Being an Expert when there are no Experts: The Impact of Knowledge Illusion on Probability Weighting

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Abstract: We empirically show that individuals have distinct attitudes towards different sources of risk. This evidence contradicts the common theoretical assumption of risk constituting a unique source of uncertainty. Instead, the processing of objective probabilities in decisions under risk depends on an individual's knowledge illusion regarding the underlying source. We conduct an experiment involving three different gambles, i.e., risky games where objective probabilities are known, no further information-based advantages exist, and outcomes are independent of knowledge. The gambles are chosen based on their popularity to induce variation in participants' perceived expertise. The variation is an illusion though since all objective probabilities are explicitly provided. Our results indicate that individuals engage in less severe probability weighting if their knowledge illusion regarding a gamble is more pronounced. Our finding highlights the impact of perceived (but irrelevant) expertise on decisions under risk and facilitates a better understanding of puzzling investor behavior observed in equity markets.

Keywords: risk; probability weighting; perceived expertise; stock market participation puzzle; home bias; local bias

JEL classifications: D81, D83, D91

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1. Introduction

While the literature on decisions under uncertainty showed that individuals may have distinct attitudes towards different sources of ambiguity (Abdellaoui et al. 2011), it is typically assumed that risky events, i.e., events where objective probabilities are known to the decision maker, constitute a unique source of uncertainty. In other words, current decision making models assume that an individual's behavior may vary for different sources of ambiguity, but not for different sources of risk (Nau 2006, Chew and Sagi 2008, Ergin and Gul 2009, Abdellaoui et al. 2011, Fox et al. 2018). Although the latter assumption seems intuitive from a theoretical perspective, recent empirical evidence raises doubts about its validity.

Armantier and Treich (2016) find that individuals have different attitudes towards different sources of risk depending on the complexity of the underlying event. However, in their experimental design subjects were not explicitly provided with objective probabilities but had to calculate them on their own, leaving room for calculation errors or even ambiguity aversion to explain their findings. To eliminate these identification problems, we, first, create an experimental design where subjects have complete information about the objective probabilities involved. Second, as complexity is an inherently subjective concept, we take a broader perspective and explore to what extent a subject's level of perceived expertise regarding the underlying random events influences attitudes towards risk.

It may easily be the case that subjects perceive themselves to have superior knowledge about a random event (such as being more familiar with a specific gamble). This perception, though, is utterly irrelevant (from a rational point of view) as the provided objective probabilities are the only information that should affect behavior across random events with identical outcome distributions. That is why we refer to such a decision maker suffering from knowledge illusion. She *feels* more knowledgeable about one of the events, but actually has identical information for all of them.

In this study, we conduct an experiment using three different gambles: a ticket-based lottery, roulette, and craps. These gambles strongly differ in their popularity among the general public but share the characteristic of being purely random prospects. Thus, individual skills, experience, or knowledge about the gamble (beyond objective probabilities) have no impact on the expected outcome. Thereby we can induce a variation in participants' perceived expertise regarding the respective gamble, allowing us to explore the impact of knowledge illusion on probability weighting between and within subjects. Our results indicate that an increase in perceived expertise about a gamble leads to less severe probability weighting even though all objective probabilities are provided. Hence, knowledge illusion mitigates the tendency to engage in the typically observed weighting pattern of overestimating small and underestimating high probabilities. This finding is robust across all three different measures of expertise (self-assigned, subjective, or objective) that we employ in our study.

The main contributions of this paper are threefold: First, we show that an individual's attitude towards risk depends on her perceived level of (irrelevant) expertise with respect to the underlying random events. If objective probabilities for all potential outcomes are known, better knowledge of the event or random device itself is an illusion, yet, it alters how objective probabilities are processed. We therefore provide empirical evidence that risk does not constitute a unique source of uncertainty. Behavior in decisions under risk depends on an individual's knowledge illusion regarding the underlying source of risk.

Second, we explore the impact of knowledge illusion on the valuation of risky prospects. If a prospect's attractiveness is determined by its value according to Tversky and Kahneman's (1992) Cumulative Prospect Theory (CPT), knowledge illusion and the associated mitigated probability weighting results in a comparatively higher CPT value for a broad range of prospects. When presented with a choice between different prospects, a standard CPT decision maker will therefore typically choose alternatives she feels more knowledgeable about. Knowledge illusion even alters the overall investment decision for a specific subset of these risky prospects as they yield positive CPT values for individuals with high perceived expertise and negative ones for decision makers with low perceived expertise.

Third, we discuss how these insights facilitate a better understanding of puzzling investor behavior observed in equity markets. The fact that many individuals refrain from investing in stocks although standard economic theory would predict universal participation constitutes the stock market (non-)participation puzzle (Guiso et al. 2003, Grinblatt et al. 2011). We argue that low levels of perceived expertise among the majority of potential investors and the resulting stronger probability weighting make stocks unattractive for CPT decision makers und thus prevent a stock market investment. The home and local bias refers to the phenomenon that investors tend to hold too large fractions of their wealth in equities that are geographically closer to them and thereby forgo diversification benefits (French and Poterba 1991, Coval and Moskowitz 1999). We reason that geographic proximity induces knowledge illusion as the associated higher levels of perceived expertise (Kilka and Weber 2000) are not underpinned with superior value-relevant information (Seasholes and Zhu 2010). The resulting mitigated probability weighting for home and local stocks renders them more attractive to investors than otherwise comparable, but more distant stocks.

The remainder of this paper is organized as follows. Section 2 discusses related literature. Section 3 outlines our experimental design and Section 4 presents results. Section 5 examines the impact of our findings on investor decision-making and derives further implications. Section 6 concludes.

2. Related literature

As an individual's tendency to display ambiguity aversion continues to be a robust finding in the decision making literature, the latest models trying to capture the related decision patterns allow for a different processing of probabilities depending on the source of uncertainty. Depending on whether outcome probabilities are known (risk) or unknown (ambiguity), the decision maker is assumed to apply different weighting (or "source") functions to the probabilities generated by the respective source. Moreover, based on the empirical findings in Fox and Tversky (1995) showing that individuals tend to have varying degrees of ambiguity aversion depending on their familiarity with the respective source of ambiguity, models incorporating such a source preference have been proposed in Nau (2006), Chew and Sagi (2008), Ergin and Gul (2009), Abdellaoui et al. (2011), and Fox et al. (2018). However, while decision makers are granted the opportunity to apply distinct probability weighting functions to different sources of ambiguity in these models, the weighting function applied to objective probabilities underlying risky prospects is assumed to be unique. In other words, while allowing decision makers to form distinct preferences with respect to different sources of ambiguity, preferences are commonly assumed to be homogenous for different sources of risk.

Armantier and Treich (2016) provide empirical evidence that raises doubts about the validity of this assumption. They show in their experiments that individuals have different attitudes towards risk depending on the complexity of the underlying random event. While they find utility functions to be similar across random events that differ in complexity, the estimated source function, resembling the probability weighting function in Tversky and Kahneman's (1992) Cumulative Prospect Theory (CPT), systematically varies across these events. Subjects are found to engage more strongly in probability weighting for complex than for simple events. Hence, when confronted with a more complex risky prospect, subjects tend to overestimate (underestimate) small (high) probabilities more strongly.

In their experimental design, Armantier and Treich (2016) define an event to be more complex if the respective distribution of objective probabilities is more difficult to construct. For instance, their "simple" treatment involves a single draw from one urn with eight balls. In contrast, in their "complex" treatment subjects are required to handle a simultaneous draw from two urns containing eight balls each. Arguing that it is more challenging for subjects to construct objective probabilities in the latter case, their distinction in complex and simple events becomes understandable. However, choosing this design in order to make the point that risky prospects do not constitute a unique source of risk comes at a high price as their distinction in simple and complex events is actually tainted by two other problems due to the fact that subjects had to calculate the objective probabilities on their own.

The first related problem, which is also admitted by Armantier and Treich (2016) themselves, is that it is unclear whether subjects constructed the correct objective probabilities. If the difficulty of the complex events prevented subjects from forming correct probabilities, the inference regarding the estimated probability weighting function is disturbed. The second, and perhaps more severe problem is that subjects might not have been able to construct some or even any of the objective probabilities underlying the complex events. In that case, the complex event would no longer resemble a source of risk but a source of (partial) ambiguity instead. If one follows this interpretation, it is not surprising that Armantier and Treich (2016) find similar source functions for complex risky and ambiguous bets. Hence, even though their idea to distinguish risky prospects along the dimension of complexity seems promising, it actually suffers from severe identification problems. To overcome these problems, we follow a different approach which is outlined in the next section.

3. Methodology

3.1. Experimental design

To test whether knowledge illusion has an impact on probability weighting, we conduct an experiment with 297 students at a German university. 41% of our participants are female, 30% are postgraduates, and the average age is 23 years. The computer-based experiment was run in

15 sessions with 15 to 20 subjects each. Completion time was about one hour and subjects were paid according to an incentive scheme which we will describe later in this section.

The main goal of our experimental design is to vary subjects' perceived level of expertise while still providing them with objective probabilities. To achieve this goal we transfer the idea of perceived competence in the ambiguity literature (Tversky and Fox 1995) to a pure risk setting and utilize three different gambles as random devices in our experiment, namely (1) a ticket-based lottery, (2) roulette, and (3) craps. We choose these gambles for the following two reasons: First, their popularity strongly varies in the German population. In Germany, ticket-based lotteries are generally well-known and often played, roulette is known but rarely played, and craps is virtually unknown and hence almost never played. Second, all of these gambles can be classified as purely random, i.e., an individual cannot influence its probability of winning in a specific game situation, even if she knows the gamble well. Therefore, we expect that our choice of gambles induces variation in subjects' perceived level of expertise across gambles, enabling us to explore differences in probability weighting between perceived experts and laymen between and within subject.

For each gamble, subjects had to fill out a questionnaire first which included several questions regarding their perceived expertise as well as four knowledge questions about the gamble. In addition, subjects had to indicate their overall level of perceived expertise for the respective gamble on a 7-point Likert scale. To make sure that subjects fully understood the subsequent decision situations which involved gamble specific information, the questionnaire was followed by a short introduction of the gamble. This included explanations of its general rules and clarifications of important terms. Afterwards, subjects had to report their certainty equivalents for binary bets for each gamble in which they could either win 100 experimental currency units (ECU) with seven different probabilities $p \in \{1\%, 5\%, 10\%, 40\% \ 90\%, 95\%, 99\%\}$ or get zero ECU otherwise. We chose the former and latter three probabilities since probability weighting is usually most pronounced for probabilities close to zero and one. As our meta-analysis of studies on probability weighting shows that probability overweighting usually turns into underweighting around the probability of 40% (see Appendix A), we also added this value to our experiment in order to better estimate subjects' weighting functions. The order in which the three different gambles were presented to subjects and the order of probabilities to win the binary bets within a gamble were randomized.

Probabilities were first described in terms of specific game situations of the respective gamble and then stated explicitly. This was done in two different ways in order to test for the effect of wording on probability weighting. In one treatment subjects received the objective probabilities as percentage value (e.g., “winning this lottery occurs in *p*% of the cases”) while in the other the objective probabilities were stated in successes out of a hundred games (e.g., “winning this lottery occurs in *p* out of 100 cases”). As we do not find significant differences between both treatments, we do not further distinguish between them in our analyses. The descriptions of the specific decision situations across gambles are presented in Table 1. The detailed experiment instructions and questionnaires are provided in Appendix B (translated from German).

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Similar to Kilka and Weber (2001), certainty equivalents are elicited by letting subjects indicate their choice between accepting the presented risky bet or a given sure payment of *X* ECU. To reduce the number of choices subjects have to make in the experiment and therefore increase the attention paid to each decision, we adapt the range of *X* based on the probability of winning the bet. For $p < 40\%$, *X* ranged from 1 to 40, for $p > 40\%$, *X* ranged from 40 to 99 and for $p = 40\%$, *X* covered the whole range from 1 to 99. Within these ranges *X* was increased by steps of 5 ECU in general and 4 ECU from 1 to 5 and from 95 to 99. In addition to indicating their choices for these specific offers, subjects also had to state their exact certainty equivalent for a bet, i.e., the amount they would demand as a certain payment in order to refrain from accepting the risky bet. This certainty equivalent stated by subjects themselves should lie between their last preference for a bet and their first preference for the sure payment *X*.

The final part of the experiment consists of an additional questionnaire on cognitive abilities, overconfidence, and personal information of our subjects. Afterwards, subjects were paid according to the following incentive mechanism. In addition to receiving a fixed payment of 5€, subjects were told upfront that out of the decision situations they encountered during the experiment, one will be randomly selected in the end and played out for real money. Thereby, ECU were transformed into € using a 10:1 conversion rate. Since subjects made several choices in every decision situation, one *X* will be randomly selected for the decision. Following the choice of the subject in the selected decision, she either receives $\frac{X}{10}$ € or participates in the offered bet. The outcome of the bet is settled by drawing a random number between 0 and 99. If the drawn number is smaller than the corresponding *p* of the offered bet, the subject receives a payment of 10€ and 0€ otherwise. Furthermore, an additional payment of 2€ can be gained by participants based on their answers in the overconfidence task (Blavatskyy 2009). On average, subjects were paid 11.82€.

3.2. Data and variables

Overall, we obtain data on certainty equivalents for seven different bets within three different gambles. Moreover, we elicit information on subjects' subjective and objective knowledge as well as their self-assigned expertise with respect to these gambles. In order for a subject-gamble observation to be included in our final sample we require all decisions within this gamble to meet the following two criteria: First, subjects do not switch back and forth between taking the bet and receiving the sure payment X, i.e., when X increases for a given p, subjects who prefer the amount X_1 over taking the offered bet also prefer another sure amount X_2 for all $X_2 > X_1$. Second, the certainty equivalent stated by subjects themselves must lie between their last preference for a risky bet and their first preference for the sure payment X. Applying these criteria yields our final sample of 647-subject-gamble observations for 274 different subjects.

To compare the degree of probability weighting between subjects who differ in their perceived level of expertise, we need to measure subjects' perceived expertise first. We construct three different measures which we motivate and explain in the following: (1) self-assigned expertise, (2) subjective expertise, and (3) objective expertise.

Self-assigned expertise. We measure self-assigned expertise as a subject's answer to the question whether she considers herself to be an expert in the respective gamble (rated on a 7-point Likert scale, where a higher value indicates a higher self-assigned expertise). This measure most directly captures a subject's own perception about her level of expertise. To form groups, we classify subjects as self-assigned experts in a gamble if they rated their expertise four or higher and as self-assigned laymen otherwise.

*Subjective expertise***.** This measure intents to elicit subjects' levels of expertise in a more indirect manner while still relying on purely subjective assessments. It utilizes four different questionnaire items: Whether subjects know the gamble at all (yes/no), how often they played it before, if they are well aware of the rules, and if they have an idea of the winning probabilities in different game situations. The latter two items are rated on a 7-point Likert scale, where a higher value indicates a higher self-assessment. Utilizing polychoric correlations to recognize the ordinal and binary nature of our variables, we perform an explorative factor analysis to condense the information of our variables and form one single factor, representing our measure of subjective expertise. The obtained factor has an eigenvalue larger than one and all factor loadings are well above the usual threshold of 0.4 (>0.93). To form groups, we classify subjects as subjective experts in a gamble if they belong to the top quintile in terms of subjective expertise and as subjective laymen if they belong to the bottom quintile.

Objective expertise. As subjective assessments are susceptible to over- or underconfidence, we construct a third measure that is primarily based on objectively verifiable information. For every gamble, subjects are confronted with four statements concerning the rules or general set-up of a gamble. After answering whether the respective statement is true or false, subjects had to indicate their confidence in the provided answer on a 7-point Likert scale. Objective expertise is measured by a categorical variable that only identifies subjects as experts or laymen if their actual performance on the knowledge questions is in line with their confidence in the provided answers. Hence, objective experts are subjects who answered more questions correctly than would be expected from random guessing (≥ 3 questions) and rated their confidence in the respective answers higher than six on average. Objective laymen are subjects who answered less questions correctly than would be expected from random guessing (≤ 1 question) and rated their confidence in the respective answers lower than two on average. All other subjects form the residual category.

Because our three measures rely on considerably different mechanisms to assess expertise, the number of subject-gamble observations classified as experts and laymen decreases across groups as our classification criteria get stricter. While the sample of self-assigned experts and laymen is largest, with all 647 observations assigned to one of the two groups, the subjective expertise sample is considerably smaller with 363 observations. The smallest sample is achieved for our objective expertise classification with only 143 observations. Although we only assign a subjective expert (laymen) status to the top (bottom) quintile of observations, it includes more than 40% of the original sample because 228 observations receive the lowest value for our factor variable. This is mainly driven by the fact that almost all subjects had no prior experience with craps and are therefore correctly classified as subjective laymen for this gamble.

As intended by our experimental design, we observe substantial variation in subjects' expertise across gambles, as can be seen by the different proportions of experts and laymen. Among the self-assigned (subjective, objective) experts, 39% (44%, 88%) are classified as such in the ticket-based lottery, and only 1% (0.1%, 1%) in craps. For the self-assigned (subjective, objective) laymen the opposite effect can be observed. 39% (88%, 67%) of laymen are present in craps and only 29% (8%, 4%) in the lottery.

3.3. Estimation of probability weighting functions

Before we can estimate a probability weighting function, we first need to transform the stated certainty equivalents into a subject's utility and derive the corresponding decision weights afterwards. Following Tversky and Kahneman (1992) as well as Kilka and Weber (2001), we use a power value function of the form $v(x) = x^{\alpha}$, with $\alpha = 0.88$. Since Armantier and Treich (2016) do not find significantly different parameters for the value functions across different sources of risk, we do not vary α across gambles for our main analyses.[1] The corresponding decision weights are then derived from the equation $v(CE_p) = v(100) * w(p)$, which states that the utility from the certainty equivalent should be equal to the value of winning the bet, in which case the subject wins 100 ECU, multiplied with the decision weight the subject assigns to winning the bet. This equation is then transformed into $w(p) = \frac{v(CE_p)}{v(100)}$ and yields seven decision weights per subject and gamble.

To estimate the probability weighting function, different functional specifications have been proposed. Following the literature (e.g., Tabak and Camerer 2010, Aydogan et al. 2016), we decide to utilize the Prelec (1998) one-parameter weighting function: $w(p) = e^{-(-\ln(p))^{\gamma}}$, where $\gamma > 0$ determines the curvature and $0 < \gamma < 1$ results in the typical inverse s-shape of this function. As Stott (2006) points out, more complicated weighting functions are not superior to the simpler forms, especially when paired with a power value function as done in this study.[2]

Moreover, the Prelec (1998) one-parameter weighting function with its fixed inflection point at $1/e$ (=0.37) ideally matches our experimental design with an expected inflection point at 0.4. The weighting function parameter is then estimated individually for each participant and each gamble using non-linear regressions and winsorized at 1% and 99%. We expect the curvature of the probability weighting function to be less pronounced for experts than for laymen. For $\gamma = 1$, the

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[1] Our results are robust to a variation of α across subjects and gambles (see Section 4.2.1).

[2] In a robustness test, we repeat all analyses using the Prelec (1998) two-parameter weighting function. This alternative specifications leave our findings qualitatively unchanged (see Section 4.2.2).

weighting function reduces to the identity w(p) = p, therefore a higher value for γ indicates a less pronounced curvature, hence less severe probability weighting.

4. Empirical analysis

4.1. Results

Table 2 presents the medians of stated certainty equivalents of experts and laymen across the different probabilities *p* and our three measures of expertise. In addition, it contains the corresponding z-scores of a series of Wilcoxon rank-sum tests to test for differences in certainty equivalents. Regardless of the applied measure of expertise, experts value the proposed risky bets differently than laymen. For $p < 40\%$ certainty equivalents of laymen are larger than for their expert counterparts, for $p > 40\%$ certainty equivalents of laymen are smaller than those of experts. These differences are statistically significant for almost all values of *p* for the self-assigned and subjective expertise measure and only significant for the smallest and largest value of *p* for the objective expertise measure. As expected, virtually no differences in stated certainty equivalents can be detected for any measure of expertise for $p = 40\%$.

These raw results provide initial evidence that probabilities in decisions under risk are weighted differently depending on the level of perceived expertise a subject has in the context of a specific decision situation although the outcome of the risky bet is independent of expertise. Furthermore, differences are most pronounced when the self-perception of expertise is taken into account rather than actual expertise, highlighting the importance of self-perception for the emergence of knowledge illusion.

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Figure 1 illustrates the median curvature parameters for experts and laymen across our three different measures of expertise. For all subgroups we observe curvature values between 0 and 1, indicating the typical inverse s-shape of the probability weighting function. Hence, all subgroups engage in overestimating small and underestimating large probabilities on average.

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However, the degree of probability weighting considerably differs between experts and laymen. While the curvature parameter for laymen is rather stable and around 0.69, the curvature parameters is significantly larger for experts ($p < 0.01$), ranging from 0.75 based on the objective to 0.86 based on the self-assigned expertise measure. These results suggest that, regardless of the applied measure, subjects with higher levels of perceived expertise engage less strongly in probability weighting. As all subjects are provided with the exact objective probabilities and hence the only relevant information in the purely random decision situations, the differences in perceived expertise represent knowledge illusion on the subject level. Therefore, our results provide evidence that knowledge illusion mitigates probability weighting.

In addition, we find that the difference in curvature parameters is most pronounced for our measure of self-assigned expertise, followed by the subjective and then the objective measure. This pattern suggests that source preference within the domain of risk is most strongly induced by knowledge illusion based on a subject's very own opinion, and hence most direct perception regarding her level of expertise. Objective knowledge or experience-loaded subjective assessments seem to be less powerful in this respect. Thus, a subject's self-perception can be identified as most crucial with respect to the extent that knowledge illusion mitigates probability weighting.

Figure 2 shows how these differences in parameters affect the shape of the respective probability weighting functions. Prelec (1998) one-parameter weighting functions are plotted using the median estimated γ-parameter for the expert and laymen groups for each of the three measures of expertise. For the groups of self-assigned and subjective experts the weighting function is noticeably closer to the identity than for their laymen counterparts. For objective experts this effect also exists, but is less pronounced.

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To explore whether our results also hold within subject, we perform regression analyses and control for subject fixed effects. The estimated γ-parameters are regressed on the variables we used to construct our expert and laymen groups. One advantage of this methodology is, that we do not lose information content of our variables by treating all experts and laymen as equally knowledgeable, but can discriminate between them more precisely. Table 3 reports the estimated regression coefficients for all three measures of expertise. Compared to our original sample 40 observations are dropped as information for only one gamble is available for these subjects.

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All three expertise variables have a significant and positive influence on the curvature parameter γ (at least $p < 0.05$), indicating less probability weighting for higher levels of perceived expertise even when we control for subject fixed effects. Therefore, we conjecture that differences in probability weighting cannot solely be attributed to general subject-specific differences in probability processing, but instead also exist for the very same subject when its level of perceived expertise varies. Thus, we can identify the impact of knowledge illusion on probability weighting both between subjects and within subject.

To sum up, we provide experimental evidence that risk does not constitute a unique source of uncertainty. Instead, we find that objective probabilities of purely random gambles are processed differently, depending on subjects' levels of perceived expertise. Because in our experiment all probabilities are provided explicitly and outcomes are independent of knowledge, variations in perceived expertise are an illusion. However, this knowledge illusion mitigates an individual's tendency to engage in probability weighting.

4.2. Robustness tests

4.2.1 Variation of the risk-aversion parameter

To test whether our results are robust to a variation of the assumed degree of risk aversion across subjects, we repeat our main analyses using γ-parameters based on decision weights that correspond to different risk-aversion parameters α of the applied power value function. First, we vary α deterministically and assign the chosen parameter to all subjects and gambles. Second, we randomly draw a risk-aversion parameter value for each subject which, again, is identical for the different gambles at the subject level. Third, we allow the degree of risk aversion to not only vary randomly across subjects, but also within subject across gambles.

Table 4 presents results from our within-subject analysis, in which the re-estimated γ-parameters are regressed on the variables used to construct our three expertise measures while including subject-fixed effects. In columns (1) to (3), we follow Kilka and Weber (2001) and perform a sensitivity analysis on the constant α-parameter assumed across subjects and gambles with values of 0.76, 0.88, and 1.00. Column (2) corresponds to the results from our main analyses as presented in Table 3. For the results in Column (4), we draw α-values randomly from a normal distribution with mean 0.88 and a standard deviation of 0.04 for each subject. The results in Column (5) are also based on randomly drawn α-values from the same distribution, but this time do not only vary randomly across subjects but also within subject across gambles.

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The impact of perceived expertise on the curvature parameter γ remains significantly positive and therefore proves to be robust to variations of the employed risk-aversion parameter. Furthermore, the magnitude of the effect remains largely unchanged across the alternative specifications. Hence, our finding that knowledge illusion mitigates probability weighting does not depend on the chosen α-value of the applied power value function.

Even though Armantier and Treich (2016) do not find significant differences in risk-aversion parameters between simple and more complex bets, it could still be that systematic differences in risk aversion between experts and laymen in our experimental context exist. However, a higher risk-aversion parameter should, ceteris paribus, cause subjects to accept a lower sure payment in order to forego the risk of the lottery across all probabilities. Therefore, a systematically different level of α between experts and laymen is not able to explain the higher certainty equivalents of laymen compared to experts for small probabilities and the opposite pattern for high probabilities.

4.2.2 Alternative specification of the probability weighting function

To assess whether our results also hold for a different functional specification of the probability weighting function, we repeat our analyses for the Prelec (1998) two-parameter weighting function of the following form: $w(p) = e^{-\beta(-\ln(p))^{\gamma}}$, where γ determines the curvature of the weighting function and δ determines its elevation, e.g., the point in which the weighting function crosses the identity. Parameters are again estimated at an individual level for each subject and gamble by non-linear regression. Figure 3 illustrates how the estimated parameters differ between the three expert and laymen groups when applying the Prelec (1998) two-parameter weighting function.

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Regarding the curvature parameter, we find similar results as in our main analyses: Irrespective of how we determine the expert status, the median γ-parameters for experts are higher than for their laymen counterparts. These differences are significant at the 1% level. As before, a higher γ-parameter indicates a less pronounced curvature of the weighting function and thus inplicates a lower degree of overweighting small and underweighting large probabilities. Therefore, we also find evidence for the hypothesis that knoweledge illusion significantly mitigates probabilty weighting for a different functional specification of the weighting function. Again, the difference is strongest when using the self-assigned expert classification and decreases for the subjective and objective expert groups, confirming that knowledge illusion has the strongest impact on probability weighting when it is purely based on subjects' self-perception.

When comparing the medians of the elevation parameter across groups, we do not observe significantly different δ-values for experts across classifications. A graphical representation of the resulting weighting functions for experts and laymen is presented in Figure 4. We can observe that the curvature of the laymen functions is more pronounced and it crosses the identity at a slightly lower level than the weighting functions for experts. As a result, the latter are closer to the identity thus representing less probability weighting. As indicated by the analysis of γ-value differences, the effect is largest for the self-assigned expert classification and is slightly less noticeable for the other two measures.

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Table 5 reports our analysis of differences in estimated weighting function parameters between experts and laymen while controlling for subject fixed effects. Regressing the parameters on our expertise variables while including subject fixed effects, we find that our previous results are confirmed. All three measures of expertise do have a significantly positive influence on the curvature parameter γ (at least $p < 0.05$). As a higher value for these variables indicates a higher degree of perceived expertise and a higher γ-value results in a less curved weighting function, these results are supporting evidence for the mitigating impact of knowledge illusion on probability weighting. Our regression of the elevation parameter δ on our expertise variables yields insignificant results. Hence, we cannot reject the hypothesis of equal elevation of weighting functions for expert and laymen. This finding further justifies our initial decision to utilize the Prelec (1998) one-parameter weighting function in our main analyses.

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4.2.3 Importance of self-perception

To further strengthen our argument that a subject's perception of her own expertise is key to the impact of knowledge illusion on probability weighting, we examine the behavior of subjects for which perceived expertise and actual expertise regarding a gamble diverge. Therefore, we adapt our objective expertise measure to identify subjects who misperceive their actual expertise. We classify subjects as misperceived experts who answered less than two questions correctly but rated their confidence in their provided answers six or higher (141 observations). On the other hand, subjects are classified as misperceived laymen who answered more than three questions correctly but rated their confidence in the provided answers lower than two (64 observations). Figure 5 illustrates the median curvature parameters for these two groups.

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The median curvature parameter for misperceived experts is about 0.73 and significantly larger than the one for misperceived laymen (0.69; $p < 0.01$). Hence, misperceived experts engage comparably less in probability weighting than misperceived laymen. These results suggest that it is not actual, objectively verifiable expertise about the gamble that mitigates probability weighting but rather a subject's perception of her own expertise.

As misperceived experts (laymen) can be characterized as being overconfident (underconfident) with respect to their actual expertise, these results could also be interpreted as evidence for the fact that probability weighting decreases in overconfidence. However, our analysis based on the objective expertise measure indicates that the impact of knowledge illusion on probability weighting is also present among well-calibrated subjects. As these subjects do not exhibit a mismatch between actual and perceived expertise, overconfidence cannot explain this finding. In contrast, higher self-perceived expertise can accommodate both results.

4.2.4 Role of experience

Previous studies suggest that individuals engage less in the inversed-s-shaped probability weighting pattern when making decisions based on experience rather than descriptions (e.g., Hertwig et al. 2004). Although our decision tasks are purely descriptive across gambles, the level of experience obtained before our experiment could potentially vary across subjects and gambles. As experience and perceived expertise are likely to be positively correlated, we need to rule out variations in experience as an alternative explanation for our findings.

In order to control for the influence of experience, we repeat our within-subject analysis for an inexperienced subsample, i.e., we only include subject-gamble-observations if the subject has never played the respective gamble before, leaving us with a total of 172 subject-gamble observations. We then regress the γ-parameter on our measure of self-assigned expertise while including subject-fixed effects.[3] The obtained coefficient of 0.019 is significant ($p<0.05$) and even slightly larger compared to our main results (0.016). This suggests that experience does not seem to be the driver of the mitigating influence of perceived expertise on probability weighting. Instead, we find evidence that perceived expertise mitigates probability weighting beyond experience.

5. Implications

5.1. Impact of knowledge illusion on CPT values

Our findings outlined above have important implications beyond providing a better understanding on the richness of the domain of risk. If individual decision makers do not process objective probabilities in a unique way but distinguish between different sources of risk based on their perceived expertise, this behavior might be able to explain puzzles where perceived expertise and (objective) probability distributions crucially interact. In order to examine these phenomena, we first want to illustrate the consequences of knowledge illusion and the resulting mitigated probability weighting for the decision making process.

In the following, we will evaluate how a change in the γ-parameter of the probability weighting function affects the attractiveness, i.e., the CPT value, of a risky prospect. We initially assume that the outcome x of the underlying risky prospect is normally distributed with $\mu = 10\%$ and $\sigma = 25\%$. We assume two CPT decision makers with $\alpha = 0.88$ and $k = -2.25$ that only differ in their weighting function parameter γ. Decision makers that engage more strongly in probability weighting (laymen; $\gamma = 0.70$) overweight small probabilities more strongly which leads to fatter tails of the applied probability distribution compared to the case of less probability weighting (experts; $\gamma = 0.86$). In addition, outcomes in the middle of the distribution, i.e., those with high probabilities, are underweighted more strongly. This distortion of the applied probability distribution is shown in Panel A in Figure 6.

--- *INSERT FIGURE 6 HERE* ---

Panel B in Figure 6 depicts the resulting valuation effects for the underlying prospect. The differences in value contributions between experts and laymen are more pronounced in case of

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[3] As the number of times a subject played a gamble before is one of the items that is used to construct our subjective expertise measure, it is not feasible to meaningfully explore the impact of subjective expertise on γ using the inexperienced subsample. We also cannot perform this analysis for the objective expertise measure because the group size of respective experts in the inexperienced subsample is too small (8 subject-gamble observations).

extreme outcomes. The stronger overweighting of small probabilities will yield stronger CPT value contributions (in absolute terms) for both negative and positive extreme outcomes. However, the additional negative value contributions are larger (in absolute terms) than the additional positive value contributions due to loss aversion. The stronger underweighting of outcomes in the middle of the outcome distribution causes two opposing effects. Stronger underweighting of highly probable but negative outcomes benefits the prospect's attractiveness while more pronounced underweighting of highly probable but positive outcomes compromises it.

Panel C in Figure 6 shows how these effects add up and result in the overall CPT value for the risky prospect when cumulating the CPT value contributions (Panel B in Figure 6) from the most negative outcome up to a given outcome *x*. The stronger overweighting of extremely negative outcomes causes the cumulative CPT value for laymen to decline steeper than the one for experts. When moving to outcomes close to zero, the gap in CPT values first slightly narrows due to the stronger underweighting of highly probable negative mid-distribution outcomes. After entering the gain domain, the gap widens again due to the stronger underweighting of highly probable positive mid-distribution outcomes. The larger CPT value contributions laymen exhibit for extremely positive outcomes are not able to overcompensate the experienced disadvantages up to that point, causing the final CPT value to be negative in total. In contrast, the CPT value for experts is positive in this example.

Figure 6 therefore shows that decision makers who engage more strongly in probability weighting (laymen) will assign a lower CPT value to the underlying risky prospect. In this case, the lower γ-parameter even causes a sign flip of the resulting CPT value, implying that experts would deem the risky prospect attractive and invest in it while laymen would not. Hence, a lack of perceived expertise and the resulting stronger probability weighting, first, lowers the CPT value of the given prospect and, second, is even able to qualitatively alter the overall investment decision.

The above discussion points to the fact that the relative importance of the channels through which probability weighting affects the CPT value crucially depends on a prospect's probability distribution. To explore the generalizability of the conclusion that stronger probability weighting reduces CPT values, we analyze the marginal effect of γ on the CPT value for different probability distributions of the underlying risky prospect. We calculate CPT values for varying μ [-0.3; 0.6], σ]0; 0.6], and γ [0.4; 1] parameters. For each μ-σ-combination, we regress the CPT value on γ to identify its marginal effect (β_γ). A positive marginal effect ($\beta_\gamma > 0$) implies that stronger probability weighting (smaller γ-parameter) corresponds to a declining CPT value as observed above. A negative marginal effect ($\beta_\gamma < 0$) indicates that the CPT value increases in probability weighting.

Figure 7 plots the obtained marginal effects. For the vast majority of μ-σ-combinations, β_γ is positive, implying that a risky prospect is considered to be more attractive if the decision maker weights probabilities less strongly. This holds for all prospects with a positive expected outcome ($\mu > 0$), regardless of their level of risk (σ). Even for prospects with negative expected outcomes ($\mu < 0$) we observe $\beta_\gamma > 0$ if the level of risk exceeds a given threshold. Only prospects with negative expected outcomes and comparatively low levels of risk (white area in the bottom-left corner of Figure 7) exhibit negative marginal effects ($\beta_\gamma < 0$). These results suggest that stronger probability weighting leads to a decrease in CPT value for a very broad range of risky prospects with normally distributed outcomes and common risk-return profiles (in particular for all prospects with $\mu > 0$). Hence, experts will typically perceive the same risky prospect to be more attractive than laymen.

--- *INSERT FIGURE 7 HERE* ---

In addition to this upward shift in attractiveness, it is important to understand how the overall decision outcome might be influenced by a change in probability weighting. To do so, we analyze whether a change in probability weighting from the layman level ($\gamma = 0.70$) to the expert level ($\gamma = 0.86$) induces a sign switch (from negative to positive) in the CPT value for a given risky prospect. Such a sign switch would indicate that laymen would not invest in the underlying risky prospect (negative CPT value) while experts would invest (positive CPT value).

The grey area in Figure 8 highlights prospects with μ-σ-combinations for which a sign switch of the CPT value is observed. This area closely evolves along a straight line formed by prospects with a σ-μ-ratio of 2:1. This implies that risky prospects for which the amount of risk (σ) is about twice as high as the expected outcome (μ) yield a positive CPT value for experts and a negative CPT value for laymen. While laymen would not consider investing in prospects with such a risk-return profile, experts would invest.

--- *INSERT FIGURE 8 HERE* ---

To sum up, mitigated probability weighting due to knowledge illusion typically increases the CPT value of a normally distributed risky prospect and even induces a sign flip of the CPT value if the prospect's level of risk is about twice as large as its expected outcome.

5.2. Knowledge illusion as an explanation for puzzling investor behavior

The insights from the previous section suggest that a standard CPT decision maker with higher perceived expertise regarding a source of risk will typically judge the attractiveness of a risky prospect with a normally distributed outcome and a common risk-return profile to be higher than one with lower perceived expertise. For a specific range of prospects (σ-μ-ratio of about 2:1), mitigated probability weighting due to knowledge illusion even changes the decision outcome when comparing experts (positive CPT value) to laymen (negative CPT value).

Knowledge illusion can therefore predict two distinct behavioral patterns: First, whenever a decision maker is confronted with a risky prospect that has a σ-μ-ratio of about 2:1, the decision maker's level of perceived expertise and hence the degree of knowledge illusion will determine whether she will (experts) or will not (laymen) decide to invest. Second, whenever a decision maker has to choose between two or more risky prospects which are identical except for the decision maker's perceived expertise, the decision maker will typically opt for the prospect she perceives her levels of expertise to be higher.

Hence, knowledge illusion lends itself to explain puzzles where (a) the level of perceived expertise positively correlates with the likelihood to invest in a risky prospect (that falls into the 2:1 σ-μ-corridor) or (b) the choice from a set of otherwise identical risky prospects is tilted towards investments the decision maker perceives her expertise to be higher. In the following, we will discuss the puzzlingly low stock market participation rates among investors as an example for (a) and the home and local bias observed in equity markets as an example for (b).

The stock market (non-)participation puzzle refers to the fact that many individuals do not invest in stocks even though traditional economic models would prescribe universal participation (Guiso et al. 2003, Grinblatt et al. 2011). While previous studies have identified several explanations for the low participation rates, it is noticeable that the most prominent ones point to the importance of investor expertise. Regardless whether measured rather directly as financial literacy (van Rooij et al. 2011, Bianchi 2018) or more indirectly in the form of financial awareness (Guiso and Japelli 2005), cognitive abilities (Grinblatt et al. 2011), or even trust (serving as knowledge substitute only for low education investors; Guiso et al. 2008), all of these factors have been found to be strong predictors of stock market participation.

In addition, perceived expertise seems to be more important than actual expertise. Allgood and Walstad (2016) explore the impact of both actual and perceived financial literacy on the likelihood to hold stocks. They find that subjects with high perceived but low actual financial literacy are more likely to hold stocks than subjects who score low in both dimensions. The increase in probability is stronger than the one found for subjects with high actual but low perceived financial literacy. In addition, within the group of investors with high actual financial literacy, the switch from low to high perceived financial literacy increases the likelihood to own stocks significantly. Hence, perceived expertise is important in affecting investor behavior beyond actual expertise, emphasizing the importance of self-perception.

Our experimental results propose the degree of probability weighting as the mechanism by which perceived expertise influences participation. If an investor's perceived expertise is low, she will engage more strongly in probability weighting. As Golez and Koudijs (2018) show that an investment in the stock market has an average σ-μ-ratio close to 2:1 (annual real return: μ=7.27; σ=15.20), stocks belong to the group of risky prospects where a change in probability weighting from the expert to the layman level will cause a sign switch of the CPT value. As a consequence, perceived laymen will exhibit a negative CPT value for investing in stocks and refuse to participate in the market, while perceived experts will face a positive CPT value and hold stocks. Since financial illiteracy is a global phenomenon (Lusardi and Mitchell 2011) and actual and perceived literacy are positively correlated (van Rooij et al. 2011, Bianchi 2018), the prevailing low levels of perceived expertise among investors and the resulting stronger probability weighting can explain why so many refrain from participating in the stock market.

The home bias puzzle refers to the fact that investors tend to hold stock portfolios that are tilted towards equity from their home country, thereby failing to benefit from more strongly diversifying internationally (French and Poterba 1991, Cooper and Kaplanis 1994, Tesar and Werner 1995, Coval and Moskowitz 1999, Ahearne et al. 2004, Ivkovic and Weisbenner 2005, Massa and Simonov 2006, Campbell 2006, Graham et al. 2009, Schumacher 2017). Moreover, Coval and Moskowitz (1999) show that the tendency to prefer investments that are geographically closer to the investor's location also exists within country, constituting the so-called local bias. Several explanations for the home and local bias have been suggested (most of them related to capital or information immobility), but so far none seems to be generally accepted (for an overview see Kang and Stulz 1997, Lin and Viswanathan 2015).

We propose knowledge illusion and the resulting differences in probability weighting as a potential explanation. While geographic proximity increases individuals' levels of perceived expertise regarding an investment (Kilka and Weber 2000, Ackert et al. 2005), this is typically not underpinned with superior value-relevant information (Seasholes and Zhu 2010). Therefore, geographic proximity gives rise to knowledge illusion, which induces less severe probability weighting. This, in turn, increases the attractiveness of a geographically closer investment for a CPT decision maker relative to an otherwise identical, but more distant alternative.

Graham et al. (2009) find that investors who feel more competent about investing in foreign assets are less prone to the home bias, i.e., are willing to invest a larger fraction of their wealth in foreign assets. Thus, they provide empirical evidence for the existence of a link between the level of perceived expertise and the degree of home bias. We contribute to their findings by proposing adjustments to the probability weighting function as the channel through which perceived expertise affects the degree of home bias. Further evidence that stronger probability weighting is related to less diversified equity portfolios is provided by Dimmock et al. (2018).

It is important to distinguish our home and local bias explanation based on knowledge illusion and probability weighting from the familiarity argument made in Huberman (2001). Huberman (2001) suggests that the higher familiarity with home equity is a utility generating attribute that adds value for the decision maker beyond the traditional risk-return trade-off. In this sense, the home bias puzzle would simply be an expression of investors "comfort with the known and discomfort with […] the alien and distant". As Huberman (2001) sees better knowledge about the familiar – actual or perceived – as the defining property of familiarity, our construct of perceived expertise and his idea of familiarity are closely tied by definition. However, the proposed mechanism on how familiarity or perceived expertise actually affects preferences are quite distinct. While Huberman (2001) positions familiarity as an additional nonpecuniary dimension beyond the traditional portfolio selection theory that demands integration (while being silent on how this should be done), we propose that perceived expertise actually works at the very heart of the existing theories, specifically when modelling how probabilities are processed by individuals. Our experimental findings suggest that when applying CPT to risky prospects, it is required to allow for different probability weighting functions that depend on the individual's perceived expertise regarding the respective source of risk.

5.3. Managerial and policy implications

Our results indicate that low perceived expertise and the resulting stronger probability weighting can cause CPT decision makers to reject investment opportunities which they would have invested in at higher levels of perceived expertise. Moreover, whenever a decision maker has to choose from a set of risky prospects with common and identical risk-return profiles, differences in perceived expertise will tilt choices towards alternatives which the individual feels more knowledgeable about (even if this perception is not based on superior information).

The globally low stock market participation rates and strong presence of the home and local bias suggest that such investor behavior is a severe challenge for financial intermediaries and financial advisors who are in the business of selling investment products to their clients. Apparently, the current design of the (advised) investment process is not able to overcome these habits, causing substantial welfare losses for investors due to not holding stocks in the first place (Cocco et al. 2005) or, if they do, not diversifying internationally (French and Poterba 1991). As private retirement savings become increasingly important across countries (and in particular in countries operating pay-as-you-go pension schemes; Braunstein and Welch 2002, Oehler and Kohlert 2009), these welfare losses become a growing concern for policy makers.

Our findings imply that improving investor levels of perceived expertise are key to raise stock market participation rates. As actual and perceived literacy are found to be positively correlated (van Rooij et al. 2011, Bianchi 2018), fostering financial literacy among investors via financial education programs seems a natural starting point (van Rooij et al. 2011, Erner et al. 2016). However, such programs currently focus almost exclusively on enhancing actual knowledge levels and tend to overlook their impact on investors' perceived expertise (Hadar et al. 2013). Given that our experimental results as well as Allgood and Walstad (2016) emphasize the importance of self-perception, investor education interventions will have to put a much stronger emphasis on increasing investors' perceived expertise to overcome their low levels of effectiveness (e.g., Danes and Haberman 2007, Mandell 2009, Fernandes et al. 2014, Miller et al. 2015). Restricting the provided information to the most relevant and easy to understand might be a promising guideline towards achieving that goal (Hadar et al. 2013).

To help investors avoid exhibiting the home and local bias, two mutually exclusive remedies emerge: First, one could ensure that decision makers feel equally knowledgeable about the risky alternatives in their choice set. Second, one could eliminate all elements from the decision situation that might induce differences in perceived expertise.

Generating a level playing field in terms of perceived expertise across alternatives would prevent this factor from influencing a decision maker's preference ordering. This measure might require initiatives to educate investors regarding foreign stock markets and to point out the large similarities between home and foreign investments (in particular when only considering developed markets). This could be done during the investment process but should also be an integral part of financial education programs.

The second approach requires to create a decision environment that is free of elements which potentially induce differences in perceived expertise. The risk-return distributions of different stocks could be presented without initially revealing the fact whether the respective investment constitutes home or foreign equity (assuming that the country of origin is indeed negligible). Experimental evidence for the effectiveness of this approach is provided by Ackert et al. (2005). They show that the home bias does not arise when the firm's name and location is not revealed to investors. The home bias is even avoided when only the firm's name is eliminated while its location is still provided.

One important criterion that determines the attractiveness of the two approaches concerns the overall decision situation. If the decision maker intends to definitely choose one of the risky alternatives (i.e., not investing is not an option), then the elimination approach is preferable because it is less expensive and requires less information processing by the decision maker. As the decision maker is put in a situation where none of the alternatives induces feelings of knowledge, the probability weighting will be comparably stronger and hence CPT values lower. If the absolute CPT value level is only employed to rank alternatives and not to decide on whether to invest or not, this effect is negligible. In case of the latter (i.e., not investing is an option), the level-playing-field approach is preferable, because higher perceived expertise will reduce probability weighting and hence increase CPT values. If the decision maker will only choose to invest given that the best alternative surpasses a particular CPT threshold, it is important to reduce the impact of a perceived lack of expertise on probability weighting.

6. Conclusion

This paper provides experimental evidence that individuals engage less strongly in probability weighting if their level of perceived expertise regarding a decision under risk is higher. In order to vary the level of perceived expertise in a purely random decision situation, we utilize three different gambles that vary in popularity and for which outcomes are independent of knowledge. Our results indicate that, even though objective probabilities and hence all relevant information are explicitly provided for all random gambles, the curvature of a subject's probability weighting function decreases in the level of perceived expertise. Thus, individuals overweight (underweight) small (high) probabilities less strongly if they feel more knowledgeable about a decision involving outcomes that are completely random. Since the explicit provision of objective probabilities ensures that subjects actually possess all decision-relevant information regardless of their own level of expertise, the perceived variation in expertise constitutes an illusion. However, this knowledge illusion is sufficient to alter how individuals process objective probabilities. This finding suggests that the domain of risk is not perceived as a unique source of uncertainty which contradicts an important assumption that is commonly made in current decision making models.

We furthermore show in this study that our results have important implications beyond providing a better understanding of the domain of risk. For a broad range of risky prospects, knowledge illusion and the associated mitigated probability weighting result in higher prospect attractiveness, i.e., higher CPT values. When choosing from a set of prospects with identical risk-return profiles, a standard CPT decision maker will therefore typically prefer alternatives for which her level of perceived expertise is higher. For a specific set of risky prospects, we even observe that knowledge illusion causes a sign switch of the CPT value and hence alters the overall decision outcome. While individuals with higher perceived expertise deem these prospects attractive (positive CPT value), decision makers with low perceived expertise will reject them (negative CPT value).

These patterns provide important insights to better understand investor behavior. We argue that knowledge illusion and related differences in probability weighting can explain the low stock market participation rates and the home and local bias observed in equity markets. Widespread financial illiteracy and the corresponding low levels of perceived expertise among potential investors result in stronger probability weighting and thus render stocks an unattractive investment when using the CPT value as decision criterion. This can explain why many individuals refrain from participating in the stock market in the first place. In addition, knowledge illusion can serve as an alternative explanation for the home and local bias. Since geographic proximity to a company increases an individual's perceived but unfounded level of expertise, it gives rise to knowledge illusion. For a CPT decision maker, this promotes the attractiveness of a geographically closer investment relative to an identical, but more distant alternative.

We also discuss managerial and policy implications of our findings. In order improve stock market participation rates, policy makers should take the importance of self-perception more strongly into account. Financial literacy programs should not only focus on increasing the actual knowledge of participants but also try to foster perceived expertise. Furthermore, we propose two potential approaches as remedies for the home and local bias. First, it could be ensured that decision makers feel equally knowledgeable about all alternatives in their choice set. Second, elements which potentially induce differences in perceived expertise across alternative stock investments could be eliminated. While the applicability and benefits of these mutually exclusive approaches depend on the given decision situation, both approaches are able to mitigate that investment choices are affected by an individual's knowledge illusion.

Appendix A

Authors	Probability weighting function specification	Curvature parameter	Elevation parameter	Inflection point	Number of subjects
Abdellaoui (2000)	Lattimore et al. (1992)	0.6	0.65	0.25	46
Abdellaoui (2000)	Lattimore et al. (1992)	0.65	0.84	0.38	46
Abdellaoui (2000)	Tversky, Kahneman (1992)	0.6	-	0.33	46
Abdellaoui (2000)	Tversky, Kahneman (1992)	0.7	-	0.38	46
Abdellaoui et al. (2011)	Lattimore et al. (1992)	0.65	0.7	0.27	61
Abdellaoui et al. (2011)	Lattimore et al. (1992)	0.73	0.78	0.28	61
Bleichrodt et al. (1999)	Tversky, Kahneman (1992)	0.668	-	0.37	172
Bleichrodt, Pinto (2000)	Tversky, Kahneman (1992)	0.713	-	0.39	51
Bleichrodt, Pinto (2000)	Lattimore et al. (1992)	0.573	1.127	0.57	51
Bleichrodt, Pinto (2000)	Prelec (1998) 1 Parameter	0.589	-	0.37	51
Bleichrodt, Pinto (2000)	Prelec (1998) 2 Parameter	0.604	0.938	0.43	51
Bleichrodt, Pinto (2000)	Tversky, Kahneman (1992)	0.674	-	0.37	51
Bleichrodt, Pinto (2000)	Lattimore et al. (1992)	0.55	0.816	0.39	51
Bleichrodt, Pinto (2000)	Prelec (1998) 1 Parameter	0.533	-	0.37	51
Bleichrodt, Pinto (2000)	Prelec (1998) 2 Parameter	0.534	1.083	0.31	51
Brandstätter et al. (2002)	Lattimore et al. (1992)	0.71	0.88	0.39	81
Brandstätter et al. (2002)	Wu, Gonzalez (1996)	0.75	1.4	0.39	81
Bruhin et al. (2010)	Lattimore et al. (1992)	0.415	0.845	0.43	179
Bruhin et al. (2010)	Lattimore et al. (1992)	0.417	1.025	0.51	179
Bruhin et al. (2010)	Lattimore et al. (1992)	0.425	0.862	0.44	118
Bruhin et al. (2010)	Lattimore et al. (1992)	0.451	1.059	0.53	118
Bruhin et al. (2010)	Lattimore et al. (1992)	0.245	1.315	0.59	151
Bruhin et al. (2010)	Lattimore et al. (1992)	0.309	0.937	0.48	151
Camerer, Ho (1994)	Tversky, Kahneman (1992)	0.56	-	0.31	125
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.47	0.74	0.36	37
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.47	1.1	0.54	37
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.56	0.88	0.43	54
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.57	1	0.50	54
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.41	0.79	0.40	40

Authors	Probability weighting function specification	Curvature parameter	Elevation parameter	Inflection point	Number of subjects
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.47	1.06	0.53	40
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.56	1	0.50	50
Fehr-Duda et al. (2006)	Lattimore et al. (1992)	0.57	1.14	0.58	50
Gonzalez, Wu (1999)	Lattimore et al. (1992)	0.44	0.77	0.39	10
Hartinger (1999)	Tversky, Kahneman (1992)	0.8	-	0.43	64
Hartinger (1999)	Tversky, Kahneman (1992)	0.78	-	0.42	64
Hartinger (1999)	Tversky, Kahneman (1992)	0.76	-	0.41	64
Hartinger (1999)	Tversky, Kahneman (1992)	0.7	-	0.38	64
Hartinger (1999)	Tversky, Kahneman (1992)	0.8	-	0.43	64
Hartinger (1999)	Tversky, Kahneman (1992)	0.74	-	0.40	64
Kusev et al. (2009)	Lattimore et al. (1992)	0.6	0.49	0.14	60
Kusev et al. (2009)	Lattimore et al. (1992)	0.72	0.79	0.30	60
Kusev et al. (2009)	Lattimore et al. (1992)	0.63	0.63	0.22	60
Takahashi et al. (2010)	Prelec (1998) 1 Parameter	0.58	-	0.37	18
Takahashi et al. (2010)	Prelec (1998) 1 Parameter	0.56	-	0.37	18
Tversky, Fox (1995)	Lattimore et al. (1992)	0.69	0.77	0.30	40
Tversky, Kahneman (1992)	Tversky, Kahneman (1992)	0.61	-	0.34	25
Tversky, Kahneman (1992)	Tversky, Kahneman (1992)	0.69	-	0.38	25
Wu, Gonzalez (1996)	Lattimore et al. (1992)	0.68	0.84	0.37	420
Wu, Gonzalez (1996)	Wu, Gonzalez (1996)	0.721	1.565	0.35	420
Wu, Gonzalez (1996)	Tversky, Kahneman (1992)	0.71	-	0.39	420
Wu, Gonzalez (1996)	Prelec (1998) 1 Parameter	0.74	-	0.37	420
Subject-weighted mean for the inflection point of the probability weighting function				0.40	

Table A.1. Overview of estimated parameters and corresponding inflection points of probability weighting functions in selected studies.

Appendix B

1. Introduction

The Chair of Finance is conducting an experiment regarding the decision making process of individuals. In this experiment, you are going to answer questions and face decision situations in three different kinds of gambles.

You receive 5€ for your participation in this experiment. In addition, you have the possibility of a variable compensation, which depends on your decisions during the experiment. After the experiment, one of your decisions is selected at random and is being played out in the respective gamble, giving you the chance for an additional compensation. In the decision situations, all payments are expressed in experimental currency units (ECU). 100 ECU in the decision situation of the experiment are equivalent to 10€.

Take your time to answer the questions in the experiment. The experiment will last approx. 1 hour. If you click "Continue", the experiment will start with the first gamble.

2. Ticket-based lottery

If you click "Continue", the experiment part for the gamble ticket-based lottery will start.

a. Questionnaire

Please answer the following questions regarding the gamble ticket-based lottery.

- Do you know the gamble "ticket-based lottery"? (Yes/No)
- I know the rules of a ticket-based lottery well. (7-point Likert scale)
- I am able to evaluate the chances of winning in different gamble situations in a ticket-based lottery. (7-point Likert scale)
- How many times have you participated in a ticket-based lottery?
- How many months ago was the last time you played a ticket-based lottery?
- I am an expert in the gamble ticket-based lottery. (7-point Likert scale)

Indicate whether the following statements about the gamble ticket-based lottery are true or false. Afterwards, please state how certain you are about your assignment to the true or false category.

- "Tear-off envelopes" or "lots" are part of a ticket-based lottery (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- The probability of winning is determined by the amount of winning lots and blanks in the lottery pot. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- The outcome of the ticket-based lottery does not solely depend on the figure shown on the lot, but also on an additional event, e.g. a sporting event. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- You can usually participate in ticket-based lotteries at fairs. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)

b. Explanation of the gamble

The following concerns the gamble ticket-based lottery. A lottery pot contains a predetermined amount of winning tickets and blanks. The player pulls out a ticket, opens it, and sees a printed symbol, which represents either a winning ticket or a blank. Consequently, the player instantly finds out, whether she won or lost.
You can choose between participating in a ticket-based lottery, in which you earn 100 ECU with a given probability and 0 ECU with the complementary probability, or a sure payment. The participation in the ticket-based lottery is free of charge. You cannot lose money.
State for every decision situation, whether you prefer participating in the ticket-based lottery or the sure payment.

c. Decision situations

1) You have the choice between participating in a ticket-based lottery with a prize of 100 ECU or receiving a sure payment. You win the 100 ECU, if you directly pull out a winning ticket from the lottery pot. The lottery pot contains 100 tickets of which 1 is a winning ticket and 99 are blanks. Winning this ticket-based lottery occurs in 1% of the cases on average.[4] State for each of the decision situations, whether you prefer participating in the ticket-based lottery or the sure payment.

Participate in the ticket-based lottery	○	○	Sure Payment of 1 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 5 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 10 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 15 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 20 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 25 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 30 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 35 ECU
Participate in the ticket-based lottery	○	○	Sure payment of 40 ECU

State the smallest sure payment that would make you forego your participation in the ticket-based lottery:

[For brevity, decision situation 2-7 are left out here, short descriptions of decision situations can be found in Table 1 in the main part of this paper]

[4] Alternative wording for the second treatment group, which applied to all decision situations in all gambles: "Winning this ticket-based lottery occurs in 1 out of 100 cases on average."

3. Roulette

If you click “Continue”, the experiment part for the gamble roulette will start.

a. Questionnaire

Please answer the following questions regarding the gamble roulette.

- Do you know the gamble “roulette”? (Yes/No)
- I know the rules of roulette well. (7-point Likert scale)
- I am able to evaluate the chances of winning in different gamble situations in roulette. (7-point Likert scale)
- How many times have you played roulette?
- How many months ago was the last time you played roulette?
- I am an expert in the gamble roulette. (7-point Likert scale)

Indicate whether the following statements about the gamble roulette are true or false. Afterwards, please state how certain you are about your assignment to the true or false category.

- The fields on a roulette wheel are colored red, black and green. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- If a player bets on one of the dree dozen (1-12, 13-24, 15-36) and wins, she receives a payment at odds of 3 to 1 to her stake. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- Doing a “Split”, a player bets on two numbers next to each other on the wheel (e.g. 19 and 20 or 11 and 12). (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- Betting on one of the colors black and red is an “insight bet”. They are called “Insight bets”, because they are located inside the roulette table. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)

b. Explanation of the gamble

The following concerns the gamble roulette. A French roulette wheel is being used. The wheel contains the numbers from 0 to 36. The field of the number 0 is green, the fields of the other numbers are either red or black. There are 18 red and 18 black fields. An employee at the casino, the croupier, lets a ball fall into the spinning roulette wheel. The objective of the game is to predict the field on which the ball is going to land prior to spinning the wheel. A player places her stake before the wheel is being spun. The player can place her bet on a number, a color or different combinations of numbers.

You can choose between participating in roulette, in which you earn 100 ECU with a given probability and 0 ECU with the complementary probability, or a sure payment. The participation in roulette is free of charge. You cannot lose money.

State for every decision situation, whether you prefer participating in roulette or the sure payment.

c. Decision situations

1) You have the choice between participating in roulette with the possibility of winning 100 ECU or receiving a sure payment. You win the 100 ECU, if you win in three consecutive rounds of roulette, each time betting on two different Carrés (four adjacent numbers on the wheel). This occurs in 1% of the cases on average. State for each of the decision situations, whether you prefer participating in roulette or the sure payment.

Participate in roulette	○	○	Sure payment of 1 ECU
Participate in roulette	○	○	Sure payment of 5 ECU
Participate in roulette	○	○	Sure payment of 10 ECU
Participate in roulette	○	○	Sure payment of 15 ECU
Participate in roulette	○	○	Sure payment of 20 ECU
Participate in roulette	○	○	Sure payment of 25 ECU
Participate in roulette	○	○	Sure payment of 30 ECU
Participate in roulette	○	○	Sure payment of 35 ECU
Participate in roulette	○	○	Sure payment of 40 ECU

State the smallest sure payment that would make you forego your participation in roulette:

[For brevity, decision situation 2-7 are left out here, short descriptions of decision situations can be found in Table 1 in the main part of this paper]

4. Craps

If you click “Continue”, the experiment part for the gamble craps will start.

a. Questionnaire

Please answer the following questions regarding the gamble craps

- Do you know the gamble “craps”? (Yes/No)
- I know the rules of craps well. (7-point Likert scale)
- I am able to evaluate the chances of winning in different gamble situations of craps. (7-point Likert scale)
- How many times have you played craps?
- How many months ago was the last time you played craps?
- I am an expert in the gamble craps. (7-point Likert scale)

Indicate whether the following statements about the gamble craps are true or false. Afterwards, please state how certain you are about your assignment to the true or false category.

- Craps is played with two dice. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- If the player throwing the dice the first time throws a 6 or a 10 as a sum of the two dice, she instantly wins. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- If the player throwing the dice placed her stake on the "pass line" of the craps-table before throwing the dice and then wins, she receives a payment at odds of 1 to 1 to her stake. (True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)
- There are two possible outcomes of the first throw of the dice of a player: Either she wins or she can throw the dice again. This result is called "point".(True/False)
- How certain are you about your answer to the previous question? (7-point Likert scale)

b. Explanation of the gamble

The following concerns the gamble craps. The player places her stake and then simultaneously throws two dice with 6 sides. If the sum of the players numbers on the two dice is

- 7 or 11, she instantly wins.
- 2, 3 or 12, she instantly loses. This situation is called "crap".
- 4, 5, 6, 8, 9 or 10, she may throw the dices again. This situation is called "point".

Coming from a "point":
If the player throws the dice a second time and gets

- the same sum of numbers on the dice as in her first "point", she wins.
- a 7, she loses.
- Every other sum of numbers, she may throw the dice again.

You can choose between participating in craps, in which you earn 100 ECU with a given probability and 0 ECU with the complementary probability, or a sure payment. The participation in craps is free of charge, your stake is 0 ECU. You cannot lose money.
State for every decision situation, whether you prefer participating in craps or the sure payment.

c. Decision situations

1) You have the choice between participating in craps with the possibility of winning 100 ECU or receiving a sure payment. You win the 100 ECU, if you win after exactly 4 throws of the dice and throw an 8 in your first throw. This occurs in 1% of the cases on average. State for each of the decision situations, whether you prefer participating in craps or the sure payment.

Participate in craps	○	○	Sure payment of 1 ECU
Participate in craps	○	○	Sure payment of 5 ECU
Participate in craps	○	○	Sure payment of 10 ECU
Participate in craps	○	○	Sure payment of 15 ECU
Participate in craps	○	○	Sure payment of 20 ECU
Participate in craps	○	○	Sure payment of 25 ECU
Participate in craps	○	○	Sure payment of 30 ECU
Participate in craps	○	○	Sure payment of 35 ECU
Participate in craps	○	○	Sure payment of 40 ECU

State the smallest sure payment that would make you forego your participation in craps:

[For brevity, decision situation 2-7 are left out here, short descriptions of decision situations can be found in Table 1 in the main part of this paper]

5. Concluding questions

You have now answered all questions regarding the three gambles. Click on "Continue" to get to the last part of the experiment.

1) Please answer the following questions about picking balls from an urn and the corresponding probabilities.

   An urn contains 10 balls, of which 7 are white and 3 are black.
   Balls pulled out of the urn are not being replaced.

   - What is the probability of pulling out a white ball at the first draw?
   - What is the probability of pulling out a black ball at the first draw and a white one at the second?

2) During the experiment you answered four knowledge questions about each of the three gambles (12 knowledge questions in total). You can now choose between one of the following three alternatives, which gives you the chance of winning another 20 ECU (=2€).

   - Alternative 1: One of the questions is selected at random. You receive 20 ECU, if your answer was correct.
   - Alternative 2: From a box containing 12 cards numbered from 1 to 12, one card is randomly drawn. You receive 20 ECU, if the number on the card is smaller or equal to the total number of your correctly answered questions.
   - Alternative 3: One of the two alternatives can be selected at random, because the two alternatives are the same for me.

3) Personal Information: Please answer the following questions on your personal information.

- Gender (male/female)
- Age
- Course of Study
- Highest degree (A-levels/Bachelor/Master/PhD/Other)

6. Payout information

We are now going to prepare your payout.
For your payout, one of the 282 decisions was randomly selected. In the selected decision, you had the choice between participating in the gamble XX with the winning probability of XX or a sure payment of XX ECU. *[next section depends on individual choice]*

- You decided to play the gamble. The outcome of the gamble was randomly determined based on the respective winning probability. You [won/lost]. Therefore, your additional payment from this decision is [100/0] ECU.
- You decided to take the sure payment. Therefore, your additional payment from this decision is XX ECU.

By answering the knowledge questions for the respective gambles, you had the chance to receive an additional payment of 20 ECU. You answered XX out of 12 questions correctly. Your additional payment was determined using the payout mechanism you chose in the previous section. It amounts to XX ECU.
Your overall payment (including the 5€ for participating) amounts to XX Euro.
We will now prepare your payout.

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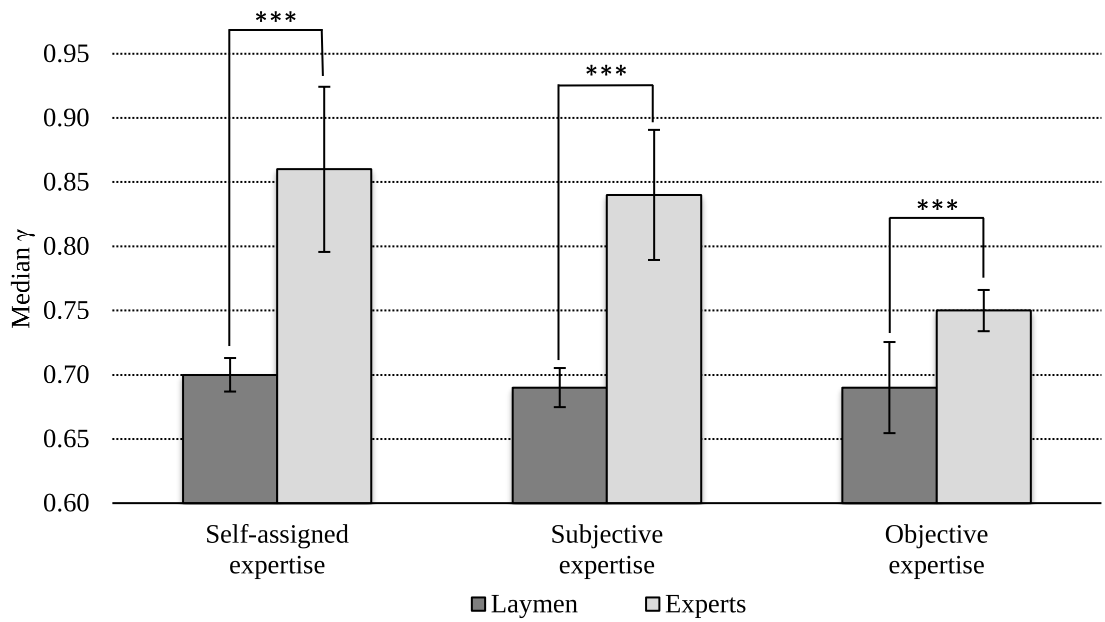

Figure 1. Probability weighting function γ-parameters for different measures of expertise. This figure shows the median γ-values from estimating Prelec (1998) one-parameter weighting functions and their 95% confidence interval for experts and laymen. Classifications are based on the respective measure of expertise (self-assigned, subjective, or objective). Differences in medians are assessed with quantile regressions using cluster-robust standard errors. Clustering is performed on a subject-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

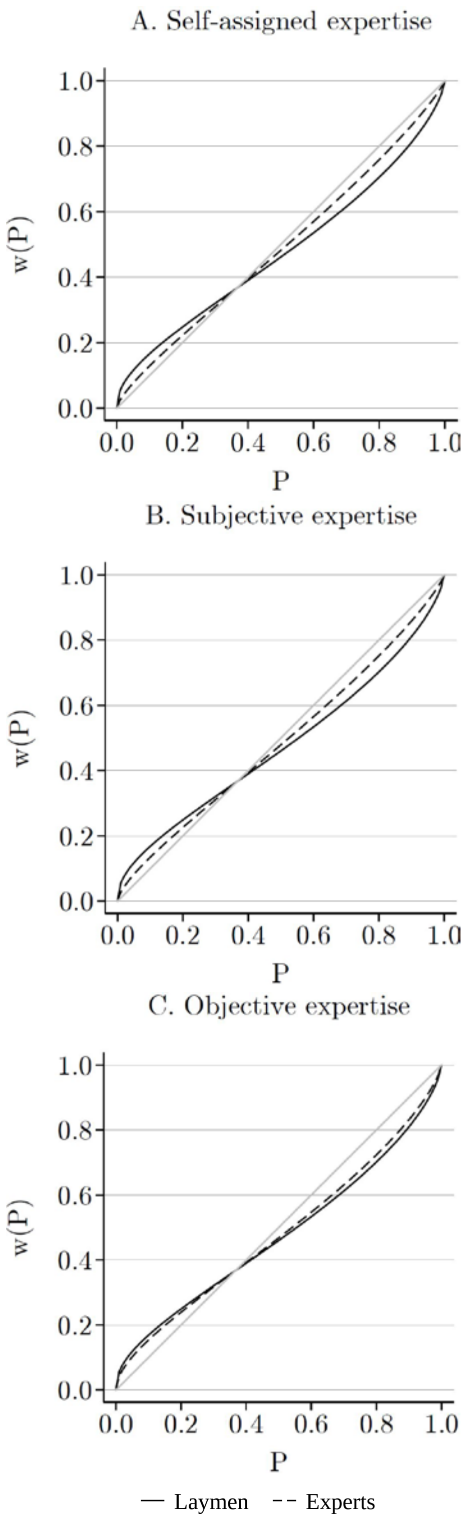

Figure 2. Weighting functions for experts and laymen for different measures of expertise. Prelec (1998) one-parameter weighting function. γ-parameter based on median of estimations on subject-gamble-level for experts and laymen.

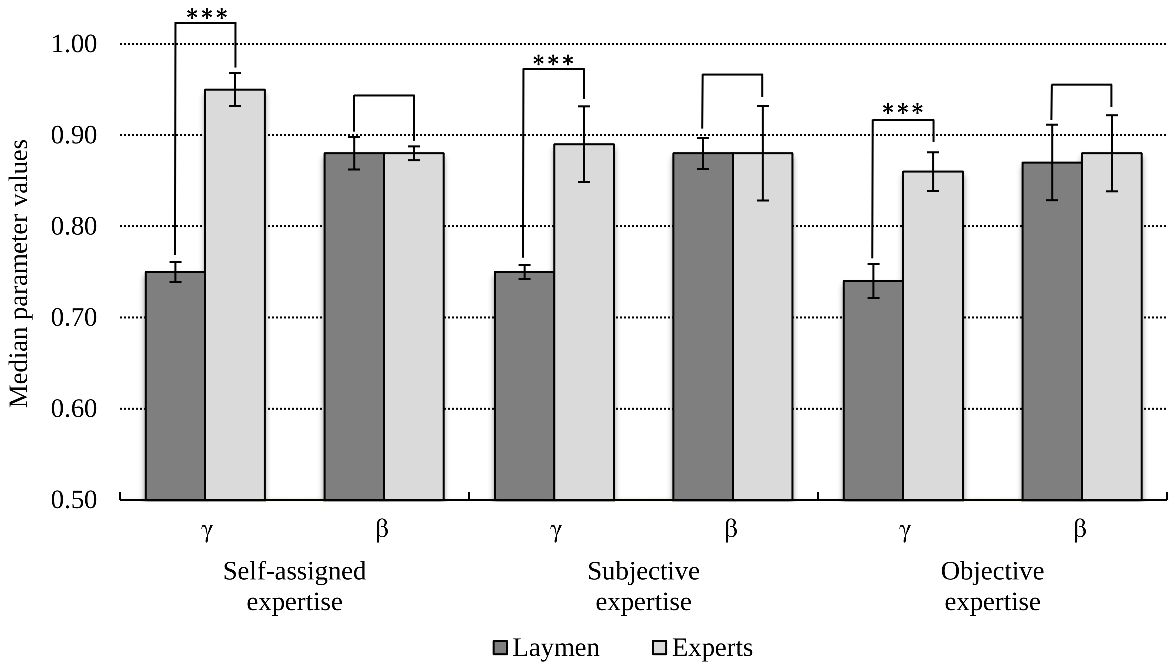

Figure 3. Probability weighting function γ- and δ-parameters for different measures of expertise. This figure shows the median γ- and δ-values from estimating Prelec (1998) two-parameter weighting functions and their 95% confidence interval for experts and laymen. Classifications are based on the respective measure of expertise (self-assigned, subjective, or objective). Differences in medians are assessed with quantile regressions using cluster-robust standard errors. Clustering is performed on a subject-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

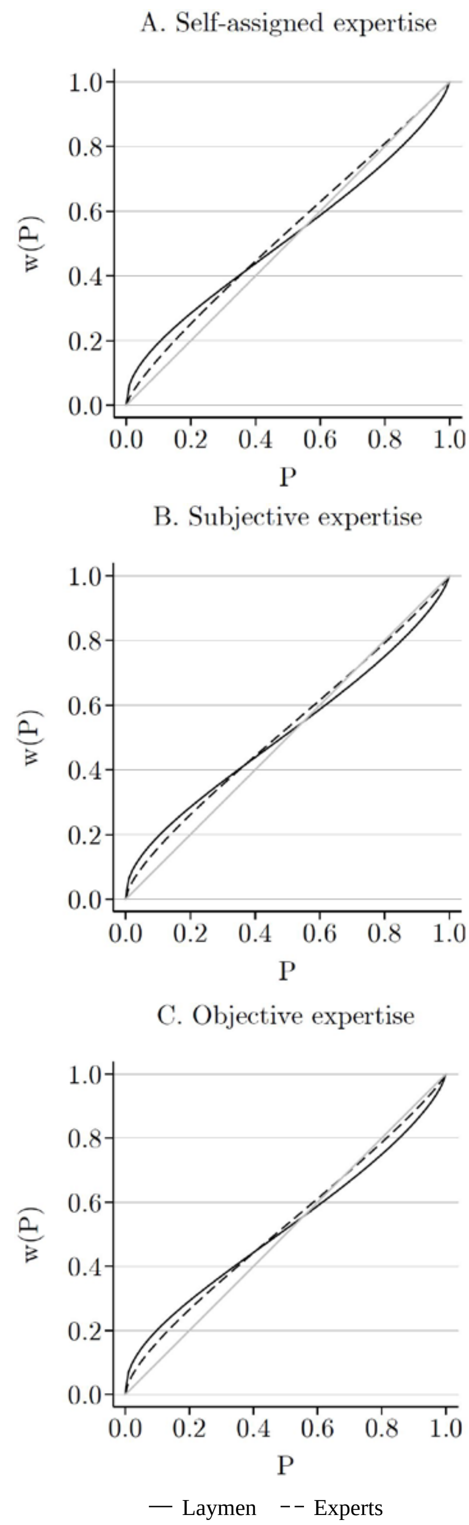

Figure 4. Two-parameter weighting functions for experts and laymen for different measures of expertise. Prelec (1998) two-parameter weighting function. γ- and δ-parameters based on median of estimations on subject-gamble-level for experts and laymen.

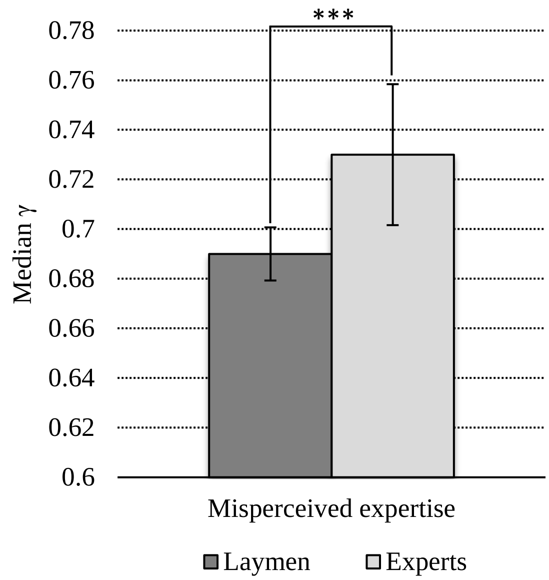

Figure 5. Probability weighting function γ-parameters for misperceived experts and laymen. This figure shows the median γ-values from estimating Prelec (1998) one-parameter weighting functions and their 95% confidence interval for misperceived experts and laymen. Differences in medians are assessed with quantile regressions using cluster-robust standard errors. Clustering is performed on a subject-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

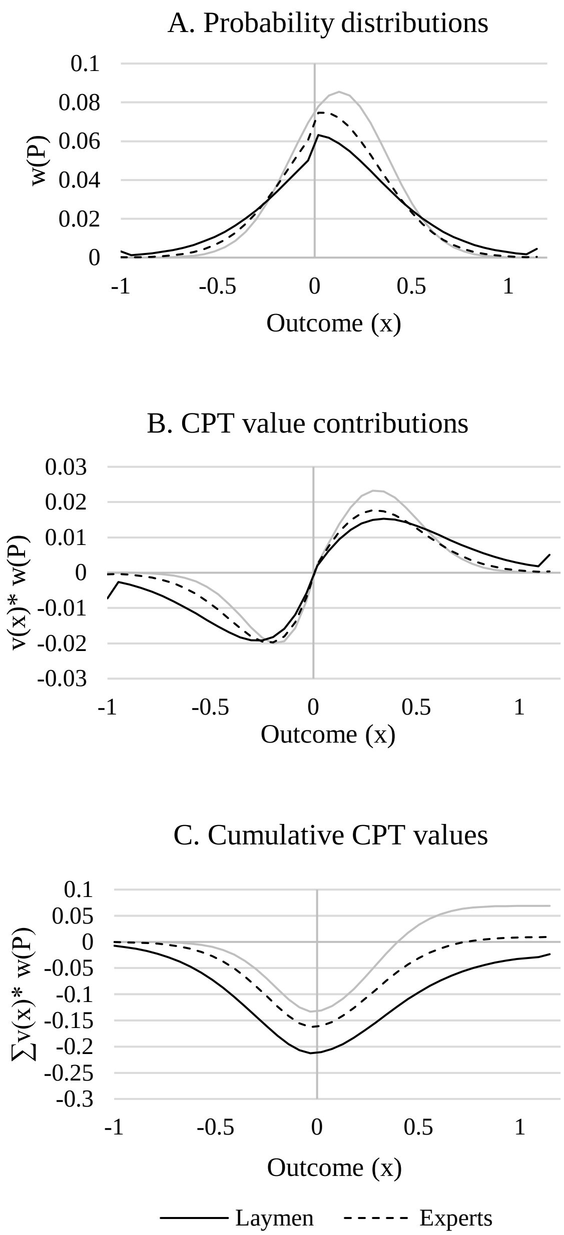

Figure 6. Impact of probability weighting on applied probability distributions, CPT value contributions, and CPT values for laymen and experts. Panel A illustrates how the differences in probability weighting between experts and laymen affect the applied probability distribution function. Panel B shows the CPT value contribution for each probability-outcome combination. Panel C plots the development of the resulting CPT value by cumulating the CPT value contributions from the most negative outcome up to outcome x. The final cumulative CPT values at the very right hand side of Panel C indicate the overall CPT values of the underlying risky prospect for laymen and experts. In all panels, the grey curve resembles the case of no probability weighting.

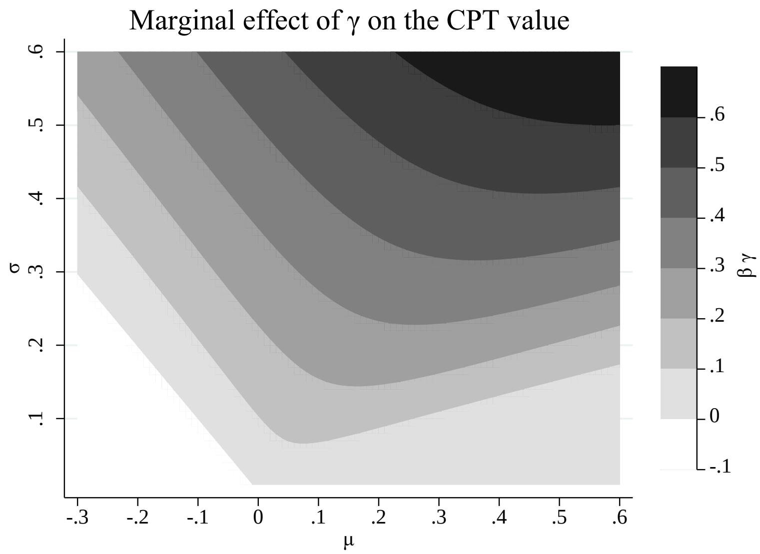

Figure 7. Marginal effect of probability weighting on the CPT value. This figure shows how a marginal change in probability weighting (γ) alters the CPT value of a risky prospect with the given risk(σ)-return(μ)-profile. The outcomes of the risky prospects are assumed to be normally distributed and the valuation is conducted for a standard CPT decision maker ($\alpha = 0.88$, $k = -2.25$). Grey areas resemble positive marginal effects indicating that stronger probability weighting reduces the CPT value. The white area resembles negative marginal effects indicating that stronger probability weighting increases the CPT value.

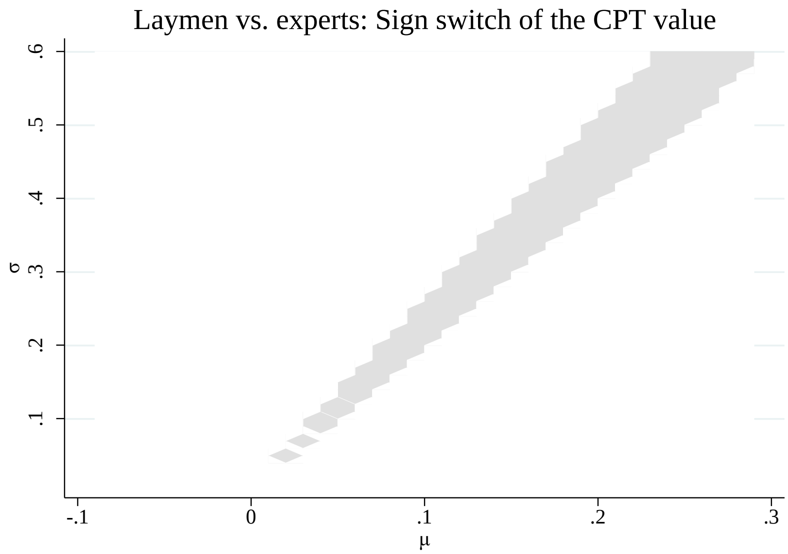

Figure 8. Sign switch of the CPT value due to stronger probability weighting. The grey area in this figure highlights risky prospects (μ-σ-combinations) for which the resulting CPT value is negative for laymen ($\gamma = 0.70$) and positive for experts ($\gamma = 0.86$). The outcomes of the risky prospects are assumed to be normally distributed and the valuation is conducted for a standard CPT decision maker ($\alpha = 0.88$, $k = -2.25$).

p	Ticket-based lottery	Roulette	Craps
1%	drawing a winning ticket out of a pot with 1 winning ticket and 99 blanks	win in three consecutive rounds of roulette, each time betting on two different Carrés (four adjacent numbers on the wheel)	win a round of craps after exactly 4 throws of the dice and throw an 8 in your first throw
5%	drawing a winning ticket out of a pot with 5 winning ticket and 95 blanks	win in one round of roulette, betting on a Split (two adjacent numbers on the wheel)	win a round of craps with your first throw by throwing an 11
10%	drawing a winning ticket out of a pot with 10 winning ticket and 90 blanks	win at least once in four consecutive rounds of roulette, each time betting on one number	throw a 5 or a 6 in your first throw and throw a winning number afterwards
40%	drawing a winning ticket out of a pot with 40 winning ticket and 60 blanks	win in one of six consecutive rounds of roulette at least once, each time betting on a Transversale (three adjacent numbers on the wheel)	win the round of craps if the first throw is a 5
90%	drawing a winning ticket out of a pot with 90 winning ticket and 10 blanks	win in one of six consecutive rounds of roulette at least once, each time betting on one of the Dozens (1-12, 13-24, 25-36)	win more than 2 times in 10 rounds of craps
95%	drawing a winning ticket out of a pot with 95 winning ticket and 5 blanks	win in one of eight consecutive rounds of roulette at least once, each time betting on one of the Dozens (1-12, 13-24, 25-36)	win at most 7 times in 10 rounds of craps
99%	drawing a winning ticket out of a pot with 99 winning ticket and 1 blank	win in one of seven consecutive rounds of roulette at least once, each time betting on one color, Red or Black	win at least once in 7 rounds of craps

Table 1. Complementary descriptions of specific game situations to illustrate objective probabilities across gambles.

		p						
		1%	5%	10%	40%	90%	95%	99%
Self-assigned expertise	Laymen	5	10	12	40	85	90	96
	Experts	3	6	11	40	90	95	99
	z-score	*1.78**	*1.95**	*1.37*	*-1.47*	*-3.99****	*-4.53****	*-2.66****
Subjective expertise	Laymen	5	10	14	40	85	90	96
	Experts	3	6	11	40	89	94	99
	z-score	*2.29***	*1.86**	*1.95**	*-0.70*	*-2.68****	*-3.94****	*-3.37****
Objective expertise	Laymen	7	10	13	41	85	90	95
	Experts	4	7	11	40	85	91	98
	z-score	*2.13***	*1.64*	*0.71*	*0.36*	*-0.69*	*-1.10*	*-2.62****

Table 2. Comparison of certainty equivalents across expert classifications. This table reports the median certainty equivalents for laymen and experts for each probability p and for all three applied measures of expertise (self-assigned, subjective, or objective). It also provides the z-score of Wilcoxon rank-sum tests conducted to compare the certainty equivalents of experts and laymen. ***, **, and * indicate significant differences in medians across subgroups at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	γ		
	(1)	(2)	(3)
Self-assigned expertise	0.016** (0.006)		
Subjective expertise		0.017** (0.006)	
Objective expertise			0.059** (0.023)
Subject fixed effects	YES	YES	YES
N	607	607	607
Adj. R^2	0.66	0.66	0.66

Table 3. Impact of perceived expertise on probability weighting within subject. This table reports coefficients from OLS-regressions. The curvature parameter γ of the Prelec (1998) one-parameter weighting function is regressed on the respective measure of expertise (self-assigned, subjective, or objective). Subject fixed effects are included. Standard errors (in parentheses) are clustered on the expert group-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	γ				
Alpha variation:	(1) $\alpha = 0.76$	(2) $\alpha = 0.88$	(3) $\alpha = 1.00$	(4) $\alpha_i \sim N(0.88,0.04)$	(5) $\alpha_{ij} \sim N(0.88,0.04)$
Panel A					
Self-assigned expertise	0.015**	0.016**	0.017**	0.016**	0.016**
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Panel B					
Subjective expertise	0.016**	0.017**	0.018**	0.017**	0.018**
	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Panel C					
Objective expertise	0.059***	0.059**	0.056*	0.060**	0.062**
	(0.019)	(0.023)	(0.028)	(0.023)	(0.022)
Subject fixed effects	YES	YES	YES	YES	YES

Table 4. Impact of perceived expertise on probability weighting within subject while varying the risk-aversion parameter α. This table reports coefficients from OLS-regressions. The curvature parameter γ of the Prelec (1998) one-parameter weighting function is regressed on the respective measure of expertise (self-assigned, subjective, or objective). γ is estimated on the subject-gamble level assuming different risk-aversion parameters α. Regressions (1) to (3) utilize a constant α across subjects and gambles of 0.76, 0.88, and 1.00. For Regressions (4) and (5), α-values are randomly drawn from a normal distribution with $\mu = 0.88$ and $\sigma = 0.04$ and are either subject-specific (4) or subject-gamble-specific (5). Subject fixed effects are included. Standard errors (in parentheses) are clustered on the expert group-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	γ			δ		
	(1)	(2)	(3)	(4)	(5)	(6)
Self-assigned expertise	0.032***			0.004		
	(0.006)			(0.007)		
Subjective expertise		0.039***			0.005	
		(0.010)			(0.009)	
Objective expertise			0.122**			0.054
			(0.051)			(0.044)
Subject fixed effects	YES	YES	YES	YES	YES	YES
N	607	607	607	607	607	607
Adj. R^2	0.55	0.55	0.56	0.64	0.64	0.64

Table 5. Impact of perceived expertise on curvature and elevation of the probability weighting function within subject. This table reports coefficients from OLS-regressions. The curvature parameter γ and the elevation parameter δ of the Prelec (1998) two-parameter weighting function are regressed on the respective measure of expertise (self-assigned, subjective, or objective). Subject fixed effects are included. Standard errors (in parentheses) are clustered on the expert group-gamble level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.