Investment Behaviors Under Epistemic versus Aleatory Uncertainty

Daniel J. Walters, Assistant Professor of Marketing, INSEAD Asia, Marketing Department, daniel.walters@insead.edu

Gülden Ülkümen, Gülden Ülkümen, Associate Professor of Marketing at University of Southern California, 701 Exposition Boulevard, Hoffman Hall 516, Los Angeles, CA 90089-0804, ulkumen@marshall.usc.edu

Carsten Erner, UCLA Anderson School of Management, 110 Westwood Plaza, Los Angeles, CA, USA 90095-1481, carsten.erner@outlook.com

David Tannenbaum, Assistant Professor of Management, University of Utah, Salt Lake City, UT, USA, (801) 581-8695, david.tannenbaum@utah.edu

Craig R. Fox, Harold Williams Professor of Management at the UCLA Anderson School of Management, Professor of Psychology and Medicine at UCLA, 110 Westwood Plaza #D511 Los Angeles, CA, USA 90095-1481, (310) 206-3403, craig.fox@anderson.ucla.edu

Abstract

We provide evidence that investor behavior is sensitive to two dimensions of subjective uncertainty concerning future asset values. Investors vary in the extent to which they attribute market uncertainty to: (1) missing knowledge, skill, or information (epistemic uncertainty), and (2) chance or stochastic processes (aleatory uncertainty). Investors who view stock market uncertainty as higher in epistemicness (knowability) are more likely to reduce uncertainty by seeking guidance from experts and are more influenced by available information when choosing whether or not to invest. In contrast, investors who view stock market uncertainty as higher in aleatoriness (randomness) are are more likely to reduce uncertainty through diversification and are more sensitive to their risk preference when choosing whether or not to invest. We show, further, that attributions of uncertainty can be perturbed by the format in which historical information is presented: charts displaying absolute quarterly stock prices promote perceptions of epistemicness and greater willingness to pay for financial advice, whereas charts displaying the change in stock prices from one quarter to the next promote perceptions of aleatoriness and a greater tendency to diversify.

Keywords: Uncertainty, Epistemic, Aleatory, Investing, Financial Decision Making

Investment Behavior Under Epistemic versus Aleatory Uncertainty

Among the most important financial decisions we make are how to invest our savings, and different people approach investment decisions in dramatically different ways. Whereas some investors carefully select individual assets such as stocks based on research and financial advice, others diversify among larger bundles of assets, for instance by purchasing index funds. These stylized tendencies map onto two principal market segments: as of the end of 2017, about 45% of U.S. equity assets were held in passively managed funds and the remainder in either actively managed funds or individual stocks (Bloomberg, 2018). Predicting when consumers will pursue these different styles of investing, and understanding why they do so, presents both a theoretical challenge for behavioral scientists and a practical concern for marketing professionals in the financial services sector.

In this paper we argue that distinct investment strategies are driven by investors' beliefs concerning the fundamental nature of market uncertainty. To illustrate, consider two investors, Warren and Burt. Warren views investment as primarily a game of skill: with the right information and investment strategy, one can identify winning and losing assets in advance and outperform the market. As a result, Warren spends considerable time and money researching individual assets and consulting experts. In contrast, Burt views investment as primarily a game of chance: prices fully incorporate all available information and expectations so that movements of assets are inherently stochastic and nobody can reliably pick winners and losers in advance. Instead, Burt focuses his efforts on maintaining a diversified portfolio of assets that reflect his appetite for risk.

We propose that Warren's and Burt's mental models reflect an intuitive distinction that most investors make about the nature of stock market uncertainty. Market uncertainty can be

viewed as *epistemic* in nature, arising from deficiencies in one's knowledge, information, or skills in assessing an event that is, in principle, knowable in advance. Market uncertainty can also be viewed as *aleatory* in nature, arising from processes that are treated, for all intents and purposes, as random or stochastic. Simple examples of pure epistemic uncertainty include whether or not one has correctly answered a trivia question or solved a math problem, while examples of pure aleatory uncertainty include whether or not one has correctly predicted the outcome of a coin flip or the spin of a roulette wheel.

While the ontological distinction between epistemic and aleatory uncertainty has historical roots in the foundations of modern probability theory (Hacking 1975), the psychological distinction between these dimensions has only recently been investigated empirically (e.g., Fox, Goedde-Menke and Tannenbaum, 2021; Fox, Tannenbaum, Ülkümen, Walters and Erner, 2021; Tannenbaum, Fox, and Ülkümen 2017; Ülkümen, Fox, and Malle 2016). This research finds that perceptions of epistemic and aleatory uncertainty affect how people communicate their beliefs, judge probabilities, and make decisions. People tend to communicate degrees of epistemic uncertainty using expressions such as “I’m 90% sure” or “I’m fairly confident” whereas they tend to communicate degrees of aleatory uncertainty using expressions such as “I think there’s a 90% chance” or “I’d say there’s a high likelihood” (Ülkümen, Fox, and Malle 2016). Forecasters tend to make more extreme probability judgments when they view relevant uncertainty to be more epistemic in nature, and tend to make more regressive judgments when they perceive uncertainty to be more aleatory in nature (Tannenbaum, Fox, and Ülkümen 2017). When evaluating others, managers prefer to tie a greater proportion of workers’ compensation to performance-based pay to the extent that such forecasts are made under epistemic uncertainty, whereas they prefer to have longer evaluation windows to the extent that such forecasts are made under aleatory uncertainty (Fox,

Tannenbaum, Ülkümen, Walters and Erner, 2021). The present article extends this stream of work to the important domain of investment decisions.

We pause to emphasize two unique features of the present framework that distinguish it from previous treatments of variants of uncertainty (most notably, Kahneman and Tversky 1982; for references to additional frameworks see Fox and Ülkümen, 2011). First, we treat epistemic and aleatory as distinct dimensions of subjective uncertainty. Thus, one investor may see stock movements as *both* more knowable and more random than another, just as one investor may exhibit both more information seeking and more diversification than another. Second, we distinguish subjective *nature* of uncertainty (epistemic or aleatory) from *level* of uncertainty. Individuals can experience high or low levels of uncertainty, regardless of whether they view that uncertainty as epistemic or aleatory in nature. For instance, two people may see future stock movement as entirely knowable in principle (i.e., epistemic in nature) but differ in how much confidence they have in their predictions (i.e., vary in their judged level of epistemic uncertainty). Likewise, two people may both see future stock movement as entirely stochastic (i.e., aleatory in nature) but differ in their assessment of the entropy of the probability distribution over possible outcomes (i.e., vary in their judged level of aleatory uncertainty).

To keep the distinction between nature and level of uncertainty clear, we refer to the perceived nature of market uncertainty as *epistemicness* and *aleatoriness.* We measure these two dimensions using an instrument developed elsewhere, the Epistemic-Aleatory Rating Scale (EARS; Fox et al., 2021). To empirically distinguish the *nature* from *level* of uncertainty, we either manipulate or measure each construct in most of our studies. Our central thesis is that: (1) when investors perceive greater epistemicness they are more sensitive to the level of epistemic uncertainty (i.e., how much relevant knowledge, skill, or information they think they have at their disposal), and (2) when investors perceive greater aleatoriness they are more sensitive to the

level of aleatory uncertainty (i.e., assessed volatility of a particular investment or entropy in the probability distribution over outcomes).

In the context of financial investing, people are generally understood to attempt to maximize expected returns while minimizing variability in possible returns (e.g., Markowitz 1952). Because epistemic uncertainty is attributed to missing knowledge, information, or skill, investors who view the market as more epistemic in nature should be more sensitive to relevant information they have available when making investment decisions. Thus, we expect that such investors will attempt to reduce uncertainty by seeking information or consulting experts, will express a greater willingness to pay for financial information or advice, and will make investment decisions that are more responsive to the financial advice they obtain. In contrast, because aleatory uncertainty is attributed to stochastic and inherently unpredictable processes, risk averse investors who view the market as more aleatory in nature should be more likely to engage in general risk management strategies such as asset diversification[1]. This prediction accords with prior research showing that when people have greater difficulty distinguishing between identified options they tend toward even allocations over those options (e.g., Fox, Ratner and Lieb 2005).[2] When uncertainty is seen as aleatory in nature, investors treat different outcomes as draws from random distributions and therefore do not focus on singular events or distinguish which event will obtain (for example, which stock will perform best in a particular time frame). Note that such "spreading" strategies do not necessarily imply optimal diversification (Benartzi and Thaler 2001), but rather a naive attempt to reduce risk exposure (Reinholtz, Fernbach, and De Langhe 2020). In addition, we expect that individuals who treat uncertainty as more random in nature will make decisions that accord more closely with their degree of risk tolerance when making choices involving chance gambles. To summarize, we predict that under epistemic uncertainty investors focus on reducing their ignorance and are more

responsive to information and advice, whereas under aleatory uncertainty they focus on reducing their risk exposure and are more responsive to volitility levels and risk preferences.

While most prior research on equity trading and portfolio choice has treated uncertainty as a single dimension (e.g., Capon, Fitzsimons, and Prince 1996; Cohn et al. 1975; Goetzmann and Kumar 2008), the economics literature has long acknowledged the relevance of second-order uncertainty to decision making. Keynes (1921) argued that decision makers ought to prefer to bet on probabilities that are supported by a larger weight of evidence, and Knight (1921) proposed that entrepreneurs are compensated for exposing themselves to *uncertainty* (unknown probability distributions over outcomes) as opposed to *risk* (known probability distributions over outcomes). More recently this has given rise to a robust literature on ambiguity aversion (Ellsberg, 1961; for reviews see Camerer and Weber, 1992; Machina and Siniscalchi, 2014). While economic theories typically model ambiguity using second-order probability distributions, multiple priors, or multi-stage lotteries, psychologists have provided experimental evidence that ambiguity aversion reflects reluctance to act in situations where the decision maker feels relatively ignorant, unskilled, or uninformed (Heath and Tversky, 1991; Fox and Tversky, 1995; Fox and Weber, 2002). Thus, in our framework, the distinction between risk and ambiguity can be construed as a distinction between purely aleatory uncertainty and uncertainty that is at least partly epistemic in nature (Fox and Ülkümen, 2011), and ambiguity aversion can be interpreted as reluctance to bet in situations where one experiences higher levels of epistemic uncertainty (Fox, Goedde-Menke and Tannenbaum, 2021).

In this paper we depart from this prior literature on ambiguity and investing in three important respects. First, we are not interested in the relationship between levels of uncertainty and investment behavior, but rather the relationship between perceived nature of uncertainty and sensitivity to these dimensions (for example, the relationship between perceived epistemicness or

aleatoriness and the desire to reduce ignorance or riskiness, respectively). Second, we do not treat epistemicness and aleatoriness as objective features of investments but rather as subjective appraisals of market uncertainty that may vary between individuals or even within-individuals as a function of how market data are presented. Third, unlike prior empirical work that is purely correlational we experimentally manipulate the extent to which market uncertainty is seen as epistemic versus aleatory and examine resulting investment strategies.

A visual depiction of the main hypotheses that follow from our conceptual model is presented in Figure 1. The first panel (Figure 1A) displays predictions concerning financial advice seeking. We expect assessments of greater epistemicness to be more strongly associated with an increased tendency to seek expert advice (path a) than assessments of greater aleatoriness (path b). The second panel (Figure 1B) displays predictions concerning naïve diversification. We expect assessments of greater aleatoriness to be more strongly associated with an increasing tendency toward asset diversification (path c) than assessments of greater epistemicness (path d), especially under conditions of higher volitility (path e).[3]

The final panel (Figure 1C) presents predictions concerning willingness to invest in a particular asset. First, we expect that assessments of greater epistemicness will amplify the impact of expert advice on willingness to invest (path f) more than assessments of greater aleatoriness (path g). Thus, to the extent that investors view market uncertainty as epistemic in nature, they should make investment decisions that are more strongly influenced by expert advice. Second, we expect that assessments of greater aleatoriness (i.e., an increased tendency to view stock investment as a chance gamble) will amplify the impact of an investor's risk preference on their willingness to invest (path h) more than assessments of greater epistemicness (path g).

Overview of Studies

We test our conceptual framework (depicted in Figure 1) across a number of studies (see Table 1). In Study 1 we examine actual investment decisions using a panel of retail investors and find that those who view stock market uncertainty as higher in epistemicness are more likely to rely on financial advice (i.e., Figure 1, path a), whereas those who view stock market uncertainty as higher in aleatoriness are more likely to engage in diversification (i.e., Figure 1, path c). In Studies 2 and 3 we directly manipulate assessments of epistemicness and aleatoriness by altering the presentation of historical stock information. In Study 2, we find that framing stock movements to focus on absolute price trends increases willingness to pay for an analyst's advice, due to greater perceived epistemicness (Figure 1, path a). In contrast, in Study 3 we find that when historical stock information is framed to focus on changes in price, participants are more likely to diversify, due to greater perceived aleatoriness (Figure 1, path c). In Study 3 we observe that participants' tendency to diversify under aleatoriness is amplified as their level of uncertainty increases (Figure 1, path d). In Study 4 we show that ratings of epistemicness moderate sensitivity to expert forecasts when making investment decisions (Figure 1, path f). In Study 5A - C we show that ratings of aleatoriness moderate the association between risk preference and willingness to invest (Figure 1, path h).

Transparent Reporting

For all studies we determined sample sizes in advance of data collection, always at 50+ per cell. With the exception of Studies 1 and 5, we preregistered hypotheses and analysis plans for all studies. Materials, data, and code for all studies can be found at https://researchbox.org/180&PEER_REVIEW_passcode=OQUOTP.

Study 1: Uncertainty Management Among Investors

In our first study we explore the association between the assessed nature of stock market uncertainty and uncertainty management strategies. We recruited a sample of retail investors who reported their actual investment behavior and rated the degree to which they viewed the nature of market uncertainty to be epistemic or aleatory. We predicted that investors who see greater epistemicness in the stock market would be more apt to manage their uncertainty by obtaining financial advice, while investors who see greater aleatoriness in the stock market would be more apt to manage their uncertainty by diversifying their portfolio. Thus, Study 1 represents a correlational approach to examining paths a and c in Figure 1.

Method

We recruited participants from a Qualtrics panel to complete a survey in exchange for $10. The Qualtrics panel was comprised of over 525,000 respondents ranging in age from 18 to 50 with a broad range of professional experience. Before completing the questionnaire, we screened participants to verifty that they met a minimum threshold of both financial literacy and self-rated financial expertise.

Criteria for eligibility. To be eligible for the study, participants were required to own at least $1,000 in stock market investments, be between the ages of 18 and 65 years old, report making their own investment decisions, and rate their knowledge of the stock market as a three or higher on a five-point scale. To be included in the study we also required participants to correctly answer three simple financial literacy screening questions. A complete list of these questions, along with complete materials for all studies in this paper, can be found in the Web Appendix. Of the 7,191 individuals who responded to the initial screening questions, 354 passed the screening. The average age was 35 years (range: 19–50 years), with the median respondent

reporting their total investment assets (excluding home and pension equity) between $50,000 and $100,000 and investments in the stock market between $5,000 and $20,000.

EARS ratings. Participants first evaluated stock market uncertainty using a 6-item version of the Epistemic-Aleatory Rating Scale (EARS; see Table 2). They rated each statement on 7-point scales (1 = *not at all*, 7 = *very much*), and the order of the six statements was randomized for each participant. We computed ratings of epistemicness and aleatoriness by averaging the three items for each subscale (Cronbach's α was 0.81 for the epistemicness subscale, and 0.73 for the aleatoriness subscale). In the Web Appendix we report factor analytic results for all studies, which consistently return a two-factor solution corresponding to our constructs of epistemic and aleatory uncertainty.

Financial advisor. Participants reported whether they currently did or did not employ a financial advisor (0 = *no*, 1 = *yes*).

Diversification. Participants reported the number of distinct stocks they currently held. We operationalized stock diversification as the absolute number of distinct stocks held, with a greater number of stocks representing a less concentrated stock portfolio (i.e., in general, a more diversified portfolio). We winsorized the data at a maximum of 100 stocks (meaning that values of more than 100 stocks were transformed to 100 stocks). Of our 354 respondents, 5 reported holding more than 100 distinct stocks.[4]

Risk perception. As a control variable, we measured the perceived *level* of risk (as opposed to *nature* of uncertainty that we measured with the EARS) using three risk perception items from the financial decision subscale of the Domain-Specific Risk Taking Scale (DOSPERT; Weber, Blais, and Betz 2002). Participants rated the amount of risk involved in various financial decisions (e.g., "Investing 10% of your annual income in a moderate growth mutual fund") on 7-point scales (1 = *not at all risky*, 7 = *extremely risky*). We found that these

three items exhibited poor internal consistency (Cronbach's α = 0.44), so for all regression analyses below we entered each item separately rather than combining them into a single index. Our results do not meaningfully differ when using a combined index for the three items.

Other measures. Participants also reported the percentage of their assets (from 0-100%) they invest in each of the following categories: individual stocks; stock mutual funds; stock index funds; individual bonds; bond mutual funds; bond index funds; individual commodities; commodities mutual funds; commodities index funds; individual real estate; real estate mutual funds; real estate index funds; home; pension; annuities; cash; and other. Participants provided responses in open text boxes that were required to sum to 100%. Participants also reported the total value of their investments in one of seven ranges (1 = *$0 to $1,000*, 2 = *$1,000 to $50,000*, 3 = *$50,000 to $100,000*, 4 = *$100,000 to $250,000*, 5 = *$250,000 to $500,000*, 6 = *$500,000 to $1,000,000*, and 7 = *$1,000,000 or more*), the total value of other assets in the same seven ranges, the frequency with which they made changes to their investments (1 = *more than every day*, 7 = *fewer than one change every 12 months*), and the average period of time that they held stocks and mutual funds (1 = *several hours*, 6 = *many years*). If a participant did have a financial advisor, they then reported in an open text box the fee they paid to the financial advisor as a percentage of assets under management. While not part of our main analysis, we report an exploratory analysis of the relationship between EARS scores and trading frequency, as well as the relationship between EARS scores and fees paid to financial advisors in the Web Appendix.

At the end of the study, participants completed a 3-item financial literacy test (Lusardi, Mitchell, and Curto 2010). Participants also provided basic demographic information.

Results and Discussion

We first considered the prediction that reliance on expert advice would be uniquely predicted by ratings of greater epistemicness in stock returns. We conducted a logistic regression

on whether the investor paid a financial advisor (0 = *no*, 1 = *yes*), with ratings of epistemicness and aleatoriness as our predictor variables. Table 3 displays the log odds coefficients from the logit model. Consistent with our predictions, only epistemicness ratings were reliably and positively associated with paying for financial advice (Table 3, Column 1). This pattern holds when including additional controls for perceptions of market risk, the investor's total investment asset value, value of all other assets, number of stocks held by the investor, and financial literacy (Table 3, Column 2). In addition, our conceptual model (Figure 1) predicts relationships to be stronger for solid lines than corresponding dotted lines (in this case, path $a > b$). We tested whether the average marginal effect for rated epistemicness was larger than that for rated aleatoriness using an equality of coefficients test. Consistent with our model, rated epistemicness was a stronger predictor of paying for financial advice than rated aleatoriness (without controls $z = 1.92$, $p = 0.054$; with controls $z = 1.85$, $p = 0.065$).

We next examined diversification. Our conceptual model predicts that greater aleatoriness would be uniquely associated with less concentrated stock portfolios (i.e., greater diversification). Thus, we conducted an OLS regression with the number of stocks owned as our dependent variable, and epistemicness and aleatoriness ratings as our independent variables. Consistent with our predictions, only aleatoriness ratings were significantly and positively associated with the total number of stocks held (Table 3, Column 3). This pattern holds when including our additional set of controls (Table 3, Column 4). Using an equality of coefficients test we find that, consistent with our model, rated aleatoriness was a stronger predictor of diversification than rated epistemicness (i.e., a comparison of paths *c* and *e* in Figure 1: without controls $t(351) = 1.73$, $p = 0.085$; with controls $t(343) = 2.06$, $p = 0.040$).

Taken together the results of Study 1 suggest that individual differences in assessments of the nature of stock market uncertainty are associated with distinct strategies for reducing

uncertainty. Investors who viewed stock market uncertainty as relatively epistemic in nature were more likely to pay for financial advice. Meanwhile, investors who viewed stock market uncertainty as relatively aleatory in nature held less concentrated stock portfolios. Importantly, we note that just as perceptions of high epistemicness and aleatoriness are not mutually exclusive, neither is reliance on both financial advice and diversification to manage uncertainty. We next turn to separate experimental investigations of advice-seeking and diversification.

Study 2: Managing Epistemic Uncertainty by Seeking Expert Advice

The results of Study 1 are correlational and as such only provide suggestive evidence that perceptions of epistemicness and aleatoriness influence investment behavior. Study 1 also screened for participants with basic knowledge of the stock market, which may have limited the generalizability of our findings. In the next two studies, we directly manipulate assessments of epistemicness and aleatoriness by presenting participants with financial information in one of two distinct (but informationally equivalent) ways.

Investors frequently consult data on past performance of the investments they are considering. As illustrated in Figure 2, an analyst's past performance can be depicted by displaying predicted prices alongside realized prices (i.e., an absolute price chart), or by displaying the predicted price changes alongside realized price changes from period to period (i.e., a relative price chart). In the absolute price chart, asset prices are plotted in a time series; in the relative price chart, changes in asset prices are plotted as changes from one period to the next (i.e., returns). We pause to emphasize that both kinds of price charts contain the same objective information.

We predicted that charts highlighting overall trends in an asset's value will augment impressions of its inherent knowability (i.e., epistemicness), whereas charts that highlight changes in an asset's value from period to period will augment impressions of its fundamentally stochastic nature (i.e., aleatoriness). Two features of absolute price charts promote stronger impressions of knowability. First, to the extent that overall trends exist in a given asset's history, absolute price charts make such trends more salient than relative price charts. Thus, by making past trends more easily discernible, absolute price charts may give the impression that future stock prices are more fundamentally knowable (at least in situations where there are distinct upward and/or downward trends over time). Second, unlike relative price charts, absolute price

charts promote a misleading impression of the correspondence between predictions and prices. An analyst knows the previous period's price when making a forecast concerning the next period's price, and this fact may be obscured when performance is presented alongside forecasts in an absolute price chart. For instance, as illustrated in Figure 2, even when forecasted and realized *price changes* are virtually uncorrelated ($r = -0.01$), forecasted and realized *absolute prices* can be highly correlated ($r = 0.96$). This can convey the illusion that market prices are more knowable than they truly are. In contrast, relative price charts present price changes from one period to the next — which not only eliminate spurious trend information but also draws attention to short-term fluctuations in prices and variability in the direction of those changes. Thus, relative price charts should give the impression of greater randomness in stock prices, compared to absolute price charts — whether forecasts are included or not.

In Study 2 we focus on the relationship between perceptions of epistemicness and willingness to pay for financial advice. We predicted that participants would pay more for an analyst's advice concerning a stock after they had viewed prior predictions of stocks that were presented in absolute price charts than relative price charts, and that this effect would be statistically mediated by assessments of epistemicness (but not necessarily aleatoriness) of future stock prices. This latter prediction derives from our conceptual model in which seeing epistemicness in the market uniquely provides motivation to seek financial advice.

Method

We recruited 407 participants (49% male, mean age = 31 years, range: 18–65 years) from an online labor market (Prolific Academic[5]) to participate in a brief study for £0.40 each. Participants read that they would make an investment decision after viewing stock recommendations from a professional stock analyst. Participants were also told that stock prices shown in the study came from real companies whose identities had been concealed. We avoided

using real stock names in order to reduce variation in behavior due to differences in stock familiarity (Song and Schwarz 2008) or company-specific understanding (Long, Fernbach, and De Langhe 2018).

We next showed participants a chart of an analyst's past performance in predicting a stock price (generated from simulated data), using a version[6] of one of the price charts displayed in Figure 2. That is, participants were randomly assigned to view predicted and realized outcomes either in terms of absolute prices (*absolute price chart*) or as the percentage change in the stock price relative to the previous period (*relative price chart*). Data points in both charts represent quarterly intervals from 2003 to 2020, and participants were told that the analyst made forecasts exactly three months in advance.

After viewing the stock chart, we asked participants to imagine having $1,000 to invest between the company displayed in the price chart (Stock A) and another company (Stock B). Next we asked them to indicate their maximum willingness to pay (WTP) to see price forecasts for Stocks A and B from a different analyst, from a list of 11 prices ranging from $0 to $400 (logarithmically spaced). Note that we elicited willingness to pay for a *new analyst* to help ensure that WTP is driven by perceived knowability of future stock prices and not by the perceived skill of the original analyst.

We then asked participants to rate epistemicness and aleatoriness of the task of forecasting the price of the stock over three months, using the 6-item EARS. Participants also rated their level of uncertainty associated with the stock depicted in the price chart, by providing their 90% confidence interval over the next month's average return for the stock (cf. Soll and Klayman, 2004). We randomized for each participant the order of the EARS and the confidence interval elicitation.

Finally, participants completed a comprehension check. In particular, we presented them with the original stock chart again and asked them to indicate by how much the analyst had missed their first quarter forecast. We gave participants two response options: 1 percentage point or 10 percentage points (the latter being the correct response). Finally, participants indicated their sex and age and were debriefed.

Results and Discussion

Comprehension check. The majority of participants correctly interpreted that the analyst missed the first forecast by 10 percentage points when the charts were presented in absolute prices (89% responding correctly) and in relative prices (83% responding correctly), $z = 1.84$, $p = .065$. We retain all participants in the analysis reported below because this is what we specified in our preregistration analysis plan; restricting the analysis to participants who correctly answered all comprehension check questions does not change the direction or statistical significance of our findings.

Manipulation check. As expected, participants rated the stock as entailing greater epistemicness when viewing absolute prices ($M = 4.79$, $SD = 1.24$) than relative prices ($M = 4.01$, $SD = 1.17$), $t(405) = 6.53$, $p < 0.001$, $d = 0.65$. Participants also rated the stock as entailing greater aleatoriness when viewing relative prices ($M = 4.86$, $SD = 1.04$) than absolute prices ($M = 4.54$, $SD = 1.30$), $t(405) = 2.72$, $p = 0.007$, $d = 0.27$. We also examined whether chart type had any meaningful effect on perceived level of uncertainty. Ratings of perceived uncertaintly level (i.e., confidence interval width) did not reliably differ when outcomes were presented as absolute prices ($M = 1.25$, $SD = 14.13$) or relative prices ($M = 1.18$, $SD = 10.52$), $t(405) = 0.06$, $p = 0.953$, $d = 0.01$. Thus, our manipulation appears to have reliably shifted perceptions of the nature of uncertainty while not meaningfully altering perceptions of the level of uncertainty.

Willingness to pay. As predicted, willingness to pay was higher when outcomes were presented as absolute prices (M = 6.07, SD = 2.58) than relative prices (M = 5.51, SD = 2.61), $t(405) = 2.19$, $p = 0.029$, $d = 0.22$. The median response in the absolute chart condition corresponded to a willingness to pay of $25, whereas the median response in the relative chart condition corresponded to a willingness to pay of $13. As a robustness check we regressed willingness to pay onto chart type and rated level of uncertainty, and found that chart type continued to predict willingness to pay ($b = 0.56$, 95% CI = [0.57, 1.07], $p = 0.029$), whereas level of uncertainty did not reliably predict willingness to pay ($b = 0.00$, 95% CI = [–0.030, 0.040], $p = 0.785$).

Mediation analysis. We next examined whether the treatment effect of chart type on willingness to pay was statistically explained by differences in perceived nature of uncertainty across conditions. We tested this using a path model with WTP as the dependent variable, chart type as the independent variable (0 = *relative price chart*, 1 = *absolute price chart*), and ratings of epistemicness, aleatoriness, and level of uncertainty as separate mediator variables. We estimated all indirect effects using bias-corrected bootstrapped confidence intervals based on 10,000 resamples. As predicted, we found a statistically reliable indirect effect through ratings of epistemicness ($b = 0.61$, 95% CI = [0.38, 0.92], $p = 0.001$). We find a weaker, marginally significant indirect effect through ratings of aleatoriness ($b = –0.09$, 95% CI = [–0.22, –0.02], $p = 0.056$), and no reliable indirect effect through uncertainty level, ($b = 0.00$, 95% CI = [–0.03, 0.05], $p = 0.982$).

The results of Study 2 suggest that participants were more willing to pay more for financial advice when a stock chart was presented in an absolute price format as opposed to a relative price format. Presenting information in an absolute versus relative price format only appeared to meaningfully impact the perceived nature of uncertainty, and not the perceived level

of uncertainty. Consistent with our predictions, our treatment effect was statistically mediated by the perception of greater epistemicness (Figure 1, path a).

In the Web Appendix we provide additional data (Supplemental Study 1) that replicates the results of Study 2 using a within-participant design. In that study we presented participants with the same forecasted and realized price information using the two different price chart formats, less than five minutes apart. Despite this, participants were willing to pay roughly twice as much for the same financial advice when past performance was presented in absolute terms compared to relative terms, echoing the results presented here. An additional experiment (Supplemental Study 2) replicates this effect using an alternative manipulation in which we either promoted perceptions of high epistemicness by asking participants to read a news article about a value investor or promoted perceptions of low epistemicness by asking participants to read a news article about errors by stock gurus.

Study 3: Managing Aleatory Uncertainty Through Diversification

Study 2 provides evidence that heightened perceptions of epistemicness increase willingness to pay for financial advice (Figure 1, path a). We next turn to the prediction that heightened perceptions of aleatoriness increase the tendency to engage in (naïve) diversification (Figure 1, path d). Because Study 3 focuses on the role of perceived aleatory rather than epistemic uncertainty, performance of an analyst's forecasts is no longer relevant. Thus, we modified our stock chart manipulation by omitting forecast data.

In Study 3 we orthogonally manipulate the nature and level of uncertainty in a 2 (chart type) x 2 (chart volatility) between-participant design to test our prediction that the propensity to diversify will be amplified when facing a higher level of stock market uncertainty that is viewed as aleatory in nature. Study 3 also employs financial incentives tied to choices.

Method

We recruited 602 participants (49% male, mean age = 29 years, range: 18–71 years) from Prolific Academic to complete a short survey in exchange for £0.50 plus the possibility of receiving additional bonus money. Participants were randomly assigned to evaluate four stocks, displayed in either a relative price chart (designed to promote impressions of aleatoriness) or an absolute price chart (designed to promote impressions of epistemicness). We also randomly assigned participants to view a chart with either high or low volatility stocks to experimentally manipulate level of subjective uncertainty. The charts were generated based on four fictional stocks from a random walk algorithm with either high or low volatility (see Figure 3). We told participants that these were real stocks (labeled A, B, C, and D) with the names hidden.

After we presented participants with a stock chart in either absolute or relative price format we asked them to allocate $100, to be invested over the ensuing six months, across the four stocks. We told participants that one randomly-selected respondent would receive the realized value of their investment portfolio at the end of six months.[7] On the next page, participants rated the "task of forecasting the prices of the four stocks listed above six months in the future" using the 6-item EARS. Finally, participants evaluated the subjective level of stock price uncertainty by answering the following questions:

> Imagine that you invested $100 evenly across the four stocks ($25 in Stock A, $25 in Stock B, $25 in Stock C, and $25 in Stock D). What is your best estimate of how much this investment would be worth in 1 month? $__
>
> Consider your estimate above. Please assess the probability that the actual value of your investment would fall within $5 of your estimate. __%

Thus, providing a smaller probability estimate to the second question measures the degree that participants perceived greater dispersion in the stock price (i.e., greater level of uncertainty). Participants then provided their age and gender and were debriefed.

Results and Discussion

EARS manipulation check. We first tested the EARS manipulation check using a 2 x 2 analysis of variance (ANOVA) with aleatoriness as the dependent variable and chart type (0 = *absolute*, 1 = *relative*), chart volatility (0 = *low*, 1 = *high*) and their interaction as independent variables. As expected, we find a reliable main effect of chart type such that participants rated relative prices as higher in aleatoriness (M = 5.27, SD = 1.09) than absolute prices (M = 4.94, SD = 1.11), $F(1, 598) = 13.80$, $p < 0.001$, $\eta^2 = 0.023$. We did not find a significant main effect of chart volatility, $F(1, 598) = 0.81$, $p = 0.367$, nor did we find a significant interaction between chart type and chart volatility, $F(1, 598) = 1.10$, $p = 0.294$. Thus, ratings of aleatoriness (i.e., nature of uncertainty) were reliably impacted by chart type, but not by volatility (i.e., level of uncertainty).

We then conducted the same analysis but using ratings of epistemicness as the dependent variable. We find a reliable main effect of chart type such that participants rated absolute prices as higher in epistemicness (M = 4.35, SD = 1.20) than relative prices (M = 4.13, SD = 1.22), $F(1, 598) = 5.10$, $p = 0.024$, $\eta^2 = 0.008$. Unexpectedly, we also find a reliable main effect of chart volatility such that participants rated low volatility stocks as higher in epistemicness (M = 4.35, SD = 1.22) than high volatility stocks (M = 4.13, SD = 1.20), $F(1, 598) = 4.83$, $p = 0.028$, $\eta^2 = 0.008$. We do not find a significant interaction between chart type and chart volatility, $F(1, 598) = 1.14$, $p = 0.286$.

Uncertainty level manipulation check. We next examined perceived level of uncertainty using the same analysis as before, but with confidence in one's forecasted point

estimate (i.e., level of uncertainty) as the dependent variable. As expected, we find a reliable main effect of chart volatility such that participants judged the level of stock uncertainty to be higher when viewing high volatility stocks (M = 48.01, SD = 22.70) than low volatility stocks (M = 56.55, SD = 26.33), $F(1, 597) = 17.99$, $p < 0.001$, $\eta^2 = 0.029$. We failed to find a reliable main effect of chart type, with participants viewing uncertainty level to be similar in the absolute chart (M = 51.76, SD = 24.51) compared to the relative chart (M = 52.84, SD = 25.39, $F(1, 598) = 0.25$, $p = 0.620$, and we did not find a reliable interaction between chart type and chart volatility, $F(1, 598) = 1.43$, $p = 0.232$. Thus, level of uncertainty was reliably impacted by chart volatility but not by whether the chart was presented as absolute or relative prices.

Diversification. We measured diversification as the variance in proportion invested across all four stocks (i.e., average squared deviation from 25%), with smaller numbers reflecting greater (naïve) diversification and larger numbers reflecting greater concentration. We first tested the prediction that participants would be more likely to rely on diversification as a strategy to manage high levels of perceived uncertainty when outcomes were presented as relative as opposed to absolute prices. We tested this prediction using a 2 x 2 ANOVA with diversification as the dependent variable, and found reliable main effects for both chart type, $F(1, 597) = 16.53$, $p < 0.001$, $\eta^2 = 0.027$, and chart volatility, $F(1, 597) = 9.04$, $p = 0.003$, $\eta^2 = 0.015$. The chart type main effect indicates that participants engaged in greater diversification when presented with relative prices than with absolute prices; the chart volatility main effect indicates that participants engaged in greater diversification for high than low volatility charts. More importantly, and confirming our primary prediction, we found a reliable interaction such that diversification behavior was especially sensitive to changes in volatility when presented in the relative price chart format, $F(1, 598) = 11.04$, $p < 0.001$, $\eta^2 = 0.018$. When participants viewed the relative price chart, they diversified more in the high volatility condition (M = 466.04, SD =

673.53) than in the low volatility condition (M = 825.47, SD = 757.43), $F(1, 598) = 20.10$, $p < 0.001$. In contrast, when participants viewed the absolute price chart, their diversification behavior did not reliably differ across the high volatility (M = 466.04, SD = 673.53) and the low volatility conditions (M = 825.47, SD = 757.43), $F(1, 598) = 0.05$, $p = 0.824$.

The results of Study 3 suggest that presenting past stock price information in terms of relative rather than absolute prices can elevate perceptions of aleatoriness and promote greater portfolio diversification, especially under conditions of high volatility (Figure 1, paths c and d). In the Web Appendix we provide a replication of this study using a simpler design that allowed us to test mediation (see Supplemental Study 3). Notably, we find that perceptions of aleatoriness statistically mediate the relationship between chart type and diversification (b = 73.15, bias-corrected 95% CI = [27.44, 139.48], p = 0.011), whereas we found no reliable indirect effect through perceptions of epistemicness, b = –0.77, bias-corrected 95% CI = [–21.01, 12.24], p = 0.920. Furthermore, in Supplemental Study 4 we replicated the main results of Study 3 using an alternative manipulation of perceived nature of uncertainty. In particular, we promoted perceptions of greater epistemicness by asking financially sophisticated participants to write single prediction scenarios about future earnings of familiar target companies (to prompt singular thinking) or we promoted perceptions of greater aleatoriness by asking participants to write three distinct prediction scenarios concerning future earnings for the same target companies (to prompt distrubutional thinking).

Study 4: Epistemic Uncertainty Amplifies Sensitivity to Expert Advice

Studies 1–3 focused on the relationship between perceptions of the nature of stock market uncertainty and the strategies participants use to manage uncertainty in their investments. Our results so far suggest that perceptions of epistemicness increase advice-seeking (Figure 1, path

a), whereas perceptions of aleatoriness increase diversification behavior (path c). We next turn to the relationship between perceptions of the nature of stock market uncertainty and willingness to invest. Using an incentive-compatible experimental design, we test the prediction that participants who view stocks as higher in epistemicness will be more responsive to expert investment advice when deciding how to invest (path f).

Method

We recruited a sample of 195 participants from Prolific Academic (67% male, mean age = 35 years, range: 18–70 years). Participants were each paid £0.25 for their participation, plus the potential to receive a bonus payment.

Round 1: Baseline Investment. We first asked participants to invest any amount from $0 to $100 in Apple stock over the following six months. We told participants that any uninvested amount would be held in cash, which would earn no return over this same period. Participants were informed that one randomly-selected respondent would receive the realized value of their investment (i.e., the market value of stock and cash investments) at the end of six months.

Round 2: Post-Information Investment. After completing investment round 1 participants were presented with a real analyst research report predicting that the Apple stock price would increase in the coming months (see Web Appendix). We then asked participants to complete the same investment task as in investment round 1 and told them that this second investment decision was the choice to be honored should they be selected as the "real money" participant. Afterwards, participants rated the uncertainty of "the stock price of Apple 6 months in the future" using the 6-item EARS. Finally, participants provided demographic information and were debriefed.

Results and Discussion

We predicted that participants who view stock market uncertainty as more epistemic in nature will be more responsive to expert advice and therefore show a greater increase in willingness to invest in Apple stock from round 1 to round 2. Because our study uses a repeated-measures design, we calculated all test statistics and *p*-values using robust standard errors clustered by participant.

Investment decision. Using OLS, we regressed dollars invested in Apple stock (out of a possible $100) onto: investment round (0 = *before receiving advice*, 1 = *after receiving advice*), epistemicness rating, aleatoriness rating, and interaction terms between investment round and each dimension of subjective uncertainty. As predicted, we found a positive interaction between investment round and rated epistemicness: respondents with higher epistemicness perceptions displayed a larger increase in dollars allocated to Apple stock after receiving positive advice from an analyst, $b = 6.29$, 95% CI = [2.68, 9.90], $p = 0.001$. In contrast, the interaction between investment round and ratings of aleatoriness was not significant, $b = –0.21$, 95% CI = [–3.09, 2.66], $p = 0.884$. Furthermore, using an equality of coefficients test, we find that the investment round x epistemicness interaction was reliably larger in magnitude than the investment round x aleatoriness interaction, $t(194) = 3.13$, $p = 0.002$. Figure 4 plots the change in investments after receiving advice from an analyst as a function of rated epistemicness and aleatorniness.

The results of Study 4 thus support our prediction that stock advice has a greater influence on investors who view uncertainty in future stock price as more (versus less) epistemic in nature (Figure 1, path f). Meanwhile, we do not observe a similar effect of expert advice on willingness to invest for those who view the uncertainty in stock price as more versus less aleatory in nature (path i). In the Web Appendix we report an additional study (Supplemental

Study 5) which replicates the results of Study 4 while also statistically controlling for perceived level of uncertainty.

Study 5: Aleatory Uncertainty Amplifies Sensitivity to Risk Preference

In Studies 5A–5C we test the prediction that perceptions of aleatoriness will uniquely moderate the effect of risk preferences on willingness to invest (Figure 1, path h). To do this we recruited three independent samples of participants. All three studies use a correlational design in which participants first make a prediction about the movement of stocks or stock indices, and then are given the opportunity to bet on their prediction by choosing between a smaller certain amount of money or a larger amount of money contingent on their stock prediction being correct. We also control for confidence (i.e., judged probability of one's prediction being correct) in order to rule out level of uncertainty as a potential confound. Study 5A involved movement of the S&P 500 index; Study 5B involved the movement of individual stocks; and Study 5C involved the movement of a single stock over different time horizons. Furthermore, Studies 5A and 5B employed incentive-compatible designs.

Method

Study 5A. We recruited 564 participants[8] (44% male, mean age = 36 years, range: 18–85 years) from Amazon.com's Mechanical Turk labor market (MTurk) who were each paid $0.40 for their participation. Participants first indicated the current value of their stock market investments in U.S. dollars and rated their investment knowledge on a 5-point scale (1 = *low*, 5 = *high*).

Next, participants reported their risk preference by completing a short task adapted from Barsky et al. (1997), in which they accepted or rejected two chance gambles. Participants were told: "Below you will find a choice between a sure gain and a 50/50 coin flip prospect. Please

indicate if you prefer the sure gain or the coin flip prospect in the following scenario." In the first round participants chose between "Gain $50 for sure" or "If the coin turns up heads you gain $150, if the coin turns up tails you gain $0." Participants who selected the risky option in the first round were then presented in the second round with a choice between $50 for sure and a 50% chance of $100. Participants who instead selected the safer option in the first round were then presented in the second round with a choice between $50 for sure and a 50% chance of $200. This two-step titration procedure categorizes participants into one of four levels of risk preference, ranging from those who always chose the certain prospect (1 = *strongly risk averse*) to those who always chose the risky prospect (4 = *risk seeking*).

We then asked participants to rate the nature of uncertainty concerning "whether the S&P 500 will go up or down over the next six months" using the 6-item EARS. Next, participants predicted whether the S&P 500 would increase or decrease in value over the next six months (0 = *S&P 500 decreases in value or remains the same*, 1 = *S&P 500 increases in value*). Participants then chose between: (a) receive $90 if your prediction was correct and $0 otherwise, or (b) receive $30 for sure. We informed participants in advance that some respondents would be selected at random to have their choice honored for real money. As a control variable, participants assessed the likelihood that their prediction would be correct on a scale from 50%–100%. Finally, participants provided basic demographic information and were debriefed.

Study 5B. We recruited 365 participants (58% male, mean age = 35 years, range: 18–70 years) from MTurk who were each paid $0.50 for their participation, along with the potential to receive a bonus payment. Participants first indicated the current value of their stock market investments in dollars and rated their investment knowledge on a 5-point scale (1 = *low*, 5 = *high*). We then elicited their risk preference using the same procedure as in Study 5A.

Participants next evaluated the return of eight individual stocks relative to the S&P 500 over the subsequent week, in a randomized order: Amazon.com, Wal-Mart, Netflix, the Coca-Cola Company, Rowan Companies, Covidien, Vornado Realty Trust, and the Mosaic Company.[9] For each stock, participants first read a paragraph from Reuters providing general information about the company, such as its customers, suppliers, and products. Participants then rated the nature of uncertainty concerning "the return of [stock] relative to the S&P 500 over the course of one week" using the 6-item EARS.

Next, participants predicted whether the return of that stock, including any dividends or buybacks, would be greater than the return of the S&P 500 over the following week (0 = *stock returns less than or the same as the S&P 500*, 1 = *stock returns more than the S&P 500*). We then asked participants to choose between: (a) receive $90 if your prediction was correct and $0 otherwise, or (b) receive $30 for sure. We informed participants in advance that some respondents would be selected at random to have one of their choices honored for real money. As a control variable, participants assessed the likelihood that each prediction would be correct, on a scale from 50%–100%. After completing this task for all eight stocks, participants provided basic demographic information and were debriefed.

Study 5C. We recruited 404 participants (46% male, mean age = 33 years, range: 18–71 years) from MTurk who were each paid $0.50 for their participation. Participants first indicated the current value of their stock market investments in dollars and rated their investment knowledge on a 5-point scale (1 = *low*, 5 = *high*). We then elicited their risk preference using the same procedure as in Study 5A.[10]

Participants then assessed the movement of Apple stock over six time periods: the next day of trading, the next week, the next month, the next year, the next 5 years, and the next 20 years. Approximately half of our participants encountered time periods in an ascending order and

half encountered time periods in a descending order. We found no significant effects of order on any of our reported results, so we combined order conditions in all analyses that follow.

For each time period, participants also rated the nature of uncertainty concerning "the return of Apple stock relative to the S&P 500 over the next [time period]" on the 6-item EARS. Next, participants predicted whether Apple stock would exceed the return of the S&P 500 over that same time period (0 = *less than or equal to the S&P 500*, 1 = *more than the S&P 500*). As a control variable, we also measured participants' confidence in their forecast on a 7-point scale (1 = *not at all confident*, 7 = *extremely confident*). Participants then chose between: (a) receive $150 if your prediction is correct and $0 otherwise, or (b) receive $50 for sure. As a second control variable, participants assessed the likelihood that their prediction would be correct on a scale from 50%–100%. Finally, at the end of the study, participants rated their knowledge of Apple stock on a 5-point scale (1 = *low*, 5 = *high*) and provided basic demographic information.

Results and Discussion

We predicted that perceptions of aleatoriness would moderate the impact of participants' own risk tolerance on their willingness to invest. Because Studies 5B and 5C used repeated-measures designs, for those two studies we calculated test statistics and *p*-values using robust standard errors clustered by participant.

For each study we conducted a logistic regression with investment decision as the dependent variable (0 = *certain payout*, 1 = *bet on their prediction*). For each model our predictor variables were ratings of aleatoriness, epistemicness, risk preference, as well as interaction terms between risk preference and each dimension of subjective uncertainty. Table 4 provides results for each study, both with and without additional controls. In all three studies we found, as predicted, a significant positive interaction between risk preference and aleatoriness: risk preferences were most predictive of investment decisions for participants who viewed the

market as more aleatory in nature (see the shaded in row in Table 4). Figure 5 illustrates, for each study, the predicted probability of accepting the risky investment prospect as a function of ratings of aleatoriness for the most extreme risk preference groups (strongly risk averse and risk seeking). For all three studies the Figure shows an association between risk preference and willingness to invest that is stronger for higher levels of rated aleatoriness.[11] Also consistent with our framework, Table 4 indicates that for all three studies there was no significant interaction effect between risk preference and perceptions of epistemicness.

As previously noted, the present account predicts that rated aleatoriness more strongly moderates the relationship between risk tolerance and willingness to invest than does rated epistemicness (i.e., in Figure 1 path h is stronger than path g). Using equality of coefficients tests we found that the aleatoriness x risk preference interaction on choice was larger than the epistemicness x risk preference interaction in Study 5A (without controls: $z = 2.95$; $p = 0.003$; with controls, $z = 2.52$, $p = 0.012$), in Study 5B (without controls: $z = 1.95$; $p = 0.051$; with controls, $z = 2.19$, $p = 0.029$), and in Study 5C (without controls: $z = 3.20$; $p = 0.001$; with controls, $z = 3.75$, $p < 0.001$).

In summary, we find support for the prediction that the more people see uncertainty in investment outcomes as aleatory in nature, the more their investment decisions are sensitive to their own risk preference. In contrast, we find no evidence that the relationship between risk preference and investment decisions is reliably moderated by perceptions of epistemicness.

General Discussion

In this paper we demonstrate that investors differ in their perception of stock market uncertainty along two distinct dimensions: the extent to which they see future movement of stocks and markets as inherently knowable or epistemic, and the extent to which they see future

movement as inherently random or aleatory. Second, we provide evidence that these two dimensions of subjective uncertainty are related to the actions investors take to reduce uncertainty: those who perceive uncertainty to be more epistemic in nature are more likely to seek information or expertise, whereas those who perceive uncertainty as more aleatory in nature are more likely to diversify their assets. Third, we provide evidence that these two dimensions of subjective uncertainty are related to investment behaviors. Investors who perceive market uncertainty to be more epistemic in nature are more responsive to expert advice, whereas investors who perceive market uncertainty to be more aleatory in nature are more likely to act in accordance with their general attitudes towards risk as measured using chance gambles.

In Study 1 we examined real investment decisions and found that investors who perceive stock market uncertainty to be more epistemic in nature are more likely to seek financial advice, while investors who perceive stock market uncertainty to be more aleatory in nature have less concentrated stock portfolios. In Studies 2 and 3 we manipulated perceptions of epistemicness and aleatoriness through graphical displays of an analyst's past performance. When we presented stock forecasts and outcomes as absolute prices rather than as changes in prices, participants viewed market uncertainty as more epistemic in nature. They were also willing to pay more money for stock advice (Figure 1, path a) and were more responsive to expert advice in their investment decisions (path f). When stock outcomes were presented as relative changes in prices rather than as absolute prices, participants viewed market uncertainty as more aleatory in nature. They were more likely to engage in (naïve) diversification to manage risk, especially for higher levels of volatility (paths c and d). In Study 4 we found that participants were more responsive to stock advice when they perceived stock market uncertainty as more epistemic in nature (path f), and in Study 5 we found that that investment decisions accorded more closely with risk attitudes for chance gambles when investors perceived stock market uncertainty to be more aleatory in

nature (path h). We measure perceptions of epistemicness and aleatoriness and provide correlational evidence for our conceptual model in Studies 1, 4 and 5; we manipulate perceptions of epistemicness or aleatoriness and provide causal evidence in Studies 2 and 3. We conducted our studies across a variety of investment contexts, employed incentive-compatible designs in four studies, and in one study measured real investment behaviors of a panel of retail investors.

Our studies also address how investors — at least those in our samples — view the nature of stock market uncertainty. Do investors tend to view the stock uncertainty as relatively high in both epistemicness and aleatoriness, relatively low in both, or as some combination of high and low? Figure 6 displays the joint distribution of epistemic and aleatory uncertainty ratings, as scatterplots, from all studies. Ratings among our panel of investors in these studies reveal a great deal of heterogeneity on both dimensions, with many respondents seeing the market as relatively moderate to high in both epistemicness and aleatoriness, several respondents seeing uncertainty as high on one dimension and low an another, and few participants viewing stock market uncertainty as relatively low in both. The tendency for many respondents to view stock uncertainty as both knowable and random may help explain why many investors both pay a significant amount for financial advice and also engage in substantial diversification.

Related Constructs

Prior research has found that willingness to invest increases with subjective knowledge (Hadar, Sood, and Fox 2013), feelings of competence (Graham, Harvey, and Huang 2009), one's sense of understanding (Long, Fernbach and De Langhe 2018), and familiarity with an asset or investment decision (Huberman 2001). We assert that these constructs are associated primarily with the *level* of (epistemic) uncertainty an investor perceives in these investments, rather than the subjective *nature* of uncertainty. According to our framework the impact of subjective knowledge, competence, sense of understanding, and/or familiarity should be moderated by the

extent to which that uncertainty is perceived to be epistemic in nature (for more on this topic see Fox, Goedde-Menke and Tannenbaum, 2021). In our studies we manipulate or statistically control for level of uncertainty. In addition we control for subjective knowledge of the stock market, and relevant demographic variables such as financial literacy and investment net worth. Likewise, we again note that prior studies have documented an association between ambiguity attitudes (as measured in a decision theoretic manner) and investment behaviors including willingness to invest in stocks as well as a preference to invest in domestic stocks (Dimmock, Kouwenberg, Mitchell and Piejnenburg, 2016). The present studies depart from this previous work in that we examine the impact of perceived *nature* of uncertainty (rather than preferences to act under conditions of ambiguity) on sensitivity to one's level of knowledge when investing and on the weight given to expert advice.

Past research also finds that heightened risk perceptions are associated with a decreased willingness to invest in an asset (Weber, Blais, and Betz 2002). One difficulty with interpreting subjective measures of risk perception, however, is that they tend to conflate risk with related constructs (Fox, Erner, and Walters 2015). Notably, risk perception may be associated with both unfamiliarity (Long, Fernbach and De Langhe 2018) and high variance in outcomes (c.f., Slovic 1987). In our framework perceived "risk" that is associated with unfamiliarity is epistemic in nature, whereas perceived "risk" that is associated with volatility is aleatory in nature. Thus, one contribution of this paper is to tease apart epistemic and aleatory components of subjective riskiness and identify their distinct consequences for investor behavior.

Managerial Implications

Understanding individual differences in perceptions of epistemicness and aleatoriness may be important for segmenting investors and providing effective financial advice. For instance, Vanguard clients complete a financial survey that includes risk preferences, investment

horizon, and subjective knowledge (see Web Appendix). Evaluation of uncertainty using an EARS-like measure could provide a fast assessment of diversification preferences, investment management style preferences (e.g., active selection of particular assets versus indexing and automatic rebalancing), and willingness to pay for financial advice. Our results demonstrate that perceptions of epistemicness and aleatoriness predict unique investment behaviors after statistically controlling for risk preference, risk perception, investment horizon, subjective knowledge, financial literacy, and other demographic variables.

In Study 2, we found that individual investors presented with a stock analyst's past predictions as absolute price charts rather than as relative price charts were willing to pay roughly double the amount for subsequent advice from another analyst. In this study, financial forecasts were, in fact, uncorrelated with stock movements—but the absolute price chart gives the impression of greater epistemicness. To the extent that our findings generalize to other settings, financial advisors and regulatory agencies should also be aware of how the communication of financial information may impact perceptions of epistemicness and willingness to pay for financial advice.

A recent audit by Walters et al. (in progress) suggests that the overwhelming majority of analyst reports — nearly 99% in their sample — presented past performance in absolute prices, rather than in terms of relative prices. This suggests that the way in which analyst performance is typically presented to consumers also likely inflates the degree to which consumers see such investment tasks as inherently knowable. We note that the two bodies governing analyst disclosure in the United States — the Securities and Exchange Commission and the Financial Industry Regulatory Authority — do not require disclosure of past analyst performance and do not specify whether past performance, when disclosed, must be in terms of absolute or relative prices. Our research suggests that many equity research firms are (deliberately or unwittingly)

presenting this optional financial information in a way that artificially inflates perceptions of epistemicness and therefore the perceived value of that advice to consumers.

Broader Implications

While we have been agnostic in this article concerning the appropriateness of attributing stock market uncertainty to epistemic or aleatory factors, we surmise that most people perceive greater epistemicness in the stock market than is warranted. We note that this hypothesis accords with ample research demonstrating that people are biased to see patterns where none exist (e.g., Gilovich, Vallone, and Tversky 1985). We speculate that consumers may benefit from interventions that dampen perceived epistemicness of the market and amplify perceived aleatoriness. Past research suggests that paying a financial advisor is an investment strategy that generally incurs additional costs with no incremental returns (Bender, Osler, and Simon 2013; Sharpe 1991), while diversification is the cornerstone of portfolio theory (Markowitz 1952). In addition, the efficient-market hypothesis (Basu 1977; Malkiel and Fama 1970) holds that all publicly available information useful for predicting a future stock price has already been incorporated into the current stock price. Thus, based on modern finance theory, stock market uncertainty *ought to* be viewed as fairly low in epistemicness, with information-seeking strategies doing little to reduce such uncertainty.

Interestingly, investment professionals appear to have a different view of stock market uncertainty than investment amateurs. In a preliminary exploration of these differences we compared perceptions of epistemicness and aleatories from the sample of novice investors in Study 1 to a convenience sample of 37 practicing financial advisors (recruited through an executive education program at UCLA). Naturally, inferences across different populations should be interpreted with caution. This said, we found that perceptions of aleatoriness did not reliably differ between financial advisors (M = 4.97, SD = 1.36) and non-professional investors

(M = 5.32, SD = 1.04), t(39.32, unequal variances assumed) = 1.47, p = 0.149, d = 0.32. In contrast, despite having considerably less experience and less knowledge, non-professional investors perceived greater epistemicness in stock market uncertainty (M = 4.91, SD = 1.32) compared to professional financial advisors (M = 3.04, SD = 1.29), t(42.74) = 8.24, $p < 0.001$, d = 1.42.

Finally, we note the asymmetric consequences of overestimating epistemicness versus aleatoriness in an investment context. Overestimation of epistemicness may lead to poor investment decisions, such as overpaying experts for financial advice (Bender, Osler, and Simon 2013; Sharpe 1991), purchasing over-priced mutual funds (Chen, Jegadeesh, and Wermers 2000), the tendency to overinvest in the domestic stock market relative to foreign markets (French and Poterba, 1991), and overinvesting 401(k) savings in company stocks (Benartzi and Thaler 2001). Overestimation of true epistemicness may also be quite costly over an investor's lifetime and help to explain why more than $4 trillion was held in actively managed funds in 2018 (Bloomberg, 2018), even though investors tend to earn similar or better returns when investing in low fee index funds (Carhart 1997). In contrast, overestimating true aleatoriness is likely to lead to relatively desirable (or at least, benign) consequences, such as increased diversification and portfolios that accord more closely with risk preferences. Thus, educators and advisors may best serve consumers' interests by tempering their impressions of stock market epistemicness, but not aleatoriness. Further research is needed to better understand the accuracy of investor perceptions of the nature of market uncertainty.

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Endnotes

[1] In the present studies we do not measure diversification in its technical sense. Instead, we use degree of portfolio concentration as an inverse measure of naïve diversification.

[2] Note that one might also see naïve diversification in situations involving epistemic uncertainty when it is difficult to pick a "winner" either because: (a) predicted returns of different investments are similar or (b) investors are ignorant about investments (and cannot readily obtain information or consult experts) so that they are in no position to distinguish between them. Thus, while aleatoriness may be a sufficient condition for naïve diversification, epistemicness is not.

[3] We note that these predictions reflect two implicit assumptions: (i) most investors feel they are less knowledgeable than a professional financial advisor and therefore can benefit from professional financial advice, and (ii) most investors are risk averse and therefore prefer to expose themselves to lower variance over outcomes. A sample drawn from Studies 5A-5C where we measured risk preference and subjective knowledge on a sample from Amazon Mechanical Turkers supports these assumptions: participants rated their knowledge of investments as relatively low on a 7-point scale (M = 3.17, SD = 1.32, N = 1,547), and most participants were risk averse (82% risk averse, N = 1,538).

[4] We winsorized this measure of diversification because the distribution of stocks held by individuals was highly skewed ($p < 0.001$, by a Shapiro-Wilk test). We also re-ran our analysis taking the logarithm of the number of stocks and found a similar pattern of results to those reported here. We also observed a reliable Spearman rank-ordered correlation between aleatoriness and the raw number of stocks an individual holds ($\rho = 0.18$, $p < 0.001$).

[5] All studies run on Prolific Academic recruited participants only from the United Kingdom and United States.

[6] In Study 2 we plotted absolute prices as a continuous line chart rather than separate dots as in Figure 2, to enhance ecological validity (in the financial services industry price charts are usually depicted using line graphs whereas price change charts are usually drawn using dots). In Supplemental Study 1 (see Web Appendix) we experimentally vary whether the absolute price chart was depicted using dots or lines and replicate the major results of Study 2, with no statistically significance differences between dots versus lines. Furthermore, in Supplemental Study 1, we scaled the absolute and relative price charts so that the visual magnitude (i.e., vertical length) of analyst errors was equivalent across presentation formats.

[7] We paid one participant based on investment performance from a simulation of a six month period.

[8] A number of participants (n = 78) started but did not finish the survey and were excluded from analysis, as choice data were not recorded for these participants.

[9] We selected these companies because we found in a pretest that they encompassed a wide range on ratings of epistemicness and aleatoriness.

[10] As a control variable we asked participants if they preferred stocks with low, medium, or high volatility, based on a scale used by the investment advisory company Vanguard. Because this measure did not correlate with other measures of risk preference we dropped it from our analysis. Including it in our analysis does not change our results.

[11] As a robustness check we conducted these same regressions where we interact all control variables with risk preference, and this does not qualitatively change the results. This analysis is included in the Web Appendix.

Table 1: Overview of Predictions

Study	Prediction	Paths Tested in Conceptual Model
1	• Epistemicness (but not aleatoriness) predicts willingness to pay for financial advice	$a > 0$, $a > b$
	• Aleatoriness (but not epistemicness) predicts naïve diversification	$c > 0$, $c > e$
2	• Epistemicness affects willingness to pay for financial advice	$a > 0$
3	• Aleatoriness affects naïve diversification, especially when level of uncertainty is high	$c > 0$, $d > 0$
4	• Epistemicness amplifies the influence of expert advice on willingness to invest	$f > 0$, $f > i$
5A–C	• Aleatoriness (but not epistemicness) amplifies the effect of of risk tolerance on willingness to invest	$h > 0$, $h > g$

Table 2: Epistemic-Aleatory Rating Scale (EARS)

Consider the task of evaluating the approximate total return of an individual stock over 1 year. The approximate total return of an individual stock over 1 year ...
(1 = *Not at all*, 7 = *Very much*)
E1 ... is knowable in advance, given enough information.
E2 ... is something that becomes more predictable with additional knowledge or skills.
E3 ... is something that well-informed people would agree on.
A1 ... is determined by chance factors.
A2 ... could play out in different ways on similar occasions.
A3 ... is something that has an element of randomness.

Table 3: Study 1 regression estimates of investment uncertainty on investment behaviors

Dependent Variable	Financial Advisor		Diversification	
	(1)	(2)	(3)	(4)
Epistemicness	0.346***	0.346***	0.877	0.595
	(0.093)	(0.099)	(0.694)	(0.731)
Aleatoriness	0.014	0.013	2.801***	2.985***
	(0.113)	(0.118)	(0.834)	(0.884)
Risk Perceptions 1 (DOSPERT)		0.052		–0.070
		(0.053)		(0.424)
Risk Perceptions 2 (DOSPERT)		–0.102		–0.424
		(0.056)		(0.493)
Risk Perceptions 3 (DOSPERT)		0.041		0.780
		(0.059)		(0.537)
Net investment value		0.090		2.503**
		(0.096)		(0.867)
Other assets		–0.026		–1.150
		(0.101)		(0.866)
Number of stocks held		–0.007		
		(0.006)		
Financial Literacy		–0.115		–0.144
		(0.199)		(1.982)
Constant	–1.803**	–1.701	–7.211	–12.242
	(0.604)	(0.970)	(4.963)	(7.721)
Observations	354	352	354	352
R-squared			0.035	0.069

Note: Robust standard errors in parentheses. For the "financial advisor" column, estimates represent the log odds coefficients from a logit model. For the "Diversification" columns, estimates represent OLS coefficients. Financial Advisor was binary coded (0 = no, 1 = yes); Diversification was coded as the number of stocks held. All other variables were coded as their raw values.
*$p < 0.05$, **$p < .01$, *** $p < .001$

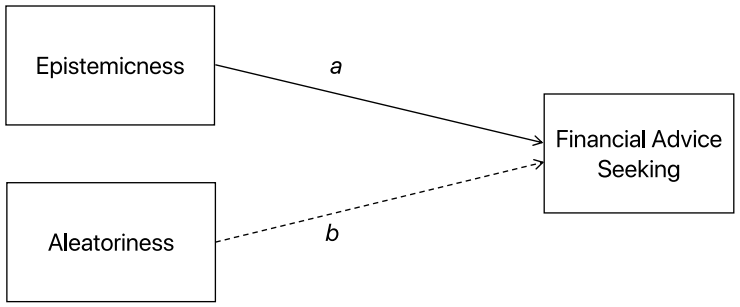
Table 4: Study 5 regression estimates of the interaction of aleatoriness and risk preference on investment decisions

Investment Prospect	Study 5a		Study 5b		Study 5c	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Preference	0.109	–0.357	0.142	0.142	0.406	0.384
	(0.492)	(0.523)	(0.283)	(0.304)	(0.390)	(0.445)
Aleatory Uncertainty	0.183	–0.019	0.352**	0.229*	0.393***	0.222
	(0.159)	(0.161)	(0.112)	(0.116)	(0.107)	(0.115)
Epistemic Uncertainty	–0.463**	–0.463**	–0.345**	–0.347**	–0.200	–0.304
	(0.171)	(0.177)	(0.106)	(0.119)	(0.131)	(0.159)
Epistemic x Risk Preference	–0.097	–0.025	–0.025	–0.029	–0.074	–0.078
	(0.070)	(0.071)	(0.045)	(0.045)	(0.048)	(0.053)
Aleatory x Risk Preference	0.216**	0.251**	0.100*	0.121*	0.121*	0.172**
	(0.080)	(0.086)	(0.043)	(0.050)	(0.058)	(0.065)
Prediction		0.236		0.773***		0.400*
		(0.211)		(0.130)		(0.169)
Probability		0.034***		0.026***		0.033***
		(0.009)		(0.004)		(0.005)
Total Investment Assets		–0.003		0.039		0.056
		(0.035)		(0.028)		(0.036)
Gender		0.137		0.267		–0.043
		(0.213)		(0.168)		(0.220)
Age		–0.001		0.016		0.020*
		(0.009)		(0.008)		(0.010)
General Knowledge		0.082		–0.083		–0.252
		(0.079)		(0.090)		(0.153)
Specific Company Knowledge				0.025		–0.030
				(0.038)		(0.073)
Confidence						0.179**
						(0.068)
Constant	–0.318	–2.201	–1.549*	–3.859***	–2.057*	–4.522***
	(1.034)	(1.212)	(0.695)	(0.874)	(0.886)	(1.116)
Observations	564	549	2,920	2,873	1,834	1,744

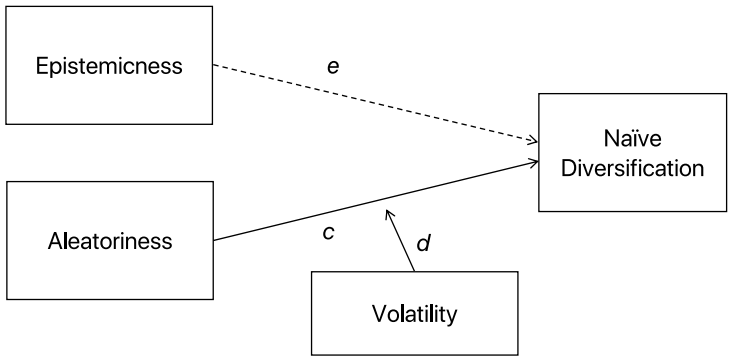
Note: Robust standard errors in parentheses. Estimates represent log odds coefficients from a logistic regression. Company fixed effects are included in column 4 and time period fixed effects are included in column 6. Investment Prospect was binary coded (0 = reject, 1 = accept); Prediction was binary coded (0 = down, 1 = up); participant gender was binary coded (0 = female, 1 = male). All other variables were coded as their raw values.
*$p < 0.05$, **$p < .01$, *** $p < .001$

Figure 1: Conceptual framework

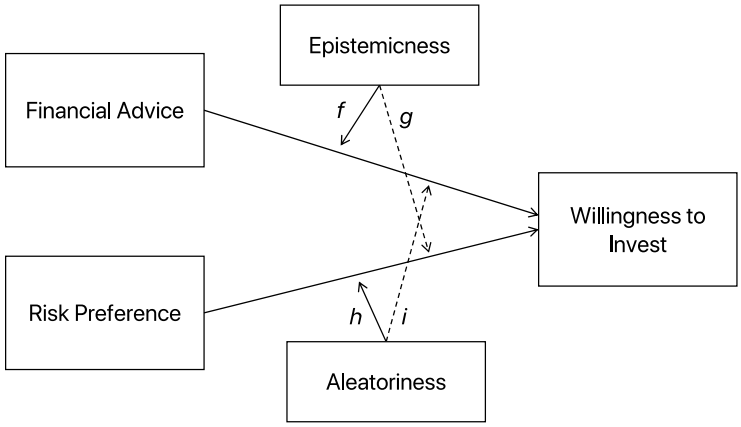
A. Advice Seeking



B. Naïve Diversification



C. Willingness to Invest



Note: Solid lines indicate relationship between variables predicted to be relatively strong and reliable, dashed lines indicate relationships predicted to be relatively weak or unrelated.

Figure 2: Illustration of absolute and relative price charts used in Studies 2. The absolute price chart shows the actual and forecasted price whereas the relative price chart shows the actual and forecasted return.

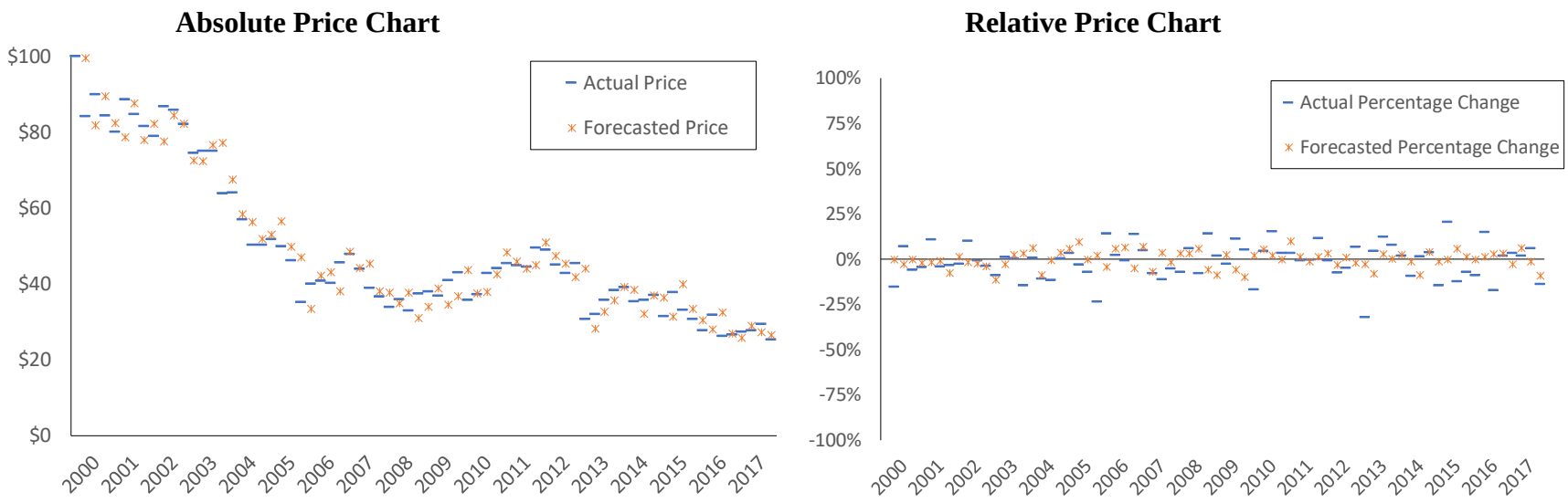


Figure 3: Illustration of absolute and relative price charts used in Study 3. The absolute price chart shows the actual price whereas the relative price chart shows the actual monthly return.

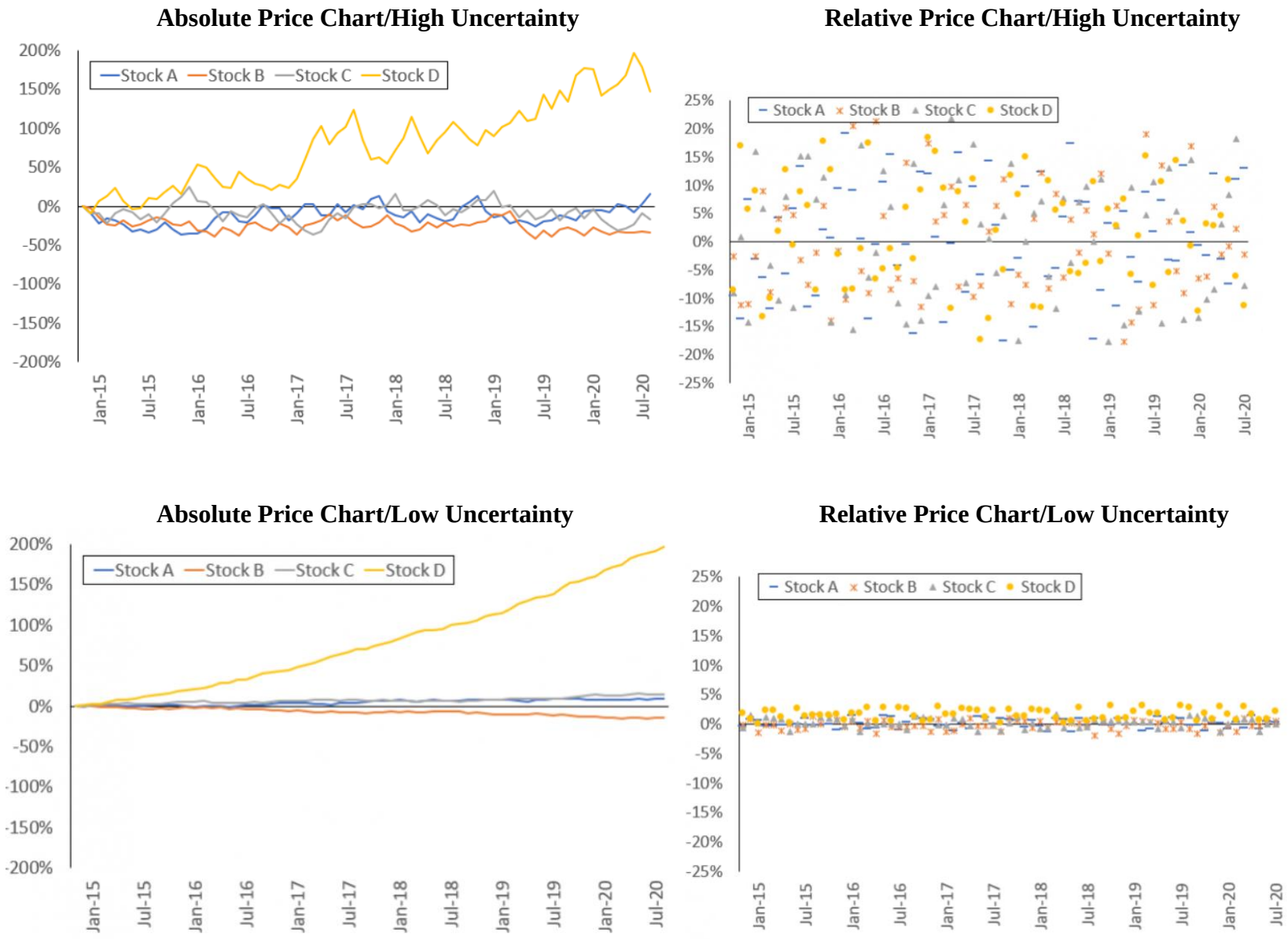


Figure 4: Study 4 Results. The y-axis represents the difference in dollars invested from investment round 1 to round 2 (i.e., after receiving expert advice) as a function of rated epistemicness (orange line and markers) and rated aleatoriness (gray line and markers). Lines represent best fit from the OLS model described in the results section, and error bands indicate 95% confidence intervals.

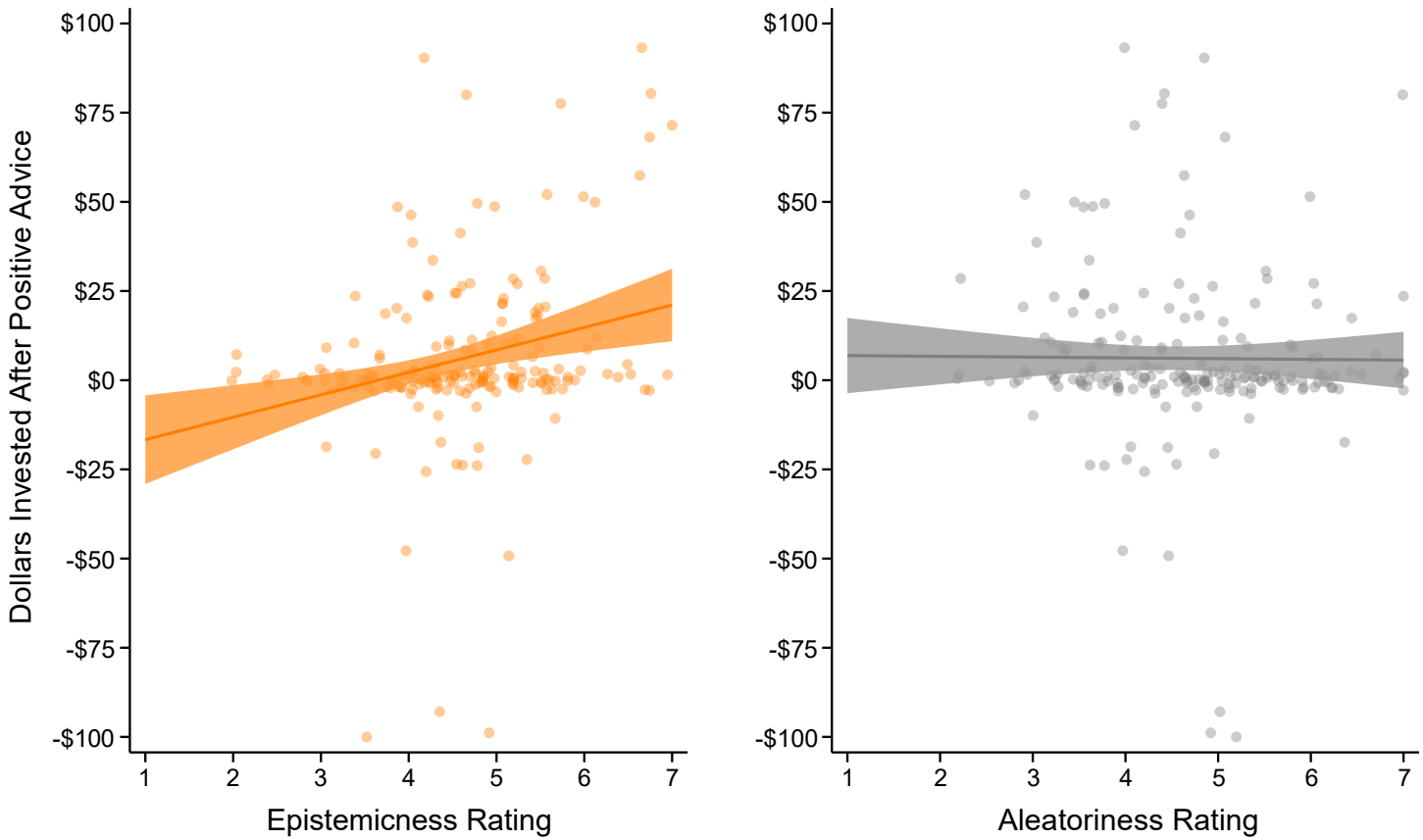


Figure 5: Results from Study 5. Plots represent the interaction between aleatoriness and risk preferences in Studies 5A–5C on the probability of accepting an investment (versus taking a sure payment). Orange lines represent the predicted average marginal effect (based on the logistic regression discussed in the results) for strongly risk averse participants (risk preference of 1 out of 4) and gray lines represent the average marginal effect for risk seeking participants (risk preference of 4 out of 4). Error bands represent 95% confidence intervals.

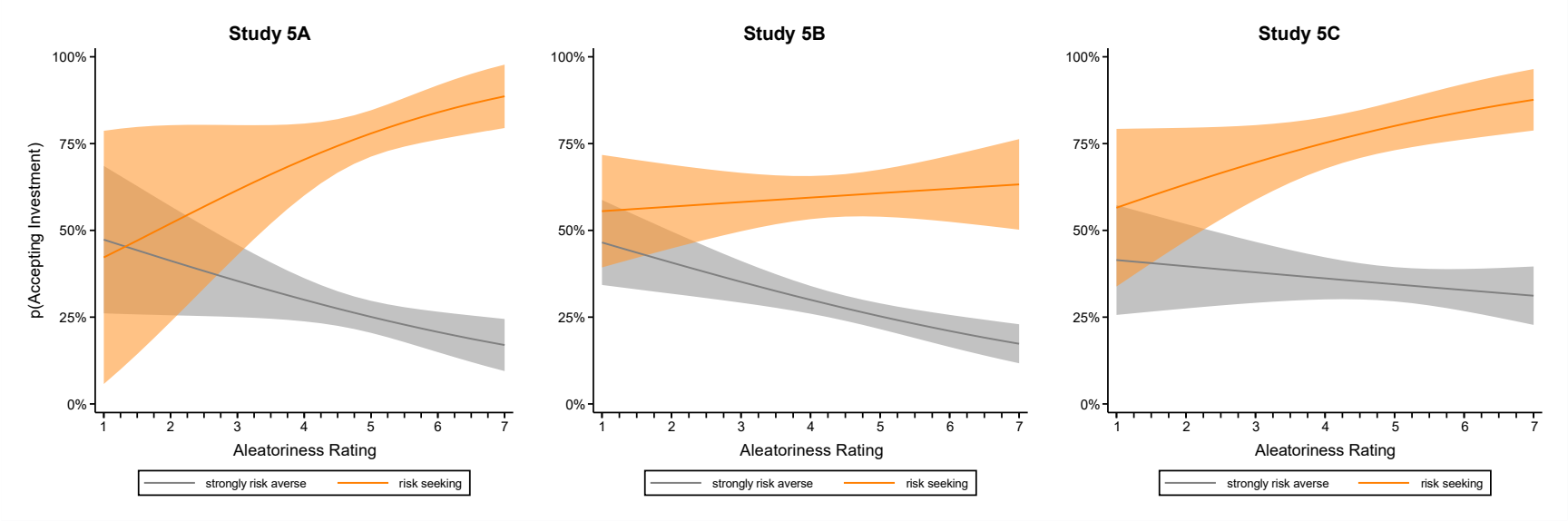


Figure 6: Joint distribution of epistemic and aleatory uncertainty ratings from all studies. Samples include investors from a Qualtrics panel with at least $1,000 in stock market investments (Study 1), and novice participants from Prolific Academic (Studies 2, 3, and 4) and Amazon Mechanical Turk (Studies 5A-C). We added a small amount of jitter to the data points in order to indicate density. For studies with repeated measures, data points represent observations at the participant-trial level.