + independent_variable_1 +
independent_variable_2,
            data = dataset)
Regression_3 <- lm(dependent_variable ~ main_independent_variable + independent_variable_3,
            data = dataset)
Regression_4 <- lm(dependent_variable ~ main_independent_variable + independent_variable_4,
            data = dataset)
Regression_5 <- lm(dependent_variable ~ main_independent_variable + independent_variable_5,
            data = dataset)
Regression_6 <- lm(dependent_variable ~ main_independent_variable +
                        independent_variable_3 +
                        independent_variable_5,
            data = dataset)

# Regression table
screenreg(list(Regression_1,
          Regression_2,
          Regression_3,
          Regression_4,
          Regression_5,
          Regression_6),
      digits = 3)
```

8.8.12 Logit regression models

```
Regression_1 <- glm(dependent_variable ~ main_independent_variable,
           data = dataset,
           family = binomial(link = "logit"))
Regression_2 <- glm(dependent_variable ~ main_independent_variable +
                  independent_variable_1 +
                  independent_variable_2,
           data = dataset,
           family = binomial(link = "logit"))
Regression_3 <- glm(dependent_variable ~ main_independent_variable +
                  independent_variable_3,
           data = dataset,
           family = binomial(link = "logit"))
Regression_4 <- glm(dependent_variable ~ main_independent_variable +
                  independent_variable_4,
           data = dataset,
           family = binomial(link = "logit"))
Regression_5 <- glm(dependent_variable ~ main_independent_variable +
                  independent_variable_5,
           data = dataset,
           family = binomial(link = "logit"))
Regression_6 <- glm(dependent_variable ~ main_independent_variable +
                  independent_variable_1 +
                  independent_variable_2 +
                  independent_variable_3 +
                  independent_variable_4 +
                  independent_variable_5,
           data = dataset,
           family = binomial(link = "logit"))
ME_1 <- margins(Regression_1)
ME_2 <- margins(Regression_2)
ME_3 <- margins(Regression_3)
ME_4 <- margins(Regression_4)
ME_5 <- margins(Regression_5)
ME_6 <- margins(Regression_6)
as_texreg_ame <- function(marg_obj) {
  s <- summary(marg_obj)
  texreg::createTexreg(
    coef.names = s$factor,
    coef       = s$AME,
    se         = s$SE,
    pvalues    = s$p
  )
}
```

```
# Regression table (AMEs)

screenreg(
  list(
    as_texreg_ame(ME_1),
    as_texreg_ame(ME_2),
    as_texreg_ame(ME_3),
    as_texreg_ame(ME_4),
    as_texreg_ame(ME_5),
    as_texreg_ame(ME_6)
  ),
  digits = 3,
  custom.model.names = c("AME (1)", "AME (2)", "AME (3)",
                         "AME (4)", "AME (5)", "AME (6)")
)
```

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ARTIFICIAL INTELLIGENCE

In the context of writing this thesis, the artificial intelligence tool ChatGPT (OpenAI) was used in a strictly assistive manner. Its use was limited to helping with the reformulation of certain passages, the clarification of methodological and statistical concepts (in particular to correctly rewrite R code), as well as support in organising and structuring the text. All analyses, interpretations, methodological decisions, and conclusions presented in this work are the result of the author's own reasoning.

EXECUTIVE SUMMARY

This thesis investigates whether gender differences in investment behaviour persist when financial decisions are made in a professional context. While behavioural finance literature widely documents differences between male and female investors, most evidence is derived from individual investors or experimental settings. This study contributes to the literature by focusing exclusively on investment professionals, whose decisions are shaped by institutional constraints, standardised processes, and regulatory frameworks.

The analysis is based on original survey data collected from investment professionals and tests seven hypotheses related to risk tolerance, overconfidence, trading frequency, investment horizon, portfolio diversification, investment style, and ESG considerations. The empirical methodology combines descriptive statistics, appropriate parametric and non-parametric tests, and multivariate regression models using OLS and LOGIT specifications.

The results indicate that most gender differences identified in prior research are significantly reduced or disappear altogether in a professional setting. In particular, no statistically significant gender effect is found for overconfidence, trading frequency, or investment horizon once professional characteristics are controlled for. Portfolio composition and diversification patterns also appear largely similar across genders. Although some differences emerge in relation to ESG preferences and maximum acceptable loss, these effects remain modest in magnitude. These findings should nevertheless be interpreted in light of certain limitations, notably the survey-based nature of the data and the size and composition of the professional sample.

Overall, the findings suggest that the professional investment environment plays a key role in mitigating behavioural biases commonly associated with gender. Institutional constraints and regulatory oversight appear to promote more homogeneous investment behaviour, reducing the relevance of gender-based distinctions observed among non-professional investors. These results underscore the importance of context in behavioural finance research and contribute to ongoing discussions on gender diversity in the financial industry.

KEYWORDS: Behavioural Finance, Gender Differences, Investment Behaviour, Financial Decision-Making, Finance Professionals.

WORD COUNT: 19.967

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