Behavioral Risk Profiling:

Measuring Loss Aversion of Individual Investors

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Abstract: Loss aversion has been shown to be an important driver of people's investment decisions. Encouraged by regulators, financial institutions are in search of ways to incorporate clients' loss aversion in their risk classifications. The most critical obstacle appears to be the lack of a valid measurement method for loss aversion that can be straightforwardly incorporated into existing processes. This paper presents the results of two large-scale implementations of such a method within a risk-profiling application of an established financial institution. In total, we elicit loss aversion for 1,040 employees and 3,740 clients. We find that the observed distributions align with existing findings and that loss aversion is largely independent of the risk-return preferences commonly used for investor classification. Furthermore, the correlations we observe between these two preferences and individuals' background characteristics align with those observed in the literature. Loss aversion is strongly related to education—higher educated individuals being more loss averse—whereas risk aversion is related to gender, age, and clients' financial situation—women, more senior, and less financially well-off participants being more risk averse. These findings support the conjecture that risk and loss aversion are complementary in capturing investor preferences.

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1. Introduction

Prospect theory is widely regarded as the best available theory to describe people's decisions under risk and uncertainty (Wakker 2010; Barberis 2013; Ruggeri et al. 2020). One of its central components is loss aversion, the assumption that people are more sensitive to losses than to commensurate gains (Kahneman and Tversky 1979; Tversky and Kahneman 1992; Brown et al. 2022). Whereas initial evidence for loss aversion derived from decisions made by student subjects in low-stakes laboratory experiments, subsequent research has provided evidence that it generalizes to real-world investment decisions. First, experiments show that loss aversion is not limited to students and that private investors and financial professionals also behave in accordance with loss aversion (Haigh and List 2005; Abdellaoui, Bleichrodt, and Kammoun 2013; Lee and Veld-Merkoulova 2016; Gajewski and Meunier 2020). Second, individual-level survey measures of loss aversion have been found to explain real-world investment decisions made by both private investors and financial professionals (Dimmock and Kouwenberg 2010; Bodnaruk and Simonov 2016; Lee and Veld-Merkoulova 2016; Iqbal et al. 2021).[1] Last, archival data and field experiments have shown investment patterns in line with the hypothesis of loss aversion (Gurevich, Kliger, and Levy 2009; Kliger and Levit 2009; Kliger and Levy 2009; Hwang and Satchell 2010; Larson, List, and Metcalfe 2016).[2]

In both the United States and Europe, financial institutions must perform "suitability assessments" when providing clients with investment advice or portfolio management to ensure that their recommendations or strategies are suitable for the client. An essential element of this suitability assessment is determining the client's willingness to take on risk (FINRA Rule 2111; FSA 2011; ESMA 2017; 2018). Despite the empirical evidence for the importance of loss aversion, financial institutions typically do not take this concept into account and instead measure risk preferences under the (implicit) assumption that clients make rational tradeoffs between risk and expected returns, in line with traditional financial models.

Financial regulators have recently stressed the importance of using behavioral insights to improve client risk profiles. For example, the European Securities and Market Authority (ESMA) calls for the "assessment of suitability in the light of behavioral finance findings" and explicitly mentions loss aversion as one of the findings to be incorporated (ESMA 2017; 2018). Studies conducted by French

[1] An exception is Farago et al. (2022), who find no statistically significant relation between fund managers' loss aversion and the Sharpe ratio, volatility, and performance of the funds they manage.

[2] In the context of investments, loss aversion is often combined with the assumption that people are myopic: they pay too much attention to short-term gains and losses and react strongly to negative short-term volatility. The idea of myopic loss aversion was initially introduced by Benartzi and Thaler (1995) as an explanation for the equity premium puzzle, which is the observation that stocks have historically outperformed bonds to such a degree that one would need to assume an implausibly large coefficient of relative risk aversion to explain it using the conventional expected utility framework (Mehra and Prescott 1985). In this paper, we focus on measuring the preference component of loss aversion, rather than the cognitive component of myopia.

(AMF) and Italian (CONSOB) financial regulators have also stressed the importance of loss aversion when considering clients' willingness to take on risk (Picard and de Palma 2011; Linciano and Soccorso 2012). However, this advice has thus far not led to the large-scale adoption of loss aversion elicitations in the construction of client risk profiles. The most critical obstacle appears to be the lack of a measurement method that can be straightforwardly incorporated into the advisory process.

This paper presents the results of two novel large-scale implementations of a theoretically valid loss aversion elicitation method within the risk profiling application of an established financial institution. We employ the method introduced by Abdellaoui et al. (2016), which allows for the measurement of loss aversion at the individual level under both risk and uncertainty. We report on an initial pilot conducted in April and May of 2018 under both employees and customers of a large Belgian bank.[3] Subsequently, we present the results from a large-scale implementation of the method between July 2020 and March 2021 in the advisory process of the Irish subsidiary of the bank. By doing so, we contribute to the literature in four ways.

First, we show how this theoretically sound elicitation method for loss aversion can be incorporated into the investment advisory process. We leverage the means of digitization to elicit loss aversion interactively. Clients complete the process by themselves on the digital platform—via a web portal or mobile banking app. Clients potentially receive human assistance when completing the digital process in a branch. Overall, clients express that they are happy with the procedure and accept the final risk profile, which combines a risk-return preference elicitation with the measurement of loss aversion at greater rates than they did standard risk profiles, which ignored loss aversion.[4]

Second, by employing this method, we obtain loss aversion measures for thousands of private investors and hundreds of financial professionals. Thereby, we contribute to a growing body of literature that aims to measure loss aversion beyond the typical student subject pools at universities and investigate the heterogeneity within such populations. We find that the distribution of individual levels of loss aversion aligns with established research (Brown et al. 2022). In terms of heterogeneity, loss aversion is positively related to education: those with higher education levels are considerably more loss averse. This matches the recent findings of Chapman et al. (2018; 2022), who find that loss

[3] The bank is an integrated bank-insurance group catering mainly to retail, private banking, SME, and mid-cap clients. Geographically, the bank focuses on its core markets of Belgium, Bulgaria, the Czech Republic, Hungary, Slovakia, and (until mid-2021) Ireland. The bank has over 12 million clients and 41,000 staff, spread over 1,300 branches in its six core markets.

[4] In the Irish implementation, 99.2% of participants accepted the suggested classification. According to the bank, this percentage was 90% under the previous classification procedure, which ignored loss aversion. Note that other factors, next to the inclusion of loss aversion, may have contributed to this higher acceptance rate, such as a preference for choice-based over survey-based information gathering.

aversion has a strong positive correlation with various measures of cognitive ability in several large-scale, incentivized, representative surveys of the US population.

Third, we show that our loss aversion measurement is largely independent of clients' preferences regarding risk-return tradeoffs. The weak correlation we observe even goes in the opposite direction than one might expect, with more risk-averse clients being slightly less loss averse. We obtain this result both when we elicit these risk-return preferences using a conventional survey-based elicitation method and when we elicit it using a choice-based elicitation method. In addition, risk aversion relates to the background characteristics of our investors in a way that is consistent with the existing literature but different from loss aversion. Whereas loss aversion is only related to education, we find that risk aversion is significantly related to gender, age, and the financial situation of the participant: female, older, and less well-off participants are more risk averse than male, younger, and more well-off participants. These findings support the conjecture that loss aversion and risk aversion are distinct concepts that serve complementary roles in capturing investor preferences.

Finally, we show that a simpler measure of loss aversion that does not control for probability weighting is not a valid alternative to the theoretically sound measure. The simple measure of loss aversion is only weakly correlated to the theoretically sound measure. Furthermore, whereas the sophisticated measure is largely independent of risk preferences, the more naïve measure for loss aversion strongly correlates with participants' risk preferences. This suggests that if we do not account for participants' probability weighting, we blur the boundaries between their feelings toward losses and their feelings toward risk.

The paper proceeds as follows. Section 2 introduces prospect theory and the elicitation procedure for measuring loss aversion. Section 3 describes the implementation of the elicitation procedure in the Belgian prototype and the Irish production version. Section 4 presents the empirical results. Section 5 discusses practical considerations. Section 6 concludes.

2. Prospect theory and eliciting loss aversion

2.1 Binary prospect theory

Our elicitation procedure uses two-outcome risky prospects $x_p y$, signifying that the decision-maker obtains €x with probability p and €y with probability $1-p$. We will denote the decision maker's preferences over prospects using the conventional notation: $\succ$ for strong preference, $\succcurlyeq$ for weak preference, and $\backsim$ for indifference.

According to prospect theory, preferences are defined relative to a reference point x_0. Payoffs that are higher than x_0 are gains, and payoffs that are lower than x_0 are losses. We use the term *mixed* *prospect* to refer to a prospect that involves both a gain and a loss. For such prospects, the notation $x_p y$ signifies that x is a gain and y is a loss. We will use the term *gain prospect* for prospects that do not involve losses (i.e., both outcomes are at least as great as x_0) and the term *loss prospect* for prospects that do not involve gains. For gain and loss prospects, the notation $x_p y$ signifies that the absolute value of x is greater than that of y (i.e., for gains $x \geq y$ and for losses $x \leq y$).

Under both the original version of prospect theory (Kahneman and Tversky 1979) and under cumulative prospect theory (Tversky and Kahneman 1992), the decision maker's preferences over risky binary prospects $x_p y$ are evaluated by:

$w^+(p)U(x) + w^-(1-p)U(y)$, for mixed prospects, and

$w^i(p)U(x) + \left(1 - w^i(p)\right)U(y)$, for gain and loss prospects,

where $i = +$ for gains and $i = -$ for losses. $w^i(\cdot)$ is a strictly increasing (but not necessarily additive) *probability weighting function* that satisfies $w^i(0) = 0$ and $w^i(1) = 1$, and that may thus differ between gains and losses. $U(\cdot)$ is a real-valued strictly increasing utility function that satisfies $U(x_0) = 0$. This function is defined as a ratio scale, and one is free to choose the utility of one outcome other than the reference point.[5]

We will take the common approach to decompose this overall utility function into a basic utility function $u(\cdot)$ that captures the decision maker's attitudes towards final outcomes (sometimes interpreted as the *rational* part of utility), and a loss aversion coefficient $\lambda > 0$ that reflects the different processing of gains and losses (Sugden 2003; Köbberling and Wakker 2005; Kőszegi and Rabin 2006). Formally,

$$U(x) = \begin{cases} u(x) & \text{if } x \geq 0 \\ \lambda u(x) & \text{if } x < 0. \end{cases}$$

If $\lambda > 1$, people give more weight to losses than to gains, which is typically referred to as *loss aversion*. If $\lambda < 1$, people give more weight to gains than to losses (referred to as *gain seeking*). If $\lambda = 1$, people treat gains and losses equally (referred to as *loss neutrality*).

[5] Tversky and Kahneman's (1992) cumulative prospect theory can also be applied in settings where decision makers face ambiguous prospects, in which the probabilities associated to outcomes are unknown. In this case, the *probability weighting function* $w^i(\cdot)$ needs to be replaced by the *event weighting function* $W^i(\cdot)$, which assigns a number $W^i(E)$ to each event E from state space S such that: (i) $W^i(\emptyset) = 0$, (ii) $W^i(S) = 1$, and (iii) $W^i(\cdot)$ is monotonic (i.e., $W^i(E) \geq W^i(F)$ if $E \supseteq F$). Like the probability weighting function, the event weighting function may differ between gains and losses and be non-additive. The method we will employ to elicit loss aversion works both for risky and ambiguous prospects. In our applications, we use risky prospects.

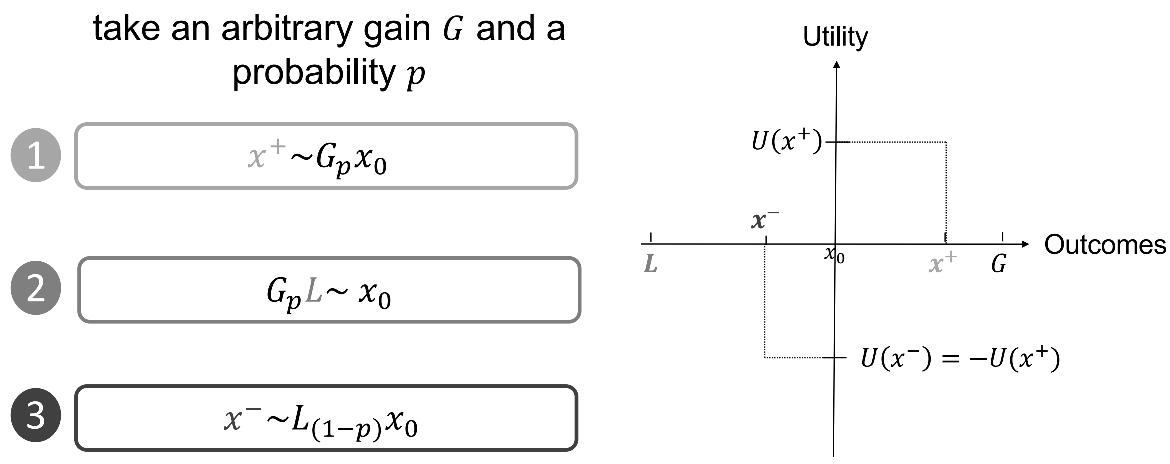

Figure 1: The three-step procedure to measure loss aversion. The left part of the figure displays the three indifferences that need to be elicited (elicited values in different shades of gray). The right part of the figure visually displays the result of the elicitation procedure: we obtain a gain and a loss that have the same absolute utility value.

2.2 Measurement of loss aversion

Abdellaoui et al. (2016) introduce a simple, non-parametric method to measure utility and, therefore, loss aversion under prospect theory. The method does not require simplifying assumptions regarding prospect theory's parameters and can quantify loss aversion through only three preference elicitations.[6]

Figure 1 illustrates the three elicitations. To perform the elicitations, we must fix a potential gain G and a probability p.[7] In addition, we need to assume a reference point x_0.

In the first step, we elicit the certainty equivalent x^+ such that $x^+ \sim G_p x_0$. Under prospect theory, this indifference implies that:

$$U(x^+) = w^+(p)U(G)$$

In the second step, we elicit the loss L such that $G_p L \sim x_0$. This indifference implies that:

$$w^+(p)U(G) + w^-(1-p)U(L) = U(x_0) = 0$$

In the third and final step, we elicit the certainty equivalent x^- such that $x^- \sim L_{1-p} x_0$, implying that:

$$U(x^-) = w^-(1-p)U(L)$$

[6] The full method that Abdellaoui et al. (2016) introduces consists of three stages. The three elicitations that we use constitute their first stage. In their second and third stage they employ the trade-off method proposed by Wakker and Deneffe (1996) to elicit further points of the utility function for both gains and losses.

[7] Alternatively, one can also fix a potential loss L instead of the gain G. The crucial aspect is that at least one monetary amount needs to be fixed prior to the elicitation. The steps need to be reordered if the loss L rather than the gain G is fixed (Step 2 then needs to preceed Step 1).

Together, these three equalities imply that:

$$U(x^+) = -U(x^-)$$

Hence, we have elicited a gain and a loss with the same absolute utility value.[8]

Following Köbberling and Wakker (2005), we define loss aversion as the kink of utility at the reference point.[9] Formally, they define loss aversion as $U'_\uparrow(x_0)/U'_\downarrow(x_0)$, where $U'_\uparrow(x_0)$ is the left derivative and $U'_\downarrow(x_0)$ is the right derivative of $U(\cdot)$ at the reference point x_0. Empirically, these derivatives cannot be observed directly but can be estimated by $U(x^-)/x^-$ and $U(x^+)/x^+$, respectively. Given that $U(x^+) = -U(x^-)$, the ratio of these two estimates is equal to $x^+/{-x^-}$. Hence, the three elicitations described above directly provide an estimate of Köbberling and Wakker's (2005) loss aversion coefficient.

3. Implementation

We implemented the loss elicitation method in the context of the risk profiling application of an established financial institution. We first piloted a prototype version under both employees and clients of a large Belgian bank. Subsequently, the method was implemented in the actual advisory process at the Irish subsidiary of the bank. Here, we will describe the details of these implementations, starting with the Belgian prototype and following up with the Irish production version.

3.1 The Belgian prototype version

The prototype was piloted in April and May 2018. Participants were employees and clients of a large Belgian bank. The bank invited a random set of clients who had previously expressed their willingness to participate in experiments by email. Employees were informed about the experiment via intranet communication channels. For both clients and employees, a hyperlink gave access to a dedicated, temporary website that people could access on a computer, tablet, or smartphone. The website allowed for anonymous data collection as it did not require a password or ask for identifiable information. The website could only be consulted via the link in the email or intranet invitation and was active for six weeks. In total, 339 clients and 1,040 employees completed the elicitation.

[8] For ambiguous prospects (with unknown probabilities), the elicitation of x^+ and x^- can be done in a similar fashion, by replacing the known probability p with the event E that has unknown probability, and the decision weights $w^+(p)$ and $w^-(1-p)$ by $W^+(E)$ and $W^-(E^c)$, respectively (where E^c is the complement of E).

[9] Several indexes of loss aversion have been proposed in the literature, but the one proposed by Köbberling and Wakker (2005) is generally preferred for empirical applications as it provides a clear decomposition between loss aversion and the other components of prospect theory and because many of the other definitions have been found to be too strict for empirical applications, leaving many participants unclassified (Abdellaoui, Bleichrodt, and Paraschiv 2007; Abdellaoui et al. 2016). The idea that a kink at the reference point reflects the degree of loss aversion has long been accepted in the literature (Benartzi and Thaler 1995; Kahneman 2003).

Table 1: Overview of the Belgian prototype and Irish production version

The table provides an overview of the Belgian prototype and the Irish production version. Panel A provides some general information regarding the implementation. Panel B describes the procedure that participants went through. Panel C gives details regarding the elicitation of loss and risk aversion. Panel D summarizes which additional variables were collected.

	Prototype	Production
A. General information		
Geography	Belgium	Ireland
Timeframe	April 2018 – May 2018	July 2020 – March 2021
Data collection method	Website accessible upon invitation	Digital as part of the advisory process
Participants	339 clients; 1,040 employees	3,401 investment clients
Feedback to participant	Description of risk profile	Description of risk profile
Incentives	None	Direct effect on financial advice
B. Procedure		
	Age and gender questions ⇓ Choice investment amount ⇓ Loss aversion elicitation ⇓ Survey-based risk preference elicitation ⇓ Education question ⇓ End and feedback	Financial questions and choice investment amount ⇓ Loss aversion elicitation ⇓ Visual risk preference elicitation ⇓ Survey-based risk preference elicitation ⇓ Question about financial knowledge ⇓ End and feedback
C. Loss and risk aversion elicitation		
Investment amount	Selected from: {1K,2K,3K,4K,5K,10K,20K,50K,100K}	Selected from a range determined by the participant's income and financial capacity
G	20% of the investment amount	20% of the investment amount
p	0.5	0.5
x_0	0	0
Loss aversion	Choice-based elicitation	Choice-based elicitation
Risk aversion	Survey-based elicitation	Choice-based elicitation
D. Other variables		
	Gender Age Education	Income, Surplus income Savings, Investments, Planned expenditures Financial knowledge

Table 1 provides a comprehensive summary of the implementation, including general information, the procedure participants underwent, details about the elicitation of loss and risk aversion, and the additional variables measured.

The main component of the prototype was the loss aversion elicitation, as detailed in Section 2.2. The elicitation requires the prior specification of three stimuli. First, we needed to determine a winning probability p. For the sake of simplicity, we asked clients to consider prospects in which the chance of winning was equal to 50 percent. Second, we needed to assume a reference point x_0. Here, we made the common assumption that the reference point that distinguishes between gains and losses was equal to zero.

Finally, we needed to fix a potential gain G. If we were eliciting loss aversion in a laboratory experiment with students, we would likely have chosen to keep G constant across all participants. However, in the context of risk profiling, it makes sense to tailor the process to the investor's situation. To this end, participants were asked to select how much money they could invest from a set of nine options: €1,000, €2,000, €3,000, €4,000, €5,000, €10,000, €20,000, €50,000, and €100,000. The default choice was €1,000. The measure $x^+/-x^-$ is most likely to be a valid estimate of the kink at the reference point, $U'_\uparrow(x_0)/U'_\downarrow(x_0)$, if the amounts x^+ and x^- are relatively small. At the same time, participants may not take the elicitation seriously if the amounts are too small. Considering these two countervailing considerations, we set the amount G to 20 percent of the chosen investment amount.

We did not directly ask participants for their indifference values at each step. Instead, we used the so-called bisection method, which uses binary questions to zoom in on the participant's indifference. Figure 2A shows a typical decision that participants were asked to make. By observing the participant's choice of one of the two prospects, we learn about the interval in which their indifference must fall. The next question is dynamically determined to narrow down the interval further. This process continues until the interval has been sufficiently narrowed down.[10] The midpoint of the resulting interval serves as our estimate of the indifference value. Table A1 in the Appendix presents several examples of the bisection procedure. Previous research suggests that such a choice-based elicitation procedure produces more reliable results than directly asking for indifference values (Bostic, Herrnstein, and Luce 1990).

To encourage engagement on the part of the participant, considerable effort went into creating a visually appealing setting, and animations were added to create a feeling of "flowing through" the experiment. The elicitation was announced as a game in the initial invitation.

Following the loss aversion elicitation, participants were asked to answer a survey question to elicit their preferences between risk and reward. This question, shown in Figure 2B, was taken from the risk-profiling questionnaire that the bank employed at that time. Participants had to select from four answer options. Those who selected the first option are classified as *very defensive*, those who selected the second as *defensive*, those who selected the third as *dynamic*, and those who selected the fourth as *very dynamic*. Contrary to the loss aversion elicitation, which was choice-based, this elicitation is survey-based. In the Irish production version, both loss aversion and risk aversion are measured using a choice-based method.

[10] The bisection continued until (i) a participant switched back and forth between the two options twice, or (ii) the change in amounts fell below a very low threshold (in particular: 5 euro) or (iii) if the number of one-sided clicks exceeded a high threshold (in particular: 7).

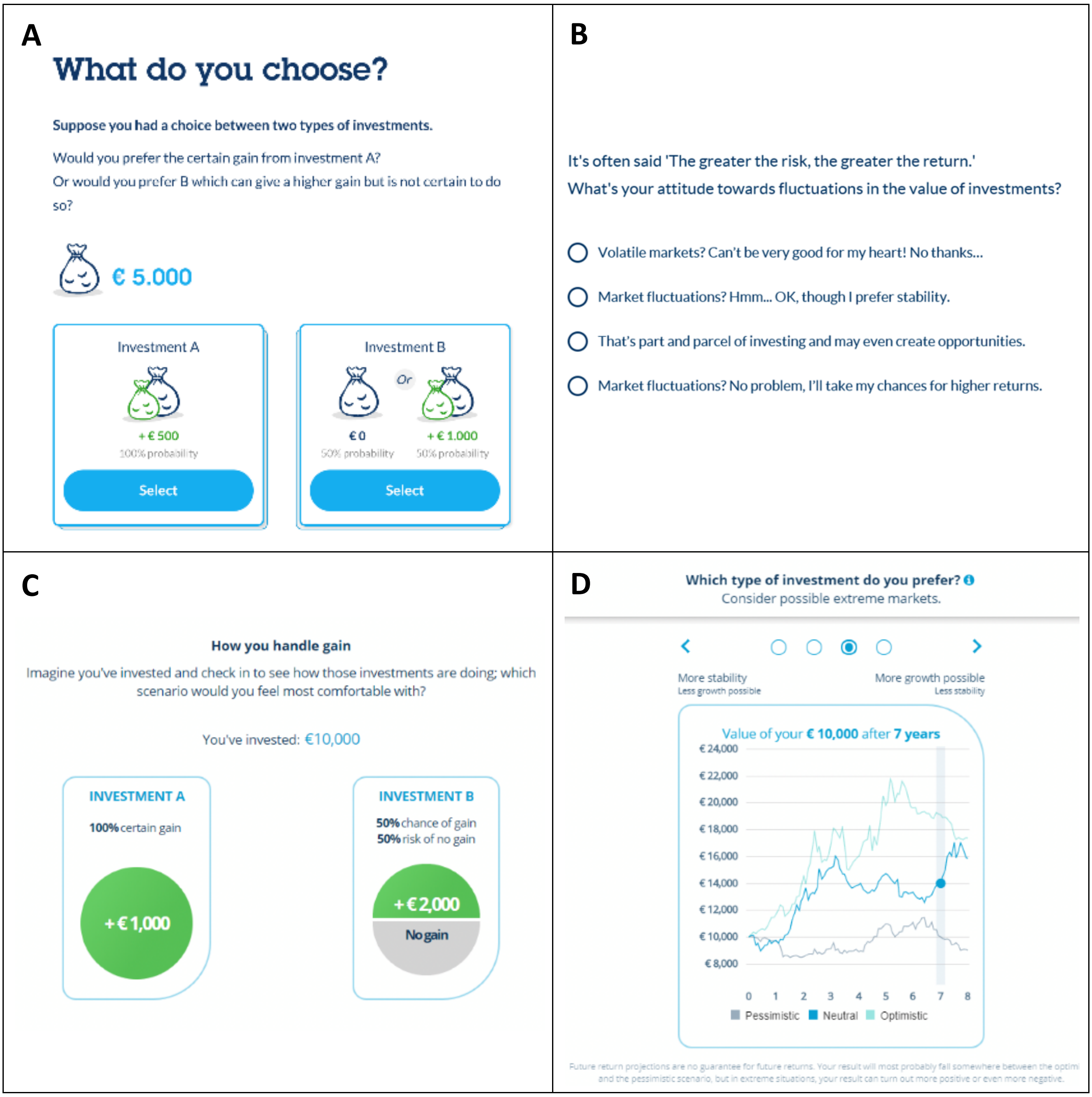

Figure 2: Screenshot of the (A) Belgian loss aversion, (B) Belgian risk aversion, (C) Irish loss aversion, and (D) Irish risk aversion elicitation. Panel A provides an example of a choice to elicit loss aversion in the Belgian pilot. This example shows the first question used in the elicitation of x^+ for an investor who says they can invest €5,000. Panel B presents the survey question used to elicit risk aversion in the Belgian pilot. Panel C presents an example of a choice to elicit loss aversion in the Irish production version. This example shows the first question used in the elicitation of x^+, for an investor who invests €10,000. Panel D shows a screenshot of the elicitation of risk aversion in the Irish production version. The graph shows representative simulations of future trajectories of a dynamic portfolio in highly pessimistic, neutral, and highly optimistic market conditions. The simulations were based on the bank's expected returns, volatilities, and correlations for representative, diversified asset class benchmarks. In this example, the participant would invest €10,000 and had an investment horizon of 7 years. Participants could choose between four different graphs, showing the simulated performance of four different portfolios that differed in their mean-variance tradeoff.

In addition to the elicitations of loss and risk preferences, participants were asked a few demographic questions. At the start, participants were asked to state whether they usually feel like a man or a woman and their age. At the end, they were asked for their level of education (options: primary education, secondary education, college, university).

Clients received feedback on their investment profile at the end of the procedure. Participants were divided into four categories based on their risk preferences. These were communicated to participants using a travel-based metaphor. They were classified as a *hiker* if their risk-return preferences were *very defensive*, a *traveler* if they were *defensive*, an *explorer* if they were *dynamic*, and an *adventurer* if they were *very dynamic*. The degree of loss aversion determined the adjective that would be added to the classification. Loss aversion is a continuous measure and was split into three categories when communicating the result: participants with a loss aversion below one were classified as *courageous*, those with a loss aversion between one and 2.75 were classified as *enthusiastic,* and those with a loss aversion of 2.75 or above were classified as *alert*. These thresholds were chosen with the aim to achieve three roughly equally sized groups.[11] A person with dynamic risk-return preferences and a loss aversion of two would, in this Belgian prototype, thus be classified as an *enthusiastic explorer*. Combining the two dimensions leads to twelve potential categories. Participants received a brief description of the meaning behind their specific classification.

The elicitation was not incentivized; participants were not paid according to their choices. However, if participants valued receiving a description of their risk classification that reflected their true investment preferences, this would incentivize them to answer truthfully.

3.2 The Irish production version

The production version was incorporated in the advisory process of the Irish subsidiary of the bank from July 2020 onwards. Our data are from the period between July 2020 and March 2021.[12] During this period, investment clients completed this procedure as part of the advisory process in preparation for receiving investment advice or executing an investment order. Clients either completed the procedure by themselves or with advisor assistance. In both cases, the data were collected digitally on a computer, tablet, or smartphone. In total, 3,401 investment clients completed the elicitation. Table 1 provides a comprehensive summary of the implementation.

[11] Participants within each group will show varying degrees of loss aversion as the latter is a continuous measure. In any implementation, it is up to the service provider to decide how to map the continuous measure into an investor profile. Here, the purpose of assigning each participant to one of a limited number of groups was to facilitate easy communication of the result.

[12] In April 2021, the bank announced that it was planning to exit the Irish Market.

The elicitation of the client's loss aversion in the Irish production version was similar to that in the Belgian prototype. However, some components around the elicitation had to be altered to comply with the regulatory requirements for investor risk profiling. Here, we focus on the alterations that were made to the design.

The bank is required to take the participant's periodic income and financial capacity into account in the advisory process. Therefore, the elicitation started by asking the participant to state their income sources (options: salary, dividends and interest, rental income, pensions, bonuses, other income), their (overall) monthly income, and how much of that income they could put away each month if they wanted to. They were also asked about their long-term assets and their liquid assets. For their long-term assets, they were asked for the types of assets they held that they could not or did not want to release (options: family home, other real estate, pension fund, art collection, other valuables, none). Regarding their liquid assets, they were asked about the money in their accounts, their existing investments, and their planned large expenditures in the next four years.

The amount used for eliciting loss aversion was linked to the participant's financial situation. The participant's answers to the financial questions above led to a suggested (default) investment amount. The participant could alter this amount within a range around that suggested amount. The suggested amount and the range are thus personal and different for each participant. To balance the countervailing forces of wanting to elicit x^+ and x^- relatively close to the reference point but, at the same time, wanting to employ substantial enough amounts such that participants take the elicitation seriously, we again set the amount G to 20 percent of the investment amount.[13,14]

After the financial questions, the participant proceeded to the loss aversion elicitation. This was very similar to the prototype version, albeit with a slightly more stripped-down visual presentation, giving it a more serious feel. To provide some idea of the look of the experiment, Figure 2C provides a screenshot of one of the choice-based elicitations.

Following the elicitation of loss aversion, the investors' preferences between risk and reward were elicited. In contrast to the Belgian prototype version, where the elicitation was done using a conventional survey question, here we used a visual choice-based procedure to elicit clients' risk aversion. First, investors were asked for the length of their investment horizon (minimum: 1 year; maximum: over 15 years). After this, they had to choose between four graphs that showed representative simulations of future trajectories for portfolios that differed in their risk-return (mean-variance) tradeoff. The simulations that fed the visual were based on expected returns, volatilities,

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[13] This amount was purely for the purpose of the elicitation and did not imply actual investments.
[14] As in the Belgian prototype, we asked clients to consider prospects in which the chance of winning was equal to 50 percent and assumed a reference point of zero.

and correlations for representative, diversified asset class benchmarks. Each graph showed the path of a portfolio under extremely positive conditions, extremely negative conditions, and neutral conditions. Figure 2D shows an example of such a graph. As in the prototype, participants were classified as "very defensive", "defensive", "dynamic", or "very dynamic", depending on their choice.

After the visual elicitation, the participants had to answer a more conventional survey question regarding their desire for stability or growth. Specifically, participants were asked: "What do you believe should be the main objective for any financial investment?". They could answer: (1) "To keep the invested money intact at all times, noting that any growth does not keep up with inflation and may lose some of its value over time."; (2) "The invested money should at least keep up with inflation and be worth as much as it is today"; (3) "The invested money should beat inflation and be worth a little more than it is today"; (4) "The invested money should comfortably beat inflation and be worth a lot more than it is today". The survey question served as a consistency check on the visual elicitation. If the answer to the survey question diverged too much from the choice in the visual elicitation, the participant was notified of this inconsistency and had to perform both steps again.[15]

As in the prototype version, clients received feedback on their investment profile at the end of the procedure. Participants were divided into four categories based on their risk preferences, and the labels used were those given above (very defensive, defensive, dynamic, very dynamic). Furthermore, participants were divided into four categories based on their loss aversion. Participants with a loss aversion below 1 were classified as *neutral*, those with a loss aversion between 1 and 1.75 were classified as *progressive,* participants with a loss aversion between 1.75 and 4 were classified as *balanced*, and those with a loss aversion 4 or above were classified as *careful.*[16] As before, these thresholds were chosen with the aim of achieving roughly equally sized groups. Combining these two dimensions leads to sixteen categories. For example, a participant with dynamic risk-return preferences and a loss aversion of two would be classified as *dynamic balanced*. Participants received a brief description of the meaning behind their specific classification. After reading the description, participants could indicate whether they felt that the profile accurately described their preferences. If they selected "Yes, that's me", then this component of the advisory process was completed. If they selected "Hmm, that's not me", they could amend the profile by shifting the classification of risk

[15] This was the case if: (i) the participant was classified as *very dynamic* after to the visual method but answered that it is most important to keep the money intact in the survey question (option 1), or (ii) the participant was classified as *very defensive* after to the visual method but stated that they expected a lot of growth in this survey question (option 4).

[16] The cutoff levels are a design choice. While the elicitation method quantifies the level of loss aversion as a real, positive number it is the financial service provider who ultimately defines the number of categories and/or cutoff levels.

aversion to a more conservative category. Participants could not amend the classification of loss aversion.

In this production version, it was incentive-compatible for participants to answer the questions according to their true preferences. This was the case as the client risk profile being created had an immediate and direct impact on the investment advice the client would receive. Vandenbroucke (2019) describes the methodology used by the bank to provide portfolio advice that aligns with the investor's measured attitudes toward risk and loss.

4. Results

This section analyzes the loss aversion measurements obtained in the Belgian prototype and Irish production versions of the elicitation procedure. We will start by looking at the obtained distributions of loss aversion (Section 4.1), followed by further analyses of the correlation between risk aversion and loss aversion (Section 4.2) and explorations of the heterogeneity observed in both these preferences (Section 4.3). Finally, we explore whether a simpler measure of loss aversion leads to similar results as our theoretically sound measure (Section 4.4).

4.1 Loss aversion measurements

Figure 3 shows the distributions of loss aversion obtained in our prototype elicitation conducted in Belgium (separately for clients and employees) and our final production implementation in Ireland. For comparison, we also show the distribution obtained by Abdellaoui et al. (2016) in their original laboratory experiment with student participants at Erasmus University Rotterdam in the Netherlands.[17] Table 2 provides the median, interquartile range, and the percentage of participants classified as loss averse, gain seeking, and loss neutral in each sample.

[17] As in both our implementations, Abdellaoui et al. (2016) asked participants to consider prospects in which the chance of winning was equal to 50 percent and assumed a reference point of zero. In contrast to our implementations, they fixed the amount G to €2,000 for all participants.

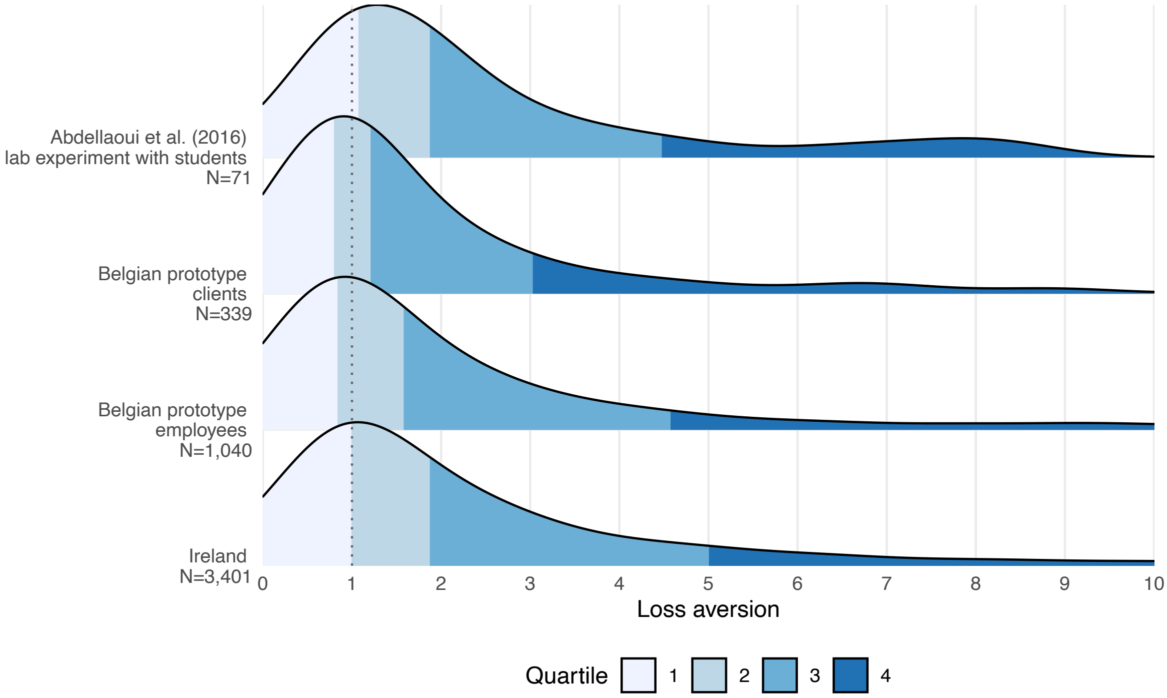

Figure 3: Loss aversion measurements. The figure shows the distribution of loss aversion measures obtained in the original laboratory experiment of Abdellaoui et al. (2016), the prototype elicitation conducted in Belgium (separately for clients and employees), and the final production implementation in Ireland. The distributions are truncated at a loss aversion of ten. The dotted line indicates a loss aversion of one; colors indicate quartiles.

We reject the hypothesis that all samples originate from the same distribution (Kruskal-Wallis H Test, $Chi^2(3) = 35.61$, $p < 0.001$). The distribution of loss aversion we observe among investment clients in Ireland is very similar to the distribution that Abdellaoui et al. (2016) initially observed in their experiment: the median loss aversion coefficient is 1.88 in both samples. In our Belgian prototype, we observe somewhat lower levels of loss aversion: the median loss aversion coefficient was 1.20 for clients and 1.59 for employees. In line with recent findings by Chapman et al. (2018; 2022), we observe that gain-seeking behavior is less common in the student sample than in the broader population samples. Overall, our measures align with what has been previously observed in the literature, although the parameter for Belgian clients is on the lower end (Neumann and Böckenholt 2014; Walasek, Mullett, and Stewart 2018; Brown et al. 2022).

Table 2: Loss aversion measurements

The table depicts the loss aversion measurement in the original laboratory experiment of Abdellaoui et al. (2016), the prototype elicitation conducted in Belgium (separately for clients and employees), and the final production implementation in Ireland. The table displays the medians and interquartile ranges and the percentage of loss-averse (LA), gain-seeking (GS), and loss-neutral (LN) participants.

			Classification (%)		
	N	Median [IQR]	LA	GS	LN
Abdellaoui et al. (2016)	71	1.88 [1.07—4.47]	79	17	4
Belgian prototype clients	339	1.20 [0.78—3.06]	59	33	8
Belgian prototype employees	1,040	1.59 [0.82—4.58]	64	32	4
Irish production clients	3,401	1.88 [0.99—5.00]	72	26	2

There are several differences between the elicitations, so it is unclear what caused these differences in loss aversion. The estimates were obtained in different countries, with different sampling procedures, and the elicitations were conducted in different ways. Although cross-cultural differences in loss aversion have been observed, it seems unlikely that loss aversion would be markedly lower in Belgium than in the culturally similar countries of the Netherlands and Ireland (l'Haridon and Vieider 2019; Brown et al. 2022). Differences in individual characteristics of people within the samples do seem to play a role: the Belgian clients and employees took part in the same elicitation procedure but showed significantly different levels of loss aversion (Mann-Whitney test, z = 2.544, p = 0.011). In Section 4.3, we will investigate these differences in more detail.

Finally, differences in the way the elicitation was conducted may have caused participants to approach it with a different mindset. It seems reasonable to assume that participants in the Abdellaoui et al. (2016) experiment and our Irish production version approached the elicitation with a more serious mindset than the participants in our Belgian prototype. In the Abdellaoui et al. (2016) experiment, participants completed the elicitation in a controlled laboratory environment under the direct guidance of an experimenter. Although they were not incentivized to answer truthfully, this context and the one-on-one interaction with the experimenter will likely have triggered them to consider their answers seriously. In our Irish production version, participants either completed the elicitation by themselves or with the assistance of an investment advisor. Importantly, all participants knew that their answers would impact the financial advice they would receive and were thus incentivized to consider their choices carefully. Participants in the Belgian prototype completed the elicitation individually on the digital device of their choice and knew that their answers would have no material repercussions. This may have led them to give their choices less consideration. More than the other two elicitations, the Belgian prototype was framed as a game, and this framing may also have led participants to be a bit more cavalier.

4.2 The relationship between loss and risk aversion

In addition to loss aversion, participants' preferences regarding risk-return tradeoffs were elicited in both the Belgian prototype version and the Irish production version. The former did so by a survey question, while the latter used a visual choice-based procedure (see Sections 3.1 and 3.2 for details). In both, participants were classified into four categories: "very defensive", "defensive", "dynamic", or "very dynamic". In the Belgian prototype version, 4 percent of participants are classified as *very defensive* (59/1,379), 22 percent as *defensive* (306/1,379), 64 percent as *dynamic* (886/1,379), and 9 percent as *very dynamic* (128/1,379). In the Irish production version, 2 percent of participants are classified as *very defensive* (59/3,401), 22 percent as *defensive* (753/3,401), 49 percent as *dynamic* (1,664/3,401), and 27 percent as *very dynamic* (925/3,401).[18]

Here, we explore the relationship between clients' loss and risk aversion. Doing so is important: if the correlation is highly positive, this could indicate that the measures are picking up the same underlying trait, which would speak against adding a measure for loss aversion to the procedure. To investigate this relation, we create an ordinal variable for risk aversion, where higher values signify a greater degree of risk aversion (1 = *very dynamic*, 2 = *dynamic*, 3 = *defensive*, 4 = *very defensive*).

In the Belgian data, risk aversion is weakly, but statistically significantly, negatively correlated with loss aversion (Kendall's tau-b = -0.086, $p < 0.001$). Hence, participants who are *more* risk averse are slightly *less* loss averse.

A potential concern is that this lack of correlation results from the different measurement methods used to elicit risk and loss aversion: risk aversion is obtained using a survey-based method, whereas loss aversion is obtained using a choice-based method. However, further inspection suggests this is not the case.

First, in the Irish production version, both risk and loss aversion were measured using a choice-based approach. Despite this, we similarly find a weak negative correlation between risk and loss aversion in the Irish data (Kendall's tau-b = -0.024, $p = 0.075$).

Second, in both the Belgian and Irish versions, we can use the first step in the elicitation of loss aversion—eliciting x^+ such that $x^+ \sim G_{0.5} 0$—to obtain a behavioral measure of risk aversion. Specifically, we can calculate the risk-aversion index $RA = (0.5G - x^+)/(0.5G)$. This index takes the

[18] This is after the consistency check using the survey question, but before adjusting the risk profile of participants who had no interest in or knowledge about the financial world to be *defensive* if they had originally come out as *dynamic* or *very dynamic*. This adjustment based on knowledge and experience was made for 16 participants, and it is a policy choice of the bank to prevent participants with too little understanding of the financial world from taking too much risk. We also ignore potential changes that participants made to their risk profile after getting the feedback at the end of the elicitation. Participants could only amend the level of risk aversion and could only change it to a more conservative classification. In total, 82 participants clicked on the button that enabled changes, but only 25 participants effectively increased their level of risk aversion.

value of zero if the participant is risk neutral, approaches one if the participant is highly risk averse, and approaches minus one if the participant is highly risk seeking. This choice-based index of risk aversion, which derives from the same elicitation procedure as the loss aversion measure, is significantly positively correlated to both the survey-based elicitation of risk aversion in the Belgian pilot (Kendall's tau-b = 0.340, $p < 0.001$) and the visual choice-based elicitation of risk aversion in the Irish production version (Kendall's tau-b = 0.349, $p < 0.001$).

We thus observe that loss aversion is consistently weakly negatively correlated with risk aversion. The fact that this is the case both if we obtain risk aversion with a survey-based method and a choice-based method suggests that it is not the different elicitation method driving this result. The fact that a measure of risk aversion that can be obtained from the loss aversion elicitation is strongly positively correlated with these two risk aversion measures further indicates that the negative correlation is not method-driven. Overall, these results strengthen the argument that risk aversion and loss aversion should be considered as separate constructs that need to be considered independently.

4.3 Heterogeneity in loss and risk aversion

In this section, we will further explore the patterns in loss aversion and risk aversion observed in the Belgian prototype and the Irish production version. Although we do not know much about the participants, we do know their age, gender, and education level in the Belgian prototype, and we have information on their financial situation in the Irish production version.

4.3.1 Heterogeneity in Belgium

Table 3, panel A provides an overview of the demographics for the Belgian sample. Overall, 66 percent of the participants are male, the average age is approximately 40 (min: 18; max: 72), and 87 percent have completed higher education.[19] About a quarter of the sample are clients; the rest are employees. The median investment amount selected for the elicitation is €4,000.

[19] We did not observe the education level for 13 participants (6 out of 1,040 employees, 7 out of 339 clients). These participants are omitted from all analyses in this section.

Table 3: Summary statistics

The table depicts the summary statistics for the Belgian prototype and the Irish production version. *Gender* (*Education*/*Client*) is a dummy variable that takes the value one if the participant is male (completed higher education/is a client) and zero otherwise. Age is the participant's age in years. *Investment amount* is the investment amount used to elicit loss aversion (in both the prototype and production version) and risk aversion (in the production version). *Income* denotes the participant's monthly income. *Surplus income* is the amount they could put aside each month if they wanted to. *Savings* is how much money they have in their accounts. *Existing investments* is the size of their existing investment portfolio. *Planned expenditures* is the total amount they plan to spend on large expenditures in the next four years. *Investment horizon* describes how many years participants want to put their money aside. All monetary amounts are denominated in euros (€).

	Mean	SD	Min	Q1	Median	Q3	Max
Panel A: Belgian prototype (N = 1,366)							
Gender (male=1)	0.66	0.48	0	0	1	1	1
Age (years)	39.8	11.7	18	29	38	50	72
Education (high = 1)	0.87	0.34	0	1	1	1	1
Client (client = 1)	0.25	0.43	0	0	0	0	1
Investment amount	7,098	13,382	1,000	2,000	4,000	5,000	100,000
Panel B: Irish production version (N = 3,401)							
Income	3,809	2,784	83	2,500	3,000	4,500	50,000
Surplus income	942	1,439	1	200	500	1,000	45,000
Savings	86,278	219,762	0	10,000	30,000	90,000	5,000,000
Existing investments	80,281	268,726	0	0	10,000	65,000	5,000,000
Planned expenditures	14,076	66,541	0	0	0	10,000	2,000,000
Investment amount	73,360	179,849	1,000	9,000	26,000	73,000	5,180,000
Investment horizon	8.01	3.86	1	5	7	10	15

Exploring the correlations between these demographic variables on the one hand and risk and loss aversion on the other is informative regarding the validity of our measures, as the demographics we observe have been found to correlate with loss and risk aversion in specific ways. In two recent large-scale studies using several incentivized, representative samples of the US population, Chapman et al. (2018; 2022) convincingly showed, perhaps surprisingly, that loss aversion has a strong positive correlation with cognitive ability: those with higher cognitive ability tend to be *more* loss averse. At the same time, loss aversion is not consistently related to age and gender (Chapman et al. 2018; Bouchouicha et al. 2019; Chapman et al. 2022).[20] In contrast, risk aversion has been found to be consistently and strongly related to age and gender—with women and older individuals being more risk averse—whereas the relationship between risk aversion and other characteristics such as cognitive ability or education is considerably weaker and more domain-specific (see Frey et al. (2021)

[20] In line with this positive relationship between cognitive ability and loss aversion, the recent meta-analysis by Brown et al. (2022) shows that students participants show a higher degree of loss aversion than participants from the general population.

for an overview and recent empirical evidence).[21] Replicating these established patterns in our data would provide evidence for the validity of our measures.

We conduct regression analyses to estimate the relation between these demographic variables and loss aversion. As Figure 3 shows, the distribution of loss aversion is heavily right-skewed. A standard ordinary least squares regression is sensitive to outliers and will not provide robust results. Therefore, we perform quantile regressions to estimate the effects of the demographic variables on the median and the first and third quartiles of loss aversion (for completeness, Table A2 in the Appendix displays the univariate correlations).

Table 4, Panel A shows the results. Participants who completed higher education are more loss averse than less educated participants. The difference is considerable: a 40-year-old female client who states that she can invest €1,000 is expected to have a λ of 1.10 if she did not complete higher education, but a λ of 1.57 if she did complete higher education (not tabulated). This finding aligns with the recent results of Chapman et al. (2018; 2022), who report that loss aversion is strongly positively correlated with cognitive ability. Controlling for education, none of the other variables is statistically significantly related to loss aversion.[22,23]

To investigate whether our measure of risk aversion is related to these demographic characteristics, we conduct an ordered Probit regression (for completeness, Table A2 in the Appendix displays the univariate correlations). Table 5, Panel A shows the results. In line with the dominant finding in the literature, men are significantly less risk averse than women: male participants are 8.2 percentage points more likely to be classified as very dynamic as compared to female participants and 7.8 percentage points more likely to be classified as dynamic, while they are 11.6 and 4.4 percentage points less likely to be classified as defensive or very defensive, respectively. Furthermore, risk aversion increases with the amount at stake and with age. In contrast to loss aversion, but in line with the existing literature on risk preferences, there is no significant correlation between education and risk appetite.

[21] The gender difference in risk taking has long been established both by economists (Eckel and Grossman 2008; Croson and Gneezy 2009) and psychologists (Byrnes, Miller, and Schafer 1999). The literature on the relationship between age and risk preferences is more recent, but shows compelling evidence that risk aversion decreases during adolescence, reaches its lowest point in young adulthood, and increases with aging thereafter (Tymula et al. 2013; Josef et al. 2016; Mata, Josef, and Hertwig 2016; Dohmen et al. 2017). For a meta-analysis of the relationship between cognitive ability on risk preferences, see Lilleholt (2019).

[22] Hence, the earlier observed difference between clients and employees appears to reflect differences in education between these two groups (67% of clients and 93% of employees have completed higher education).

[23] Recent neuro-economic work suggests a potential curvilinear relationship between age and loss aversion, with loss aversion first decreasing and then increasing over the life course (Guttman et al. 2021). We have explored potential non-linear age trends for both loss and risk aversion but found no evidence for either. In Subsection 4.3.3, we discuss the robustness of our results to alternative specifications.

Table 4: Quantile regression results for loss aversion

The table reports coefficients of quantile regression analyses that estimate the conditional first quartile, median, and third quartile of participants' loss aversion in the Belgian prototype elicitation (Panel A) and the Irish production version (Panel B). The independent variables are defined as in Table 3. For all financial variables, we take the natural logarithm. All continuous variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are in parentheses. Asterisks denote significance at the one ***, five **, and ten * percent levels, respectively.

	Loss aversion		
	Q1	Median (Q2)	Q3
Panel A: Belgian Prototype			
Gender (male = 1)	0.092**	-0.111	-0.381
	(0.045)	(0.140)	(0.650)
Age (in years)	-0.085***	-0.089	0.057
	(0.028)	(0.058)	(0.308)
Education (high = 1)	0.200**	0.471***	1.460**
	(0.079)	(0.142)	(0.572)
Client (client = 1)	-0.047	-0.164	-0.497
	(0.056)	(0.137)	(0.631)
Investment amount (log)	-0.003	-0.025	0.421
	(0.029)	(0.065)	(0.539)
Constant	0.587***	1.234***	3.349***
	(0.080)	(0.220)	(0.852)
Observations	1,366	1,366	1,366
Panel B: Irish Production version			
Income (log)	-0.030*	-0.005	-0.318
	(0.017)	(0.047)	(0.226)
Surplus income (log)	0.010	-0.047	-0.072
	(0.018)	(0.070)	(0.351)
Savings (log)	-0.018	0.055	-0.981**
	(0.016)	(0.037)	(0.409)
Existing investments (log)	-0.009	0.029	0.531**
	(0.023)	(0.058)	(0.222)
Planned expenditure (log)	-0.017	-0.039	0.062
	(0.022)	(0.057)	(0.208)
Investment amount (log)	0.093***	0.320***	1.123***
	(0.030)	(0.074)	(0.322)
Constant	0.969***	1.936***	5.169***
	(0.015)	(0.043)	(0.308)
Observations	3,401	3,401	3,401

Table 5: Ordered probit regression results for risk aversion

The table reports coefficients and average marginal effects of an ordered Probit regression analysis of participants' risk aversion in the Belgian prototype version (Panel A) and the Irish production version (Panel B). The dependent variable measures participants' risk aversion, where higher values indicate a preference for a more defensive investment strategy (1 = *very dynamic*, 2 = *dynamic*, 3 = *defensive*, 4 = *very defensive*). All independent variables are defined as in Table 3. For all financial variables, we take the natural logarithm. All continuous variables are standardized to have a mean of zero and a standard deviation of one. Robust standard errors are in parentheses. Asterisks denote significance at the one ***, five **, and ten * percent levels, respectively.

	Parameter	Marginal effects			
	estimates	P(1)	P(2)	P(3)	P(4)
Panel A: Belgian prototype version					
Gender (male = 1)	-0.516***	0.082***	0.078***	-0.116***	-0.044***
	(0.070)	(0.012)	(0.012)	(0.015)	(0.007)
Age (in years)	0.136***	-0.022***	-0.021***	0.031***	0.012***
	(0.035)	(0.006)	(0.005)	(0.008)	(0.003)
Education (high = 1)	-0.074	0.012	0.011	-0.017	-0.006
	(0.107)	(0.017)	(0.016)	(0.024)	(0.009)
Client (client = 1)	0.077	-0.012	-0.012	0.017	0.007
	(0.082)	(0.013)	(0.012)	(0.018)	(0.007)
Investment amount (log)	-0.174***	0.028***	0.026***	-0.039***	-0.015***
	(0.036)	(0.006)	(0.006)	(0.008)	(0.004)
α_1	-1.772***				
	(0.127)				
α_2	0.277**				
	(0.116)				
α_3	1.430***				
	(0.123)				
Observations	1,366	1,366	1,366	1,366	1,366
Panel B: Irish production version					
Income (log)	-0.072***	0.022***	-0.001**	-0.018***	-0.003***
	(0.025)	(0.008)	(0.001)	(0.006)	(0.001)
Surplus income (log)	-0.187***	0.058***	-0.004***	-0.046***	-0.008***
	(0.025)	(0.008)	(0.001)	(0.006)	(0.001)
Savings (log)	0.006	-0.002	0.000	0.002	0.000
	(0.022)	(0.007)	(0.000)	(0.006)	(0.001)
Existing investments (log)	0.016	-0.005	0.000	0.004	0.001
	(0.025)	(0.008)	(0.001)	(0.006)	(0.001)
Planned expenditure (log)	0.004	-0.001	0.000	0.001	0.000
	(0.019)	(0.006)	(0.000)	(0.005)	(0.001)
Investment amount (log)	0.151***	-0.047***	0.003**	0.037***	0.006***
	(0.027)	(0.008)	(0.001)	(0.007)	(0.001)
Investment horizon (years)	-0.274***	0.085***	-0.006***	-0.068***	-0.012***
	(0.023)	(0.007)	(0.002)	(0.006)	(0.001)
α_1	-0.648***				
	(0.024)				
α_2	0.764***				
	(0.025)				
α_3	2.219***				
	(0.059)				
Observations	3,401	3,401	3,401	3,401	3,401

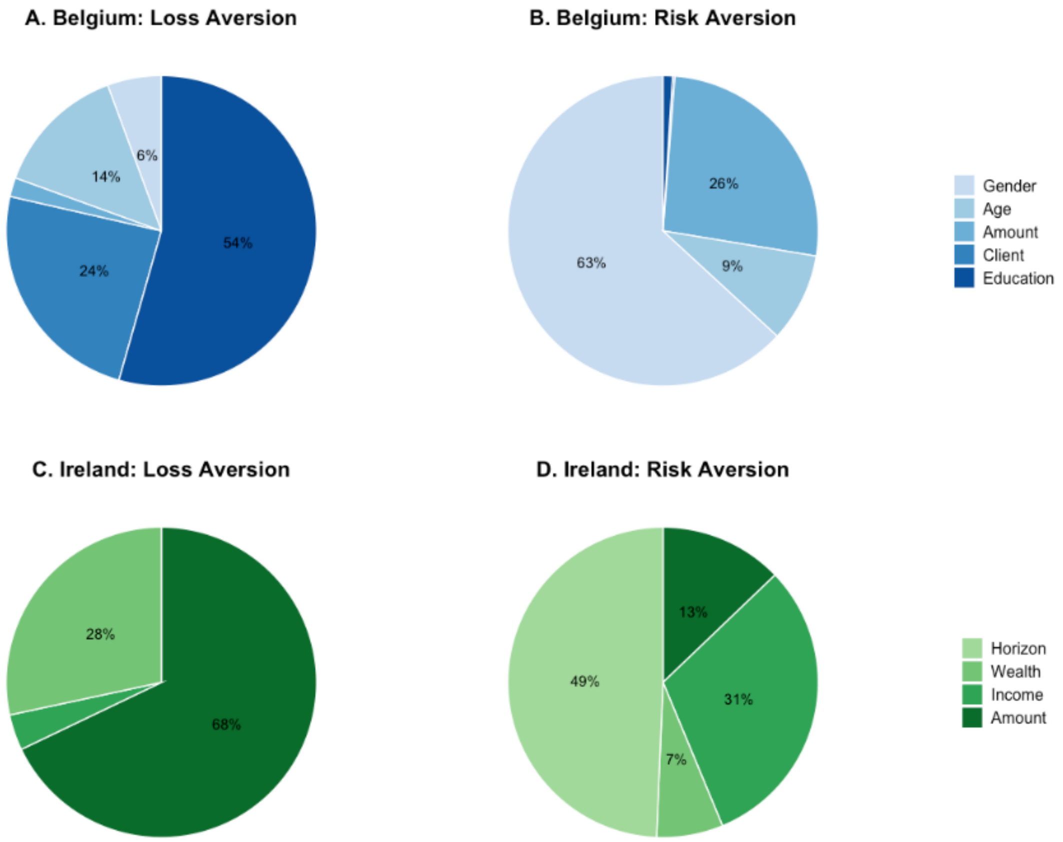

Figure 4: General dominance analyses. The figure shows the results of general dominance analyses for the regressions on loss and risk aversion in Belgium (Panels A and B) and Ireland (Panels C and D). Each pie chart decomposes the improvement in fit relative to the null model into additively separable contributions associated with each of the independent variables (or sets of variables in the case of wealth and income in Ireland). For loss aversion, the models studied are the quantile regression models explaining the median reported in Table 4. For risk aversion, it are the models presented in Table 5.

Finally, we perform general dominance analyses to determine the relative contribution of these background variables to the models' ability to explain loss and risk aversion. General dominance analysis decomposes the overall fit of a given model into additively separable contributions associated with each independent variable (Budescu 1993; Azen and Budescu 2003). This decomposition is derived by calculating the average contribution of each independent variable across all possible combinations of other variables.[24]

General dominance analysis can, in principle, be done for any measure of fit. As we employ different types of models for loss and risk aversion, we cannot use the same fit measure for both. Rather, for each model, we take the improvement in the objective function relative to the null model as the measure of fit. The quantile regression explaining the median loss aversion is estimated by minimizing the sum of absolute residuals, and we thus determine each variable's relative contribution to the

[24] Hence, if there are *k* variables, this requires the estimation of 2^k sub-models.

reduction of this metric. The ordered Probit maximizes the log-likelihood, and we thus determine each variable's relative contribution to the increase in this metric.

Figures 4A and 4B show the results of the dominance analyses for loss and risk aversion, respectively. For loss aversion, education is responsible for more than half of the improvement in fit. After that, the most important variable is whether a person is a client or an employee, which accounts for roughly a quarter of the improvement in fit. The amount, age, and gender play only minor roles. For risk aversion, gender is responsible for over sixty percent of the improvement in fit, while the amount at stake explains about a quarter. Although statistically significant, age explains only nine percent. Education and client or employee status do not meaningfully help to explain risk aversion.

4.3.2 Heterogeneity in Ireland

For the Irish production version, we do not have information on demographic characteristics such as age, gender, and education. However, we have information regarding the participants' financial situation. Here, we will explore the relationship between these financial variables and participants' loss and risk aversion.

Table 3 provides summary statistics for the financial variables. The median person in our data has a monthly income of €3,000, of which they could put away €500 a month if they wanted to. Furthermore, they have €30,000 in their bank account, €10,000 in existing investments, and no large expenditures planned over the next four years. Based on this financial information, a (default) investment amount was suggested to the participants to assess their feelings towards uncertainty. The participant could alter this amount within a range around that suggested amount. In the end, the median investment amount used in the elicitations was €26,000, considerably higher than the median of €4,000 in the Belgian prototype. The median investment horizon that participants selected in the elicitation of risk preferences was seven years.

To investigate the relationship between loss aversion and the participant's financial situation, we again perform quantile regressions to estimate the effects of the variables on the median and the first and third quartiles of loss aversion. Table 4, Panel B shows the regression results (for completeness, Table A3 in the Appendix displays the univariate correlations). We find that loss aversion is not significantly related to any of the financial background variables. It is, however, statistically significantly related to the amount used for the elicitation: participants who face higher amounts are more loss averse. This is in line with several studies that suggest that loss aversion is especially pronounced for large stakes (Harinck et al. 2007; Ert and Erev 2013; Mukherjee et al. 2017).

It begs the question of why we observe a relation between loss aversion and investment amount in the Irish production version but not in the Belgian prototype. Two potential explanations seem likely. First, there is considerably more variation in the investment amount in the Irish production version than in the Belgian prototype (see Table 3). It is possible that the variation in the Belgian pilot, where most people consider amounts between €1,000 and €5,000, was insufficient to detect an effect of stake size on loss aversion. Second, the way the investment amount was determined differed between the Belgian and the Irish version: in the former, it was entirely up to the participant, while in the latter, this amount was primarily determined by the participant's financial situation. If more loss-averse participants tended to select lower investment amounts in the Belgian prototype, this could have obscured a potentially positive effect of the stake size on loss aversion in that elicitation. In the Irish production version, where participants had only limited ability to adjust the investment amount, such confounding is less likely to occur.

To investigate whether our measure of risk aversion is related to the participant's financial situation, we conduct an ordered probit regression (for completeness, Table A3 in the Appendix displays the univariate correlations). Because participants were also asked to consider a specific investment horizon for this elicitation, we also controlled for the investment horizon they selected. Table 5, Panel B shows the results. In line with Decreasing Absolute Risk Aversion (DARA), more affluent participants seem less risk averse when considering a given amount of money than less well-off participants: people with higher income and higher surplus income are more willing to take on risk. In addition, people are more risk averse when considering more significant amounts and when considering a shorter investment horizon.

Finally, we perform general dominance analyses to determine the relative contribution of these financial variables to the models' ability to explain loss and risk aversion. For the sake of clarity, we treat the two income variables (income and surplus income) as a set describing the investor's income and determine their joint contribution to the model's fit. Similarly, we treat the three wealth variables (savings, existing investments, and planned expenditures) as a set describing the investor's wealth and determine their joint contribution to the fit.

Figures 4C and 4D show the results for loss and risk aversion, respectively. In line with the regression that showed that none of the financial variables other than the amount at stake significantly influence loss aversion, we observe that this variable is responsible for almost seventy percent of the overall improvement in fit. For risk aversion, the investment horizon is most important, being responsible for about half of the improvement in fit, followed by the income variables, which combined account for roughly thirty percent. The amount at stake and the person's wealth only contribute marginally to the model's fit.

4.3.3 Multiverse analysis

In this section, we explore the robustness of the heterogeneity analyses reported above. Although our analytical choices were relatively straightforward, it is possible that other defensible analytical choices would lead to different results (Silberzahn et al. 2018; Botvinik-Nezer et al. 2020; Huntington-Klein et al. 2021; Schweinsberg et al. 2021; Breznau et al. 2022; Menkveld et al. 2023). To investigate whether that is the case, we conduct a multiverse analysis: we investigate the robustness of our results across a wide set of alternative analytical choices (see, for example, Steegen et al. 2016; Simonsohn, Simmons, and Nelson 2020).

In particular, we vary both the regression model employed and the specification of the independent variables. First, for each dependent variable, we consider one alternative regression approach. As the distribution of loss aversion is heavily right-skewed, we used quantile regression to estimate the effects of independent variables on the median. As an alternative, we use Box-Cox regression, which transforms the non-normal dependent variable into an approximately normally distributed one through a parametric power transformation (Box and Cox 1964).[25] For risk aversion, which is measured on an ordinal scale, we used an ordered Probit regression. As an alternative approach, we use the ordered Logit regression.

Second, we consider different specifications of the independent variables. In Belgium, we used a dummy variable for education, indicating whether a person had completed higher education or not. In the alternative specification, we distinguish the four different levels of education that were answer options in the online questionnaire (primary education, secondary education, college, and university). Furthermore, we explore whether incorporating quadratic effects for age and the investment amount alters our conclusions. In Ireland, we explore whether incorporating quadratic effects for the investment amount, the income variables, the wealth variables, and the investment horizon affects our conclusions.

Figure A1 in the Appendix shows how the results of the general dominance analysis vary across the different specifications for the Belgian data. Overall, the qualitative conclusions are very robust. For risk aversion, the relative contributions of age, education, gender, and the investment amount are very stable, with gender contributing most to the model's fit irrespective of the analytical choices made. For loss aversion, we find that education consistently contributes most to the model's fit. Here, however, there is one notable finding: in the Box-Cox regression models, the investment amount helps explain the level of loss aversion, while this was not the case in the quantile regressions. Hence, the

[25] The transformation is given by $y' = \frac{y^{\lambda}-1}{\lambda}$, where λ is the transformation parameter. This parameter is selected to optimize the likelihood that the transformed data follows a normal distribution.

initial discrepancy between Belgium and Ireland, where the amount did help explain loss aversion in the latter but not in the former, is not as strong as it seems and is partially model-dependent.

Figure A2 in the Appendix shows how the results of the general dominance analysis vary across specifications for the Irish data. Again, the qualitative conclusions are robust. For loss aversion, there are no major shifts, and the amount at stake is the financial variable that contributes most to the model's fit, irrespective of the analytical choices made. For risk aversion, however, some shifts do occur. Most notably, the relative contribution of the wealth variables relative to the income variables is very dependent on the parametrization: although the effect of income variables is very robust, wealth variables contribute little to the fit if we include them in a linear fashion but contribute significantly when we allow for quadratic effects. Regardless of which model we would select, our main conclusions would remain unaltered.

Taken together, these results are reassuring. Both our measure of loss aversion and our measure of risk aversion are related to participants' demographic characteristics in ways that are consistent with existing findings in the literature, and these findings are highly robust: loss aversion is significantly positively related to education, whereas risk aversion is higher for women and older individuals. Furthermore, the patterns in risk aversion vary across participants' financial situations in a plausible way. The finding that risk aversion and loss aversion show different relations with the demographic variables provides further support for the claim that these are distinct constructs that need to be considered separately in the context of risk profiling and suggests that a lack of correlation between them is not due to measurement error.

4.4 A simpler measure of loss aversion

Risk aversion was measured using only a single question, whereas loss aversion required eliciting three indifferences. Eliciting these three indifferences allowed us to measure loss aversion without making any simplifying assumptions regarding participants' probability weighting for gains and losses. In contrast, most elicitations of loss aversion either ignore probability weighting (Pennings and Smidts 2003; Baltussen, van den Assem, and van Dolder 2016) or assume equal weighting for gains and losses (Gächter, Johnson, and Herrmann 2022). Taking such an approach is attractive, as it allows for the elicitation of loss aversion in a single question.

A potential alternative and simpler (single question) approach to measure loss aversion would be to only elicit the loss L such that $G_{0.5}L{\sim}0$, currently our second step, and then define loss aversion as the ratio $G/{-L}$, instead of $x^{+}/{-x^{-}}$. This method provides a valid measure of loss aversion if the decision weight that participants attach to an event that occurs with a probability of 50 percent is the same in the gain and the loss domain.[26] To investigate whether this assumption is valid and, thus, whether the simpler method provides a reasonable alternative, we compare the measures obtained using this simpler approach to those obtained using our more sophisticated method.

We find that the naive measure of loss aversion is only weakly to moderately positively correlated to the theoretically sound measure (Belgian prototype: Kendall's tau-b = 0.141, $p < 0.001$; Irish Production version: Kendall's tau-b = 0.223, $p < 0.001$). This suggests that the assumption does not hold and that differences in probability weighting between the gain and loss domains have a considerable influence.

Furthermore, whereas the sophisticated measure was only very weakly and even negatively correlated to risk aversion, the naïve measure for loss aversion shows a strong positive correlation with risk aversion (Belgian prototype: Kendall's tau-b = 0.355, $p < 0.001$; Irish production version: Kendall's tau-b = 0.362, $p < 0.001$). This suggests that by not accounting for participants' probability weighting, the simple measure blurs the boundaries between their feelings toward losses and their feelings toward risk.[27] Taken together, the simpler method does not appear to be a viable alternative to the theoretically sound measure.

5. Practical considerations

Thus far, this article has focused on describing our implementation and providing empirical evidence for the validity of the elicitation method outside the laboratory with non-student populations. This section will elaborate on practical considerations when implementing this elicitation method. First, we discuss how the method can fill a growing need for digital assessment of investor preferences in general and behavioral preferences in particular. Second, we discuss issues surrounding its communication to clients and potential different ways in which the loss aversion measure can be used by financial advisors when attempting to help their clients select the most optimal products.

Demonstrating the feasibility of measuring loss aversion in a digital context is of practical importance, as it shows a path forward for financial institutions to address calls to incorporate behavioral insights

[26] More formally, given that $p = 0.5$, $G/{-L}$ is only a valid measurement of loss aversion if $w^+(0.5) = w^-(0.5)$. For $G/{-L}$ to be a valid measurement of loss aversion regardless of the chosen p, it would be necessary that $w^+(p) = w^-(1-p)\ \forall\ p$, which would be the case if there is no probability weighting. Prior to the introduction of the loss aversion elicitation method by Abdellaoui, Bleichrodt, and Paraschiv (2007) all elicitation methods made such simplifying assumptions. We employ the more recent method developed by Abdellaoui et al. (2016), as this method is arguably simpler for participants to understand.

[27] Additionally, if we conduct the same regression as depicted in Table 4, Panel A for this simple loss aversion measure, we find no significant relationships between this simple measure and education (or any other background characteristics). Additionally, if we conduct the regressions in Table 4, Panel B for this simple loss aversion measure, we find patterns that strongly mirror those for risk aversion in Table 5, Panel B, with income and surplus income having strong negative effects on loss aversion.

into their risk profiles. Financial regulators have recently stressed the importance of using behavioral insights to improve client risk profiles. For example, the European Securities and Market Authority has called for behavioral findings, and loss aversion, in particular, to be incorporated in suitability assessments (ESMA 2017; 2018). The recent "Retail Investment Strategy" of the European Commission also calls for the inclusion of behavioral elements, most notably loss aversion, that are currently ignored in risk profiling (European Commission 2020). Similarly, the Financial Conduct Authority in the UK has also called for firms to recognize and take account of consumers' behavioral biases (FCA 2022). In addition, the method also fits well with recent calls from the European Commission for replacing risk-profiling questionnaires with more dynamic quantitative methods (European Commission 2020) and for the investor risk assessments to be better adapted for use in an online environment (European Commission 2022). The elicitation proposed in this paper improves standard risk profiling practices in content and method, thus addressing recent calls for change.

After obtaining a measure of loss aversion, there are multiple ways in which firms can make these actionable. The elicitation does not impose how to define risk profiles or how to formulate investment advice. Rather, the definition of a risk profile and the formulation of investment advice are both practical aspects where financial service providers may have very different approaches to differentiate themselves and add value for the client.

Our method provides a continuous measure of loss aversion. The financial institution we worked with categorized people in either three (Belgium) or four (Ireland) categories based on their loss aversion score. In both versions, one category distinguished participants who were gain seeking (loss aversion of 0.99 or lower). The remaining categories were chosen so that each had roughly the same number of observations. Such a categorization has two potential benefits over the continuous measure. First, a classification based on how loss averse a client is relative to the population is arguably easier to communicate to a client than a purely numerical value. Second, such a classification deals with outliers in a reasonable way. Some participants will end up with extremely low or high measures of loss aversion, implying implausibly high levels of gain seeking or loss aversion. Such extreme scores likely reflect some degree of measurement error. Nevertheless, there is information value in such measurements: a participant who is very loss averse will likely not end up with a loss aversion measure close to zero, even if they make errors in the elicitation. Therefore, classifying participants with an extremely low (high) score as among the less (more) loss-averse participants provides a reasonable way to deal with such extreme measures. Having said that, depending on the aim, one may want to opt for a continuous measure of loss aversion. In such cases, one can either decide to elicit loss aversion a second time if the initial measurement is sufficiently extreme or to truncate the distribution.

An important question is how to use the loss aversion measure in the advisory process. Overall, there seem to be two normative perspectives a financial advisor can take with regard to their client's loss aversion. First, one can accept loss aversion as a valid preference and try to maximize the welfare of the client subject to this preference. Second, one can see loss aversion as a bias that needs to be corrected (Bleichrodt, Pinto, and Wakker 2001; Andersson et al. 2016). In practice, financial advisors likely need to find a balance between these two views and take an approach that respects the client's emotions regarding losses but at the same time recognizes that such emotions can stand in the way of the client reaching their investment goals and that sound financial advice may help bridge this gap.

On the one hand, it seems wise to take account of the client's loss aversion when constructing the investment portfolio. If a client has strong emotional reactions to losses, then encountering significant interim losses may lead them to make short-sighted decisions. Limiting the potential of such losses will arguably increase the likelihood that the client feels sufficiently confident to continue with the investment plan, even if there is a period in which the market is down. There is extensive literature that shows how loss aversion can be incorporated into portfolio optimization (Benartzi and Thaler 1995; Barberis, Huang, and Santos 2001; Berkelaar, Kouwenberg, and Post 2004; Gomes 2005; Fortin and Hlouskova 2011; van Bilsen, Laeven, and Nijman 2020). The Irish bank took this approach and offered clients portfolios that matched their elicited risk profiles, including loss aversion. To build the portfolios, they used the method proposed by Vandenbroucke (2019), which aligns the long-term asset class allocation with the investor's attitude towards risk (mean-variance) and enters interim, algorithmic deviations from this long-term benchmark (adaptivity) in alignment with the investor's attitude towards loss. The bank, therefore, links both aspects of the elicitation to the proposed investment with the purpose of reflecting the client's preferences both in the allocation and in the management of the advised portfolio.

On the other hand, loss aversion can potentially stand in the way of the client reaching their long-term goals. This can be seen as especially problematic given that the impact that loss aversion has on the client's decisions depends on psychological perceptions of reference points that are sensitive to strategically irrelevant reframings of decisions and on the frequency by which a client evaluates her portfolio. The advisor can potentially counsel loss-averse clients to ensure their loss aversion does not unduly hinder their long-term goals. For example, it is well-known that loss aversion will especially strongly affect a person's willingness to invest if they are myopic and adopt a short-term view of investments. Such a combination of myopia and loss aversion will lead an investor to pay too much attention to short-term volatility and to react negatively to downward shocks (Benartzi and Thaler 1995; Gneezy and Potters 1997; Thaler et al. 1997; Gneezy, Kapteyn, and Potters 2003; Haigh and List 2005; Larson, List, and Metcalfe 2016; Iqbal et al. 2021). If the advisor can help loss-averse clients take a long-term perspective and refrain from evaluating their portfolio too frequently, this is one way in which the negative effect of the client's loss aversion on their long-run returns can be tempered.[28]

6. Conclusion and Discussion

Loss aversion has been shown to be an important driver of people's investment decisions. Encouraged by regulators, financial institutions are in search of ways to incorporate clients' loss aversion in their risk classifications. The most critical obstacle appears to be the lack of a valid measurement method that can be straightforwardly incorporated into existing processes.

This paper presents the results of two large-scale implementations of a theoretically valid measure of loss aversion within a risk profiling application of an established financial institution. By doing so, we add to the literature in four ways. First, we demonstrate how a theoretically sound elicitation method for loss aversion can be incorporated within the investment advisory process. This is good news for financial institutions looking to comply with regulatory guidance and move towards a more behavioral approach to risk profiling.

Second, in our two implementations, we elicit loss aversion for a total of 1,040 employees and 3,740 clients of the financial institution. Thereby, we contribute to a growing literature that aims to measure loss aversion beyond the typical student subject pools at universities and to investigate the heterogeneity within such populations. We find that the observed distributions align with previous observations. In line with recent findings, we also find that loss aversion is strongly related to education, with higher-educated individuals being more loss averse.

Third, we show that loss aversion is largely independent of the risk-return preferences commonly used for investor classification and that the correlations between these two preferences and clients' background characteristics are markedly different. Whereas loss aversion is only related to education, risk aversion is strongly related to a client's gender, age, and financial situation: women, more senior, and less affluent participants are more averse to risk. This observation does not depend on whether we elicit risk aversion using a survey or choice-based elicitation method. These findings support the conjecture that risk and loss aversion are complementary in capturing investor preferences.

Finally, we show that a simpler measure of loss aversion that does not control for probability weighting is not a valid alternative to our theoretically sound measure: the simple measure is only weakly related to the theoretically sound measure. Furthermore, the simple measure shows a considerable correlation with risk preferences, whereas the theoretically sound measure does not. This suggests

[28] Analogously, recent work on clients investing through robo-advisors also has argued that reducing interaction frequencies between client and advisor can mitigate the effect of client's loss aversion on investment decisions (Capponi, Ólafsson, and Zariphopoulou 2022).

that if we do not consider probability weighting, we blur the lines between participants' feelings toward losses and their feelings toward risk.

Our demonstration that this theoretically sound elicitation method of loss aversion can be incorporated into a risk profiling application should also be of interest to experimentalists interested in eliciting loss aversion outside the laboratory with non-student subjects. In the initial implementation, Abdellaoui et al. (2016) had at most two subjects at a time performing the elicitation under close supervision by an experimenter. All subjects were economics students who first received detailed instructions and were required to complete several training questions. Our implementation shows that their method is simple enough to be used to elicit loss aversion for broader subject populations and with relatively minimal instructions. This opens up the possibility of using this decision-theoretically sound method outside of the laboratory, for example, when conducting experiments online.

A limitation of our study is that we cannot link the risk and loss aversion measures to the actual financial decisions of the investors or their emotional responses to actual fluctuations in their investment portfolio. Future research should investigate the relations between risk and loss aversion measures and such real-world outcome measures, as doing so can help guide the choice of the most optimal measures to be included in investor risk classifications.

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Appendix

Table A1: Three Illustrations of the bisection method

The table depicts three illustrations of the bisection method, for an investor with €5,000 to invest. The choices of the investor are in bold.

	Choices in elicitation x+	Choices in elicitation L	Choices in elicitation x-
1	$\mathbf{500}$ vs. $1{,}000_{0.5}0$	$1{,}000_{0.5}$-1000 vs. $\mathbf{0}$	-220 vs.$\mathbf{0_{0.5}}$-$\mathbf{440}$
2	250 vs.$\mathbf{1,000_{0.5}0}$	$\mathbf{1,000_{0.5}}$-$\mathbf{250}$ vs. 0	-110 vs.$\mathbf{0_{0.5}}$-$\mathbf{440}$
3	$\mathbf{380}$ vs. $1{,}000_{0.5}0$	$1{,}000_{0.5}$-630 vs. $\mathbf{0}$	**-50** vs.$0_{0.5}$-440
4	-	-	**-80** vs.$0_{0.5}$-440
5	-	-	-95 vs.$0_{0.5}$-$\mathbf{440}$
Value	**315**	**-440**	**-90**

Table A2: Correlation matrix for the Belgian prototype version

The table depicts the Kendall tau-b correlation coefficients. *Loss aversion* is the participants' elicited loss aversion coefficient. Risk aversion is an ordinal variable taking the value 1 if the participant is classified as very dynamic, 2 if they are classified as dynamic, 3 if they are defensive, and 4 if they are very defensive. All other variables are defined as in Table 3. P-values are in parentheses.

	1	2	3	4	5	6	7
1. *Loss aversion*	1.000						
	-						
2. *Risk aversion*	-0.086	1.000					
	(0.000)	-					
3. *Gender*	0.005	-0.214	1.000				
	(0.811)	(0.000)	-				
4. *Age*	-0.018	0.050	0.004	1.000			
	(0.315)	(0.021)	(0.865)	-			
5. *Education*	0.091	-0.049	-0.032	-0.046	1.000		
	(0.000)	(0.056)	(0.236)	(0.042)	-		
6. *Client*	-0.059	0.016	0.138	-0.160	-0.323	1.000	
	(0.008)	(0.526)	(0.000)	(0.000)	(0.000)	-	
7. *Investment* amount	0.034	-0.125	0.142	0.244	0.118	-0.194	1.000
	(0.084)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	-

Table A3: Correlation matrix for the Irish production version

The table depicts the Kendall tau-b correlation coefficients. *Loss aversion* is the participants' elicited loss aversion coefficient. Risk aversion is an ordinal variable taking the value 1 if the participant is classified as very dynamic, 2 if they are classified as dynamic, 3 if they are defensive, and 4 if they are very defensive. All other variables are defined as in Table 3. P-values are in parentheses.

	1	2	3	4	5	6	7	8	9
1. *Loss aversion*	1.000								
	-								
2. *Risk aversion*	-0.024	1.000							
	(0.075)	-							
3. *Income*	0.007	-0.120	1.000						
	(0.558)	(0.000)	-						
4. *Surplus income*	0.022	-0.080	0.343	1.000					
	(0.064)	(0.000)	(0.000)	-					
5. *Savings*	0.020	0.134	0.120	0.236	1.000				
	(0.082)	(0.000)	(0.000)	(0.000)	-				
6. *Existing investments*	0.062	0.140	0.028	0.125	0.291	1.000			
	(0.000)	(0.000)	(0.027)	(0.000)	(0.000)	-			
7. *Planned expenditure*	-0.005	0.009	0.074	0.112	0.180	0.077	1.000		
	(0.723)	(0.548)	(0.000)	(0.000)	(0.000)	(0.000)	-		
8. *Investment amount*	0.073	0.133	0.087	0.232	0.426	0.574	0.032	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	-	
9. *Investment horizon*	-0.027	-0.241	0.082	-0.082	-0.175	-0.143	-0.064	-0.138	1.000
	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	-

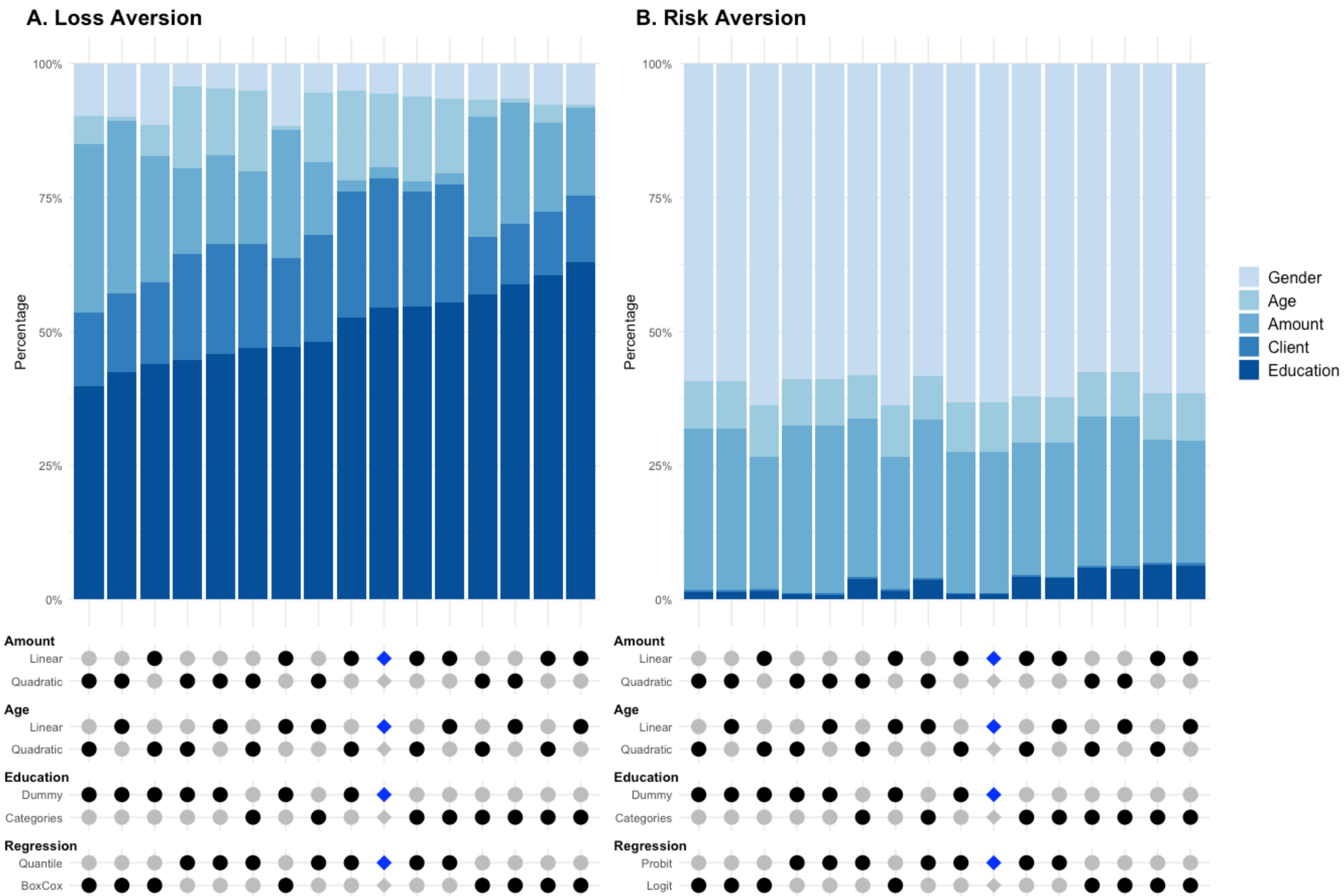

Figure A1: Multiverse analysis Belgium. The figure shows how the results of the general dominance analyses for loss and risk aversion in Belgium for a wide set of analytical choices. The different specifications vary the regression model used (Quantile and BoxCox regression for loss aversion; ordered Probit and ordered Logit regression for risk aversion). Furthermore, they vary whether education is included as a dummy variable identifying whether a person has completed higher education or not or whether they distinguish between all four categories (primary education, secondary education, college, university) and whether they allow for quadratic effects for the investment amount and age. The models indicated by the blue diamonds are the ones reported in the paper.

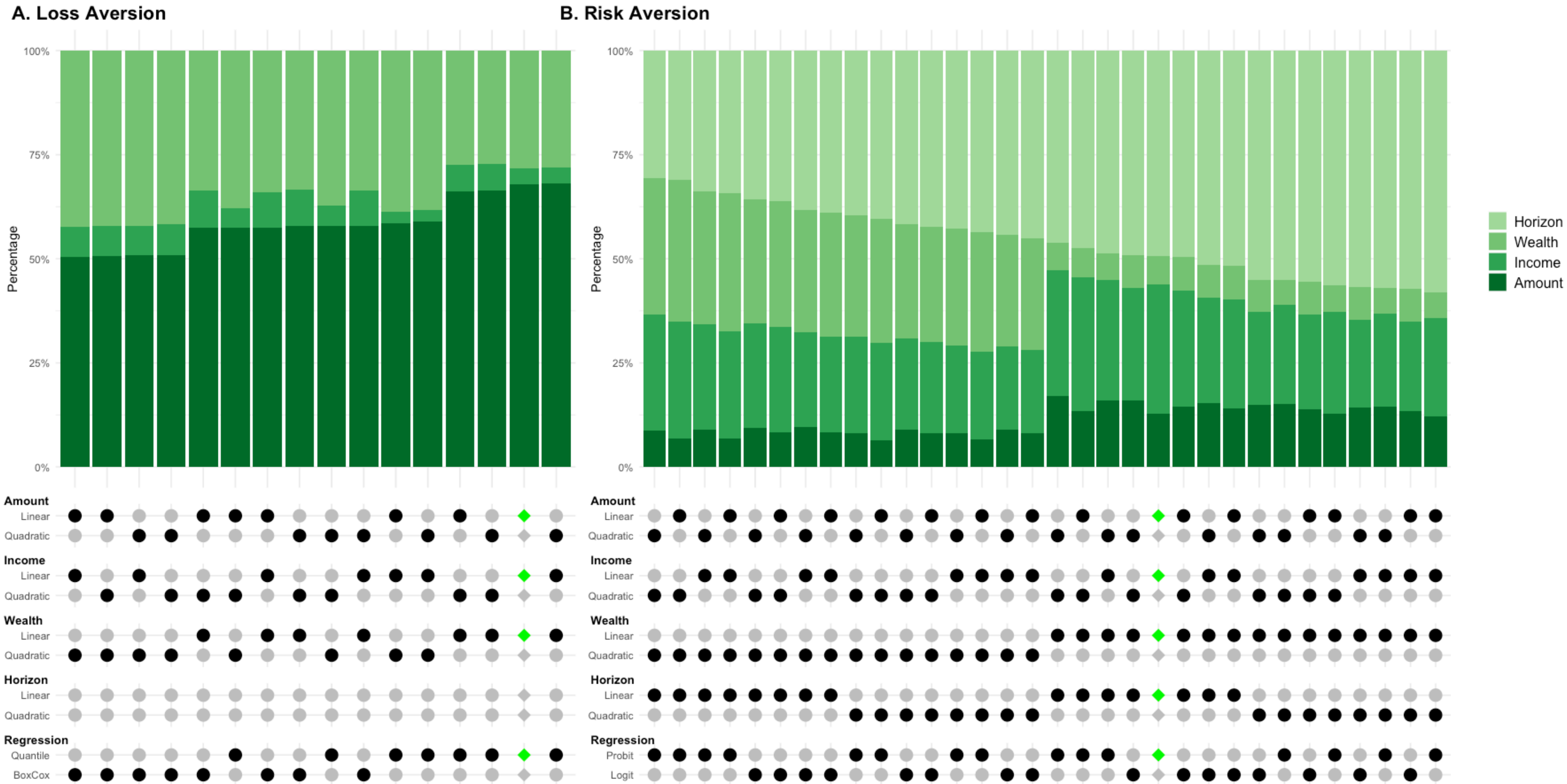

Figure A2: Multiverse analysis Ireland. The figure shows how the results of the general dominance analyses for loss and risk aversion in Ireland for a wide set of analytical choices. The different specifications vary the regression model used (Quantile and BoxCox regression for loss aversion; ordered Probit and ordered Logit regression for risk aversion). Furthermore, they vary whether they allow for quadratic effects of the investment amounts, income variables, wealth variables, and the investment horizon. The models indicated by the green diamonds are the ones reported in the main paper. The loss aversion models did not include the investment horizon as that was only elicited later in the survey and only for the purpose of the elicitation of risk aversion. Figure A3 shows that adding the investment horizon to the loss aversion models would not materially affect the results.

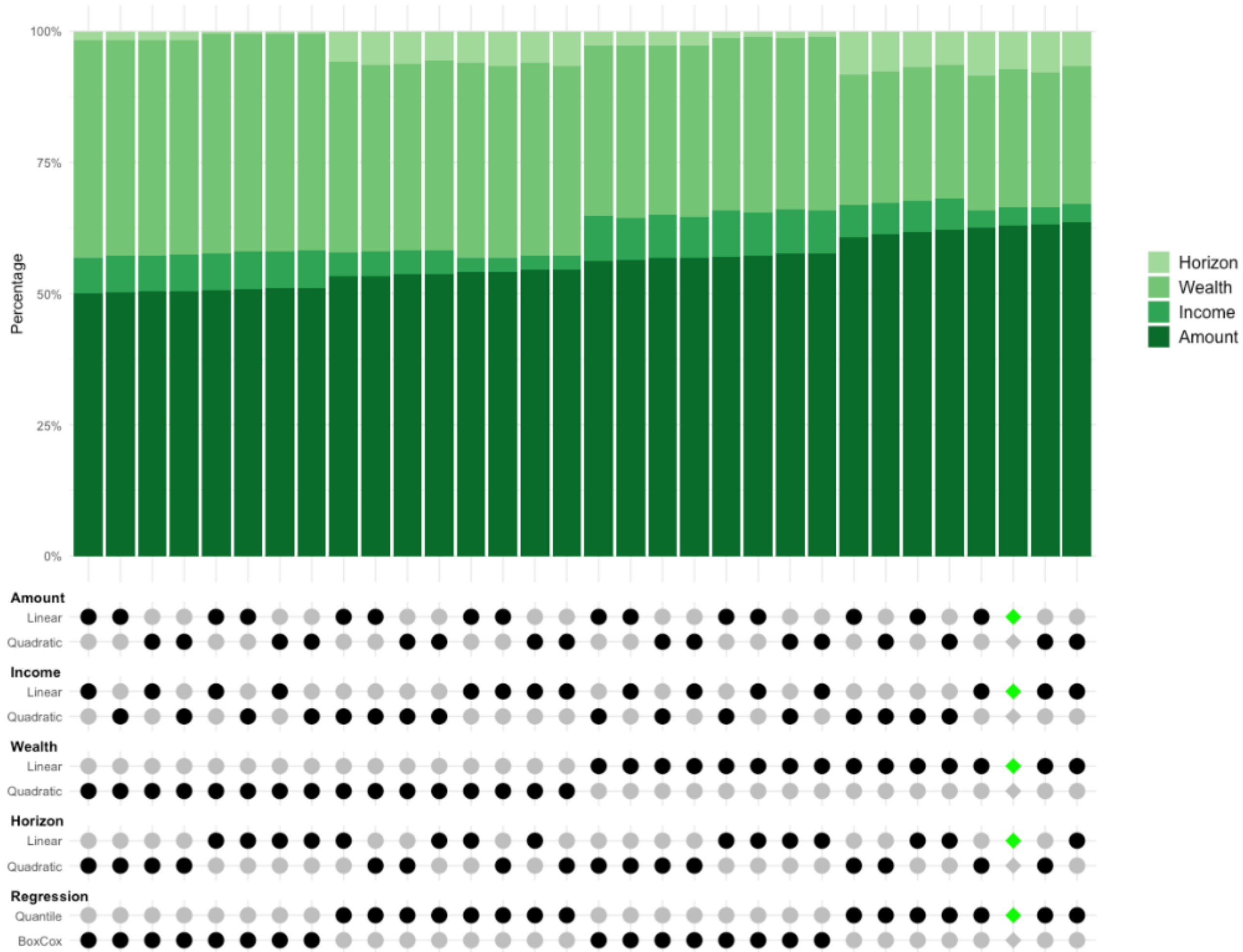

Figure A3: Multiverse analysis Ireland for loss aversion with investment horizon included as a variable. The figure shows how the results of the general dominance analyses for loss aversion in Ireland for a wide set of analytical choices. The different specifications vary the regression model used (Quantile and BoxCox regression for loss aversion; ordered Probit and ordered Logit regression for risk aversion). Furthermore, they vary whether we allow for quadratic effects of the investment amounts, income variables, wealth variables, and the investment horizon. The models indicated by the green diamonds are the ones reported in the main paper, with the only difference being that now the investment horizon is included as an independent variable.