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Ignorance illusion in decisions under risk: The impact of perceived expertise on probability weighting

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Abstract

Current decision-making models assume that an individual's attitude towards risk is unique. Hence, a decision maker's processing of probabilities and the resulting degree of probability weighting should not vary within the domain of risk. This paper provides evidence that challenges this assumption. We conduct two experiments involving different gambles, that is, risky games where objective probabilities are known, no further information-based advantages exist, and outcomes are independent of knowledge. Even though all probabilities are explicitly provided, we find that individuals exhibit more pronounced inverse-S-shaped probability weighting if they perceive their level of expertise regarding a gamble to be lower. This result suggests that individuals are subject to ignorance illusion in decisions under risk, constituting expertise-dependent risk attitudes. We document that ignorance illusion stems from the wrongly assigned importance of perceived expertise in the decision-making process and that it occurs in both the gain and the loss domain.

KEYWORDS
decision making, ignorance illusion, perceived expertise, probability weighting, risk

JEL CLASSIFICATION
D81, D83, D91

1 | INTRODUCTION

It is widely accepted that individuals do not process probabilities as normatively prescribed by Subjective Expected Utility Theory (Savage, 1954). Instead, probabilities are transformed nonlinearly, that is, people tend to overweight low (tail) probabilities and underweight high probabilities (e.g., Kahneman & Tversky, 1979; Quiggin, 1982; Tversky & Kahneman, 1992). This behavior results in an inverse-S-shaped probability weighting function. Even though current decision-making models do account for nonlinear probability distortions, they typically assume that risky events, that is, events where objective probabilities are known to the decision maker, constitute a unique source of uncertainty[1] (Abdellaoui et al., 2011; Chew & Sagi, 2008; Ergin & Gul, 2009; Nau, 2006). These models therefore claim that an individual's risk attitude and hence probability weighting function does not vary across decisions within the domain of risk.

Recent experimental evidence, however, suggests that the perception of one's own expertise crucially alters economic behavior in decisions under risk. Individuals with higher perceived expertise are more willing to pursue risky investments (Hadar et al., 2013), hold larger fractions of risky assets in their portfolios (Frijns et al., 2008), and prefer securities they feel more knowledgeable about (Ackert et al., 2005; Fellner et al., 2004). These findings are remarkable given that the amount of actual information concerning the underlying choices was held constant across levels of perceived expertise. The fact that previous studies have shown that an individual's value function is stable across sources of uncertainty (Abdellaoui et al., 2016; Armantier & Treich, 2016) points to the importance of the probability weighting function for explaining expertise-dependent variation in risk attitudes.

Allowing for probability weighting is also important to better understand risk attitudes and risky choices in the insurance domain (Hansen et al., 2013; Kairies-Schwarz et al., 2017). When individuals judge the attractiveness of insurance, processing (loss) probabilities is central to the decision-making process. More pronounced inverse-S-shaped probability weighting increases, ceteris paribus, the willingness to pay for insurance because low probability outcomes with large positive claims are overweighted while high probability, no-claim outcomes are underweighted (Hansen et al., 2013; Harrison & Ng, 2016; Schmidt, 2016; Werner, 2016). According to the models cited above, insurance demand should not vary across different insurance contexts if the respective adverse events occur with the same probability (and magnitude). The documented framing effects on the willingness to pay for insurance (Jaspersen, 2016; Johnson et al., 1993) refute this prediction and suggest that individual perceptions shape risk attitudes in insurance decisions.

[1]Throughout this paper, the term uncertainty captures both risk (known outcome probabilities) and ambiguity (unknown outcome probabilities).

In this paper, we test whether perceived expertise regarding a decision under risk affects an individual's probability weighting function. In the domain of risk, actual knowledge differences regarding outcome probabilities cannot exist by definition. However, the decision maker might irrationally *feel* less knowledgeable about one of the risky events, despite having identical information regarding the relevant statistical properties for all of them. Thus, we refer to a decision maker who displays different attitudes towards risk due to variation in perceived expertise as being subject to *ignorance illusion*.

Indirect evidence for the impact of perceived expertise on risk attitudes is provided by Armantier and Treich (2016). They find that individuals have different attitudes towards risk depending on the complexity of the underlying event. In their experiment, however, 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 create an experimental design where subjects have complete information about the objective probabilities involved. Also, instead of focusing on complexity, we directly explore the impact of perceived expertise on probability weighting.

To examine how perceived expertise affects an individual's processing of probabilities in decisions under risk, we first 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, skill, experience, or knowledge about the gamble (beyond objective probabilities) have no impact on the expected outcome. Thereby, we can induce variation in participants' perceived expertise regarding the respective gamble, enabling us to explore its impact on probability weighting, both between and within subjects.

Our results indicate that lower perceived expertise about a gamble leads to more pronounced inverse-S-shaped probability weighting even though all objective probabilities are provided. Hence, we observe ignorance illusion, that is, an individual's attitude toward risk depends on the level of perceived expertise. The degree of probability weighting therefore varies within the domain of risk, challenging the assumption of risk constituting a unique source of uncertainty.

We identify an individual's self-perception of expertise as the main driver of our results. Differences in probability weighting are most pronounced when employing a measure of expertise that is purely based on an individual's self-assessment while using more indirect measures of perceived expertise yields smaller effects. Moreover, even when individuals objectively lack gamble-specific knowledge (beyond the provided probabilities) but perceive themselves as experts, they engage less in inverse-S-shaped probability weighting than participants who are objectively well informed but perceive themselves as laymen. Hence, the observed differences in probability weighting cannot be the result of better actual (though irrelevant) knowledge regarding a gamble. Furthermore, we document that perceived expertise mitigates inverse-S-shaped probability weighting beyond an individual's experience regarding a risky choice.[2]

Given the identified importance of a subject's self-perception, we conduct a second experiment to explore whether informing subjects about the irrelevance of perceived expertise in the decision-making process alters the degree of probability weighting, that is, the presence of ignorance illusion. Our results suggest that this is the case. While participants in the control

[2] List (2003, 2004) provides evidence that more experienced individuals are more likely to behave in accordance with neoclassical predictions in decisions under risk.

groups exhibit ignorance illusion to a similar degree as in the first experiment, we do not find any differences in probability weighting between experts and laymen when subjects are made aware of the fact that perceived expertise should not affect decisions under risk. Our second experiment furthermore provides evidence that ignorance illusion prevails in both the gain and loss domain and that our findings are robust to the employed estimation approach for eliciting a subject's value function parameter.

The main contributions of this paper are threefold. First, we provide experimental evidence that individuals are subject to ignorance illusion in decisions under risk. We find more pronounced inverse-S-shaped probability weighting for lower levels of perceived expertise which implies that risk does not constitute a unique source of uncertainty. Second, we show that the phenomenon of ignorance illusion is driven by an individual's self-perception of expertise, which can, but does not have to align with the actual knowledge level regarding the risky event. Third, we document that ignorance illusion stems from the fact that decision makers are unaware of the irrelevance of perceived expertise in decisions under risk. Our results suggest that perceived expertise can serve as counter-bias mechanism to achieve more linear probability processing among decision makers and thereby affect investment and insurance behavior.

This paper proceeds as follows: Section 2 outlines related literature. Section 3 presents our first, and Section 4 our second experiment. Section 5 concludes.

2 | RELATED LITERATURE

Current decision-making models assume that the weighting function applied to objective probabilities underlying monetary outcomes of risky prospects is invariant (Abdellaoui et al., 2011; Chew & Sagi, 2008; Ergin & Gul, 2009; Nau, 2006).[3] Recent empirical evidence raises doubts about the validity of this assumption, pointing to an important role of perceived expertise in decisions under risk.[4]

Since value functions have been found to be stable across sources of uncertainty (Abdellaoui et al., 2016; Armantier & Treich, 2016), observing expertise-related variation in risk attitudes hints at a potential impact of perceived expertise on the degree of probability weighting. In an fMRI study based on a sample of 16 subjects, Chew et al. (2008) document that individuals favor more familiar over less familiar stocks when confronted with “almost-objective” 50/50 prospects. However, given that distortions of probabilities around 50% have been shown to be rather small (Abdellaoui et al., 2011), it is unclear whether their results are due to differences in probability weighting or subjective misperceptions of the involved, though not explicitly provided probabilities. Hadar et al. (2013) provide experimental evidence that risk-taking behavior is affected by an individual's level of subjective knowledge. They show that higher levels of subjective knowledge increase the attractiveness of risky investments and the willingness to invest in them. Similarly, Frijns et al. (2008) find that the share of risky assets in an investor's

[3]The invariance assumption concerns the processing of objective probabilities within subjects. Heterogeneity in probability weighting between subjects (e.g., Bruhin et al., 2010; Choi et al., 2021; Fehr-Duda et al., 2006; Millroth & Juslin, 2015; Traczyk & Fulawka, 2016) can be accommodated by the aforementioned decision-making models.

[4]As this study focuses on risky prospects involving standardized monetary outcomes for which probability-outcome independence can be expected to hold (Rottenstreich & Hsee, 2001), we do not discuss empirical evidence concerning affect-rich decision situations and the related effect of emotions on probability weighting (e.g., Kusev et al., 2009; Mukherjee, 2011; Petrova et al., 2019; Rottenstreich & Hsee, 2001; Suter et al., 2016).

portfolio increases in self-assessed financial expertise. Bruhin et al. (2018) show that a subject's belief about relative skill drives differences in behavior in skill and luck gambles.

The behavior toward compound lotteries provides further evidence for a potential link between perceived expertise and risk attitudes. Compound objective lotteries are typically valued less than simple lotteries with the same reduced probability (Abdellaoui et al., 2015; Budescu & Fischer, 2001; Dillenberger, 2010). Complexity is discussed as one of the main reasons for compound lottery aversion. If one assumes that a decision maker's perceived expertise decreases in event complexity, this could explain the difference in risk attitude between simple and compound risks. Armantier and Treich (2016) explore how the complexity of random events affects probability weighting functions and hence provide an indirect test on the impact of perceived expertise on probability weighting. They find that subjects engage less strongly in probability weighting for simple compared with complex events. However, their results suffer from two potential confounders stemming from the fact that subjects had to calculate the objective probabilities on their own.

As discussed by Armantier and Treich (2016) themselves, it is unclear whether subjects constructed the correct objective probabilities. If the difficulty associated with the complex events prevented subjects from forming correct probabilities, inferences regarding the estimated probability weighting function are disturbed. Even worse, 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 instead a source of (partial) ambiguity. It might thus not be surprising that Armantier and Treich (2016) find similar source functions for complex risky and ambiguous prospects.

To overcome these problems and to examine the impact of perceived expertise on the degree of probability weighting in decisions under risk directly, we follow a different approach that is outlined in the next section.

3 | EXPERIMENT I

3.1 | Methodology

3.1.1 | Experimental design

To test whether perceived expertise has an impact on probability weighting, we conducted an experiment with 297 students at a German university. 41% of our participants are female, 30% are graduate students, and the average age is 23 years. The computer-based experiment was run in 15 sessions with 15–20 subjects each. Completion time was about 1 h, and subjects' choices were incentivized. In addition to receiving a fixed payment of 5 €, subjects were told upfront that one of their decisions made throughout the experiment would be randomly selected and played out for real money. Experimental currency units (ECU) were transformed into € using a 10:1 conversion rate. On average, subjects were paid 11.82 €.

The main challenge in our experimental design is to vary subjects' perceived expertise while providing them with objective probabilities. To achieve this, we transfer the idea of perceived competence in the ambiguity literature (Tversky & Fox, 1995) to a pure risk setting and utilize three different gambles as random devices, namely, (1) a ticket-based lottery, (2) roulette, and (3) craps. We chose these gambles for two reasons. First, their popularity strongly varies in Germany. Ticket-based lotteries are typically well-known and oftentimes already played in childhood. Roulette is one of the most popular casino games, while craps, also offered in casinos, is hardly known and rarely played. Second, all of these gambles can be classified as purely random, that is, an individual cannot influence the 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 expertise, enabling us to explore differences in probability weighting across perceived experts and laymen, both between and within subjects.

For each gamble, subjects had to first fill out a questionnaire, consisting of questions regarding their perceived expertise as well as four knowledge questions about the gamble and their confidence in the provided answers. To ensure that subjects fully understood the subsequent decision situations involving 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. The subjects then had to indicate certainty equivalents for binary prospects for each gamble, in which they could either win 100 ECU with seven different probabilities $P \in \{1\%, 5\%, 10\%, 40\%, 90\%, 95\%, 99\%\}$ or receive 0 ECU otherwise. We chose the lower and higher three probabilities since probability weighting is found to be most pronounced for probabilities close to 0 and 1 (see, e.g., Tversky & Kahneman, 1992). We also included the medium probability of 40% to observe weighting patterns around the expected inflection point, which is commonly found to be close to $P = 40\%$.[5] The order in which the three different gambles were presented to subjects and the order of probabilities to win the binary prospects within a gamble were randomized.

Probabilities were first described in terms of specific game situations of the respective gamble and then stated explicitly.[6] Descriptions of the specific game situations across gambles are presented in Table 1.

The game situations were chosen because they approximate the stated objective probabilities well while being concise and easy to understand.[7] The latter criterion is vital to our experiment, given the numerous choices subjects had to make. The detailed experimental instructions and questionnaires are provided in Supporting Information Appendix B (translated from German).

Similar to Kilka and Weber (2001), certainty equivalents are elicited using a choice list format, that is, subjects indicate their choice between accepting the presented risky prospect or a given sure payment of X ECU. To reduce the number of choices subjects had to make in the experiment and therefore increase the attention paid to each decision, we adapted the range of X based on the probability of winning the prospect. For $P \in \{1\%, 5\%, 10\%\}$, X ranged from 1 to 40. For $P \in \{90\%, 95\%, 99\%\}$, X ranged from 99 to 40. For $P = 40\%$, X covered the whole range from 1 to 99. Within these ranges, X was varied in steps of 5 ECU in general and 4 ECU from 1 to 5 and from 99 to 95. In addition to indicating their choices for these specific offers, subjects had to state their exact certainty equivalent for a prospect, that is, the amount they would demand as a certain payment to refrain from accepting the risky prospect.

[5] Our overview of studies on probability weighting in Supporting Information Appendix A shows that probability overweighting usually turns into underweighting around the probability of $P = 40\%$.

[6] To explore the effect of wording on probability weighting we presented probabilities in two ways. Half of the participants received objective probabilities as a percentage value (e.g., "winning this lottery occurs in P% of the cases"). For the other half, objective probabilities were stated as 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 groups, we do not further distinguish between them in our analyses.

[7] To ensure that our results are not affected by potential approximation-related differences in probability weighting, we conduct two robustness tests. First, to account for the possibility that the pattern of gamble-specific deviations might affect the degree of probability weighting, we rerun our main regressions (cf. Section 3.2.2) while also including gamble fixed effects. This alternative specification leaves our results qualitatively unchanged. Second, we utilize different game situations in our second experiment for which implied and stated probabilities are equal up to the fourth decimal place. Our main findings are robust to this alteration.

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

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 rounds of roulette, each time betting on two different Carrés (four adjacent numbers)	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)	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 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 at least once in one of six rounds of roulette, each time betting on a Transversale Plein (three adjacent numbers)	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 at least once in one of six rounds of roulette, each time betting on one of the Dozens (12 adjacent numbers)	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 at least once in one of eight rounds of roulette, each time betting on one of the Dozens (12 adjacent numbers)	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 at least once in one of seven rounds of roulette, each time betting on one color, red or black	Win at least once in 7 rounds of craps

The final part of the experiment consisted of an additional questionnaire regarding a subject's cognitive abilities, overconfidence, and personal information. Following Blavatskyy (2009), the overconfidence task was incentivized, offering subjects the chance to win another 20 ECU.

3.1.2 | Data and variables

Overall, we obtain data on participants' certainty equivalents for seven different prospects for each of the three gambles, which enables us to estimate one probability weighting parameter for each subject and gamble (subject-gamble observation). Moreover, we elicit information on subjects' subjective and objective knowledge as well as their self-assigned expertise with respect to these gambles. To be included in our final sample, all of a subject's choices within a gamble have to fulfill two criteria. First, subjects do not switch back and forth between choosing the risky prospect and receiving the sure payment X, that is, when X increases for a given P, subjects who prefer the amount X_1 over choosing the prospect also prefer the amount X_2 over choosing the prospect for all $X_2 > X_1$. Second, the stated certainty equivalent must lie between the sure payment X_{last} that was offered when subjects preferred the risky prospect for the last time and the sure payment X_{first} that made them prefer the sure payment for the first time (certainty equivalent $\in [X_{last}, X_{first}]$). Applying these criteria yields our final sample of 4529 certainty equivalents provided by 274 subjects, yielding 647 subject-gamble observations.

We construct three different measures to quantify the level of subjects' perceived expertise regarding the gambles.

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 opinion about her level of expertise. For our pooled analyses, we classify subjects as self-assigned experts in a gamble if they rated their expertise as four or higher and as self-assigned laymen otherwise.

Subjective expertise

This measure intends to elicit subjects' levels of expertise in a more indirect manner while still relying on subjective assessments. It is based on 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 1 and all factor loadings are well above the usual threshold of 0.4 (>0.93). To form groups for our pooled analyses, 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.[8] All other subjects form the residual category.

Objective expertise

Our third measure is solely based on objectively verifiable information. It enables us to distinguish between actual expertise regarding a gamble and the perception thereof. For every gamble, subjects were confronted with four statements concerning its rules or general setup and had to indicate whether the respective statement if true or false. Objective expertise is measured as the number of correct answers at the subject-gamble level and hence ranges from 0–4. For our pooled analysis, we classify subjects as objective experts with at least three correct answers because such individuals have answered more questions correctly than would be expected from random guessing. Consequently, subjects with 1 or 0 correct answers are classified as objective laymen. All other subjects form the residual category.

Table 2 provides summary statistics for the three expertise measures as well as their pairwise correlation coefficients. While self-assigned expertise measures perceived expertise in the most direct manner, incorporating inferred subjective or even objective expertise assessments

[8]In an unreported robustness test, we classify subjects as subjective experts (laymen) in a gamble if they belong to the top (bottom) 10% [30%] in terms of subjective expertise. The obtained results are qualitatively unchanged.

TABLE 2 Summary statistics and correlation coefficients for measures of expertise

	A. Summary statistics				B. Correlation coefficients		
	Mean	Standard deviation	Minimum	Maximum	Self-assigned expertise	Subjective expertise	Objective expertise
Self-assigned expertise	1.790	1.226	1.000	7.000	1.000		
Subjective expertise	0.000	0.906	−0.989	2.607	0.793	1.000	
Objective expertise	2.728	1.107	0.000	4.000	0.155	0.253	1.000

Note: Summary statistics for all three measures of expertise (self-assigned, subjective, or objective) as well as their pairwise correlation coefficients are reported.

dilutes the impact of perception. In line with this argument, differences in experts' and laymen's answers to the question whether they consider themselves to be experts in the respective gamble decrease as we measure perceived expertise more indirectly. While experts rate themselves significantly higher ($p < 0.01$) than laymen regardless of the applied measure, the difference is higher for self-assigned expertise (Δ3.15) compared with subjective (Δ2.48) and objective (Δ0.33) expertise. Differences-in-differences are statistically significant ($p < 0.01$). These results are in line with the observed decrease in correlation with the self-assigned expertise measure when moving from the subjective ($\rho = 0.793$) to the objective ($\rho = 0.155$) measure. We hypothesize that perceived expertise mitigates the degree of probability weighting and that the mitigating effect is strongest for the most direct, self-assigned measure of perceived expertise, followed by the subjective and then the objective measure.

Because our three measures rely on considerably different mechanisms to assess expertise, the respective number of subject-gamble observations classified as experts and laymen varies. The sample of self-assigned experts and laymen is the largest, with all 647 observations assigned to one of the two groups (12% self-assigned experts; 88% self-assigned laymen). The sum of expert and laymen observations based on the subjective expertise measure amounts to 363 (37% subjective experts; 63% subjective laymen). The objective expertise classification captures 484 observations (79% objective experts; 21% objective laymen).

3.1.3 | Estimation of probability weighting functions

To estimate probability weighting functions, we first need to transform the stated certainty equivalents into a subject's utility and then derive the corresponding decision weights as follows:

$$v(CE_{\mathrm{P}}) = v(100)\cdot w(\mathrm{P}). \tag{1}$$

Equation (1) states that a subject's utility from its stated certainty equivalent for a given probability P equals the value of winning the prospect, in which case the subject wins 100 ECU, multiplied by the decision weight the subject assigns to winning the prospect.

We use the commonly employed power value function of the form $v(x) = x^{\alpha}$ (e.g., Balcombe & Fraser, 2015; Kilka & Weber, 2001; Tversky & Kahneman, 1992) to determine the utility of outcomes. Since we did not vary payoffs and probabilities independently in Experiment I, a joint identification of the value function parameter α and the degree of probability weighting is not feasible. We therefore follow the literature and assume in the subsequent analyses that utility is linear ($\alpha = 1$; e.g., Enke & Graeber, 2021; Kilka & Weber, 2001).[9,10] Equation (1) is then transformed into $w(\text{P}) = \frac{CE_\text{P}}{100}$ and yields seven decision weights per subject and gamble.

To estimate the probability weighting function, different functional specifications have been proposed. We follow, for example, Tanaka et al. (2010) and Aydogan et al. (2016) and utilize the Prelec (1998) one-parameter weighting function $w(\text{P}) = e^{-(-\ln(\text{P}))^\gamma}$, 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 simpler forms, especially when paired with a power value function as done in this study. Moreover, the chosen specification with its fixed inflection point at $\text{P} = 1/e$ (≈ 0.37) matches the probability weighting pattern observed in previous studies (cf. Supporting Information Appendix A).

The weighting function parameter is then estimated individually for each participant and each gamble using nonlinear regressions. Estimated parameters are winsorized at the 1st and 99th percentiles. For $\gamma = 1$, the weighting function reduces to the identity $w(\text{P}) = \text{P}$, capturing the case of rational probability processing (no probability weighting). A smaller value for γ indicates more pronounced inverse-S-shaped probability weighting.

To ensure that our results do not depend on the chosen functional form of the probability weighting function, we conduct two robustness tests. First, we repeat our main analyses following the nonparametric approach proposed by Dimmock et al. (2020) (cf. Supporting Information Appendix C). Second, as Balcombe and Fraser (2015) provide evidence in favor of using the Prelec (1998) two-parameter weighting function, we also rerun our main analyses using this alternative specification (cf. Supporting Information Appendix D). Both robustness tests leave our findings qualitatively unchanged.

3.2 | Results

3.2.1 | Differences in certainty equivalents

Table 3 presents medians of stated certainty equivalents for experts and laymen across different probabilities P and measures of expertise. In addition, it contains the corresponding z-scores of Wilcoxon's rank-sum tests to analyze differences in certainty equivalents between experts and laymen.

For all three measures of perceived expertise, experts value the proposed risky prospects differently than laymen. For $\text{P} \in \{1\%, 5\%, 10\%\}$, certainty equivalents of laymen are typically larger than those of their expert counterparts. For $\text{P} \in \{90\%, 95\%, 99\%\}$, certainty equivalents of laymen are mostly smaller than those of experts. These differences are statistically significant for almost all values of P for the self-assigned and subjective expertise measures and only significant for the lowest value of P for the objective expertise measure. Virtually no differences in stated certainty equivalents can be detected for any measure of expertise at the expected inflection point ($\text{P} = 40\%$). These raw results provide initial evidence that probabilities in

[9]This assumption is supported by findings obtained in Experiment II, which was designed to allow for a joint identification of the value function parameter and the degree of probability weighting. Neither the median nor the mean of the estimated value function parameter is significantly different from one in the gain domain. This also holds for perceived experts and perceived laymen separately. Furthermore, we observe a very high correlation between the elicited degree of probability weighting based on estimated or assumed ($\alpha = 1$) value function parameters ($\rho = 0.953$).

[10]In an unreported robustness test, we assume parameters implying concavity of the value function ($\alpha \in \{0.76, 0.88\}$; see, e.g., Kilka & Weber, 2001). The obtained results are qualitatively unchanged.

TABLE 3 Certainty equivalents for experts and laymen by probability and measure of expertise

	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	6	10	12	40	85	90	95
Experts	5	10	12	40	85	90	97
z-score	1.69*	1.46	0.31	0.63	0.15	0.31	−0.97

Note: The median certainty equivalents for experts and laymen for each probability P and for all three measures of expertise (self-assigned, subjective, or objective) are reported. The *z*-scores of Wilcoxon's rank-sum tests conducted to compare the certainty equivalents of experts and laymen are also provided. ***, **, and * indicate significant differences in medians across subgroups at the 1%, 5%, and 10% levels, respectively.

decisions under risk are weighted differently by perceived experts than by perceived laymen, even though the outcome of the underlying risky prospects is independent of expertise.

3.2.2 | Differences in probability weighting estimates

We start our analyses by pooling all subject-gamble observations and compare the elicited probability weighting function parameters between the respective expert and laymen groups. Figure 1 illustrates median estimates as well as 95% confidence intervals for experts and laymen across our three different measures of expertise. Standard errors are bootstrapped at the subject level to account for the inherent estimation uncertainty in our γ-estimates (10,000 bootstrap replications). 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 overweighting low (tail) probabilities and underweighting high probabilities.

However, the degree of probability weighting differs between experts and laymen. While γ for self-assigned and subjective laymen is about 0.7, the corresponding experts exhibit a significantly larger value (about 0.85; $p < 0.01$). We do not observe significant differences in probability weighting for our measure of objective expertise.

These results suggest that, first, subjects with lower levels of perceived expertise exhibit more pronounced inverse-S-shaped probability weighting. As subjects are explicitly provided with outcomes and objective probabilities, that is, all relevant information for making the underlying risky choices, the difference in probability weighting due to variation in perceived expertise constitutes ignorance illusion. Second, ignorance illusion is particularly severe when

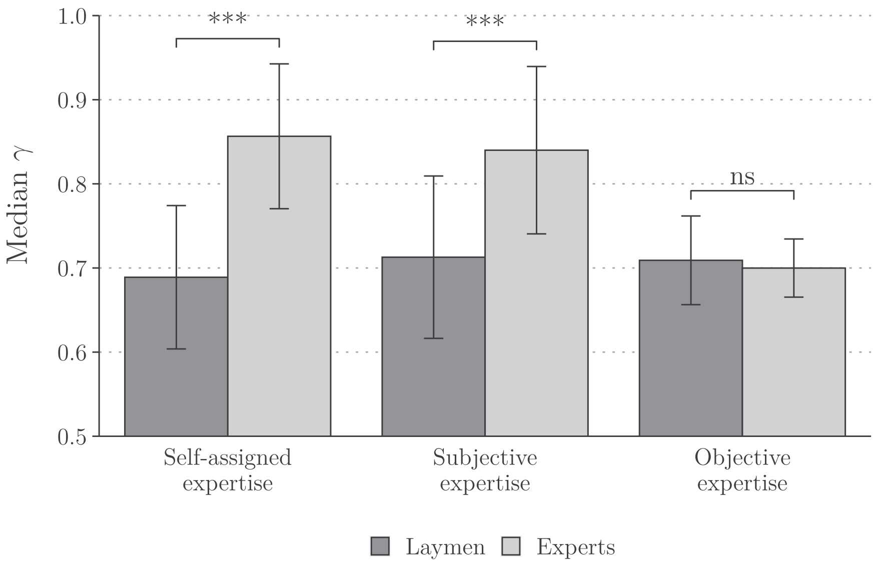

FIGURE 1 Probability weighting function γ-estimates for experts and laymen. This figure shows the median γ-values from estimating Prelec (1998) one-parameter weighting functions and their 95% confidence interval for experts and laymen. Expert and layman classifications are based on the respective measure of expertise (self-assigned, subjective, or objective). Differences in medians are assessed with quantile regressions using bootstrapped standard errors clustered at the subject level based on 10,000 bootstrap replications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the employed expertise measure most directly reflects a subject's very own opinion about her level of expertise (difference in γ is largest for self-assigned expertise). More indirect measures of perceived expertise based on subjective assessments or objective knowledge seem to be less powerful in this respect.[11]

We next conduct a within-subjects analysis to explore how a change in perceived expertise affects the degree of probability weighting at the subject level. To this end, we regress γ on our measures of expertise while controlling for subject fixed effects. We thereby compare estimated γ-values for the very same subject if the level of perceived expertise changes across gambles. This allows us to rule out unobserved individual traits as explanation for the expertise-dependent differences in probability weighting.

For a meaningful comparison of the obtained regression coefficients across our measures of expertise, we need to eliminate the inequality of the underlying scales and potential differences in responsivity at the individual level. We therefore conduct a within-subjects z-transformation which expresses each individual's perceived expertise regarding a gamble relative to her mean and standard deviation across gambles (Bush et al., 1993). This transformation of raw scores is accomplished for each subject and expertise measure by, first, subtracting a subject's mean

[11] Figure E.1 in Supporting Information Appendix E shows how the observed differences in γ-estimates affect the shape of the respective probability weighting functions. For the groups of self-assigned experts, the weighting function is noticeably closer to the identity than for their laymen counterparts. For subjective experts this effect also exists but is less pronounced. No effect is observed for objective experts.

perceived expertise across gambles and, second, dividing by a subject's standard deviation. Within subjects, all transformed measures have a mean of 0 and a standard deviation of 1.

As a consequence, we yield an identical interpretation of the estimated coefficients. Regardless of the considered measure, the coefficient describes how much an individual's γ-estimate changes on average when the individual's perceived expertise increases by one standard deviation. Table 4 reports the estimated regression coefficients for all three standardized measures of expertise. To ensure that the pool of subjects used for identification (i.e., those with variation in perceived expertise across gambles) remains constant, only subjects are considered who display variation in perceived expertise across gambles in all three measures.[12]

Across expertise measures we find a positive and significant influence on the curvature parameter γ, indicating less pronounced inverse-S-shaped 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 the level of perceived expertise varies. Thus, we can identify the impact of perceived expertise on probability weighting, that is, ignorance illusion, both between and within subjects.

The results also lend further support to the notion that an individual's self-perception matters the most when it comes to ignorance illusion in decisions under risk. This is indicated by the larger coefficient for self-assigned expertise compared with the other measures. Increasing self-assigned expertise by one standard deviation raises γ by 0.026 on average. In contrast, a one standard deviation increase in subjective (objective) expertise leads to an average γ-increase of 0.020 (0.018). The implied reduction in probability weighting is therefore about 30% (44%) larger for the most direct assessment of an individual's perceived expertise compared with the more indirect subjective (objective) measure.

3.2.3 | Importance of self-perception

To further strengthen our argument that a subject's perception of her own expertise is the driver of the observed differences in probability weighting, we examine the behavior of subjects for which perceived expertise and actual expertise diverge for a given gamble. To this end, we introduce a fourth measure of expertise, *misperceived expertise*, to identify subjects who have erroneous beliefs about their level of actual expertise.

Misperceived expertise is measured as a score which is increased by one if a subject answered a knowledge question regarding a gamble incorrectly but assigned a confidence rating of six or higher to the provided answer. For each knowledge question that is answered correctly while carrying a confidence rating of two or lower, the score is decreased by one. Hence, a subject's misperceived expertise score for a given gamble can range between -4 and +4. Positive scores are indicative for misperceived experts because they reveal a tendency to be highly confident in the provided answers even though they are incorrect (58 observations, 15%). In contrast, negative scores are characteristic of misperceived laymen as they indicate a lack of confidence in the provided answers even though they are correct (340 observations, 85%).

[12]Robustness tests show that the results remain virtually unchanged if we include the whole sample of observations (not reported).

TABLE 4 Impact of perceived expertise on probability weighting within subjects

Dependent variable	γ		
	(1)	**(2)**	**(3)**
Self-assigned expertise	0.026***		
	(0.007)		
Subjective expertise		0.020***	
		(0.007)	
Objective expertise			0.018**
			(0.009)
Constant	Yes	Yes	Yes
Subject fixed effects	Yes	Yes	Yes
N	392	392	392
Adj. R^2	0.68	0.68	0.67

Note: Coefficients from ordinary least squares regressions are reported. The curvature parameter γ of the Prelec (1998) one-parameter weighting function is regressed on the respective standardized measure of expertise (self-assigned, subjective, or objective). Subject fixed effects are included. Bootstrapped standard errors (in parentheses) are clustered at the subject level and based on 10,000 bootstrap replications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Analogous to the within-subjects analyses in the previous section, we first standardize our measure of misperceived expertise by conducting a within-subjects z-transformation (see Section 3.2.2 for details). Next, we regress the estimated γ-values on our standardized measure of misperceived expertise while including subject fixed effects. Hence, we examine the impact of a change in misperceived expertise on γ within subjects, thereby ruling out subject-specific differences as the driver of our results.

Column (1) of Table 5 presents the results from this regression. The estimated regression coefficient is positive and significant ($p < 0.10$). A one standard deviation increase in an individual's misperceived expertise relates to an average increase in γ of 0.015. Misperceived experts exhibit comparably less pronounced inverse-S-shaped probability weighting than misperceived laymen. Even though the effect is smaller compared with the one established for objective expertise (about 0.019, based on the same sample of 360 observations), it is still surprisingly large, given that misperceived expertise can only increase with high confidence in incorrect answers.

These results suggest that it is not objectively verifiable gamble-specific expertise that mitigates probability weighting, but rather a subject's perception of her own expertise. In line with this, misperceived experts rated their self-assigned expertise on average 2.1 points higher on the 7-point Likert scale than misperceived laymen ($p < 0.01$), indicating that subjects indeed consider themselves to be experts regarding the gamble despite their lack of actual expertise. Hence, we identify differences in perceived expertise as the key driver of ignorance illusion.

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. We therefore conduct a robustness test only including subjects whose actual performance on

TABLE 5 Impact of perceived expertise on probability weighting within subjects: The role of misperceived expertise and experience

Dependent variable	γ				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Misperceived expertise	0.015*				
	(0.008)				
Experience		0.033***	−0.011		0.027*
		(0.013)	(0.027)		(0.014)
Self-assigned expertise			0.031**		
			(0.015)		
Self-assigned expertise (beyond experience)				0.036**	0.031**
				(0.015)	(0.015)
Constant	Yes	Yes	Yes	Yes	Yes
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
N	360	392	392	392	392
Adj. R^2	0.67	0.68	0.68	0.68	0.68

Note: Coefficients from ordinary least squares regressions are reported. In Column (1) the curvature parameter γ of the weighting function is regressed on misperceived expertise. In columns (2)–(5), γ is regressed on experience and/or self-assigned expertise. Subject fixed effects are included. Bootstrapped standard errors (in parentheses) are clustered at the subject level and based on 10,000 bootstrap replications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the knowledge questions is in line with their confidence in the provided answers (not reported). The results indicate that the impact of perceived expertise 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.

3.2.4 | Role of experience

Previous studies suggest that individuals are less prone to behavioral biases as experience intensifies (List, 2003, 2004). Because experience and perceived expertise are likely to be positively correlated, we need to rule out variation in experience as an alternative explanation for our findings.

We measure experience as a binary variable that is equal to 1 if a subject has ever played the respective gamble and is 0 otherwise. Regressing γ on experience yields a positive and significant coefficient ($p < 0.01$), indicating that experienced subjects display less pronounced inverse-S-shaped probability weighting even in our descriptive setting (Column (2) of Table 5.). Column (3) includes the standardized measure of self-assigned expertise in the regression, in which case experience becomes insignificant, while the coefficient for the expertise measure is positive and significant ($p < 0.05$). Hence, we also document the mitigating impact of self-assigned expertise on probability weighting when controlling for a subject's experience regarding a gamble.

Next, we scrutinize the impact of variation in perceived expertise that is unrelated to experience. To this end, we first regress the standardized self-assigned expertise measure on experience. Residuals from that regression are uncorrelated with experience, that is, they only contain variation in expertise that cannot be explained by differences in experience. We therefore refer to these residuals as "self-assigned expertise (beyond experience)." Column (4) of Table 5 presents results from regressing γ on self-assigned expertise (beyond experience). The obtained coefficient is positive, significant ($p < 0.05$), and even larger in size compared with our previous analyses. Column (5) shows that this result holds regardless of whether experience is added as a control variable or not. Thus, we can replicate the mitigating effect of self-assigned expertise on probability weighting when only exploiting variation in expertise that is unrelated to experience.

Our findings suggest that experience does not seem to be the driver of the mitigating influence of perceived expertise on probability weighting. Instead, we provide evidence that perceived expertise mitigates the degree of inverse-S-shaped probability weighting beyond experience.

In summary, we provide experimental evidence that risk does not constitute a unique source of uncertainty. Instead, we find that the processing of objective probabilities in purely random gambles depends on subjects' levels of perceived expertise. Lower levels of perceived expertise regarding a risky event increase inverse-S-shaped probability weighting. Because in our experiment all probabilities are explicitly provided and outcomes are independent of knowledge, our results suggest that individuals are subject to ignorance illusion in decisions under risk.

4 | EXPERIMENT II

4.1 | Methodology

4.1.1 | Experimental design

The results from Experiment I indicate that an individual's perceived expertise regarding a decision under risk affects the degree of probability weighting. Subjects who assign themselves lower levels of expertise distort objective probabilities more than subjects with higher self-assigned expertise. We conduct Experiment II to explore whether manipulating the wrongly assigned importance of perceived expertise in the decision-making process alters the degree of probability weighting, that is, the presence of ignorance illusion. In addition, we examine whether ignorance illusion also occurs in the domain of losses and scrutinize the robustness of our findings by employing estimated in addition to assumed value function parameters.

To this end, we ran an online experiment with 101 subjects, with the majority being students at a German university. 42% of our participants are female, 46% have a Bachelor's degree, and the average age is 31 years. Completion time of the experiment was about 40 min, and subjects' choices were incentivized. As a thank you for participation, each subject took part in a lottery with the chance of winning one of two shopping vouchers worth 50 €. In addition, subjects were told upfront that four participants would be randomly selected after the experiment to have one of their (randomly selected) decisions played out for real money. Experimental currency units (ECU) were transformed using a 4:1 conversion rate (i.e., 100 ECU equal 25 €). The average payout amounted to 11.19 €.

To be able to ask additional questions to test our hypothesis in the loss domain and to estimate value function parameters, we needed to reduce the number risky choices compared with Experiment I. Hence, subjects were no longer confronted with three different random gambles but only made choices involving roulette. We chose roulette because it showed the strongest balance in terms of perceived experts and laymen in Experiment I and was therefore expected to yield reasonable group sizes also in Experiment II.

As before, subjects had to first fill out the questionnaire before receiving a short introduction of the gamble. In the gain domain, subjects then had to indicate certainty equivalents for binary prospects, in which they could either win 100 ECU with seven different probabilities $P \in \{1\%, 5\%, 10\%, 40\%, 90\%, 95\%, 99\%\}$ or receive 0 ECU otherwise. In the loss domain, subjects were first endowed with 100 ECU. They then had to indicate certainty equivalents for binary prospects, in which they could either lose 100 ECU with seven different probabilities $P \in \{1\%, 5\%, 10\%, 40\%, 90\%, 95\%, 99\%\}$ or lose 0 ECU otherwise. Again, the probabilities were first described in terms of specific game situations (see Table 6) and then stated explicitly. The domains and the order of probabilities within a domain were randomized.

In the gain domain, we elicited certainty equivalents analogous to Experiment I, that is, subjects made a series of choices between accepting a risky prospect or a sure payment (see Section 3.1.1 for details). In the loss domain, the procedure is largely identical with one exception: Instead of allowing subjects to indicate their choice between accepting the presented risky prospect or receiving a sure payment of X ECU, they had to indicate their choice between accepting the risky prospect or paying a sure fee of X ECU to avoid it. Note that while this amount is negative, we always consider its absolute value whenever we refer to certainty equivalents in the loss domain.

In addition to these roulette-specific choices in the gain and loss domain, we needed to include additional prospects enabling us to estimate a subject's value function parameters. We follow Abdellaoui et al. (2011) and employ the three-stage elicitation method described in Abdellaoui et al. (2008) based on the thirteen prospects described in Table 7. The assumed power value function for gains is defined by $v(x) = x^{\alpha}$ (cf. Experiment I) and for losses by $v(x) = -\lambda(-x)^{\beta}$ with $\alpha, \beta, \lambda > 0$. Six prospects are used to estimate α (β), that is, the curvature of the value function in the gain (loss) domain. One additional mixed prospect was used to derive the loss aversion coefficient λ. Probability P_g is set to 40%, probability P_l to 60% ($=1-P_g$), and G^* to 50. The order of domains and the order of prospects within a domain was randomized.

After eliciting the certainty equivalents (CE_i) for the six gain prospects (x_i, P_g; y_i), the above parametric specification yields the following equation:

TABLE 6 Complementary descriptions of specific game situations in roulette to illustrate objective probabilities

P	Game situation
1%	Win at least 7 times in 45 consecutive rounds, each time betting on a Cheval
5%	Win at least 15 times in 88 consecutive rounds, each time betting on a Carré
10%	Win at least 10 times in 59 consecutive rounds, each time betting on a Carré
40%	Win at least 3 times in 21 consecutive rounds, each time betting on a Carré
90%	Win at most 9 times in 59 consecutive rounds, each time betting on a Carré
95%	Win at most 14 times in 88 consecutive rounds, each time betting on a Carré
99%	Win at least 2 times in 79 consecutive rounds, each time betting on a Transversale Plein

TABLE 7 Risky prospects underlying the estimation of value function parameters

	Gain domain						Loss domain						Mixed
i	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
x_i	20	40	60	100	100	100	−20	−40	−60	−80	−100	−100	50
y_i	0	0	0	0	60	80	0	0	0	0	−60	−80	*

$$CE_i = \left(w^+(P_g)\cdot\left(x_i^\alpha - y_i^\alpha\right) + y_i^\alpha\right)^{1/\alpha}, \tag{2}$$

where α and $w^+(P_g)$ are estimated through nonlinear least squares. $w^+(P_g)$ reflects the impact of probability weighting at probability P_g. Keeping probability P_g fixed at only one point has the advantage that only one point of the probability weighting function plays a role in the process of estimating the value function parameters (Abdellaoui et al., 2008). By including the decision weight as an additional parameter that has to be estimated, no assumptions regarding the functional form of a subject's probability weighting are required. Hence, the value function parameters can be estimated without specifying the probability weighting function, while still taking individual heterogeneity in probability weighting into account.

To elicit β, that is, the value function parameter in the loss domain, the procedure is largely similar. After eliciting the certainty equivalents for the six loss prospects (x_i, P_l; y_i) for which $0 \geq y_i > x_i$ the following equation can be fitted using nonlinear least squares:

$$|\,CE_i\,| = (w^-(P_l)\cdot(|\,x_i\,|^\beta - |\,y_i\,|^\beta) + |\,y_i\,|^\beta)^{1/\beta}, \tag{3}$$

where β and $w^-(P_l)$ are to be estimated. $w^-(P_l)$ reflects the impact of probability weighting at probability P_l. Note that in this setup the loss aversion parameter λ cancels out and therefore plays no role when estimating β. We winsorize α and β at the 1st and 99th percentiles.

To explore whether manipulating subjects' wrongly assigned importance of perceived expertise affects the presence of ignorance illusion, we randomly assigned participants to one of three groups. In the control group (C), the experiment was conducted as described above and no additional information was provided.

In the first treatment group (T1), we aimed at making the implicit assumption underlying ignorance illusion explicit. Thus, we provided subjects with additional statements that encouraged making use of individual expertise regarding roulette when making their choices (see Table 8 for details). Since we are merely emphasizing the role of perceived expertise which subjects seem to assign to it themselves, we expect to observe a similar difference in probability weighting between experts and laymen in the first treatment and in the control group.

Subjects in the second treatment group (T2) were provided with additional statements that highlighted the irrelevance of individual expertise regarding roulette in the respective choices instead. By stating that roulette outcomes are independent of expertise and that laymen have no disadvantage compared with perceived experts when making the decisions, we intended to disable the expertise-related mechanism underlying ignorance illusion. We therefore expect that the degree of probability weighting does not differ between experts and laymen, that is, that we do not observe ignorance illusion for the second treatment group.

The final part of the experiment consisted of an additional questionnaire regarding a subject's cognitive abilities, overconfidence, self-distancing, and personal information. Furthermore, we included a binary item as manipulation check to evaluate whether subjects believed that their expertise regarding roulette was helpful when making the respective choices.

TABLE 8 Treatment-specific information regarding the role of perceived expertise

	Statement 1 (after instructions)	Statement 2 (before each domain)
Treatment 1	"You can make use of your individual expertise regarding the gamble roulette to work through the following decision situations as good as possible. Try this even if you never or rarely played roulette and would not consider yourself an expert in roulette."	"Make use of your expertise regarding roulette when answering the questions."
Treatment 2	"Note that in the following decision situations all probabilities are explicitly provided, and that the outcome of the gamble roulette is independent of individual expertise. Hence, laymen in roulette can make as good decisions as players who would consider themselves experts."	"Whether or not you have expertise regarding roulette should not affect how you answer the questions."

Note: Statement 1 was included at the end of the roulette instructions (after the sentence: "State for every decision situation whether you prefer participating in roulette or the sure payment."). Statement 2 was included at the beginning of the gain and loss domain, after the introduction of the respective domain and before making the first choice in the domain.

The translated experimental instructions and questionnaires are provided in Supporting Information Appendix B.

4.1.2 | Data and variables

We obtain data on participants' certainty equivalents in two subsequent stages, both comprised of prospects in the gain and loss domain. First, we elicit 13 certainty equivalents required to estimate the parameters of the value function (six for each domain plus one for determining the loss aversion parameter). Second, 14 certainty equivalents are elicited to derive the probability weighting function parameters (seven for each domain). We apply the same inclusion criteria as in Experiment I to both stages. As the value function parameters are needed inputs when fitting the probability weighting functions, only subjects who provided valid answers in both stages within a domain can be included in the final sample (91 different subjects; 146 observations, 80 in the gain domain, 66 in the loss domain).

As we identified the key role of *self-assigned expertise* for ignorance illusion in decisions under risk in Experiment I, we exclusively focus on this measure in Experiment II. This decision is also based on the chosen treatments, which focus on highlighting or downplaying the role of perceived expertise in the decision-making process. Identical to Experiment I, 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). Self-assigned expertise across subjects is 3.32 on average (standard deviation: 1.77; minimum: 1; maximum: 6). Subjects are classified as self-assigned experts in roulette if they rated their expertise as four or higher (46%) and as self-assigned laymen otherwise (54%). The share of expert and layman observations within domains is almost identical (gain domain: 45% vs. 55%; loss domain: 47% vs. 53%).

4.1.3 | Estimation of probability weighting functions

We first estimate subjects' value function parameters utilizing the 13 first-stage certainty equivalents. The power estimates of the value function exhibit considerable heterogeneity ($Q^{\alpha}_{0.05} = 0.69$; $Q^{\alpha}_{0.95} = 1.56$; $Q^{\beta}_{0.05} = 0.74$; $Q^{\beta}_{0.95} = 2.10$) with a median close to one in both domains ($Q^{\alpha}_{0.50} = 1.02$; $Q^{\beta}_{0.50} = 1.08$). For gains (losses), the value function is concave if $\alpha < 1$ ($\beta > 1$), linear if $\alpha = 1$ ($\beta = 1$), and convex if $\alpha > 1$ ($\beta < 1$). Next, we employ these estimates to derive seven decision weights per subject and domain as follows:

$$w^{+}(\mathrm{P}) = \frac{(CE_{\mathrm{P}})^{\alpha}}{100^{\alpha}},\qquad w^{-}(\mathrm{P}) = \frac{(|\ CE_{\mathrm{P}}\ |)^{\beta}}{|\ -100\ |^{\beta}}. \tag{4}$$

As in Experiment I, we employ the Prelec (1998) one-parameter weighting function $w(\mathrm{P}) = e^{-(-ln(\mathrm{P}))^{\gamma}}$, where $\gamma > 0$ determines the curvature and $0 < \gamma < 1$ results in the typical inverse S-shape of this function. The weighting function parameter is estimated individually for each participant and each domain using nonlinear regressions. We winsorize the estimated parameters at the 1st and 99th percentiles.

To evaluate how the estimation of γ based on an *assumed* value function parameter ($\alpha = 1$) employed in Experiment I compares with an *estimated* value function parameter (being the default in Experiment II), we additionally fit probability weighting functions based on assumed value function parameters as described in Section 3.1.3 (with $\alpha = 1$ and $\beta = 1$). For reasons of comprehensibility, we will generally refer to using estimated (assumed) value function parameters as the $\alpha_{\text{estimated}}$ (α_{assumed}) specification, although it equally concerns the curvature elicitation of the value function in the gain domain (α) and the loss domain (β).[13]

Again, we repeat our main analyses using the nonparametric approach proposed by Dimmock et al. (2020) (cf. Supporting Information Appendix C) or the Prelec (1998) two-parameter weighting function (cf. Supporting Information Appendix D). Both robustness tests leave our findings qualitatively unchanged.

4.2 | Results

4.2.1 | Differences in certainty equivalents

Table 9 presents medians of stated certainty equivalents for self-assigned experts and laymen across different probabilities P, separately for the control and treatment groups. In addition, it contains the corresponding z-scores of Wilcoxon's rank-sum tests to analyze differences in certainty equivalents between experts and laymen.

Differences in certainty equivalents between experts and laymen in the control (C) and first treatment group (T1) are, as expected, highly similar and support the findings established in Experiment I. While experts state significantly smaller certainty equivalents for low probabilities (P < 40%) than laymen, they provide comparatively larger certainty equivalents for high probabilities (P > 40%). Only minor differences in stated certainty equivalents can be detected for P = 40%.

[13] In unreported robustness tests, we also fit probability weighting functions using homogeneous value function parameters across subjects and domains with $\alpha, \beta \in \{0.76, 0.88\}$. These alternative specifications leave our results virtually unchanged.

TABLE 9 Certainty equivalents for experts and laymen by control and treatment groups

	P						
	1%	**5%**	**10%**	**40%**	**90%**	**95%**	**99%**
Control							
Laymen	2	8	11	40	85	92	97
Experts	1	5	9	38	88	92	97
z-score	3.27***	3.21***	3.41***	0.70	−0.65	−0.34	−0.89
Treatment 1							
Laymen	3	7	12	39	86	92	96
Experts	1	5	10	39	89	94	98
z-score	4.14***	4.46***	5.11***	−0.32	−2.08**	−1.37	−1.07
Treatment 2							
Laymen	2	5	10	39	87	92	97
Experts	3	8	14	40	86	93	97
z-score	−1.09	−2.92***	−3.30***	−1.71*	0.05	−0.19	−0.11

Note: The median certainty equivalents for experts and laymen for each probability P within the respective control and treatment groups are reported. The *z*-scores of Wilcoxon's rank-sum tests conducted to compare the certainty equivalents of experts and laymen within a group are also provided. ***, **, and * indicate significant differences in medians across subgroups at the 1%, 5%, and 10% levels, respectively.

The similarity between the control and the first treatment group suggests that we indeed simply made the implicit assumption employed by the control group ("perceived expertise matters") explicit for subjects in the first treatment group. Median certainty equivalents stated by experts (laymen) in the control group do not significantly differ from the ones provided in the first treatment group for any probability level. Hence, neither experts nor laymen changed their behavior in response to the first treatment. The answers to our question serving as manipulation check confirm this. In the control group, 52% of subjects believed that expertise regarding roulette was helpful when making the respective choices. In the first treatment group, this proportion amounts to 57%, which is not significantly different from the proportion in the control group. For these reasons, we will pool all subjects from the control (C) and the first treatment (T1) groups in the further analyses, forming an extended control group.

In contrast, the expert and laymen valuations of the proposed risky prospects in the second treatment group (T2) substantially differ from the other groups. By emphasizing that roulette outcomes are independent of expertise and by highlighting that laymen have no disadvantage compared with perceived experts when making the decisions, we affected the behavior of both experts and laymen. For small probabilities, median certainty equivalents stated by experts are significantly larger compared with experts from other groups ($p < 0.01$), while they are similar for high probabilities. This pattern suggests that experts in the second treatment group behave more like laymen in the other groups, particularly for small probabilities. At the same time, median certainty equivalents stated by laymen are significantly smaller compared with laymen from other groups for small probabilities ($p < 0.05$), while they are similar for high probabilities. Hence, laymen show a tendency to behave more like experts when confronted with small probabilities. As a result, the differences in median certainty equivalents between experts and laymen are considerably smaller compared with the other groups, providing first evidence for the effectiveness of our second treatment. The effectiveness of the treatment is also underlined by answers to our question serving as manipulation check. None of the subjects (0%) in the second treatment group believed that expertise regarding roulette was helpful when making the respective choices. This proportion is significantly smaller than in the other groups ($p < 0.01$).

4.2.2 | Differences in probability weighting estimates

To scrutinize the existence of ignorance illusion across the extended control and second treatment groups, we now compare the elicited probability weighting function parameters between self-assigned experts and laymen. Figure 2 illustrates median γ-estimates for both groups. The bar charts in the top row show γ-values based on the estimated value function parameters ($\alpha_{\text{estimated}}$ specification), the bar charts in the bottom row based on assumed value function parameters (α_{assumed} specification).

The left bar chart in the top row of Figure 2 shows median γ-values for experts and laymen in the extended control group (C and T1). As γ is smaller than one for experts and laymen, both probability weighting functions exhibit the typical inverse S-shape. Hence, low (tail) probabilities are overweighted and high probabilities are underweighted regardless of the level of perceived expertise. However, experts engage much less in probability weighting than laymen as indicated by the significantly larger γ (0.92 vs. 0.81; $p < 0.01$). These results confirm the presence of ignorance illusion in decisions under risk as established in Experiment I. Utilizing curvature estimates based on assumed value function parameters (left bar chart in the bottom row) yields the same conclusion (0.95 vs. 0.85; $p < 0.05$).

Ignorance illusion is present in both domains, as the middle bar charts in the top row indicate. However, the difference in γ is more pronounced in the gain domain (0.96 vs. 0.81; $p < 0.05$) than in the loss domain (0.87 vs. 0.80; $p < 0.10$). When considering curvature estimates based on assumed value function parameters (middle bar charts in the bottom row), the results are similar. Again, the degree of ignorance illusion is more pronounced in the gain domain (0.97 vs. 0.85; $p < 0.05$) than in the loss domain (0.89 vs. 0.82; $p < 0.10$).

The right bar chart in the top row of Figure 2 presents median γ-values for experts and laymen in the second treatment group (T2). The results speak to the effectiveness of the treatment designed to disable the expertise-related mechanism underlying ignorance illusion. The estimated curvature of the probability weighting function is no different for experts than for laymen (0.83 vs. 0.84; $p = 0.87$). In fact, experts and laymen exhibit almost equally pronounced inverse-S-shaped probability weighting.[14] This equality is largely induced by the experts in the second treatment group as they display amplified inverse-S-shaped probability weighting compared with experts in the other groups ($p < 0.05$). In addition, laymen engage slightly less in probability weighting compared with laymen from the other groups ($p = 0.23$). In combination, these changes caused ignorance illusion to fully diminish. This result is confirmed when considering curvature estimates based on assumed value function parameters (right bar chart in the bottom row; 0.83 vs. 0.87; $p = 0.58$). Hence, when subjects are made aware of the irrelevance of perceived expertise in decisions under risk, they do not exhibit

[14]This result also holds when considering the gain and loss domain separately. Median γ-values for experts and laymen in the second treatment group are not significantly different within each domain ($p > 0.10$). For reasons of comprehensibility, we refrained from including the corresponding bar charts in the figure.

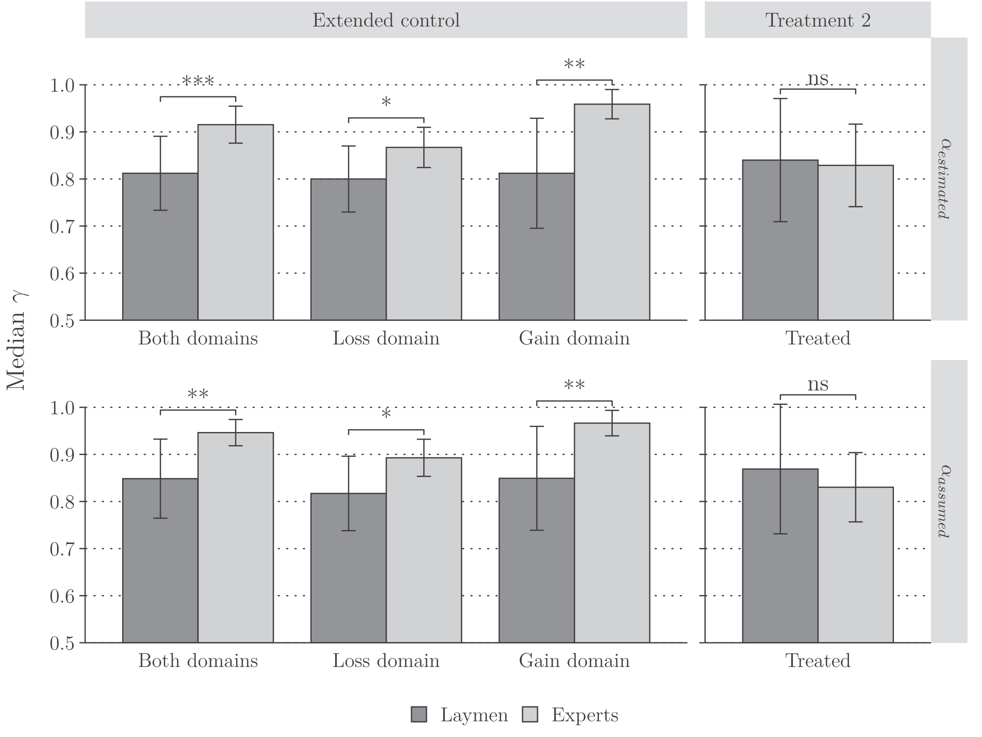

FIGURE 2 Probability weighting function γ-estimates for experts and laymen by control and treatment groups. This figure shows the median γ-values from estimating Prelec (1998) one-parameter weighting functions and their 95% confidence interval for experts and laymen, separately for the extended control and second treatment groups and both α-specifications employed ($\alpha_{\text{estimated}}$, α_{assumed}). Expert and layman classifications are based on the self-assigned measure of expertise. *Extended control* refers to subjects from the extended control group (C and T1). *Treatment 2* refers to subjects from the second treatment group (T2). Differences in medians are assessed with quantile regressions using bootstrapped standard errors clustered at the subject level based on 10,000 bootstrap replications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

ignorance illusion anymore. Consequently, perceived experts process objective probabilities in the same manner as subjects who perceive themselves as laymen.[15]

Next, we explore the marginal impact of perceived expertise on probability weighting across the extended control and second treatment groups. Table 10 reports the results from regressing γ on self-assigned expertise. In all four regression models, we interact our raw self-assigned expertise measure with a dummy variable (*Treatment 2*) that equals 1 for all subjects from the second treatment group (T2) and is 0 otherwise. The interaction effect therefore describes the difference in marginal impact of perceived expertise on probability weighting between the second treatment group and the extended control group (C and T1). As a robustness test, models (2) and (4) additionally include a dummy variable (*Loss domain*) that equals 1 for γ-estimates in the loss domain and is 0 otherwise. Models (1) and (2) employ γ-values based on estimated value function parameters ($\alpha_{\text{estimated}}$), while models (3) and (4) utilize γ-values based on assumed value function parameters (α_{assumed}).

[15]Figure E.2 in Supporting Information Appendix E nicely illustrates this effect by comparing the plots of the expertise-dependent probability weighting functions of the second treatment group with those of the other groups.

TABLE 10 Impact of perceived expertise on probability weighting within subjects by control and treatment groups

Dependent variable	$\gamma_{\alpha_{\text{estimated}}}$		$\gamma_{\alpha_{\text{assumed}}}$	
	(1)	**(2)**	**(3)**	**(4)**
Self-assigned expertise	0.028***	0.030***	0.028***	0.029***
	(0.007)	(0.007)	(0.006)	(0.006)
Treatment 2	0.081	0.095	0.125**	0.134**
	(0.073)	(0.068)	(0.060)	(0.057)
Treatment 2 × Self-assigned expertise	−0.029*	−0.033**	−0.039***	−0.042***
	(0.017)	(0.017)	(0.014)	(0.014)
Loss domain		−0.063***		−0.039**
		(0.022)		(0.018)
Constant	Yes	Yes	Yes	Yes
N	146	146	146	146
Adj. R^2	0.05	0.09	0.08	0.09

Note: Coefficients from ordinary least squares regressions, separately for both α-specifications employed ($\alpha_{\text{estimated}}$, α_{assumed}) are reported. The curvature parameter γ of the Prelec (1998) one-parameter weighting function is regressed on the raw self-assigned measure of expertise. *Treatment 2* is a dummy variable that equals 1 for subjects in the second treatment group (T2) and is 0 for subjects in the extended control group (C and T1). Bootstrapped standard errors (in parentheses) are clustered at the subject level and based on 10,000 bootstrap replications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The significant ($p < 0.01$) and positive coefficient of self-assigned expertise across models confirms the existence of ignorance illusion for subjects in the extended control group. If self-assigned expertise increases by one unit (on a 7-point scale), γ increases by about 0.03 on average, indicating less pronounced inverse-S-shaped probability weighting. In contrast, due to the slightly larger, negative, and significant (at least $p < 0.10$) interaction effect of self-assigned expertise with belonging to the second treatment group, the marginal impact of perceived expertise on probability weighting completely vanishes for the second treatment group. Hence, subjects in the second treatment group do not exhibit ignorance illusion, confirming the results from above. Furthermore, the positive and sometimes significant coefficient for *Treatment 2* indicates that laymen in the second treatment group engage slightly less in probability weighting than laymen in the extended control group.

Given that our conclusions regarding the impact of perceived expertise on probability weighting are independent of whether estimated or assumed value function parameters are employed, it can be argued that both approaches produce consistent and reliable results, thus justifying the use of the latter in Experiment I.

In summary, the findings from Experiment II further support the fact that decision makers are generally subject to ignorance illusion in decisions under risk. Lower levels of perceived expertise amplify the typical pattern of underweighting high, and overweighting small (tail) probabilities. This phenomenon occurs in both the gain and the loss domain, but is more pronounced in the former. Perceived expertise can therefore be seen as counter-bias mechanism that facilitates a more linear, that is, rational processing of objective probabilities. Informing decision makers about the irrelevance of perceived expertise in decisions under risk eliminates ignorance illusion. However, such a treatment does not facilitate perceived laymen to distort probabilities less and behave more like perceived experts. Instead, it causes perceived experts to farther astray from rational decision making and behave more like perceived laymen.

5 | CONCLUSION

This paper provides experimental evidence that individuals exhibit more pronounced inverse-S-shaped probability weighting if their level of perceived expertise is lower regarding a decision under risk. To vary the level of perceived expertise in a purely random decision situation, we utilize different gambles 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 gambles, the curvature of a subject's probability weighting function decreases in a subject's perceived expertise. Thus, individuals overweight low (tail) probabilities and underweight high probabilities more strongly if they feel less knowledgeable about a decision involving outcomes that are random.

Our results point to an overarching importance of perceived expertise across sources of uncertainty. The fact that differences in perceived expertise alter how individuals process objective probabilities suggests that individuals are subject to *ignorance illusion* in decisions under risk. These findings build on the already established impact of perceived expertise on ambiguity attitudes (Abdellaoui et al., 2011; Fox & Tversky, 1995; Heath & Tversky, 1991) and extend it to the domain of risk. Regardless of whether an individual is facing a decision under risk or ambiguity, higher levels of perceived expertise cause individuals to weight probabilities less strongly and thereby affect the attractiveness of uncertain alternatives. This insight is important as in many real-world investment and insurance contexts it is unclear whether and to what extent the decision maker is informed about the outcomes' probability distributions (Jaspersen, 2016).

Our findings imply that the domain of risk does not constitute a unique source of uncertainty which contradicts an important assumption that is commonly made in current decision-making models (Abdellaoui et al., 2011; Chew & Sagi, 2008; Ergin & Gul, 2009; Nau, 2006). Rather than only allowing probability weighting functions to vary in the domain of ambiguity, it seems required to model the same degree of freedom in the domain of risk. Developing a framework that incorporates the idea of expertise-dependent weighting functions seems advisable. This might also help to better explain differences in investment and insurance behavior caused by the perception of one's own expertise.

Our research also relates to the link between cognitive uncertainty and probability weighting recently proposed by Enke and Graeber (2021). They provide evidence that individuals who perceive their answer to a decision problem (such as stating a certainty equivalent for a price list) as more cognitively noisy (larger interval surrounding the stated certainty equivalent) exhibit stronger inverse-S-shaped probability weighting. If one assumes that perceived experts regarding a decision under risk are able to state their certainty equivalents with higher precision (being exposed to less cognitive uncertainty), our results are in line with the Enke and Graeber (2021) framework. However, even though perceived expertise might also partly capture cognitive problems in the certainty equivalent formation process, the treatment effects observed in Experiment II suggest that both concepts are complements rather than substitutes to explain risky choice. We did not vary the decision situation that participants faced in terms of cognitive uncertainty. Enke and Graeber (2021) manipulate cognitive uncertainty by switching from simple lotteries to either compound or even ambiguous lotteries. Both types of lotteries substantially increase the cognitive demands to construct probabilities and make choices. In our setting, we did not alter the level of cognitive uncertainty across treatment and control groups. Instead, we informed treated subjects about the irrelevance of perceived expertise in the decision-making process while keeping the explicitly provided outcomes and probabilities constant. Still, experts in the treatment group display more pronounced inverse-S-shaped probability weighting than experts in the control group. Moreover, the fact that laymen in the treatment group engage slightly less in probability weighting than laymen in the control group even rules out an unintended increase in cognitive uncertainty due to the treatment. If the latter were the case, a symmetric treatment effect (increase in inverse-S-shaped probability weighting for both experts and laymen) would have emerged. These results suggest that ignorance illusion affects behavior beyond cognitive limitations in decisions under risk.

Furthermore, we find that ignorance illusion prevails in both the gain and loss domain and that it emerges regardless of whether estimated or assumed value function parameters are employed. In addition, informing decision makers about the irrelevance of perceived expertise in decisions under risk eliminates expertise-dependent differences in probability weighting. However, it does not help perceived laymen to process probabilities in a more linear, that is, rational fashion, but instead causes perceived experts to distort probabilities more strongly. Hence, future research should explore how to exploit perceived expertise as a counter-bias mechanism to achieve more rational processing of objective probabilities in decisions under risk.

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Additional Supporting Information may be found online in the supporting information tab for this article.

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