Financial Loss Aversion Illusion*

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Abstract

We test the proposition that investors' ability to cope with financial losses is much better than they expect. In a panel survey with real investors from a large UK bank, we ask for subjective ratings of anticipated returns and experienced returns. The time period covered by the panel (2008-2010), with frequent losses and gains in the portfolios of investors, provides the required background to analyze the involved hedonic experiences. We examine how the subjective ratings behave relative to expected portfolio returns and experienced portfolio returns. Loss aversion is strong for anticipated outcomes with investors reacting over twice as sensitive to negative expected returns as to positive expected returns. However, when evaluating experienced returns, the effect diminishes by more than half and is well below commonly found loss aversion coefficients. It seems that a large part of investors' financial loss aversion results from a projection bias.

JEL-Classification Codes: D03, D14, D81, G02, G11

Keywords: Loss Aversion, Individual Investors, Expectations, Affective Forecasting, Projection Bias.

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1 Introduction

Loss aversion has been frequently documented in psychology and economics, with the conclusion that losses loom larger than gains and that "fair" lotteries (from an expected value perspective) are generally not accepted when they involve potential losses. The magnitude of this effect has been experimentally identified with loss aversion coefficients close to or even above two. In finance, loss aversion has been suggested to explain, for instance, the equity premium puzzle and low stock market participation (Benartzi and Thaler, 1995; Ang, Bekaert, and Liu, 2005).

In the evaluation of gains and losses, one has to distinguish between anticipated and experienced outcomes. Most experiments on gambles or lotteries focus on the trade-off between anticipated gains and losses. However, this implies that people are able to perfectly forecast the hedonic impact of gains and losses. In contrast, recent experimental evidence suggests that people's ability to cope with losses is much better than they predict (Kermer, Driver-Linn, Wilson, and Gilbert, 2006). When actually experienced, losses seem not to hurt as much as people expected.

Using a unique dataset, we test this proposition in the financial domain. In a panel survey with real investors from a large UK bank, we ask for subjective ratings of anticipated returns and experienced returns. Within the time period covered by the panel (2008-2010), we observe frequent losses and gains in the stock market and in investors' portfolios. This provides the required background to analyze the involved hedonic experiences. We examine how the subjective ratings of outcomes behave relative to expected portfolio returns and experienced portfolio returns. We calculate loss aversion coefficients for expectations and experiences and, to this end, define several potential reference points investors might use.

Loss aversion is strong for anticipated outcomes. From regressions of subjective ratings on expected returns, we infer a loss aversion coefficient of about 2.2 for a reference point of zero. This means that investors are twice as sensitive to negative expected returns as to positive expected returns. While for different reference points and model specifications loss aversion coefficients vary slightly, they are almost always close to two and statistically significant.

However, when evaluating experienced returns, the loss aversion coefficient decreases to about 1.2 and is statistically indistinguishable from one (loss neutrality). There is no reference point or regression model for which we find loss aversion for experienced outcomes. Investors do not react more sensitively to losses than to gains when they are confronted with realized portfolio performance. The loss aversion they show ex ante seems to be partly or fully a projection bias, i.e., a failure to accurately predict future utility. The result is independent of whether we use percentage return or monetary profits as the outcome variable.

As a second property of reference-based utility, we also test for diminishing sensitivity with respect to outcomes more distant from the reference point. We indeed find that investors' reaction is strongest for returns close to the reference point. An improvement from, e.g., 2% to 4% in portfolio return has a greater impact on subjective ratings than moving from 12% to 14%. This is true both for expected as well as for experienced outcomes. But while for expected returns the sensitivities in each interval are far greater for losses than for gains, this is not the case for experiences.

Our findings have far-reaching implications for individual investing. While loss aversion itself is not necessarily a judgment bias, but can be a legitimate part of people's preferences, the financial loss aversion illusion we document clearly is. If investors systematically overestimate their personal loss aversion when thinking about financial outcomes, their investment decisions will differ from what is justified by their experience of these outcomes. In particular, they will invest less riskily than would be optimal from an ex post perspective and will avoid potential losses unless they receive a substantial compensation.

To provide some evidence of the consequences of loss aversion for investment behavior, we analyze the portfolio risk investors take. We interact gains and losses with portfolio volatility and indeed find that higher loss aversion in expectation is associated with far less risky portfolios. This suggests that the loss aversion coefficients we measure are meaningful for participants' investing behavior. We assume that with greater awareness of their gain and loss experiences, investors would be prepared to take on higher portfolio volatility. An even stronger result is precluded by the aggregate nature of the loss aversion estimates.

We further investigate the nature of financial loss aversion illusion by considering the effects of learning and sophistication. We find that anticipated loss aversion is reduced after previous losses. Investors seem to learn from the immediate experience of a loss to better predict their response to future outcomes. However, this learning effect is short-lived. Financial literacy and investment experience are among sophistication measures that mitigate financial loss aversion illusion. In extensive robustness analyses we test for risk aversion as an alternative explanation, examine the exclusion of several types of observations, and analyze the impact of selection effects.

Our work is related to two strands of the literature. We contribute to research in decision theory and psychology on estimating loss aversion (Tversky and Kahneman, 1992; Abdellaoui, Bleichrodt, and Paraschiv, 2007), and apply it to the domain of individual investing. In particular, we test the prediction of differences between anticipated loss aversion and loss experience (Kermer et al., 2006), which belongs to a broader class of projection biases (Loewenstein, O'Donoghue, and Rabin, 2003). Secondly, we contribute to the large literature on loss aversion in finance (reviewed in Section 2) by showing that loss aversion is present in portfolio expectations of investors and that it is potentially responsible for the portfolio risk investors take. By revealing the discrepancy between these expectations and the actual experience of losses and gains, we shed new light on the role of loss aversion in investing.

2 Theory and Literature

When confronting a bet with equal chances for a gain and a loss, people typically require a gain that is much larger than the loss to accept the bet. Samuelson (1963) reports offering such a bet to colleagues, which was often declined even when the potential gain was $200 compared to a potential loss of $100. This cannot be explained by risk aversion alone as for gambles completely in the gain domain risk premia are generally much lower. Instead, it seems that losses loom larger than gains, in the example more than twice as large. At the same time, this means that outcomes are viewed from a reference point, which defines gains and losses relative to this reference. The idea of people adapting to a reference level can be found in psychology already around the time of Samuelson's observation (Helson, 1964).

The term "loss aversion" describes the greater sensitivity to losses as compared to gains; the expected negative feeling associated with a loss is larger than the expected positive feeling with a gain of equal size. Loss aversion is not necessarily a judgment error, it might as well reflect the true preferences of people, who strongly dislike losses. Alternatively, it is argued that loss aversion represents an emotional overreaction toward losses driven by fear (Camerer, 2005). Loss aversion is a prominent feature of prospect theory (Kahneman and Tversky, 1979), which formalizes several empirical observations in choice behavior. In prospect theory, the value function is steeper for losses than for gains, representing the greater sensitivity toward losses. The value function can be expressed in the following parametrized form (Tversky and Kahneman, 1992):

$$u(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases} \tag{1}$$

In Equation 1, λ represents the loss aversion coefficient. For any $\lambda > 1$ an individual is said to be loss averse. Köszegi and Rabin (2006) propose a more general model of reference-dependent preferences, where overall utility is the sum of consumption utility and gain-loss utility. In their case, λ is the ratio of marginal gain-loss utility for losses and gains approaching the reference point from below and above. Again, loss aversion is present if $\lambda > 1$. A similar definition is given by Köbberling and Wakker (2005). Under the assumption of linear utility, it simplifies to the ratio of the slopes of gain-loss utility for losses and gains (cp. Köszegi and Rabin, 2006):

$$u(x) = \begin{cases} \eta x & \text{if } x \geq 0 \\ \eta \lambda x & \text{if } x < 0 \end{cases} \tag{2}$$

Loss aversion coefficients have been empirically estimated mostly by using monetary lotteries. Tversky and Kahneman (1992) report a median coefficient of 2.25, while earlier Fishburn and Kochenberger (1979) find a median coefficient of 4.8. Abdellaoui et al. (2007) calculate median coefficients between 1.53 and 2.52, depending on the estimation method. Abdellaoui, Bleichrodt, and L'Haridon (2008) report coefficients between 2.24 an 3.01 for different prospects. Booij and van de Kuilen (2009) observe loss aversion coefficients between 1.73 and 2.00 depending on the estimation method and whether the lotteries involve high or low stakes. Lower loss aversion coefficients are found in other experiments: 1.43 (Schmidt and Traub, 2002), 1.8 (Pennings and Smidts, 2003), 1.58 (Booij, van Praag, and van de Kuilen, 2010), 1.23 and 1.46 (Zeisberger, Vrecko, and Langer, 2012). Many of these studies also examine individual loss aversion and conclude that a large majority of participants is loss averse.

In these elicitation tasks of loss aversion coefficients, parameters are mostly inferred from participants' choices between two lotteries or between a lottery and a certainty equivalent. People have to think about a lottery before it is played and have to anticipate how different outcomes would feel. Or more technically, they have to assign the expected utility to each outcome. Possibly, the experience with an actual outcome will differ from the expectations ex ante. Loss aversion could result from a projection bias, if people are inaccurate in assessing beforehand the personal hedonic consequences of a risky decision involving gains and losses. In particular, they might fear potential losses to a greater degree than justified. Similar forecasting errors are quite common in evaluating future utility, often due to underestimating the change in one's tastes (Loewenstein et al., 2003). For example, projection biases have been found in food choice (Read and van Leeuwen, 1998) or catalog orders (Conlin, O'Donoghue, and Vogelsang, 2007). The two different perspectives have also been labeled "decision utility" and "experienced utility" and they can differ in systematic ways (Kahneman, Wakker, and Sarin, 1997).

Only rarely do experiments on loss aversion take the perspective of experienced utility into account. As an exception, Kermer et al. (2006) compare predicted changes in happiness to experienced changes in happiness in a between-subject and a within-subject design. They find in both cases that people predict a greater emotional impact of losses compared to gains, but do not feel an experienced loss more strongly than a gain. Their ability to come to terms with losses seems to be better than they expected. We take this laboratory evidence to the field of investment decisions, for which we have a unique data set of return evaluations and actual choices by retail investors. We aim to test both predictions in this context, i.e. whether investors are loss averse with respect to their expected portfolio returns (Hypothesis 1) and whether this loss aversion declines or even disappears when evaluating experienced portfolio returns (Hypothesis 2). Our setting further allows us to test numerous additional predictions and alternative explanations. We also extend Kermer et al. (2006) in methodology by suggesting ways to calculate loss aversion coefficients and quantifying the financial loss aversion illusion.

The application to the investment context is motivated by the importance of loss aversion in financial decisions. Most investments involve potential gains and losses, and as a consequence loss aversion has found broad recognition, both theoretically and empirically. Benartzi and Thaler (1995) introduce loss aversion as an explanation for the equity premium puzzle. Combined with frequent evaluation of portfolios (myopia), loss aversion renders stock investments unfavorable relative to riskless investments. Because of the frequent losses in the short term, investors demand a high premium to invest in stocks. Haigh and List (2005) experimentally confirm the presence of myopic loss aversion for professional traders. Under the additional assumption of narrow framing, high loss aversion can even prompt people to completely abstain from the stock market (Ang et al., 2005; Barberis, Huang, and Thaler, 2006). This addresses a second financial puzzle, which exists in the globally low participation in stock markets. Dimmock and Kouwenberg (2010) empirically find lower equity market participation for households with higher loss aversion. Their study based on a Dutch household survey is among the very few to use a direct measure of loss aversion.

The relevance of loss aversion extends to portfolio choice and diversification (Dimmock and Kouwenberg, 2010; Polkovnichenko, 2005). It may also have far-reaching consequences for retirement investing (Benartzi and Thaler, 1999). In a simulation study, Barberis and Huang (2001) find support for loss aversion over individual stocks, as compared to overall portfolios. In their framework, loss aversion is able to explain a variety of stock market phenomena such as excess volatility and the value premium. Investors typically hold on to their losing investments and sell their winning investments, which constitutes the disposition effect (Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998). This behavior also implies an evaluation of each individual asset relative to a reference level, which is then supposed to alter the preferences of investors. In the loss domain, they act risk seekingly in an attempt to avoid the loss and to break even. In a different interpretation involving realization utility (Ingersoll and Jin, 2013), loss aversion is a reason to postpone realizing a loss.

3 Data

We conduct a panel survey with direct brokerage clients at Barclays Stockbrokers, one of the largest brokerage providers in the UK. Participants are self-directed retail investors holding mostly stocks and mutual funds in these portfolios. The survey was designed in collaboration with the Behavioural Finance team at Barclays and covers a time period from 2008 to 2010. During that time the survey took place quarterly, which results in a total of nine survey rounds. With the volatile stock markets over that period resulting in frequent losses and gains, the panel provides a unique opportunity to analyze loss aversion from investors' perspective.

In a first step, a sample of clients was selected based on a stratified sampling procedure, which undersampled clients with little trading activity and low portfolio value and excluded clients with less than one trade per year or a portfolio value of less than £1000. Apart from these modifications the selection was random and the final sample of 19,251 investors is largely representative of the Barclays Stockbrokers client base. These investors were invited via e-mail to participate in the online questionnaire. 617 investors participate in the panel for at least one round and we have a total of 2,135 investor-round observations, which means that respondents on average participated about 3.5 times. For each of the nine rounds we have a minimum of 130 observations.

This corresponds to a response rate of 3%, which is not much lower than in similar surveys (cp. Dorn and Huberman, 2005; Glaser and Weber, 2007a). The demographics of investors are shown in Panel A of Table 1. The participants are predominantly male, older, and more affluent than the overall UK population. In this respect, they closely resemble the investor population in other studies on online brokerage clients. The financial literacy among participants is also reasonably high (on average 3.5 correct responses out of 4 questions taken from van Rooij, Lusardi, and Alessie, 2011), which suggests that potential biases we find are not just a result of an insufficient understanding of financial market.

The two survey questions we mainly focus on are subjective ratings of expected returns and experienced returns:

1. *How would you rate the returns you expect from your portfolio held with us in the next three months?*
   Seven-point scale from "extremely bad" to "extremely good".
2. *How would you rate the returns of your portfolio (all investments held with us) over the past three months?*
   Seven-point scale from "extremely bad" to "extremely good".

The first question asks investors to provide a rating of their expected portfolio returns over the next three months. This corresponds to the time interval between two survey rounds. The second question is the mirror image of question one, asking for past portfolio returns over the last three months. The ratings are elicited on a good-to-bad scale and provide a subjective evaluation of the expected and experienced return rather than a numerical estimate (for which we also ask, see below). We interpret the rating as a proxy for the utility an investor associates with the expected or experienced return, respectively. In Equations 1 and 2 the ratings represent $u(x)$, with $x = E[r_{t,t+1}]$ for the first question and $x = r_{t-1,t}$ for the second question.

Similarly, Merkle, Egan, and Davies (2015) use the second question to determine investor happiness, while Kermer et al. (2006) directly ask "how happy" participants feel (or predict to feel) after particular outcomes. It is common in psychology to assess the hedonic quality of an item or experience on a simple good to bad scale (Kahneman, Diener, and Schwarz, 1999; Osgood, Suci, and Tannenbaum, 1957). In economic terms, the ratings express anticipated utility with a return in asking how "good" a certain outcome is expected to be. The link between such subjective evaluations and utility is advocated by economic happiness research (Frey and Stutzer, 2003; Oswald and Wu, 2010). Somewhat differently, Weber, Weber, and Nosić (2012) interpret the responses as subjective return expectations in the sense of how good investors expect the future return to be. Arguably, this also contains a utility evaluation as a subjective quality is attached to return expectations. As McGraw, Larsen, Kahneman, and Schkade (2010) point out, a common scale is important when comparing different evaluations of gains and losses. This is why we use the exact same format for both questions.

Panel B of Table 1 shows descriptive statistics for responses to these questions. The average expected portfolio return rating is 4.2 and slightly above the middle-point of the scale, while the average experienced return rating is 3.6. The poor performance of the stock market during our survey period certainly contributed to the low experience ratings. Quite reasonably, experienced return ratings are more dispersed than the expected return ratings as one can see from standard deviations and the percentiles. When thinking ahead it would be bold to expect extremely positive or extremely negative outcomes, while ex post (in particular between 2008 and 2010) participants often experience such extreme outcomes.

It is central to our approach to link the subjective ratings to numerical portfolio return data. For the anticipated ratings, we use the numerical expected portfolio returns, and for the experienced ratings the numerical perceived past portfolio returns, which correspond to the x in Equations 1 and 2. We also calculate actual past portfolio returns directly from investors portfolios, but—as Merkle et al. (2015) show—perceived values have a higher relevance for participants. Expected portfolio return and past portfolio return are elicited in the following way:

3. *We would like you to make three estimates of the return of your portfolio held with us by the end of the next three month. Your best estimate should be your best guess. Your high estimate should very rarely be lower than the actual outcome of your portfolio (about once in 20 occasions). Your low estimate should very rarely be higher than the actual outcome of your portfolio (about once in 20 occasions).*
   Please enter your response as a percent change, i.e. a rise as X%, or a fall as -X%.

4. *What do you think your return (percentage change) with us over past three months was?*
   Please enter your response as a percent change, i.e. a rise as X%, or a fall as -X%.

From question 3 we use the best estimate as our value for expected portfolio return. As Panel B of Table 1 shows, quarterly portfolio return expectations are quite high, the median estimate is 5%. They vary widely, including also negative return expectations (n=173). One might question, whether it is rational to expect negative returns for a stock portfolio. However, 41% of participants hold a negative expectation for either their portfolio or the market at least once during the survey. Thus negative expectations are quite common and not concentrated among few participants. At the same time, these expectations may not seem totally unreasonable given the frequently observed negative realized returns over that period. As the table reveals, realized portfolio returns are on average indeed negative for survey participants (−1.9% perceived and −5.1% actual).[1] While participants clearly overestimate their past returns, the correlation between perceived and actual returns is nevertheless high (0.62).

For a reference-dependent model it is important to define an appropriate reference point. The most obvious reference point is 0, which means that negative portfolio returns imply a loss and positive returns a gain. Other possible reference points include the risk-free interest rate, inflation, or stock market returns. A loss would then be defined as underperformance of the own portfolio over the last quarter compared to one of these benchmarks. In contrast to the fixed reference point at 0, the other reference points are time-varying, with the degree of variation of course largest for stock market returns.

Table 1 shows descriptive statistics for these benchmarks on a quarterly basis again conditional on survey participation. Inflation as reported by the UK Office for National Statistics was 0.8% on average, which corresponds to an average annual inflation of 3.2% (the UK has a relatively high inflation rate compared to other European countries). Short-term interest rates represented by the three month LIBOR were on average 0.6% on a quarterly basis. Stock market returns were −2.6%, which is in line with investors' negative realized portfolio returns. Again, we also consider perceived stock market returns, elicited in analogy to question 4. Perceived market returns were on average −0.8%.

In particular for anticipated loss aversion, expectations are an important reference level. Market return expectations are a natural reference to compare portfolio return expectations with. They are elicited in the same way as portfolio return expectations (see question 3). Market return expec-

[1] One reason for this result is that we report portfolio returns conditional on survey participation, which is highest for the early rounds of the survey during the immediate financial crisis. Unconditionally, over the whole period of the panel, quarterly portfolio returns are only slightly negative (−0.3%).

tations are considerably lower than portfolio return expectations, which means that investors on average expect to outperform the market. With the expected market return as a reference point, this outperformance would be considered an anticipated gain and an underperformance an anticipated loss.

A further class of reference points relies on investors' individual benchmarks. We ask in each round of the survey, what benchmark investors currently use, represented as a combination of interest rates and stock market returns (question see appendix). In the entry questionnaire of the survey, we offer a broader menu of potential benchmarks, but we find that other benchmarks such as foreign or global stock market indices or British government bonds are rarely used as a benchmark. We therefore mainly use the personally chosen combination of UK interest rates and UK stock market returns. Again, two separate benchmarks can be constructed, one backward-looking based on realized stock market returns and interest rates of the last quarter, and the other forward-looking based on expected market returns and interest rates for the next quarter. While the averages for these benchmarks of course lie between stock market returns and interest rate, they capture more closely the individually used reference point.

4 Results

4.1 Anticipated loss aversion

Higher returns feel better subjectively and they provide higher utility to investors. It is therefore not surprising that the relationship between expected portfolio returns and the subjective ratings of these returns is positive (correlation 0.40). Figure 1 displays the average subjective rating for each value of expected returns. The dots in the graph mostly represent multiple observations, as specific values of expected portfolio returns occur many times in the panel. To represent the subjective ratings by their averages allows for an easier interpretation.

Negative expected returns are mostly rated below 4, which is the middle point of the rating scale, while positive returns are mostly rated above 4. The point where expected returns cross the neutral rating appears to be somewhere between 0% and 5%. With respect to the functional form it is difficult to derive definite conclusions from the figure alone, but it seems that the slope is steeper for the lower range of expected returns and flatter for the higher range of returns. This is consistent with loss aversion. With a keen eye, one might even identify the tendency of a concave relationship for positive expected returns and a convex relationship for losses.

To substantiate these first impressions, we begin with a piecewise linear regression of expected return ratings on numerical return expectations. This corresponds to Equation 2 in which the loss aversion coefficient λ represents the ratio between the slopes below and above the reference point. We initially use 0 as a reference point, but will also report results for other potential reference points. Loss aversion is only estimated on aggregated level, as for individual loss aversion the number of observations is to small with a maximum of nine rounds per participant.

In the first column of Table 2, we estimate a simple pooled OLS model with robust standard errors for the anticipated subjective ratings of returns with expected portfolio returns a sole explanatory variable. The coefficient is positive and strongly significant. To separate the effect for the gain and loss domain, we construct a dummy variable for expected gains and losses, respectively. By interacting each dummy with expected portfolio returns, we estimate two independent coefficients conditional on whether a loss or gain is expected. For the same regression model as before, the coefficient is 7.5 for losses and 3.5 for gains (see column 2). The slope for losses is much steeper than for gains, indicating strong loss aversion.

The loss aversion coefficient λ can be calculated by dividing the coefficient for losses by the coefficient for gains ($\lambda = \frac{\eta\lambda}{\eta}$, see Equation 2). As a result we obtain a λ of 2.1, which is in the upper range of the values typically found in experiments based on lotteries. In experiments, the decisions are either hypothetically or the participants receive an endowment upfront to wager. They normally cannot lose their own money, which might attenuate loss aversion. As a caveat, in our setting only the most pessimistic investors hold negative return expectations. If those investors were also most loss averse, this might inflate our estimate.

To make use of the panel structure of our data, we estimate panel regressions in the remaining columns of Table 2. The results remain unchanged in a GLS regression with random effects and standard errors clustered by participants (column 3), and they are robust to the inclusion of survey round fixed effects (column 4). Finally, we run a fixed effects regression to control for all time-invariant individual effects (columns 5-7). While the size of coefficients changes, their ratio expressed in loss aversion λ is unaffected. We also control for investors' risk tolerance, their subjective portfolio risk perception, portfolio volatility, portfolio value, and turnover of investors, as these might influence subjective ratings of returns. The control variables are defined in the Appendix. We find that only risk tolerance has a marginally significant effect on subjective ratings, which is positive meaning that risk tolerant investors rate a given return better.

Loss aversion coefficients are significantly larger than one in all regressions with mostly $p<0.01$. To avoid non-linearities, test statistics are computed using a Wald-test for equality of the coefficients in the loss and gain domain, which is equivalent to $\lambda = 1$. We obtain similar results, when we estimate the distribution of λ with a bootstrap approach (see Online Appendix C). The economic magnitude of the effect is such that for an additional 5% in expected portfolio return in the gain domain the subjective rating rises by about 0.15. But in the loss domain the identical 5% result in a change of 0.3. This illustrates the greater sensitivity of investors toward losses.

We now turn to other potential reference points for which we repeat the same regression specifications. Table 3 only reports the loss aversion coefficients resulting from these regressions. A first alternative is that investors evaluate expected portfolio returns relative to the risk-free interest rate that can be earned over the same horizon. The current interest rate for a three-month horizon thus is the reference point for the first set of loss aversion coefficients. The results are very close to those for a reference point at 0, as quarterly interest rates are mostly below 1%. The same holds for inflation as a reference point, for which we use the three-month ahead inflation as a proxy for inflation expectations (results for current inflation are very similar).

For market expectations as a reference point, the results change to some extent. As market expectations are on average about 3%, the reference point is shifted to the right. As a consequence, a greater fraction of expected portfolio returns are in the loss region (24%). But secondly, the reference point is now also personalized, as the market return expectation of each participant is used. This is the reason, why the fixed effects regressions now make a difference. We find significant loss aversion coefficients around 1.8 in these specifications, while the results for the other models are between 1.3 and 1.4 and insignificant. For the final reference point, we not only take into account the individual market return expectations, but also which benchmark investors report to use. For these individual benchmarks we again find significant loss aversion for all regression models. Given these results, it is safe to conclude that loss aversion is present in the return expectations of investors supporting our first hypothesis. Its magnitude varies for different reference points and model specifications, but is almost always around 2. It should be noted that a possible misspecification of the reference point tends to result in an underestimation of loss aversion (see also section 4.4).

4.2 Loss experience

Anticipated loss aversion has been the primary concern of previous research, as it is relevant for evaluating possible courses of actions such as choosing a lottery or making an investment. The question is whether loss aversion is also reflected in the experience of outcomes. According to our estimates, losses are expected to be twice as painful as gains of equal size are pleasurable. The survey question for a subjective rating of past portfolio returns corresponds to this hedonic evaluation (the u(x)). Past returns in numerical terms are the associated outcomes (the x).

The correlation between perceived past portfolio returns and the rating of these returns is 0.67, which is higher than it was for the respective expectations. The linkage between the levels of returns and their subjective evaluation is very close. Figure 2 shows this almost monotonous relationship, which appears to be more linear than in the case for expectations. There is no kink easily identifiable in the graph. The correlation of the subjective ratings with actual past returns calculated from investors' portfolios is somewhat lower (0.53), which confirms that for the experience of investors, their own estimate of returns is more important than the realized value.

It is important that we run the same regressions as before to exclude the possibility that some changes in the regression specification are responsible for changes in the result. The parallel approach also satisfies the condition of McGraw et al. (2010). Therefore, we start again with a pooled OLS model and a reference point of 0, represented in columns 1 and 2 of Table 4. Perceived past portfolio returns have a positive impact on subjective ratings with a coefficient of about 6 (column 1). In economic terms, 5%-points in return change the rating by 0.3. The effect is only slightly larger in the loss domain than in the gain domain (column 2). We calculate a loss aversion coefficient λ of 1.28.

In a panel model with random effects (columns 3-4), this result remains unchanged. The coefficients slightly drop when time-fixed effects are included, as they control for the overall stock market performance over time. While expectations may remain relatively stable over different market environments, in retrospect the survey round effect is more important as it strongly influences individual portfolio returns and return ratings. However, the loss aversion coefficient is unaffected by this. For the individual-fixed effects regressions (columns 5-7), we find loss aversion even closer to one depending on the controls. We again perform a Wald-test whether loss aversion is present in the sample, i.e., whether λ is significantly different from one. Only for one out of six cases we find significance at 10%-level. Even if some tendency toward loss aversion remains, it is much reduced to about 1.2, while the corresponding regressions for expectations yielded loss aversion coefficients around 2.

Considering the regression coefficients for gains and losses in Tables 2 and 4, it seems that the change in the loss aversion coefficient λ is mainly due to a change in the sensitivity to gains. However, a direct comparison of coefficients between regressions with different dependent variables is problematic. In Online Appendix A, we normalize the ratings with respect to their mean and standard deviation and re-estimate the regressions. Results reveal that a change in sensitivity to losses is mainly responsible for the change in λ.

It is possible that investors use a different reference point when analyzing realized returns. Merkle et al. (2015) show that relative returns are important for investor happiness in the sense that they compare themselves to the market return. Table 5 shows the estimated loss aversion coefficients for alternative reference points. Interest rate or inflation make no difference as a reference point, as they are close to each other and close to 0 over a three-month horizon. More interesting are the results for past perceived market return and the individual benchmarks, as the coefficients are even smaller than those estimated before. They are all in direct vicinity of one.

For experienced returns we consider an additional reference point based on investors' previous expectations. Falling short their own portfolio return expectations might be disappointing for investors, which is why they might define gains and losses relative to their expectations. Loss aversion coefficients for this reference point are also close to one. For all results in Table 5, the hypothesis that $\lambda = 1$ cannot be rejected.

We conclude that loss aversion in return expectations has no equivalent in return experiences, which confirms our second hypothesis. Survey participants seem to be subject to a projection bias. They believe that negative returns will be very painful, but once they are confronted with actual outcomes, they are not more sensitive toward losses than toward gains. Investors are able to cope with their losses much better than they expected.

4.3 Actual returns

We make a case for perceived past portfolio returns in the analysis of experienced outcomes, as this is the portfolio return investors report in the survey and presumably have in mind when coming up with their evaluation. However, actual returns calculated from investor portfolio data can be used alternatively in the regression of Table 4. While perceived and actual past returns are positively correlated ($\rho = 0.60$), investors do not perfectly recall their portfolio performance.[2] In fact, the estimation error is large and they tend to overestimate the returns generated by their portfolio (Merkle, 2015).

For Table 6, we repeat the previous analysis based on actual returns. The first column shows that actual experienced returns also have a positive effect on ratings of returns. However, the coefficient and R^2 are lower compared to those for perceived returns, suggesting that ratings are more sensitive to perceptions than to (potentially unobserved) actual values. The loss coefficients λ in columns 2-7 are even lower than based on perceived returns, with values around 1. The coefficients are not significant and it is safe to assume that investors are not more sensitive to losses than to gains in experiencing outcomes. In this respect, we can confirm the previous analyzes.

If anything, it seems to be the opposite, but we interpret the low values of λ partly below one with caution. They might rather result from discrepancies between actual and perceived returns than carrying deep economic meaning. If investors mistakenly believe in having achieved a gain in the last quarter while their actual return recorded a loss, they will rate it differently than a model based on actual returns predicts. For column (6') we repeat the regression of column (6) only for those observations, for which the sign of the perceived return and actual return are the same. As expected, the loss coefficient goes up and is now closer to the values we observe for perceived returns.

4.4 Comparison of reference points

A question remains as to which benchmark is the "true" reference point. Most likely, some investors will use 0, others their market expectations, and still others the benchmark they report in the survey question. Since our regression models estimate slopes for the investor population as a whole, it is

[2]See the Appendix for a description how actual returns are calculated. In our sample recall is much better than, for example, in Glaser and Weber (2007b), who find zero correlation.

impossible to determine individual reference points. However, measures on goodness of fit of these models can provide some indication which model is on aggregate most appropriate. We now compare the adjusted R^2, the model's F-statistic, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) for the different reference points. We use regression (7) of Tables 2 and 4 as it represents the full model with all controls, but results are robust to the other regression specifications.

Table 7 shows the results for the different goodness-of-fit measures. Hereby a higher R^2 or F-statistic indicate better fit, while for the information criteria (AIC and BIC) lower values represent better fit. In parentheses the rank of the models relative to the competing models is displayed. The measures favor the reference point at zero for both anticipated and experienced outcomes. Inflation and interest rates as reference points come very close, as their results are almost identical due to quarterly values close to zero. Market expectations, portfolio expectations, and market realizations do far worse. While there are no significance tests on information criteria, conventional rules suggest that a difference of more than ten signals strong inferiority in terms of fit. The individual benchmark achieves a high F-statistic, but fares worse on the other measures.

We conclude that a reference point at zero explains the data best on aggregate. The further analyses and robustness tests therefore concentrate on this model, but results in general hold for the other models as well. It is interesting that a simple reference point at zero even outperforms individual benchmarks submitted by participants. It is possible that they report to use more sophisticated benchmarks, but when it comes to evaluating outcomes fall back on absolute gains and losses.

4.5 Diminishing sensitivity

A property of the prospect theory value function and of other reference-based utility functions is diminishing sensitivity. This means that the impact of a change in an outcome decreases with its distance from the reference point (Tversky and Kahneman, 1992). The condition is met, if the utility function is concave in the domain of gains and convex in the domain of losses. In Equation 1, this is the case if α and β are less than one. Empirical estimates for these parameters often vary between 0.5 and 1 (Abdellaoui et al., 2007; Tversky and Kahneman, 1992).

We would like to directly estimate the parameters of Equation 1. However, our dependent and independent variables are measured on completely different scales. This would make it necessary to make some arbitrary adjustments to one side of the equation. Instead, we continue the piecewise linear approach and split the loss and gain domain further up into a region close to the reference point and another region more distant to the reference point. To provide for a relatively even split of observations, we define returns of up to 5%-points around the reference point as close. Our results are robust to other choices.

Table 8 shows results for this piecewise linear approach, both for expected portfolio returns and experienced portfolio returns. We only report the individual-fixed effects models; the results hold for the other specifications as well. For expected returns, sensitivity is largest for small losses with a coefficient of about 20. A change in expected portfolio return of 1%-point here has an effect of 0.2 on the rating of that return. Moving from -5% to 0 thus improves the rating by a whole point. For larger losses the effect is far less strong with a coefficient around 5. A portfolio return of -10% instead of -15% improves the rating only by 0.25.

The diminishing sensitivity in the loss domain is mirrored in the gain domain, with a larger coefficient for small gains than for large gains. However, the coefficients are smaller than their counterparts in the loss domain, once more a sign for loss aversion. This allows for an alternative measurement of loss aversion. While we before took the ratio of the average slopes for gains and losses, another definition proposes loss aversion should be the ratio between the left and right derivative of the utility function at the reference point (Köbberling and Wakker, 2005). Empirically, the decreasing number of observations prohibits indefinitely small intervals around the reference point, but we take the 5%-interval as an approximation. Calculating loss aversion by the ratio of the coefficients for small gains and losses results in values for λ between 2.8 and 3.7. This is considerably larger than for the full range of outcomes. At the same time, the estimates have larger variability due to the lower number of observations. For this reason we do not attempt to decrease intervals further.

For experienced returns, diminishing sensitivity is also present. Coefficients are much higher for realizations close to the reference point, to a similar extent as for anticipated returns. But we again find loss aversion close to one and statistically mostly insignificant. In particular for column 6, the coefficients for gains and losses are almost identical. This confirms that loss aversion illusion, the contrast between loss aversion in expectations and in experiences, is also present for this alternative measurement. Additionally, this provides some evidence that not extreme observations for expected return or experienced return drive the result, but that the effect is present also for the range of returns commonly observed over quarterly horizons.

Diminishing sensitivity is also present for the other reference points. However, the alternative loss aversion measurement does not always produce significant loss aversion in expectations. The reason is that a shift in the reference point has a particularly strong effect on the narrow intervals around it. Taking market expectations as a reference point means to shift the reference level upwards by on average 3.1%. As a consequence small gains (0-5%) are often redefined as small losses, a transformation loss aversion does not survive. One may interpret this as an indication that 0 is the more genuine reference point, as results line up perfectly with the theory. We do not find loss aversion for experienced returns for any of the reference points.

4.6 Loss aversion and risk taking

A framework which is designed to examine the aggregated loss aversion in a panel is not best suited to analyze its role in individual investor behavior. Nevertheless we aim to provide some evidence as to whether loss aversion in expectation has any consequences for investing. The two main claims associated with loss aversion are that participants do not participate in the stock market at all or that they at least underinvest in stocks. In both cases, investors shy away from risky investments beyond what reasonable risk preferences would suggest (cp. Benartzi and Thaler, 1995).

The portfolio holdings of investors in our sample are primarily in equity, almost all of them hold stocks or stock funds. We thus cannot address stock market participation, as we only deal with participants (unlike, e.g., Dimmock and Kouwenberg, 2010). Due to their unknown overall wealth composition, it is also difficult to determine, whether they are underinvested in stocks. However, the riskiness of their portfolios gives an indication of their risk taking behavior. We expect the more loss averse investors to take on less portfolio risk. Importantly, for this decision expected loss aversion should play a role as this is the perspective investors take in before allocating their money.

As measures for portfolio risk, we calculate the one-year volatility of investors portfolios and the average volatility of portfolio components (ACV, cp. Dorn and Huberman, 2010). We then split the sample into less risky and risky portfolios, in case of portfolio volatility the cut-off is at 30% and for ACV at 50% to generate approximately equal samples. The high values are due to elevated levels of volatility during the survey period (a median cut-off produces very similar results). We then interact risky and less risky portfolios with the gain and loss variables of the earlier regressions and again run a panel fixed-effects model for both expected and experienced returns.

Table 9 shows the results of these regressions. Columns 1 and 2 present ratings of expected returns as dependent variable, and it is revealed that there is strong loss aversion among investors with less risky portfolios. In particular, the sensitivity toward losses is with 7.5 and 7.7 far larger than for the group of investors with riskier portfolios; the difference is significant at p=0.08 and p=0.01 (Wald-test). At the same time, the sensitivity toward gains is similar for both groups. This results in a loss aversion coefficient of almost 3 for the less risky investors and of less than 2 for the risky investors. The magnitude of this difference is large, suggesting that the higher loss aversion might play a part in risk taking behavior. The difference between the loss aversion coefficients is not statistically significant in a non-linear Wald-test (Phillips and Park, 1988). As four estimated coefficients with their respective standard errors enter a non-linear equation, the barrier for significance is very high.

Next, we test whether there is any discrepancy between the two groups in how they experience gains and losses. Less risky portfolios could be justified, if one group experienced losses more painful than the other. But, as columns 3 and 4 show, this is not the case. If anything, the result for loss experience is even reverse, with a larger coefficient for risky portfolios. There is thus no evidence that based on their subjective experience of losses, investors should have chosen the portfolios they did. But high anticipated loss aversion potentially provoked their less risky portfolio choice.[3]

4.7 Learning and sophistication

When observing a bias, a natural question is whether it can be avoided by sophistication or learning. We can reject the idea of fast and simple learning in the sense that in later rounds of the survey the loss aversion illusion would be lower than in earlier rounds. This result is intuitive as, if significant learning occurred over the relatively short survey period, we should not observe the bias in the first place. Instead, learning might depend on past outcomes. After a loss, by experiencing the associated feelings with it, investors should be aware that too high loss aversion is unjustified. Additionally,

[3]Of course, there are many other factors influencing portfolio risk (see Merkle and Weber, 2014). Unfortunately, we cannot control for these factors as this requires a regression with portfolio risk as the dependent variable. As we only estimate aggregated loss aversion, we lack a way to introduce it as an explanatory variable in such regressions.

if investors perceive their portfolios being in the loss domain, further losses are not worse than potential gains. This of course depends on when the reference point is adjusted, and whether the utility function is convex for losses (as in prospect theory). We therefore expect that anticipated loss aversion will be lower after a loss.

For this analysis, we split the sample into those participants, who experienced a negative perceived past return in the last quarter and those with returns greater or equal to zero. For those with negative past returns we find a coefficient for anticipated loss aversion of 1.6 (Table 10, column 1). In comparison, after a gain investors show a much higher loss aversion of 3.7 (column 2). To see whether this effect lasts for more than one period, we calculate the cumulative portfolio return over two survey periods. In this case we use actual portfolio returns, as perceived returns are only available for rounds of survey participation and the sample size quickly diminishes when using lags. Again, we find only moderate loss aversion after losses, but very high loss aversion after gains (columns 3 and 4). The difference between the two groups is significant using a Wald-test adjusted for non-linearity (Phillips and Park, 1988). While we obtain the same result also when using the past or lagged past actual return separately, the effect disappears when using the second lag or even more distant experiences.

To test whether this difference is also reflected in experienced outcomes, we repeat the analysis for the ratings of past returns. For the sample split, we use actual portfolio returns and have to introduce one lag, as past return is the independent variable in this model (Table 10, columns 5 and 6). Alternatively, we use cumulative actual portfolio returns as before (columns 7 and 8). After both gains and losses, further losses are not experienced more severely than gains, coefficients are between 0.8 and 1.7 and not significant. There is a mixed pattern of whether sensitivity to experienced losses is higher after previous losses or gains.

We define the magnitude of financial loss aversion illusion as the difference between the two coefficients ($FLAI = \lambda_{ant} - \lambda_{exp}$), it measures by how much ex ante loss aversion exceeds the ex post loss experience. We obtain a baseline financial loss aversion illusion of 1.04 ($2.19 - 1.15$) for the overall sample using the loss aversion coefficients calculated from regression (6) in Tables 2 and 4. After a loss, FLAI is reduced to 0.82 and -0.20 respectively, while after a gain FLAI rises to 2.47 and 3.07 (using the coefficients as stated in Table 10). This suggests that experiencing a loss contributes to evaluate anticipated gains and losses more in line with the experience of outcomes.

As mentioned above, this holds only for loss experiences in the recent past, suggesting that learning is short-lived.

Besides learning, loss aversion illusion may be mitigated by investor sophistication, which includes their individual knowledge, skill, and experience. For example, financial literacy is often argued to improve financial decision making (Lusardi and Mitchell, 2014). We use the financial literacy measure reported earlier to test whether more financially literate investors are less subject to financial loss aversion illusion. Indicator variables for participants who correctly answered all four financial literacy questions and those with less correct responses are interacted with the gain and loss variables. We find a FLAI indistinguishable from 0 for financially literate investors, while it is high and marginally significant for the less literate (see Table 11). The difference in FLAI between the two groups is also large.[4]

Wealth is also considered to be a proxy for investor sophistication (Vissing-Jorgensen, 2004; Dhar and Zhu, 2006). We compare investors with high self-reported financial wealth ($> £150,000$) to those with lower financial wealth. We again find that less sophisticated (low wealth) investors exhibit a higher FLAI. In this case the difference between the two groups is smaller. As a final sophistication variable, we employ self-reported financial market experience in years. As it was not part of the survey entry questionnaire, this variable is available only for a subset of investors. Among them, investors with an experience of at least 20 years show low FLAI, while it is high for less experienced investors and significantly differs between group. As this could be an effect of age, we repeat the test for age and find a similar but weaker effect. We conclude that experience is the driver in the reduction of FLAI. Altogether, we find considerable evidence that sophisticated investors are less prone to financial loss aversion illusion than less sophisticated investors.

5 Robustness Tests

5.1 Risk aversion

A natural alternative to an explanation based loss aversion is standard expected utility with risk-averse agents. The slope of a utility function defined over total wealth would in general be steeper for lower wealth and flatter for higher wealth, which is in line with our findings. It is important to note

[4]The non-linear tests are relatively demanding, which explains why even large differences are often not significant.

that this would not explain the discrepancy we observe between expected and experienced utility. Instead of a loss aversion illusion, we would have to deal with a risk aversion illusion. However, there are several reasons why an explanation based on risk aversion is less plausible than the proposed loss aversion. The three main arguments we will outline below are 1) unreasonable required risk levels, 2) evidence for the presence of a reference point (or kink in the utility function), and 3) convexity in the loss domain.

Although portfolio losses in the financial crisis can be quite substantial, most of the time returns result in relatively small changes of wealth, in particular if one considers overall wealth including assets outside the observed brokerage portfolio. For small stake gambles it has been argued that they imply implausibly high levels of risk aversion (also known as Rabin's critique, see Rabin, 2000). While the stakes in investing are higher than in the small stake gambles typically considered, they still result in overly high risk aversion coefficients. For illustration, we use a CRRA-utility function, which is not only one of the most prominently used utility functions in the investment context, but also allows neglecting different wealth levels of participants. From estimated coefficients, a 5% decrease in wealth is expected to be felt equally strong as a 10% increase in wealth. In this example, the resulting risk aversion coefficient γ would equal 9.7 (see Online Appendix B). This value is unreasonably high compared to theoretically assumed values and to those often found in experiments (Holt and Laury, 2002).

A necessary feature of a utility (or value) function defined over gains and losses, is a reference point. For risk aversion the curvature of the utility function changes gradually, while for proposed loss aversion there is a kink at the reference point. Results presented in Section 4.1 seem to suggest that loss aversion coefficients and goodness of fit change little for different reference points. However, quarterly interest rates and inflation were very close to zero (below 1%) for most of the sample period. Given that participants usually state their expectations and past performance in 1%-increments, there is little change to be expected for reference points this close. In contrast, for the market return reference point, results were more distinctly different. Therefore we extend the range of possible fixed reference points and estimate fixed reference points between -5% and +5% in steps of 1%. We find a maximum value for λ at 0, which means that the slopes are most distinct at this point. Goodness of fit measures also have there extreme values at this point (for details see Online Appendix B). There are only small changes in these measures as slopes adjust gradually and still capture the data quite well. As an alternative way to determine a cutoff point, we run a non-linear least-square estimation and estimate a cutoff of 0.4%.

Finally, the results on diminishing sensitivity point to a different behavior in the loss compared to the gain domain. If the sensitivity to gains decreases for higher values, this is in line with a concave utility function. Earning 3% instead of 2% return is a more important change than 13% instead of 12% return. However, the same effect is observed in the loss domain with lower sensitivity of investors to higher losses. While it might still seem reasonable that improving from -3% to -2% is more important than from -13% to -12%, this is at odds with a concave utility function. Diminishing sensitivity in the loss domain implies risk seeking preferences for losses. Of course, the presented piecewise linear model, although robust to different cutoff points, is no ultimate proof of convexity in the loss domain. However, a nonlinear estimation confirms this result. We use the prospect theory value function as described in Equation 1 and estimate parameters in line with risk aversion in the gain domain and risk seeking in the loss domain (for details see Online Appendix B).

5.2 Monetary outcomes

As our independent variable, we chose the portfolio returns of investors. Returns are a relative performance measure as they reflect the change in portfolio value corrected for inflows and outflows. In contrast, the lotteries typically used to analyze loss aversion involve monetary outcomes. Utility or value functions are also generally formulated over wealth or absolute changes in wealth. Based on their portfolio values, we are able to calculate the amount of money investors earn or expect to earn. Of course, the caveat to this approach is that the portfolio size of investors differs widely. A gain of £1,000 may be good if the portfolio is worth £20,000, but rather meager if the portfolio is worth £200,000. To partly address this, we drop extremely large portfolios with a value of more than 1 million pounds from the sample.

The median expected portfolio profit is £1,539 per quarter (mean £4,920), and its correlation with portfolio return expectations is 0.53. The median perceived realized profit is £0 (mean $£-1,255$) with a correlation to perceived portfolio past return of 0.56. Naturally, absolute returns in monetary terms and relative returns are closely related, but due to the different portfolio sizes the relationship is not perfect. We define two separate variables for monetary losses and monetary gains.

We run the same panel fixed-effects regressions as before, now with monetary profits (in £1,000) as independent variables. The unconditional coefficient for expected portfolio profits on subjective ratings is 0.02, which means that an additional £5,000 move ratings by about 0.1. Table 12 shows in columns 1-3 the conditional results for losses and gains. The effect for losses is more than twice as large. Loss aversion coefficients are around 2.7 and strongly significant.

The effect sizes for (perceived) experienced profits are similar (columns 4-6). However, loss aversion is again not present in the evaluation of past returns. The effect even turns around in the final two regressions. A reason could be that large monetary losses are shouldered by investors with large portfolios, who are able to cope with these losses well. Therefore in the loss domain, the slope would be flatter than in the case for relative returns. This requires, however, that a similar argument is not valid for the gain domain.

A general observation from Table 12 is that, while t-values and effect sizes are still high, they weaken compared to the return regressions. The R^2 is also considerably lower, and the economic significance of the results is smaller. Investors seem to evaluate performance primarily by their returns, while the absolute size of profits mostly adds noise to the equation. The monetary outcomes have a very different impact on unequally wealthy investors, while a 10% return might be interpreted fairly similar. Therefore, we rest our main analysis on portfolio returns with the results on monetary outcomes providing additional robustness.

5.3 Influential observations

A primary concern for any investigation relying on comparing slopes is that influential observation or "outliers" distort the results. For our main analyzes we did not remove any observations, as there are no obvious mistakes in the data. One may find quarterly return expectations of "+20%" unrealistic, but this alone was not enough of a reason to discard an observation. Even more so, as realized outcomes within the survey period were also quite extreme. As the results for diminishing sensitivity have already shown, we do find the same loss aversion pattern for moderate values of expectations and realizations.

We thus now employ some more sophisticated approaches to detect outliers, starting with a robust regression as proposed by Huber (1973). This regression model employs a weighting function that underweights observations with large residuals. It hereby is more robust to a strong influence of observations that are off the prediction of the model. For both, anticipated and experienced outcomes, loss aversion becomes a bit smaller with values slightly below two in anticipation and slightly below one in experience. However, the basic asymmetry between the ex ante and ex post perspective persists. We also directly calculate studentized residuals for our regressions and exclude values of above 2.5, which identifies observations, which are more than 2.5 standard errors off the regression line. Under this restriction, we obtain loss aversion coefficients of 2.02 in anticipation and 0.98 in experience.

Other measures that have been developed to identify outliers include leverage, Cook's distance, dffits and dfbeta. While leverage is directed at observations with extreme values in the independent variables, the other measures identify influential observations based on a combination of leverage and residuals. Cook's distance and dffits operate on the level of the full model (and are very similar), while dfbeta looks at the influence on each coefficient separately. We follow conventional cutoffs to exclude influential observations and rerun the regressions of Tables 2 and 4. Results are in line with the unrestricted specifications.

5.4 Interpretation of the scale

A condition for the subjective ratings to be meaningful is that there are no unintentional effects by the way the ratings are elicited. McGraw et al. (2010) point out that sensitivity toward losses is in general not larger than toward gains when assessed separately on unipolar scales. The reason is that the frame of reference is then restricted to either gains or losses. Only on a bipolar scale loss aversion is observed, because it invites the direct comparison of gains and losses. We thus not only use a bipolar scale, but an identical scale for anticipated and experienced outcomes. When we find asymmetries, it is unlikely that they are produced by different interpretations of the scale.

It is still possible that different investors populate the gain and loss domain and therefore implicitly treat it as a unipolar scale. Due to the specific survey period including the financial crisis, almost all investors experience gains and losses mitigating this concern. However, it is true that some investors never hold negative return expectations and potentially only use one part of the scale. While this would rather favor the opposite pattern of higher rating sensitivity to losses in experience and not in expectation, we still test this formally by excluding participants who never make a loss rating or never make a gain rating. Our results are robust to this restriction.

5.5 Exclusion of trivial portfolios

Potentially, investors react indifferently to losses, because the amounts of money involved are not relevant enough. While the average portfolio value in our sample is quite sizable (median £40,560), there are accounts with low values. These portfolios may draw loss aversion coefficients toward one for experiences (although it is unclear why they should not also diminish anticipated loss aversion). When excluding portfolios with a value below £10,000, our results remain unchanged.

Alternatively, not the absolute size of the portfolio might matter but its relative value compared to overall wealth or income. We therefore use self-reported wealth and income of investors to assess the relative importance of the portfolio. We use only observations for which the portfolio represents at least 25% of an investor's total financial wealth or at least 50% of annual income.[5] While the results in the regression restricting on income remain unchanged, we observe elevated loss aversion coefficients in the regression restricted on wealth. λ is 2.96 in anticipation and 1.45 in experience (using model (6) of Tables 2 and 4). This is intuitive, as losses in portfolios that are more sizable relative to overall financial wealth are more intimidating. However, the difference between loss anticipation and experience (FLAI) remains strong, and the loss experience coefficient is not significantly different from one.

5.6 Paper losses vs. realized losses

The literature on the disposition effect maintains that paper losses and realized losses are interpreted differently. In particular, recent research suggests that a burst of (dis-)utility occurs at the point in time when an asset is sold and a gain or loss is realized (Barberis and Xiong, 2011; Frydman et al., 2014; Ingersoll and Jin, 2013). While it is unclear what this would mean for expectations given that plans to sell might not yet be fully determined or considered, it certainly makes a difference for experienced outcomes. Positions investors hold on to are less important for subjective experience, as these mental accounts remain open and losses may be recouped in the future. In contrast, sold positions are closed and bear immediate consequences for the utility of investors.

Due to data limitations, we cannot determine the purchase price of many securities participants own. The history of portfolio data starts only three months before the first survey round. Therefore,

[5] Wealth and income are self-reported in the survey using intervals. The intervals are transformed into numerical values by taking the middle-point of each interval.

we rely on proxies based on the selling behavior of participants. We first interact gains and losses with an indicator variable whether or not a sale occurred within the respective quarter. Loss experience coefficients are 1.03 after at least one sale and 1.21 after no sale. When we weight sales by volume, coefficients are 1.02 and 1.37. Contrary to the prediction, investors seem to be more sensitive to paper losses (although not significant). There are two potential reasons, one is that we measure experience of outcomes not directly when assets are sold but at fixed three-month intervals. Investors might thus have already come to terms with their realized gains and losses or do not consider them for their investment experience any longer. Secondly, if investors primarily sell winners this might increase gain sensitivity, while loss sensitivity remains unchanged. Indeed, we see slightly higher coefficients for gains after sales.

To shed further light on this, we use past returns as some indication of whether a sale for a loss or gain is more likely. After the large losses of the financial crisis, it is still possible that investors own some positions which are up relative to their purchase price, but it is much less likely than after the recovery. We thus implement this in a double interaction. But even under this condition, loss experience coefficients are smaller after sales than after no sale. While this has little to say about whether realization utility exists or not, it gives a strong indication that our results are not driven by the dichotomy between paper losses and realized losses. Taking into account the temporal resolution of our survey, we favor the interpretation that realized gains and losses are already internalized by investors.

5.7 Selection

Potential selection effects are an issue in an investor panel composed of voluntary entrants. Selection can occur on two levels, selection into the survey and panel attrition over the course of the survey. Selection into the survey affects the external validity, as survey participants might be special and not representative for a more general population. From the summary statistics presented in Table 1, it is clear that participants are not representative for the UK adult population. Differences are strongest for gender, income, and wealth.[6]

[6] While 93% of participants are male, only 49% of UK adults are. Median income is about £62,500, which is about double the UK average at the time. Less different are age (51.4 to 47.7) and living as a couple (74% to 65%). For an explicit comparison also see Weber et al. (2012).

Representativity as such, e.g., in degree of loss aversion or other personal characteristics, is not of primary importance for our survey since we mainly document an asymmetry of the ex ante and ex post perspective. Most likely, a sample of equity investors will be less loss averse than the average person. But at the same time taking financial risks is a precondition to observe loss experiences. With appropriate caution, we believe our findings can be generalized to a broader population given that experimental studies with students yield similar results (Kermer et al., 2006). Moreover, participants are comparable to other investor populations as in Barber and Odean (2001), Glaser and Weber (2007a), and Dorn and Huberman (2005), who likewise report high fractions of male participants (see Panel A of Table 13). Income reported in these studies also exceeded the average income by a factor 1.5 to 2 at the respective time periods. We conclude that our sample of survey participants is not much different from other brokerage investors. Although our participants hold larger portfolios in terms of value and positions, their investing behavior appears to be in line with previous studies.

To avoid selection effects, it is also important that the 617 participants do not systematically differ from the 19,251 invited investors. Unfortunately, we only have limited information on this larger sample as data was only collected during the sampling procedure, i.e., a time period before the start of the survey. Portfolio value, holdings, and trading activity were used as sampling criteria (with minimum requirements mentioned before). Gender and age is available as basic account information. In Panel B of Table 13 compares these variables for participants and non-participants. Men and more active investors are more likely to participate in the survey. For more active investors it seems intuitive that they are also more interested in the survey. For men this is less clear, but Dorn and Huberman (2005) observe the same effect.

There is no obvious reason, why men and more active investors should be particularly prone to FLAI. On the contrary, one could argue that more active investors receive more frequent feedback and their expectations should be more in line with their experiences. Nevertheless, we run a Heckman selection model to more formally test for this type of selection. In the first stage we regress participation on the five variables available for the full sample. As expected from the univariate results, gender and the logarithm of number of trades predict participation (see Table 14). In the second stage, we rerun the models of Tables 2 and 4 including the inversed Mill's ratio from the first stage. This precludes to use individual-fixed effects, as the Mill's ratio is constant for each participant. In Table 14, we display the results of the RE-model with the full set of control variables. In the second stage we exclude gender and number of trades (exclusion restriction, columns 2 and 4). Alternatively, we include both variables (columns 3 and 5), which means that the model is identified only via the functional form. While the inverse Mill's ratio is significant or marginally significant in two of the regressions, which indicates the presence of selection, we do not find any effect on the resulting loss aversion coefficients.

A more critical selection effect might arise from panel attrition, as participants can leave (and also rejoin) the survey. In particular it might be problematic, when participants, who are especially discontent with their performance, drop out of the survey. We would then underestimate the strength of loss experiences, which could at least partly explain the lower loss coefficient λ for experiences. Unfortunately, we do not know how investors subjectively experience their portfolio performance, unless they participate in the survey. Instead, we can only examine whether participants with bad *actual* performance are more likely not to participate. We first compare the past performance overall, which is significantly worse for participants than non-participants and thus opposite the suggested selection effect. However, this is driven by higher participation rates in the early rounds of the survey, which took place during the financial crisis. Therefore, to obtain a realistic picture we have to analyze participation on a round-by-round basis.

Table 15 shows the prior three-month return for participants and non-participants for each survey round. In five rounds non-participants had a better past performance, in four rounds participants had. For the two rounds in which differences are statistically significant at 5%-level, these differences are also of opposite sign. We thus fail to detect a systematic effect of prior performance on participation. Another way to look at this issue is to test whether investors who experienced a loss are less likely to participate than investors who experienced a gain. While overall participation rates fall in later survey rounds, participation rates of investors with a prior loss are not significantly different from participation rates of investors with a prior gain (see Table 15). Similar to the results for returns, in about half the rounds participation is higher among investors with a loss.

We again employ a Heckman selection model to exclude an effect of panel attrition on our main results. We follow Wooldridge (1995) in estimating the participation equation separately for each round of the panel, including either only past portfolio performance or additional variables. For purposes of comparison, we start by using the same variables as in the model for selection into the survey. However, trades, portfolio value and positions are this time panel variables observed over the course of the survey. Finally, we consider lagged ratings of experienced returns as a predictor to participate in the following round. It could be another indicator whether investors who are disappointed drop out of the survey. We also include other lagged survey variables and the full set of controls in this specification. For ease of presentation, Table 16 shows a panel version of these regressions in columns 1-3. Overall, survey participation is hard to predict from portfolio variables or lagged survey responses. There is a marginally significant effect of the rating of return experiences on participation in the subsequent round.

When we include the inverse Mill's ratios from the three first stage models in the main regressions (columns 4-9), they are mostly not significant. More importantly, they have no effect on the estimated loss coefficients for expected returns and experienced returns. This even holds for the third specification, which is very costly in terms of observations, as it requires participation in consecutive surveys. In general, we maintain that the type of analysis based on a comparison of aggregated population effects, is less vulnerable to selection effects than a study aimed at teasing out individual effects.

6 Discussion and Conclusion

We show that financial loss aversion is an illusion. It is an illusion in the sense that the existence of loss aversion in the expectations of investors is not backed by a similar observation for their experiences. Regarding portfolio return expectations, investors react much more sensitive to losses as compared to gains. In a linear model, we establish loss aversion coefficients around two for several different reference points and specifications. On the contrary for experiences of portfolio returns, there is no significant loss aversion. The subjective rating of returns is almost monotonous over losses and gains.

Diminishing sensitivity, the other defining feature of reference-based utility or value functions, is also present in our data. Investors react less to changes in outcomes that are distant from the reference point. This is true for gains and losses, which implies concavity in the domain of gains and convexity in the domain of losses. While diminishing sensitivity can be observed for expectations and experiences alike, again only for expectations are the slopes for the different intervals in the loss domain steeper than their counterparts in the gain domain.

These findings illustrate the important distinction between anticipated utility and experienced utility. In anticipation, investors have to think about potential future outcomes of their investments and have to determine how they will feel about these outcomes. Anticipated utility is also known as decision utility, reflecting the fact that to make a decision one has to be aware of its consequences. And the consequences entail not only the factual outcome in terms of return or monetary profit or loss, but also the hedonic feelings associated with it. Loss aversion applies to this decision context, not only in the choice of monetary lotteries but also for financial decisions.

Experienced utility can differ from anticipated utility widely if investors are subject to projection biases. The financial loss aversion illusion we document is a particular form of projection bias, where people overestimate the negative experience associated with a loss. Projection biases can misguide decisions, as a choice might be optimal given the anticipated utility but not the experienced utility (cp. Loewenstein et al., 2003). In particular, an investment portfolio selected under the impression of losses looming twice as large as gains, will look quite different from a portfolio chosen with loss neutrality.

Some tentative evidence comes from the portfolios in our panel, for which we find that less risky portfolios are held by investors with higher anticipated loss aversion. But as we find no differences in the experience of gains and losses between the groups, highly loss-averse investors face a large discrepancy between their chosen portfolios and their ex post preferences. From the latter point of view they would potentially have invested more riskily. As it is not entirely clear, whether the ex ante or ex post perspective deserves priority, we do not prescribe a general change in investing behavior. But high anticipated loss aversion is in line with low participation in stock markets or the low risky share in portfolios. Financial loss aversion illusion could then at least partly explain the stock market participation puzzle and the equity premium puzzle.

The projection bias adds to the traditional explanation of these puzzles by loss aversion, as loss aversion per se does not need to be judgment bias. Similar to risk aversion it can be part of people's preferences; and economics is rather cautious to challenge the content of preferences. In contrast, the discrepancy between anticipated loss aversion and loss experience qualifies as a bias, as people are time-inconsistent with regard to their preferences. It is not necessary to assume that experienced utility is all that matters, quite possibly the worries and fears for potential bad outcomes are also an element of the overall hedonic experience. Then an investor would need to reconcile high ex ante loss aversion and loss neutrality in experiences.

One remedy to the observed financial loss aversion illusion might come from educated financial advice. It has been shown that simulations of potential investment outcomes can illustrate associated experience to investors and improve their decision process (Kaufmann, Weber, and Haisley, 2013). In particular, Bradbury, Hens, and Zeisberger (2014) experimentally find that in a choice among structured products with loss protection, participants opt for less protection after simulated experience. They realize that losses might not be as bad (and as frequent) as they thought. Such simulation techniques can support the financial decision process and should be adopted by financial advisers.

An interesting question that we cannot answer empirically is, why anticipated and experienced evaluations of portfolio returns differ so much. An answer might lie in the process of coping with a loss. When confronted with an outcome, people engage in rationalizing it and in finding reasons and explanations for it. They then also adapt emotionally to this outcome and learn to accept it. For negative events the effect is particularly strong as part of a psychological defense mechanism (cp. Wilson and Gilbert, 2005). Related to this, we show that after a loss experience there is a reduction in anticipated loss aversion. The immediate awareness of the process of coping seems to help in predicting one's reaction to future losses.

We provide tentative evidence that financial literacy and experience can mitigate loss aversion illusion. For the related endowment effect a positive influence of learning has been documented (List, 2003; Novemsky and Kahneman, 2005). However, investors need to recognize the similarity of past investment experiences with their current expectations (cp. Kermer et al., 2006). This is complicated by the tendency to attribute especially negative outcome to situational causes (Langer and Roth, 1975), which might be very specific (e.g., the financial crisis for the time period of our sample). Future research might address this and related questions by an assessment of individual loss aversion which is able to determine the magnitude of the projection bias for each investor. This would also allow to pinpoint the effects on risk taking and other aspects of investing behavior.

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Appendix

Description of variables

Variable	Origin	Description
Gender	Bank data	Gender of participants, dummy variable 1 if male, 0 if female
Age	Bank data	Age of participants in years
Couple	Survey (initial)	Marital status using the following response alternatives: Single; Married; Divorced; Widowed; Cohabiting. Dummy variable (=1) if married or cohabiting, zero otherwise.
Wealth	Survey (initial)	Self-reported wealth using 9 categories: £0–10,000; £10,001–50,000; £50,001–100,000; £100,001–150,000; £150,001–250,000; £250,001–400,000; £400,001–600,000; £600,001–1,000,000; > £1,000,000. Missing values were imputed.
Income	Survey (initial)	Self-reported income using 8 categories: £0–20,000; £20,001–30,000; £30,001–50,000; £50,001–75,000; £75,001–100,000; £100,001–150,000; £150,001–200,000; > £200,000. Missing values were imputed.
Fin. literacy	Survey (initial)	Number of correct responses in a 4-item financial literacy test using questions by van Rooij et al. (2011).
Experience	Survey (round 2)	Response (in years) to the question: *"For how long have you been investing directly, i.e. using a stock brokerage service to make investments?"*
Rating of expected returns	Survey (all rounds)	Rating on a scale 1-7 (extremly bad to extremely good) in response to question: *"How would you rate the returns you expect from your portfolio held with us in the next 3 months?"*
Rating of experienced returns	Survey (all rounds)	Rating on a scale 1-7 (extremely bad to extremely good) in response to question: *"How would you rate the returns of your portfolio (all investments held with us) over the past three months?"*
Portfolio return expectation	Survey (all rounds)	Return in % in response to survey question: *"We would like you to make three estimates of the return of your portfolio held with us by the end of the next three month. Your best estimate should be your best guess."*
Market return expectation	Survey (all rounds)	Return in % in response to survey question: *"We would like you to make three estimates of the return of the UK stock market (FTSE all-share) by the end of the next three month. Your best estimate should be your best guess."*
Past portfolio return (perceived)	Survey (all rounds)	Return in % in response to survey question: *"What do you think your return (percentage change) with us over past three months was? Please enter your response as a percent change, i.e. a rise as X%, or a fall as -X%."*
Past market return (perceived)	Survey (all rounds)	Return in % in response to survey question: *"What do you think the UK stock market (FTSE all-share) return (percentage change) over past three months was? Please enter your response as a percent change, i.e. a rise as X%, or a fall as -X%."*

Description of variables (continued)

Variable	Origin	Description
Past portfolio return (actual)	Bank data Datastream	Return in % of investors' actual portfolios calculated over past three months. Uses closing prices of the day before a participant answers the survey. For non-participants and participants for which this date is not available (round 1 and 2), we use the average over the ten-day survey window. Prices come from Datastream and cover > 90% of value-weighted portfolio holdings. For remaining holdings observed transaction prices are used.
Past market return (actual)	Datastream	Return in % of the UK stock market (FTSE all-share) over past three months.
Subj. portfolio risk	Survey (all rounds)	Rating on scale 1-7 in response to question *"Over the next 3-months, how risky do you think your portfolio is?"*
Interest rate	Datastream	London interbank offered rate (LIBOR) for three months. As the interest rate is expressed in annual terms divided by 4.
Inflation	National Statistics	Annual change of the UK consumer price index CPI reported in the month of the survey round. Adjusted to a quarterly rate.
Individual benchmark (past)	Survey (all rounds)	Rating on a scale 1-7 (1=bank interest rates, 4=a mix, 7=the market) in response to question: *"When evaluating the performance of your portfolio do you compare it to the interest rate you would have received by putting the money in a bank account, or the return you would have received by investing the money in the stock market?"* The response is converted in the following way: 1 = 100% (lagged) interest rate, 2 = 83.3% interest rate and 16.6% realized stock market return, 3 = 66.6% interest rate and 33.3% stock market return, 4 = 50% interest rate and 50% stock market return, 5 = 33.3% interest rate and 66.6% stock market return, 6 = 16.7% interest rate and 83.7% stock market return, 7 = 100% stock market return.
Individual benchmark (expectation)	Survey (all rounds)	Calculated the same way as "individual benchmark (past)", with stock market return expectations instead of realized returns and current interest rates instead of past interest rates.
Portfolio volatility	Bank data	One-year historical portfolio volatility at the time of each survey round.
Risk tolerance	Survey (all rounds)	Agreement on Likert scale 1-7 to statement *"It is likely I would invest a significant sum in a high risk investment."*
Portfolio value	Bank data	Total value of investors' portfolio value in pounds at current market prices (or if no current price is available for an asset, the last available price) at the time of each survey round.
Portfolio turnover	Bank data	Portfolio turnover is trading volume in pounds between two survey rounds divided by the sum of portfolio value at the beginning and end of survey round (we exclude portfolios <£5,000 and winsorize turnover from above at the 5%-level). The convention to use twice the portfolio value (or half of trading volume) has been introduced by (Odean, 1999).

Table 1: Descriptive statistics

Panel A	n	Mean	Median	Std.Dev.	5q	95q
Gender (male=1)	617	0.93	1	0.25	0	1
Age (in years)	613	51.4	53	12.9	29	72
Couple	616	0.74	1	0.44	0	1
Wealth (9 categories, see below)	502	4.80	5	2.39	2	9
Income	494	3.88	4	1.80	1	8
Financial literacy (4 questions)	614	3.49	4	0.68	2	4
Experience (in years)	197	19.5	20	10.3	6	38
Panel B	**n**	**Mean**	**Median**	**Std.Dev.**	**5q**	**95q**
Rating of expected return	2107	4.18	4	1.16	2	6
Rating of experienced return	2115	3.61	4	1.73	1	7
Portfolio return expectation	2108	0.061	0.050	0.112	−0.050	0.200
Past portfolio return (perceived)	2115	−0.019	0.000	0.193	−0.300	0.250
Past portfolio return (actual)	2081#	−0.049	−0.030	0.261	−0.521	0.283
Market return expectation	2121	0.031	0.030	0.103	−0.100	0.150
Past market return (perceived)	2108	−0.008	0.000	0.178	−0.250	0.220
Past market return (actual)	2135#§	−0.026	−0.081	0.128	−0.196	0.205
Interest rate	2135#§	0.006	0.004	0.005	0.001	0.014
Inflation	2135#§	0.008	0.008	0.003	0.003	0.013
Individual benchmark (past)	2135	−0.007	0.002	0.079	−0.126	0.114
Individual benchmark (expectations)	2135	0.023	0.017	0.089	−0.065	0.100

Notes: The table shows descriptive statistics (number of observations, mean, median, standard deviation, 5%-percentile and 95%-percentile) for the main survey variables. Panel A shows demographics of participants. Number of observations varies due to refusals. Gender is a dummy variable taking a value of one for male participants. Age is reported in years. Couple is a dummy variable taking the value of one for married or cohabiting participants.
Wealth categories: (1) 0–10,000£ (2) 10,000–50,000£ (3) 50,000–100,000£ (4) 100,000–150,000£ (5) 150,000–250,000£ (6) 250,000–400,000£ (7) 400,000–600,000£ (8) 600,000–1,000,000£ (9) >1,000,000£.
Income categories: (1) 0–20,000£ (2) 20,000–30,000£ (3) 30,000–50,000£ (4) 50,000–75,000£ (5) 75,000–100,000£ (6) 100,000–150,000£ (7) 150,000–200,000£ (8) >200,000£.
One £ was approximately 1.60 $, average gross yearly income in the UK was about 30,000£. Financial literacy uses 4 questions (2 basic, 2 advanced) from van Rooij et al. (2011). Experience is self-reported investing experience in years. Panel B shows participants' subjective ratings for expected portfolio return and experienced portfolio return. It further displays numerical estimates of expected portfolio return and perceived past portfolio return. Past actual portfolio return is calculated from investors' portfolios. For the UK stock market, the actual and perceived performance of the FTSE all-share index is displayed, as well as expectations for three months returns of the same index. Interest rates is the three-month LIBOR, inflation is based on the UK CPI. Individual benchmarks are calculated as described in the appendix. Observations denoted by # are reported conditional on survey round participation, observations denoted by § are constant in the cross-section. For details on the used survey questions, see appendix.

Table 2: Anticipated loss aversion

	Subjective rating of expected return						
	Pooled OLS		GLS with RE		GLS with FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expected portfolio return	4.152						
	(11.40)***						
Expected portfolio return		7.463	6.446	5.927	6.249	5.560	5.898
(if < 0)		(8.69)***	(7.28)***	(6.96)***	(5.81)***	(5.51)***	(4.54)***
Expected portfolio return		3.538	3.051	2.917	2.683	2.543	2.603
(if > 0)		(9.25)***	(7.75)***	(7.68)***	(5.86)***	(5.77)***	(5.33)***
Risk tolerance							0.041
							(1.78)*
Subj. portfolio risk							–0.057
							(–1.57)
Portfolio volatility							0.198
							(0.70)
Log portfolio value							0.035
							(1.44)
Log portfolio turnover							0.094
							(1.21)
Constant	3.925	3.994	3.935	3.699	4.044	3.792	3.432
	(135.91)***	(122.81)***	(95.68)***	(67.80)***	(118.20)***	(67.38)***	(10.07)***
R^2	0.159	0.171	0.171	0.215	0.171	0.212	0.227
Observations	2107	2107	2107	2107	2107	2107	1866
Time-fixed effects	No	No	No	Yes	No	Yes	Yes
Individual-fixed effects	No	No	No	No	Yes	Yes	Yes
Loss aversion coefficient λ	—	2.11	2.11	2.03	2.33	2.19	2.27
P-value Wald-test ($\lambda = 1$)	—	<0.001	<0.001	0.002	0.004	0.009	0.025

Notes: The table shows regressions of subjective ratings of expected portfolio return on numerical expected portfolio return and controls. Columns 1-2 are estimated by pooled OLS, the remaining columns contain results of panel regressions with random effects (columns 3-4) or fixed effects (columns 5-7). Expected portfolio return is split for gains and losses with 0 as a reference point. Risk tolerance and subjective portfolio risk are self-reported, survey-based measure as defined in the appendix. Portfolio volatility is the one-year historical volatility of investors' portfolios at the time of each survey round. Log portfolio value is the natural logarithm of the value of the investors' portfolios at Barclays in pounds. Log turnover is the natural logarithm of trading volume divided by the sum of portfolio value at the beginning and end of survey round. Time-fixed effects are included in form of round dummies for each round of the survey. Standard errors are robust and for panel models clustered by participant. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 3: Anticipated loss aversion for alternative reference points

	Based on regression model #					
	(2)	(3)	(4)	(5)	(6)	(7)
λ (interest rate)	2.09	2.09	2.02	2.29	2.16	2.24
	(<0.001)	(<0.001)	(0.002)	(0.004)	(0.009)	(0.026)
λ (inflation)	2.11	2.11	2.03	2.32	2.18	2.27
	(<0.001)	(<0.001)	(0.002)	(0.004)	(0.009)	(0.025)
λ (market expectations)	1.30	1.42	1.32	1.89	1.79	1.74
	(0.238)	(0.135)	(0.253)	(0.009)	(0.027)	(0.035)
λ (individual benchmark)	1.60	1.71	1.62	2.37	2.23	2.31
	(0.034)	(0.013)	(0.030)	(<0.001)	(<0.001)	(0.001)

Notes: The table shows loss aversion coefficients for different reference points. Regressions were estimated using the specifications of Table 2. λ (interest rate) takes the current three-months interest rate as a reference point, λ (inflation) the rate of inflation three-month ahead, λ (market expectations), the market return expectation of participants, and λ (individual benchmark) the individual benchmark of participants. In parentheses the p-values of a Wald-test are reported, testing for $\lambda = 1$.

Table 4: Loss experience

	Subjective rating of past return						
	Pooled OLS		GLS with RE		GLS with FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past portfolio return (perc.)	5.984 (22.00)***						
Past portfolio return (perc.) (if < 0)		6.662 (20.38)***	6.519 (18.11)***	4.951 (14.85)***	6.844 (16.21)***	4.848 (10.59)***	4.932 (9.70)***
Past portfolio return (perc.) (if > 0)		5.200 (8.34)***	5.394 (8.22)***	3.875 (6.43)***	5.674 (8.40)***	4.212 (6.60)***	4.618 (6.08)***
Risk tolerance							–0.031 (–1.09)
Subj. portfolio risk							–0.051 (–1.32)
Portfolio volatility							–0.400 (–0.73)
Log portfolio value							0.053 (1.58)
Log portfolio turnover							0.078 (0.47)
Constant	3.723 (125.04)***	3.820 (72.94)***	3.753 (68.07)***	3.281 (53.11)***	3.807 (65.10)***	3.315 (44.83)***	3.156 (7.59)***
R^2	0.449	0.452	0.452	0.517	0.452	0.515	0.529
Observations	2115	2115	2115	2115	2115	2115	1864
Time-fixed effects	No	No	No	Yes	No	Yes	Yes
Individual-fixed effects	No	No	No	No	Yes	Yes	Yes
Loss aversion coefficient λ	—	1.28	1.21	1.28	1.21	1.15	1.07
P-value Wald-test ($\lambda = 1$)	—	0.079	0.186	0.130	0.197	0.434	0.732

Notes: The table shows regressions of subjective ratings of past portfolio return on numerical perceived past portfolio return and controls. Columns 1-2 are estimated by pooled OLS, the remaining columns contain results of panel regressions with random effects (columns 3-4) or fixed effects (columns 5-7). Past portfolio return is split for gains and losses with 0 as a reference point. Risk tolerance and subjective portfolio risk are self-reported, survey-based measure as defined in the appendix. Portfolio volatility is the one-year historical volatility of investors' portfolios at the time of each survey round. Log portfolio value is the natural logarithm of hte value of the investors' portfolios at Barclays in pounds. Log turnover is the natural logarithm of trading volume divided by the sum of portfolio value at the beginning and end of survey round. Time-fixed effects are included in form of round dummies for each round of the survey. Standard errors are robust and for panel models clustered by participant. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for past portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 5: Loss experience for alternative reference points

	Based on regression model #					
	(2)	(3)	(4)	(5)	(6)	(7)
λ (interest rate)	1.28	1.21	1.28	1.21	1.15	1.07
	(0.079)	(0.187)	(0.129)	(0.199)	(0.434)	(0.731)
λ (inflation)	1.28	1.21	1.28	1.21	1.15	1.07
	(0.079)	(0.187)	(0.129)	(0.198)	(0.433)	(0.731)
λ (market past return)	1.13	1.10	1.03	1.05	0.88	0.85
	(0.257)	(0.361)	(0.825)	(0.658)	(0.378)	(0.288)
λ (individual benchmark)	1.11	1.07	1.04	1.06	0.92	0.95
	(0.399)	(0.605)	(0.798)	(0.629)	(0.587)	(0.741)
λ (portfolio expectations)	0.93	0.93	0.94	1.03	0.97	0.99
	(0.589)	(0.620)	(0.677)	(0.814)	(0.847)	(0.954)

Notes: The table shows loss aversion coefficients for different reference points. Regressions were estimated using the specifications of Table 4. λ (interest rate) takes the lagged three-months interest rate as a reference point, λ (inflation) the rate of inflation, λ (market past returns), the past market return as perceived by participants, λ (individual benchmark) the individual benchmark of participants, and λ (portfolio expectations) the expected portfolio return of the previous survey round. In parentheses the p-values of a Wald-test are reported, testing for $\lambda = 1$.

Table 6: Loss experience (actual returns)

	Subjective rating of past return							
	Pooled OLS		GLS with RE		GLS with FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(6')	(7)
Past portfolio return (act.)	3.427							
	(16.15)***							
Past portfolio return (act.)		3.472	3.365	1.676	3.664	1.605	1.994	1.727
(if < 0)		(14.65)***	(13.89)***	(5.94)***	(12.91)***	(4.67)***	(4.86)***	(4.91)***
Past portfolio return (act.)		3.360	3.488	1.706	3.388	1.740	1.562	1.809
(if > 0)		(5.69)***	(5.62)***	(3.61)***	(5.35)***	(3.08)***	(2.62)***	
R^2	0.267	0.267	0.267	0.390	0.267	0.388	0.522	0.397
Observations	2088	2088	2088	2088	2088	2088	1638	1859
Set of controls	No	No	No	No	No	No	No	Yes
Time-fixed effects	No	No	No	Yes	No	Yes	Yes	Yes
Individual-fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Loss aversion coefficient λ	—	1.03	0.96	0.98	1.08	0.92	1.28	0.96
P-value Wald-test ($\lambda = 1$)	—	0.879	0.869	0.956	0.725	0.843	0.558	0.916

Notes: The table shows regressions of subjective ratings of past portfolio return on numerical actual past portfolio return and controls. Columns 1-2 are estimated by pooled OLS, the remaining columns contain results of panel regressions with random effects (columns 3-4) or fixed effects (columns 5-7). Past portfolio return is split for gains and losses with 0 as a reference point. Column (6') includes only observations for which perceived and actual return have the same sign. The set of control variables is the same as used before. Time-fixed effects are included in form of round dummies for each round of the survey. Standard errors are robust and for panel models clustered by participant. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for past portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 7: Goodness of fit for different reference points

Panel A: Anticipated outcomes

Reference point	R^2	F-stat	AIC	BIC
Zero	0.187	11.74	4086.65	4169.62
(rank)	(1)	(3)	(1)	(1)
Interest rate	0.187	11.75	4087.31	4170.28
(rank)	(1)	(2)	(3)	(3)
Inflation	0.187	11.74	4086.68	4169.65
(rank)	(1)	(3)	(2)	(2)
Market expectations	0.149	11.31	4173.71	4256.69
(rank)	(5)	(5)	(5)	(5)
Individual benchmark	0.186	12.02	4090.91	4173.88
(rank)	(4)	(1)	(4)	(4)

Panel B: Experieced outcomes

Reference point	R^2	F-stat	AIC	BIC
Zero	0.569	60.52	5028.98	5111.94
(rank)	(1)	(2)	(1)	(1)
Interest rate	0.569	60.49	5028.98	5111.94
(rank)	(1)	(3)	(1)	(1)
Inflation	0.569	60.49	5028.98	5111.94
(rank)	(1)	(3)	(1)	(1)
Market past return	0.521	55.80	5226.57	5309.52
(rank)	(6)	(5)	(6)	(6)
Individual benchmark	0.567	62.23	5038.86	5121.81
(rank)	(4)	(1)	(4)	(4)
Portfolio expectations	0.565	55.56	5044.99	5127.94
(rank)	(5)	(6)	(5)	(5)

Notes: The table shows goodness-of-fit measures for models based on different reference points. R^2 is the model's adjusted R^2, F-stat the F-statistic, AIC the Aikake information criterion and BIC the Bayesian information criterion. Panel A displays results for anticipated outcomes and Panel B for experienced outcomes.

Table 8: Diminishing sensitivity

	Subjective rating of expected return			Subjective rating of past return		
	(1)	(2)	(3)	(4)	(5)	(6)
Expected or past portfolio return	5.388	4.794	5.076	6.679	4.802	4.843
(if $< -5\%$)	(5.62)***	(5.28)***	(4.41)***	(14.93)***	(10.54)***	(9.62)***
Expected or past portfolio return	19.652	19.546	19.910	18.300	10.243	9.020
(if $\geq -5\%$ and < 0)	(6.49)***	(6.51)***	(5.89)***	(7.15)***	(4.53)***	(3.65)***
Expected or past portfolio return	7.066	5.616	5.336	12.005	8.014	8.642
(if > 0 and $\leq 5\%$)	(5.12)***	(4.15)***	(3.67)***	(5.77)***	(3.62)***	(3.68)***
Expected or past portfolio return	2.761	2.575	2.624	5.567	4.239	4.688
(if $> 5\%$)	(5.87)***	(5.76)***	(5.31)***	(8.03)***	(6.44)***	(5.97)***
R^2	0.192	0.231	0.247	0.469	0.520	0.533
Observations	2107	2107	1866	2115	2115	1864
Set of controls	No	No	Yes	No	No	Yes
Time-fixed effects	No	Yes	Yes	No	Yes	Yes
Individual-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loss aversion coefficient λ (returns close to reference point)	2.78	3.48	3.73	1.52	1.28	1.04
P-value Wald-test ($\lambda = 1$)	<0.001	<0.001	<0.001	0.105	0.524	0.919

Notes: The table shows panel fixed-effects regressions with subjective ratings of portfolio return as dependent variable (columns 1-3 for expected portfolio return and columns 4-6 for past portfolio return). Independent variable is either numerical expected portfolio return (columns 1-3) or numerical past perceived portfolio return (columns 4-6). Both numerical return variables are split up in four intervals ($< -5\%$; $\geq -5\%$ and < 0; > 0 and $\leq 5\%$; $> 5\%$). The set of control variables is the same as before. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for portfolio losses and gains for the return intervals close to the reference point. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 9: Loss aversion and portfolio risk

	Subjective rating of expected return		Subjective rating of past return	
	(1)	(2)	(3)	(4)
	Split by portfolio volatility	Split by ACV	Split by portfolio volatility	Split by ACV
Loss sensitivity	4.995	3.683	4.710	4.609
(risky portfolios)	(4.69)***	(3.47)***	(10.22)***	(9.25)***
Gain sensitivity	2.548	2.35	3.902	3.941
(risky portfolios)	(5.90)***	(5.47)***	(6.10)***	(5.89)***
Loss sensitivity	7.509	7.738	5.244	5.204
(less risky portfolios)	(5.13)***	(6.23)***	(6.51)***	(9.35)***
Gain sensitivity	2.51	2.954	6.653	5.222
(less risky portfolios)	(2.72)***	(4.22)***	(5.93)***	(5.23)***
R^2	0.215	0.212	0.525	0.518
Observations	2107	2107	2115	2115
Time-fixed effects	Yes	Yes	Yes	Yes
Individual-fixed effects	Yes	Yes	Yes	Yes
Loss aversion coefficient λ (risky portfolios)	1.96	1.57	1.21	1.17
Loss aversion coefficient λ (safe portfolios)	2.99	2.62	0.79	1.00
P-value ($loss_{risky} = loss_{less\ risky}$)	0.08	0.01	0.44	0.26
P-value ($gain_{risky} = gain_{less\ risky}$)	0.95	0.37	0.02	0.20
P-value ($\lambda_{risky} = \lambda_{less\ risky}$)	0.26	0.22	0.08	0.49

Notes: The table shows panel fixed-effects regressions with subjective ratings of expected portfolio return (columns 1-2) and past portfolio return (columns 3-4) as dependent variable. The sample is split into less risky and risky portfolios by portfolio volatility (columns 1 and 3) or average component volatility (ACV, columns 2 and 4). Loss sensitivity denotes expected portfolio returns or past portfolio returns < 0, gain sensitivity expected portfolio returns or past portfolio returns > 0, estimated separately for risky and less risky portfolios. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$) and in addition whether the loss aversion coefficient for the less risky portfolios is equal to the coefficient for the riskier portfolios.

Table 10: Loss aversion and previous outcomes

	Subjective rating of expected return				Subjective rating of past return			
	Past pf. return		Cumulative pf. return		Lagged past pf. return		Cumulative pf. return	
	<0	≥0	<0	≥0	<0	≥0	<0	≥0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected portfolio return	5.694	7.905	4.129	9.728				
(if < 0)	(3.72)***	(3.22)***	(3.66)***	(4.20)***				
Expected portfolio return	3.547	2.118	2.758	2.324				
(if > 0)	(3.43)***	(3.48)***	(3.78)***	(4.87)***				
Past portfolio return (perc.)					4.377	6.571	5.848	5.979
(if < 0)					(8.49)***	(5.73)***	(13.62)***	(4.10)***
Past portfolio return (perc.)					5.522	5.214	3.438	5.355
(if > 0)					(5.10)***	(7.16)***	(1.63)	(8.20)***
R^2	0.201	0.180	0.174	0.246	0.500	0.485	0.320	0.321
Observations	992	1115	1207	900	1178	870	1211	904
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loss aversion coefficient λ	1.61	3.73	1.50	4.19	0.79	1.26	1.70	1.12
P-value Wald-test ($\lambda = 1$)	0.215	0.020	0.333	0.001	0.387	0.365	0.491	0.540
P-value ($\lambda_{loss} = \lambda_{gain}$)	0.107		0.025		0.192		0.652	

Notes: The table shows panel fixed-effects regressions with subjective ratings of expected and past portfolio return as dependent variable. The sample is split by past perceived portfolio return (columns 1, 2), by lagged past actual return (columns 5, 6), or by past actual return over the last two survey periods (columns 3, 4, 7, 8). Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$) and in addition whether the loss aversion coefficient after previous losses is equal to the coefficient after previous gains.

Table 11: Financial loss aversion illusion and sophistication

Group variable		Anticipated λ	Experienced λ	FLAI ($\lambda_{ant} - \lambda_{exp}$)	Δ FLAI groups
Full sample		2.19	1.15	1.04	
		(0.009)	(0.434)	(0.046)	
Financial literacy	low	4.31	1.32	2.99	
		(0.004)	(0.330)	(0.083)	2.75
	high	1.26	1.03	0.23	(0.106)
		(0.469)	(0.885)	(0.300)	
Wealth	low	3.43	1.50	1.93	
		(0.006)	(0.114)	(0.122)	1.14
	high	1.70	0.91	0.79	(0.257)
		(0.145)	(0.671)	(0.086)	
Experience	low	3.74	0.83	2.91	
		(<0.001)	(0.515)	(0.017)	2.18
	high	2.00	1.27	0.72	(0.075)
		(0.027)	(0.248)	(0.132)	

Notes: The table shows anticipated and experienced loss aversion coefficients for different groups of investors and reports financial loss aversion illusion (FLAI) as difference between the two coefficients. In parentheses the p-values of a Wald-test are reported, testing for $\lambda = 1$, or of a one-sided t-test testing for $FLAI = 0$ or $\Delta FLAI = 0$, respectively. Low financial literacy includes all investors with less than 4 correct responses in the financial literacy test, low wealth are investors with a financial wealth of less than £150,000, and low experience are investors with less than 20 years of investment experience (self-reported).

Table 12: Monetary outcomes

	Subjective rating of expected return			Subjective rating of past return		
	(1)	(2)	(3)	(4)	(5)	(6)
Expected portfolio profit	0.046	0.040	0.041			
(if < 0)	(5.08)***	(4.67)***	(4.91)***			
Expected portfolio profit	0.017	0.015	0.015			
(if > 0)	(4.18)***	(4.04)***	(3.61)***			
Past portfolio profit				0.032	0.011	0.010
(if < 0)				(5.08)***	(2.40)**	(1.94)*
Past portfolio profit				0.031	0.018	0.021
(if > 0)				(4.82)***	(4.82)***	(3.70)***
R^2	0.071	0.118	0.164	0.154	0.384	0.401
Observations	1990	1990	1778	1998	1998	1776
Set of controls	No	No	Yes	No	No	Yes
Time-fixed effects	No	Yes	Yes	No	Yes	Yes
Individual-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loss aversion coefficient λ	2.77	2.69	2.72	1.00	0.61	0.48
P-value Wald-test ($\lambda = 1$)	0.003	0.007	0.007	0.996	0.262	0.188

Notes: The table shows panel fixed-effects regressions with subjective ratings of portfolio return as dependent variable (columns 1-3 for expected portfolio return and columns 4-6 for past portfolio return). Independent variable is either expected portfolio profit (in £1,000, columns 1-3) or past perceived portfolio profit (in £1,000, columns 4-6). Both profit variables are split up in losses and gains. The set of control variables is the same as before. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for portfolio losses and gains for the return intervals close to the reference point. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 13: Comparison of data sets

Panel A	Current survey	Barber & Odean	Dorn & Huberman	Glaser & Weber
N (full sample)	19,251	37,664	21,528	3,079
N (participants)	617	NA	1,345	215
Response rate	3.2%	NA	6.2%	7.0%
Gender (male=1)	0.93	0.79	0.88	0.95
Age (in years)	51.4	50.4	38.9	40.0
Wealth (median)	£200,000[#]	$100,000	€ 166,000	NA
Income (median)	£62,500[#]	$75,000[§]	€ 45,000	€ 38,347
Portfolio value (median)	£41,687	$16,000	€ 28,078	€ 15,630
Annualized volatility	37%	NA	35%	NA
Number of positions	15.7	4.3	NA	6.8
Monthly trades	2.8	0.4	NA	3.6
Monthly turnover	13%	6%	18%	137%
Panel B	**Participants**	**Non-participants**	**Difference**	
Gender (male=1)	0.93	0.80	0.13***	
Age (in years)	51.4	52.6	1.2	
Median portfolio value (pre-survey)	36,961	34,995	1,966	
Number of positions (pre-survey)	14.5	14.0	0.4	
Number of trades (one year pre-survey)	33.7	28.2	5.50*	

Notes: Panel A shows descriptive statistics for the current survey and the datasets of Barber and Odean (2001) (some data reported from Barber and Odean (2000)), Dorn and Huberman (2005), and Glaser and Weber (2007a). Full sample is the number of investors who received a survey invitation (or in case of Barber and Odean (2001) for which demographic data were available), and participants is the number of respondents. Variables are displayed for participants, if available. Values in Dorn and Huberman (2005) were converted from DM to € . [#§]Derived from categorical values; [§]Truncated mean.

Table 14: Selection into the survey

	Participation	Rating expected return		Rating experienced return	
	(1)	(2)	(3)	(4)	(5)
Expected or past portfolio return (if < 0)		6.110	6.051	5.030	5.032
(if < 0)		(5.56)***	(5.54)***	(14.34)***	(14.43)***
Expected or past portfolio return (if > 0)		2.954	2.962	4.277	4.306
(if > 0)		(6.17)***	(6.26)***	(5.74)***	(5.92)***
Risk tolerance		0.029	0.028	–0.023	–0.021
		(1.72)*	(1.64)	(–1.19)	(–1.14)
Subj. portfolio risk		–0.049	–0.051	–0.053	–0.053
		(–1.62)	(–1.68)*	(–1.84)*	(–1.84)*
Portfolio volatility		0.180	0.171	–0.106	–0.091
		(1.03)	(0.96)	(–0.47)	(–0.41)
Log portfolio value	0.030	0.025	0.016	0.010	0.013
	(1.72)*	(1.37)	(0.88)	(0.49)	(0.61)
Log portfolio turnover		0.085	–0.020	0.047	–0.007
		(1.39)	(–0.28)	(0.55)	(–0.06)
Gender	0.515		0.109		0.686
	(7.91)***		(0.42)		(2.73)***
Age	–0.000	–0.008	–0.008	–0.005	–0.005
	(–0.24)	(–2.70)***	(–2.66)***	(–1.90)*	(–1.92)*
Log number of positions	–0.015	0.050	0.028	0.002	–0.010
	(–0.59)	(1.08)	(0.59)	(0.04)	(–0.23)
Log number of trades	0.094		0.085		0.074
	(6.24)***		(2.72)***		(1.94)*
Inverse Mills ratio		–0.547	–0.225	–0.554	0.495
		(–2.28)**	(–0.55)	(–1.92)*	(1.19)
Constant	–2.869	4.985	4.210	4.986	1.890
	(15.71)***	(7.57)***	(3.42)***	(6.71)***	(1.55)
(Pseudo-)R^2	0.024	0.191	0.195	0.568	0.570
Observations	19721	1825	1825	1823	1823
Time-fixed effects	No	Yes	Yes	Yes	Yes
Loss aversion coefficient λ	—	2.07	2.04	1.18	1.17
P-value Wald-test ($\lambda = 1$)	—	0.013	0.014	0.362	0.370

Notes: The table shows a two stage Heckman-regression with the first stage estimated on the larger sample of invited survey participants. The first stage (column 1) is a probit regression of a participation indicator variable on gender, age, and portfolio variables (from the year prior two the sampling procedure). The second stage (columns 2-5) is estimated as in Tables 2 and 4 including the inverse mills ratio and variables from the first stage (and without individual fixed effects). Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected or past portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table 15: Comparison of participants and non-participants

	Participants prior return	Non-participants prior return	T-test t-value	Prior loss participation rate	Prior gain participation rate	Proportion test z-value
Round 1	-9.49%	-12.00%	1.82*	80.8%	76.6%	0.87
Round 2	-37.86%	-36.91%	-0.48	61.6%	(76.5%)	-1.24
Round 3	-4.86%	-3.79%	-0.71	37.9%	35.9%	0.46
Round 4	19.50%	21.46%	-1.29	(32.0%)	33.6%	-0.17
Round 5	18.85%	19.30%	-0.38	(28.6%)	37.6%	-0.84
Round 6	-2.11%	-4.57%	2.12**	31.7%	34.6%	-0.74
Round 7	4.90%	8.50%	-3.26***	29.6%	25.3%	0.76
Round 8	-6.85%	-7.61%	0.68	22.6%	13.0%	1.80*
Round 9	10.28%	9.98%	0.34	21.9%	26.3%	-0.55

Notes: The table shows for each survey round the prior three-month portfolio returns of participants and non-participants, a t-test for the difference in return between these groups, the participation rates of investors with a prior portfolio loss and a prior portfolio gain, and a proportion test testing for differences between the participation rates. Values in parentheses denote less than 50 observations (for prior losses or gains). Differences are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Table 16: Selection within the survey

	Participation			Rating expected return			Rating experienced return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exp. or past pf ret.				6.079	6.055	6.531	5.029	5.002	4.963
(if < 0)				(5.53)***	(5.51)***	(4.58)***	(14.10)***	(13.79)***	(10.93)***
Exp. or past pf ret.				2.868	2.874	3.126	4.256	4.276	5.242
(if > 0)				(6.70)***	(6.73)***	(5.77)***	(6.35)***	(6.39)***	(6.75)***
Past pf ret. (actual)	–0.071	–0.190	–0.163						
	(–0.47)	(–1.22)	(–0.69)						
Lagged rating of			0.040						
experienced return			(1.65)*						
Risk tolerance			–0.005	0.028	0.028	0.042	–0.021	–0.021	–0.025
(or lag)			(–0.21)	(1.63)	(1.65)*	(2.11)**	(–1.16)	(–1.14)	(–1.11)
Subj. portfolio risk			–0.019	–0.057	–0.057	–0.070	–0.054	–0.054	–0.008
(or lag)			(–0.53)	(–1.89)*	(–1.89)*	(–1.89)*	(–1.92)*	(–1.88)*	(–0.22)
Portfolio volatility			–0.164	0.069	0.072	0.310	–0.167	–0.175	–0.018
			(–0.73)	(0.38)	(0.39)	(1.19)	(–0.78)	(–0.78)	(–0.06)
Log pf value		–0.018	0.019	0.016	0.013	0.005	0.011	0.007	0.018
		(–1.05)	(0.58)	(0.85)	(0.72)	(0.22)	(0.53)	(0.33)	(0.72)
Log pf turnover			0.153	–0.017	–0.017	–0.012	0.003	0.002	–0.006
			(1.24)	(–0.24)	(–0.24)	(–0.17)	(0.03)	(0.02)	(–0.05)
Gender		0.042	–0.019	0.183	0.178	0.011	0.433	0.424	0.453
		(0.19)	(–0.08)	(1.25)	(1.22)	0.06	(2.54)**	(2.51)**	(1.89)*
Age		0.008	0.003	–0.008	–0.008	–0.005	–0.006	–0.007	–0.006
		(1.91)*	(0.72)	(–2.59)***	(–2.63)***	(–1.23)	(–2.10)**	(–2.25)**	(–1.61)
Log positions		0.161	0.084	0.014	0.004	0.007	–0.006	–0.026	0.035
		(3.17)***	(1.24)	(0.29)	(0.07)	(0.12)	(–0.14)	(–0.54)	(0.60)
Log trades		0.050	0.045	0.097	0.093	0.046	0.059	0.051	0.020
		(1.71)*	(0.90)	(3.35)***	(3.22)***	(1.31)	(1.69)*	(1.47)	(0.45)
Inverse Mill's ratio				0.086			–0.175		
(model 1)				(0.17)			(–0.16)		
Inverse Mill's ratio					–0.174			–0.319	
(model 2)					(–0.72)			(–0.98)	
Inverse Mill's ratio						-0.333			–0.527
(model 3)						(–1.90)*			(–2.28)**
Constant	1.132	0.466	–0.269	3.693	3.850	4.681	3.376	3.556	4.308
	(13.99)***	(1.33)	(–0.47)	(10.06)***	(10.46)***	(10.39)***	(6.68)***	(8.14)***	(8.80)***
R^2	0.177	0.180	0.017	0.197	0.198	0.198	0.572	0.572	0.607
Observations	5202	5028	1687	1842	1842	1054	1840	1840	1053
Loss av. coeff. λ	—	—	—	2.12	2.11	2.09	1.18	1.17	0.95
P-value ($\lambda = 1$)	—	—	—	0.010	0.010	0.033	0.316	0.340	0.765

Notes: The table shows a two stage Heckman-regression. The first stage is a probit model estimated round-wise, for ease of presentation a panel version of this regression is displayed in columns 1-3. The regression in column 3 includes lagged survey variables. The other control variables are as in Table 14. The second stage (columns 4-9) is estimated as in Tables 2 and 4 including the inverse Mill's ratio of the different first stage specifications. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected or past portfolio losses and gains. A Wald-test tests for equality of these coefficients ($\lambda = 1$).

Figure 1: Portfolio return expectations and subjective ratings

Numerical expected portfolio returns and the associated average subjective rating of these returns. Most dots represent multiple obseravations.

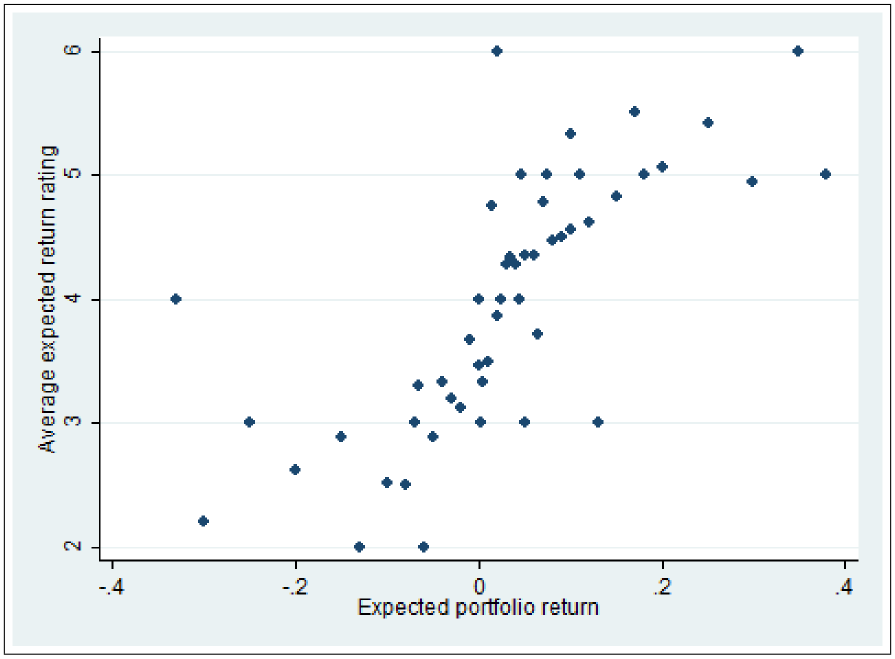
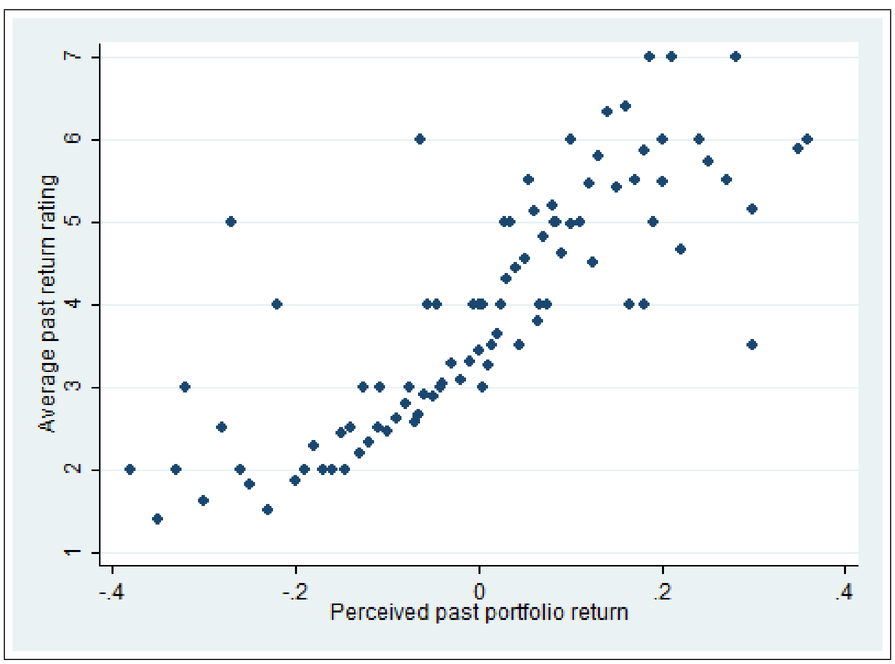


Figure 2: Past portfolio returns and subjective ratings

Numerical perceived past portfolio returns and the associated average subjective rating of these returns. Most dots represent multiple obseravations.



Online appendix

This online appendix contains supplementary material to the paper "Financial Loss Aversion Illusion". Section A presents results for normalized dependent variables and a comparison of gain and loss sensitivity. Section B reports analyzes related to the alternative of investors with expected utility preferences. Section C reports results of a bootstrap estimation.

A Normalized coefficients

For this analysis, the subjective ratings of expected and experience returns are normalized with respect to their mean and standard deviation. The adjusted ratings thus are $rating_{adj} = \frac{rating - mean(rating)}{sd(rating)}$. The normalization with respect to the mean will only change the constant term in the regressions. The normalization with respect to standard deviation will not change the sign or significance of coefficients, but only the magnitude of coefficients. Descriptive statistics for mean and standard deviation of the ratings can be found in Table 1 of the paper. The standard deviation for ratings of experienced returns (1.73) is much higher than for ratings of expected returns (1.16). Accordingly, the effect of the adjustment will be stronger for the regressions of experienced returns.

Table A.1 shows the results of the regression for ratings of expected returns. The overall sensitivity of the adjusted ratings to returns is 3.6 (see column 1). In the piecewise-linear models estimated separately for expected gains and losses, the coefficient for losses is between 4.8 and 6.4 depending on the regression specification. The coefficient for gains is between 2.2 and 3.0. This results in loss aversion coefficients above two, which are identical to the unadjusted version of the regressions. But the transformation now allows to directly compare the gain sensitivity and loss sensitivity between the ex ante and ex post regressions.

Table A.2 presents the regressions for ratings of experienced returns. Remarkably, the overall sensitivity of these ratings to past returns is with 3.5 very close to the one estimated for expected returns. Coefficients for losses are between 2.8 and 4.0, and coefficients for gains between 2.2 and 3.0. While coefficients for gains have hardly changed compared to the ex ante perspective, loss sensitivity is much reduced, which suggests that the decrease in loss aversion coefficients is mainly driven by the sensitivity to losses. To confirm this finding, we directly compare the coefficients regression by regression. The expected sensitivity to losses is always larger than the experienced sensitivity to losses (by a factor between 1.4 and 1.8) and the difference is in general significant at 1% or 5%-level. In contrast, the equivalent ratio for sensitivity to gains is between 0.7 and 1.1 and the coefficients are not significantly different.

Table A.1: Gain and loss sensitivity for anticipated returns

	Subjective rating of expected return						
	Pooled OLS		GLS with RE		GLS with FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expected portfolio return	3.564						
	(11.40)***						
Expected portfolio return		6.407	5.534	5.088	5.365	4.773	5.064
(if < 0)		(8.69)***	(7.28)***	(6.96)***	(5.81)***	(5.51)***	(4.54)***
Expected portfolio return		3.038	2.620	2.504	2.304	2.183	2.234
(if > 0)		(9.25)***	(7.75)***	(7.68)***	(5.86)***	(5.77)***	(5.33)***
Risk tolerance							0.035
							(1.78)*
Subj. portfolio risk							–0.049
							(–1.57)
Portfolio volatility							0.170
							(0.70)
Log portfolio value							0.030
							(1.44)
Log portfolio turnover							0.081
							(1.21)
Constant	–0.218	–0.159	–0.209	–0.412	–0.116	–0.333	–0.641
	(–8.81)***	(–5.68)***	(–5.93)***	(–8.80)***	(–3.96)***	(–6.88)***	(–2.19)**
R^2	0.159	0.171	0.115	0.173	0.116	0.174	0.194
Observations	2107	2107	2107	2107	2107	2107	1866
Time-fixed effects	No	No	No	Yes	No	Yes	Yes
Individual-fixed effects	No	No	No	No	Yes	Yes	Yes
Loss aversion coefficient λ	—	2.11	2.11	2.03	2.33	2.19	2.27
P-value Wald-test ($\lambda = 1$)	—	<0.001	<0.001	0.002	0.004	0.009	0.025

Notes: The table shows regressions of normalized subjective ratings of expected portfolio return on numerical expected portfolio return and controls. Columns 1-2 are estimated by pooled OLS, the remaining columns contain results of panel regressions with random effects (columns 3-4) or fixed effects (columns 5-7). Expected portfolio return is split for gains and losses with 0 as a reference point. Risk tolerance and subjective portfolio risk are self-reported, survey-based measure as defined in the appendix. Portfolio volatility is the one-year historical volatility of investors' portfolios at the time of each survey round. Log portfolio value is the natural logarithm of the value of the investors' portfolios at Barclays in pounds. Log turnover is the natural logarithm of trading volume divided by the sum of portfolio value at the beginning and end of survey round. Time-fixed effects are included in form of round dummies for each round of the survey. Standard errors are robust and for panel models clustered by participant. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for expected portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

Table A.2: Gain and loss sensitivity for experienced returns

	Subjective rating of past return						
	Pooled OLS		GLS with RE		GLS with FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past portfolio return (perceived)	3.469 (22.00)***						
Past portfolio return (perceived) (if < 0)		3.862 (20.38)***	3.779 (18.11)***	2.870 (14.85)***	3.967 (16.21)***	2.810 (10.59)***	2.859 (9.70)***
Past portfolio return (perceived) (if > 0)		3.014 (8.34)***	3.126 (8.22)***	2.246 (6.43)***	3.289 (8.40)***	2.441 (6.60)***	2.677 (6.08)***
Risk tolerance							–0.018 (–1.09)
Subj. portfolio risk							–0.029 (–1.32)
Portfolio volatility							–0.232 (–0.73)
Log portfolio value							0.030 (1.58)
Log portfolio turnover							0.045 (0.47)
Constant	0.067 (3.87)***	0.123 (4.06)***	0.084 (2.64)***	–0.189 (–5.29)***	0.116 (3.41)***	–0.170 (–3.95)***	–0.262 (–1.09)
R^2	0.449	0.452	0.452	0.517	0.452	0.515	0.529
Observations	2115	2115	2115	2115	2115	2115	1864
Time-fixed effects	No	No	No	Yes	No	Yes	Yes
Individual-fixed effects	No	No	No	No	Yes	Yes	Yes
Loss aversion coefficient λ	—	1.28	1.21	1.28	1.21	1.15	1.07
P-value Wald-test ($\lambda = 1$)	—	0.079	0.186	0.130	0.197	0.434	0.732

Notes: The table shows regressions of normalized subjective ratings of past portfolio return on numerical perceived past portfolio return and controls. Columns 1-2 are estimated by pooled OLS, the remaining columns contain results of panel regressions with random effects (columns 3-4) or fixed effects (columns 5-7). Past portfolio return is split for gains and losses with 0 as a reference point. Risk tolerance and subjective portfolio risk are self-reported, survey-based measure as defined in the appendix. Portfolio volatility is the one-year historical volatility of investors' portfolios at the time of each survey round. Log portfolio value is the natural logarithm of the value of the investors' portfolios at Barclays in pounds. Log turnover is the natural logarithm of trading volume divided by the sum of portfolio value at the beginning and end of survey round. Time-fixed effects are included in form of round dummies for each round of the survey. Standard errors are robust and for panel models clustered by participant. Coefficients are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$, t-values are shown in parentheses. The loss aversion coefficient is the ratio between the coefficients for past portfolio losses and gains. The Wald-test tests for equality of these coefficients ($\lambda = 1$).

B Risk aversion

We calculate risk aversion coefficients for the example of a constant relative risk aversion (CRRA) utility function. The function is defined as follows:

$$u(x) = \frac{x^{1-\gamma} - 1}{1 - \gamma} \tag{3}$$

Hereby, γ represents the risk aversion coefficient, with $\gamma > 0$ for risk averse agents (for $\gamma = 1$ the function is defined as $u(x) = ln(x)$). A gain g and a loss l are felt equally strong if the respective changes in utility are the same $u(x+g) - u(x) = u(x) - u(x-l)$. As we define gains and losses in terms of returns, this translates to $u(x(1+r_g)) - u(x) = u(x) - u(x(1-r_l))$. Defining gains and losses in relative terms is helpful in yet another way, as with CRRA agents with different wealth levels will respond equally to relative changes. The magnitude of gains and losses r_g and r_l matters, as due to the curvature of the utility the reaction to larger losses is stronger. We thus obtain different values for γ if we keep the ratio of r_g and r_l constant. To explain the empirically observed values, this ratio should equal λ as this is the slope estimated in the loss domain relative to the gain domain. For simplicity, we use $\lambda = 2$ for this calibration exercise.

Table B.1 contains the obtained risk aversion coefficients for different return combinations. For small returns, the level of risk aversion needs to be very high (almost 50) to explain an equally strong reaction to a 2% gain as compared to a 1% loss. The values become more reasonable, the larger the considered returns are. However, when investors report their return expectations, most values are in the region between -5% and 10% for which risk aversion provides a poor explanation. In Table 8 we estimate loss aversion for this region close to the reference point and find high values of λ. These high values are not easily explained by risk aversion.

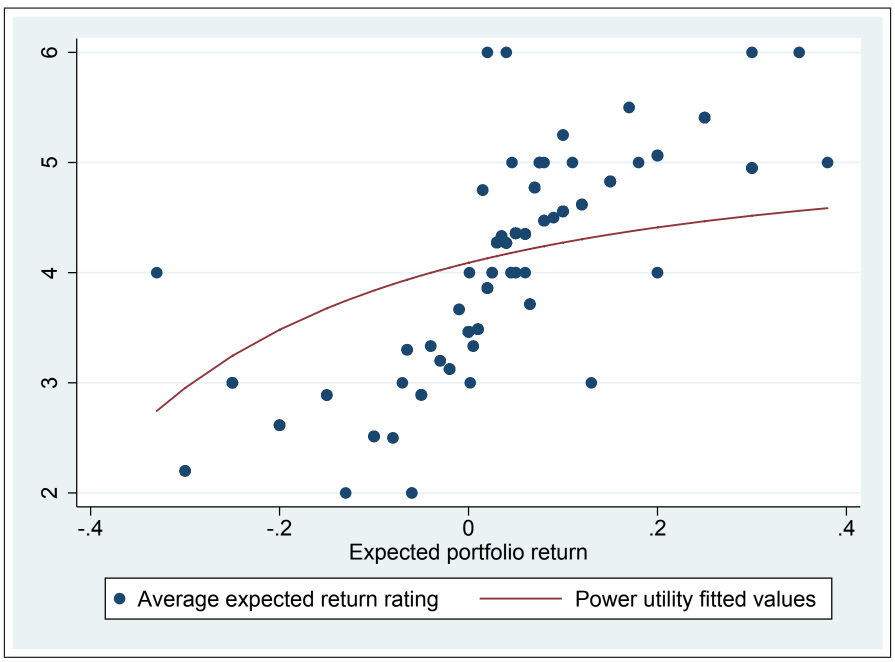
Table B.1: Risk aversion coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
r_g	2%	4%	6%	10%	20%	40%	60%
r_l	1%	2%	3%	5%	10%	20%	30%
γ	48.23	24.17	16.15	9.73	4.91	2.49	1.67

Notes: The table shows risk aversion estimates for different combinations of gains and losses. γ is determined using a CRRA utility function of the form $u(x) = \frac{x^{1-\gamma}-1}{1-\gamma}$.

Another way to obtain risk aversion coefficients, is to fit a power function directly to the observed values of the numeric expectations (x) and the associated ratings (u(x)) (for a good reference, see Wakker, 2008). The caveat to this approach is that the ratings are elicited on a discrete scale from 1-7 and it is unclear whether this estimation approach will work well on such data.[7]. We estimate the model $u(x) = \alpha - x^{1-\gamma}$. As expected utility is defined over wealth, we use expected gross returns ($x = 1 +$ expected returns). The lowest possible wealth level thus is 0. The constant takes into account that the ratings are on a positive scale. We obtain estimates for α of 5.09 and for γ of 3.19. While this value for risk aversion is still high, it is more realistic than those from the calibration exercise. However, as Figure B.1 shows, it explains the data poorly, in particular for returns around zero.

Figure B.1: Portfolio return expectations, subjective ratings, and power utility function
Numerical expected portfolio returns and the associated average subjective rating of these returns. The power utility function fitted to the data is $u(x) = 5.09 - x^{-2.19}$. Note that dots often represent multiple observations and therefore the visual impression that other parameterizations would fit the data better is deceiving.



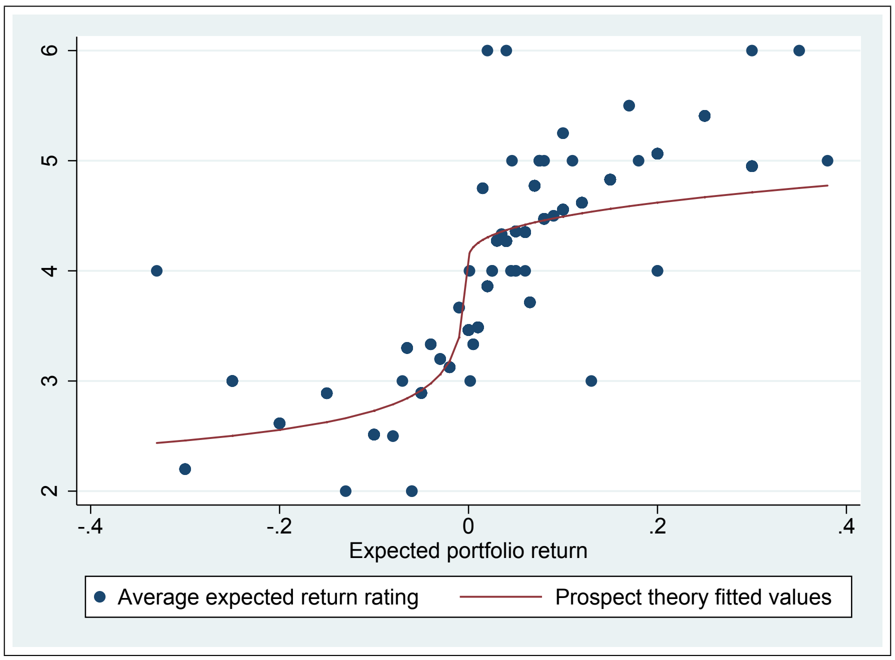
As an alternative, we fit a prospect theory model of the form:

$$u(x) = \begin{cases} \alpha + x^{1-\gamma_{gain}} & \text{if } x \geq 0 \\ -\lambda(-x)^{1-\gamma_{loss}} & \text{if } x < 0 \end{cases} \tag{4}$$

[7]For this reason, we rely on the piecewise linear model in the paper

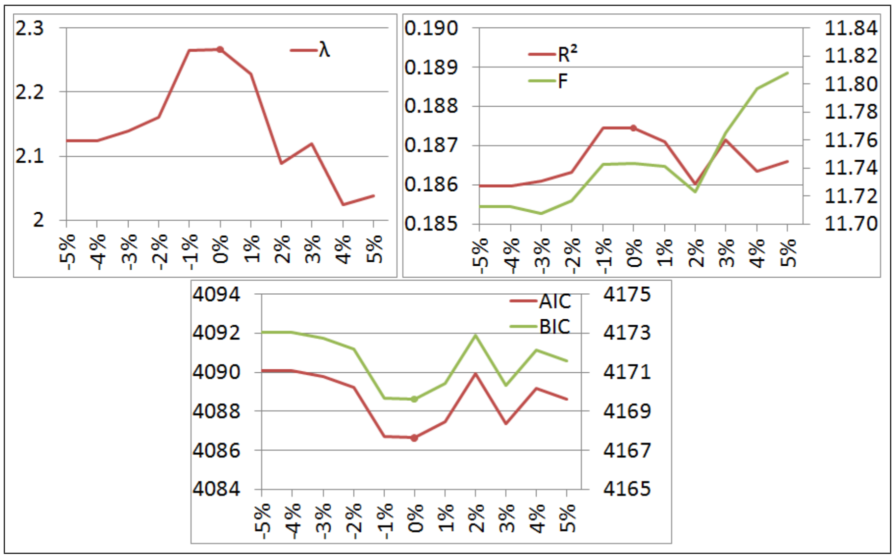
The estimation results in a value for α of 4.10, for γ_{gain} of 0.60, for γ_{loss} of 1.09 and for λ of 2.19. The coefficients for γ imply risk aversion in the gain domain (however much lower than in the expected utility models) and risk seeking for the loss domain. The loss aversion coefficient is close to those observed in the piecewise linear models. Figure B.2 shows the fit of this model. It captures well the ratings around the origin. We abstain from comparing the goodness of fit of the two models, as the additional parameters provide a natural advantage to the prospect theory model.

Figure B.2: Portfolio return expectations, subjective ratings, and prospect theory function
Numerical expected portfolio returns and the associated average subjective rating of these returns. The prospect theory function fitted to the data has the parameters stated in the text.



Finally, in addition to the reference points considered in the paper, we use arbitrary reference points between -5% and 5% in steps of 1%. Unlike for interest rates, inflation, or other benchmarks, there is no theory behind these reference points. They are supposed to provide reassurance for the existence and location of the reference point and its improvement in terms of goodness of fit to a linear model without a reference point. We calculate the loss aversion coefficient λ for each of the models, and the previously introduced goodness of fit measures: the adjusted R^2, the model's F-statistic, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC). Figure B.3 presents in the upper left graph the results for the loss aversion coefficient. It has its maximum at zero, meaning that for a reference point at zero the slopes in the gain and the loss domain are most distinct.

Figure B.3: Loss aversion coefficients and goodness of fit measures for different referent points
The upper left graph presents loss aversion coefficients estimated using regression specification (7) from Table 2. The upper right graph shows R^2 and F-statistic from these regressions. The bottom graph contains information criteria (AIC and BIC) from these regressions.



The goodness of fit criteria also have their maximum (R^2) or minimum (AIC, BIC) at a zero reference point. The F-statistic is the exception, as it further increases for positive reference points. This is due to the fact that for positive reference points the number of observations below and above the reference point is more even, which increases the statistical significance of the coefficient for the loss domain (and indirectly the F-statistic). The magnitude of the differences between reference points is not very large, as changes in the slopes occur gradually. However, differences compared to a model without a reference point are larger (R^2=17.9, AIC=4105, BIC=4183). Particularly for the information criteria, the difference is larger than the proposed rule of thumb to identify a superior model. In addition, we use a nonlinear least squares model to test for the optimal cutoff point of a piecewise linear regression function. The determined local cutoff is -0.47% with a confidence interval from -1.2% to 2.1%.

C Bootstrap of results

In this section, we present results of a bootstrap estimation of the main findings of the paper (we thank an anonymous referee for this suggestion). We perform a non-parametric bootstrap estimation of the loss aversion coefficient λ for all regressions in Tables 2 and 4. Statistics are bootstrapped based on 1,000 repetitions by re-sampling the data with replacement (Mooney and Duval, 1993). In the panel regressions re-sampling clusters are identified by survey participant. From a diagnostic point of view there are no skewed residuals or other obvious reasons that would cast doubt on the validity of the OLS or GLS estimation. Nevertheless, the bootstrap analysis is useful to establish further robustness for our results.

Panel A of Table C.1 shows bootstrap estimates for the loss aversion coefficient λ in the regression models of Table 2. Results confirm that λ is around two for expected portfolio outcomes and is significantly different from loss neutrality ($\lambda = 1$). 95%-confidence intervals mostly do not include a value of one. In contrast, estimated loss coefficients for experienced outcomes are much smaller and not significantly different from one. As a result, financial loss aversion illusion FLAI defined as the difference between the two coefficients is always positive. The significance of FLAI is weaker, as it is a non-linear combination of four estimated coefficients. A similar effect was observed for FLAI in the paper.

Table C.1: Bootstrap estimation of main results

Panel A	Estimated λ	Bootstrap Std. Err.	z-value $\lambda = 1$	z-value $\beta_{loss} = \beta_{gain}$	Confidence interval	
Model (2)	2.11	0.39	2.88***	3.69***	1.35	2.86
Model (3)	2.11	0.43	2.56***	3.28***	1.26	2.96
Model (4)	2.03	0.43	2.43**	3.04***	1.20	2.87
Model (5)	2.33	0.66	2.03**	2.83***	1.04	3.61
Model (6)	2.19	0.63	1.89*	2.56***	0.95	3.42
Model (7)	2.27	0.81	1.57	2.08**	0.68	3.85
Panel B	Estimated λ	Bootstrap Std. Err.	z-value $\lambda = 1$	z-value $\beta_{loss} = \beta_{gain}$	Confidence interval	
Model (2)	1.28	0.20	1.40	1.70*	0.89	1.67
Model (3)	1.21	0.19	1.08	1.24	0.83	1.59
Model (4)	1.28	0.24	1.15	1.43	0.80	1.75
Model (5)	1.21	0.19	1.09	1.24	0.83	1.58
Model (6)	1.15	0.22	0.68	0.76	0.71	1.59
Model (7)	1.07	0.22	0.31	0.33	0.63	1.50
Panel C	Estimated FLAI	Bootstrap Std. Err.	z-value $FLAI = 0$		Confidence interval	
Model (2)	0.83	0.42	1.96**		0.00	1.66
Model (3)	0.90	0.48	1.90*		-0.03	1.84
Model (4)	0.75	0.49	1.54		-0.21	1.71
Model (5)	1.12	0.58	1.94*		-0.01	2.26
Model (6)	1.03	0.68	1.52		-0.30	2.37
Model (7)	1.20	0.81	1.48		-0.39	2.79

Notes: The table shows in Panel A and B bootstrap estimates of loss aversion coefficient λ, standard errors, test statistics, and confidence intervals for the models of Tables 2 and 4 respectively. Panel C contains bootstrap estimates of financial loss aversion illusion FLAI. Results are significant at $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$