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# Investor Behavior Under Epistemic vs. Aleatory Uncertainty

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**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 responsive more responsive to available information when choosing whether to invest. In contrast, investors who view stock market uncertainty as higher in aleatoriness (randomness) are more likely to reduce uncertainty through diversification, and their risk preferences better predict whether they choose to invest. We show, further, that attributions of uncertainty can be perturbed by the format in which historical information is presented: charts displaying absolute stock prices promote perceptions of epistemicness and greater willingness to pay for financial advice, whereas charts displaying the change in stock prices from one period to the next promote perceptions of aleatoriness and a greater tendency to diversify.

**History:** Accepted by Yuval Rottenstreich, behavioral economics and decision analysis.



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**Keywords:** investor behavior • financial decision making • epistemic uncertainty • 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. While 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 April 2019, about 50% of U.S. equity assets were held in passively managed funds and the remainder in either actively managed funds or individual stocks (Lauricella and DiBenedetto 2019). Predicting when consumers 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 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, and makes decisions on the basis of this information and advice. 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 reflects 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 one has correctly answered a trivia question or solved a math problem, whereas examples of pure aleatory uncertainty include whether 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., Ülkümen et al. 2016, Tannenbaum et al. 2017, Fox et al. 2022a, b). 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 et al. 2016). Forecasters tend to make more extreme probability judgments when they view relevant uncertainty to be more epistemic in nature and to make more regressive judgments when they perceive uncertainty to be more aleatory in nature (Tannenbaum et al. 2017). To the extent that evaluators see uncertainty as epistemic in nature, they prefer to tie forecasters' compensation to performance-based (rather than fixed) pay; to the extent that evaluators see uncertainty as aleatory in nature, they prefer to have longer evaluation windows to assess forecaster performance (Fox et al. 2022b). The present article examines implications of the psychological distinction between epistemic and aleatory uncertainty for financial decision making.

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. 2022b). 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 that they have available when making investment decisions. Thus, we expect that such investors attempt to reduce uncertainty by seeking information or consulting experts, express a greater willingness to pay (WTP) for financial information or advice, and 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, 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.<sup>1</sup> 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 et al. 2005).<sup>2</sup> 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 obtains (for example, which stock performs best in a particular time frame). Note that such “spreading” strategies do not necessarily imply optimal diversification (Benartzi and Thaler 2001), but rather a naïve attempt to increase returns (Reinholtz et al. 2021). In addition, we expect that individuals who treat uncertainty as more aleatory in nature make decisions that accord more closely with their degree of risk tolerance derived from 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. Meanwhile, we predict that, under aleatory uncertainty, investors focus on reducing their risk exposure and make decisions that are more closely aligned with their risk preferences.

While most prior research on equity trading and portfolio choice treats uncertainty as a single dimension (e.g., Cohn et al. 1975, Capon et al. 1996, Goetzmann and Kumar 2008), the economics literature long acknowledges the relevance of second order uncertainty to decision making. Keynes (1921) argues that decision makers ought to prefer to bet on probabilities that are supported by a larger weight of evidence, and Knight (1921) proposes 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). Whereas economic theories typically model ambiguity using second order probability distributions, multiple priors, or multistage lotteries, psychologists provide experimental evidence that ambiguity aversion reflects reluctance to act in situations in which 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 in which the decision makers feels relatively ignorant, but only to the extent that uncertainty is seen as epistemic in nature (Fox et al. 2022a).

In the present paper, we depart from 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 corresponding levels of uncertainty (for example, the relationship between perceived epistemicness or aleatoriness and

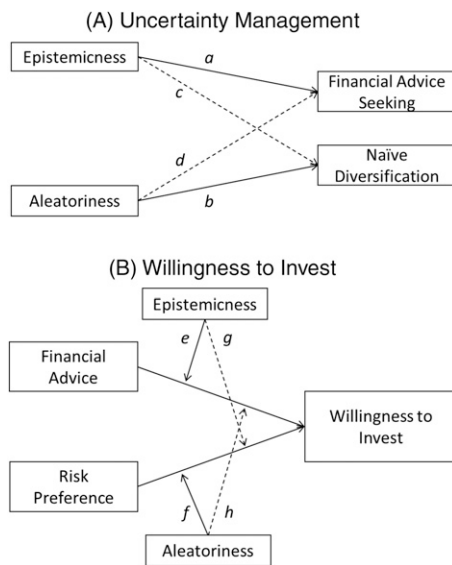
the desire to reduce ignorance or riskiness, respectively). Second, we do not treat epistemicness and aleatoriness as objective features of investments, but rather as subjective appraisals of market uncertainty that may vary between individuals or even within individuals as a function of how market data are presented. Third, unlike prior empirical work on ambiguity and investing that is purely correlational (e.g., Dimmock et al. 2016), we experimentally manipulate the extent to which market uncertainty is seen as epistemic versus aleatory and examine resulting investment strategies.

The main hypotheses that follow from our conceptual model are depicted visually in Figure 1. The first panel (Figure 1(A)) displays predictions concerning uncertainty management. 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 *d*). We expect assessments of greater aleatoriness to be more strongly associated with an increasing tendency toward asset diversification (path *b*) than assessments of greater epistemicness (path *c*).<sup>3</sup>

The second panel (Figure 1(B)) presents predictions concerning willingness to invest in a particular asset. First, we expect that assessments of greater epistemicness (i.e., an increased tendency to view stock investment as a trivia game) amplify the impact of expert advice on willingness to invest (path *e*) more than assessments of greater aleatoriness (path *h*). 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. For instance, we expect an investor who believes that stock returns are especially epistemic in nature would be more likely to follow the advice of a stock analyst to purchase or sell a specific stock than an investor who believes that stock returns are not particularly epistemic in nature. Second, we expect that assessments of greater aleatoriness (i.e., an increased tendency to view stock investment as a chance gamble) amplify the impact of an investor’s risk preference on the willingness to invest (path *f*) more than assessments of greater epistemicness (path *g*). For instance, we expect that an investor who believes stock returns are especially aleatory in nature would be more likely to invest in a stock that accords with the investor’s risk preferences (i.e., risk-averse investors tend to choose a lower risk stock, whereas risk-seeking investors tend to choose a higher risk stock) compared with an investor who believes that stock returns are not particularly aleatory in nature.

## Overview of Studies

We test our conceptual framework, depicted in Figure 1, across a number of studies. In Study 1, we examine

**Figure 1.** Conceptual Framework

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.

real 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(A), path *a*), whereas those who view stock market uncertainty as higher in aleatoriness are more likely to engage in diversification (i.e., Figure 1(A), path *b*). In Study 2, we directly manipulate assessments of epistemicness and aleatoriness by altering the presentation of historical stock information. We find that framing stock movements to focus on absolute price trends increases willingness to pay for an analyst's advice, which is associated with greater perceived epistemicness (Figure 1(A), path *a*). In contrast, when historical stock information is framed to focus on changes in price, participants are more likely to diversify, which is associated with greater perceived aleatoriness (Figure 1(A), path *b*). In Study 3, we show that ratings of epistemicness moderate sensitivity to expert forecasts when making investment decisions (Figure 1(B), path *e*). In Study 4, we show that ratings of aleatoriness moderate the association between risk preference and willingness to invest (Figure 1(B), path *f*).

### Transparent Reporting

For all studies, we determined sample size in advance of data collection. We preregistered hypotheses and analysis plans for Studies 2 and 3 as well as Studies S1–S4 in the online appendix. Materials, data, and code for all studies can be found in our ResearchBox at [https://researchbox.org/180&PEER\\_REVIEW\\_passcode=OQUOTP](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 as epistemic and 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, whereas 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 *b* in Figure 1(A).

### Method

We recruited participants from a Qualtrics panel to complete a survey in exchange for \$10. The Qualtrics panel comprised more than 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 verify 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, report making their own investment decisions, and rate their knowledge of the stock market as 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 can be found in our ResearchBox. 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 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. The median respondent owned five individual stocks, and 95% of respondents owned at least one individual stock.

**EARS Ratings.** Participants first evaluated stock market uncertainty using a six-item version of EARS (see Table 1). They rated each statement on a seven-point scale (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  $\alpha$  was 0.81 for the epistemicness subscale and 0.73 for the aleatoriness subscale). In the online

**Table 1.** Epistemic-Aleatory Rating Scale

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Consider the task of evaluating the approximate total return of an individual stock over one year. The approximate total return of an individual stock over one 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.

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appendix, we report factor analytic results for all studies, which consistently return a reliable two-factor solution corresponding to our constructs of epistemicness and aleatoriness.

**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.<sup>4</sup>

**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 et al. 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 seven-point scales (1 = not at all risky, 7 = extremely risky). We combined these measures into a single index of risk perception (Cronbach’s  $\alpha = 0.63$ ). Our results do not meaningfully differ if we treat each risk perception item as a separate covariate in our analyses.

**Other Measures.** Participants also reported the percentage of their assets (from 0% to 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, the participant 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 online appendix.

At the end of the study, participants completed a three-item financial literacy test (Lusardi et al. 2010) and provided basic demographic information.

## Results and Discussion

We first considered the prediction that reliance on expert advice is 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 2 displays the log odds coefficients from the model. Consistent with our predictions, only epistemicness ratings were reliably and positively associated with paying for financial advice (Table 2, Model 1). For an investor one standard deviation above the mean in rated epistemicness, the predicted probability of having a financial advisor was 60.6%, 95% confidence interval (CI) = [53.0%, 68.2%]. For an investor one standard deviation below the mean in rated epistemicness, the predicted probability of having a financial advisor was 38.1%, 95% CI = [30.5%, 45.8%]. This pattern holds when including a number of additional controls: 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 2, Model 2). In addition, our conceptual model (Figure 1(A)) predicts relationships to be stronger for solid lines than corresponding dotted lines (in this case, path  $a > d$ ). Using an equality of coefficients test,<sup>5</sup> we found that rated epistemicness was stronger than rated aleatoriness as a predictor of paying for financial advice (without controls  $z = 1.92, p = 0.054$ ; with controls  $z = 1.66, p = 0.096$ ).

We next examined diversification. Our conceptual model predicts that ratings of greater aleatoriness should be uniquely associated with less concentrated stock portfolios (i.e., greater diversification). We conducted an ordinary least squares (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 2, Model 3). For an investor one standard deviation below the mean in rated aleatoriness, the predicted quantity of stocks held was 9.06, 95% CI = [7.08, 11.04]. For an investor one standard deviation above the mean in rated aleatoriness, the predicted number of stocks held increased to 14.91, 95% CI = [11.79, 18.02]. This pattern holds when including our additional set of controls (Table 2, Model 4). Using an equality of coefficients test, we find that, consistent with our model, rated aleatoriness was stronger than rated epistemicness as a predictor of diversification (i.e., a comparison of paths *b* and *c* in Figure 1(A): without controls,  $t(351) = 1.73, p = 0.085$ ; with controls,  $t(343) = 2.05, p = 0.041$ ).

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 more epistemic in nature were more likely to pay for financial advice. Meanwhile, investors who viewed stock market uncertainty as more 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.

## Study 2: Manipulating Perceived Epistemicness and Aleatoriness

The results of Study 1 are correlational and, as such, only provide suggestive evidence that perceptions of epistemicness and aleatoriness influence investment behavior. In this study, 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 returns alongside realized returns 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 note that both kinds of price charts contain the same relevant objective information.

We expected that an absolute price chart, by highlighting overall trends in an asset's value, augments impressions of its inherent knowability (i.e., epistemicness), whereas a relative price chart, by highlighting changes in an asset's value from period to period, augments impressions of its fundamentally stochastic nature (i.e., aleatoriness). Two features of absolute price charts may 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 in which there are distinct upward 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

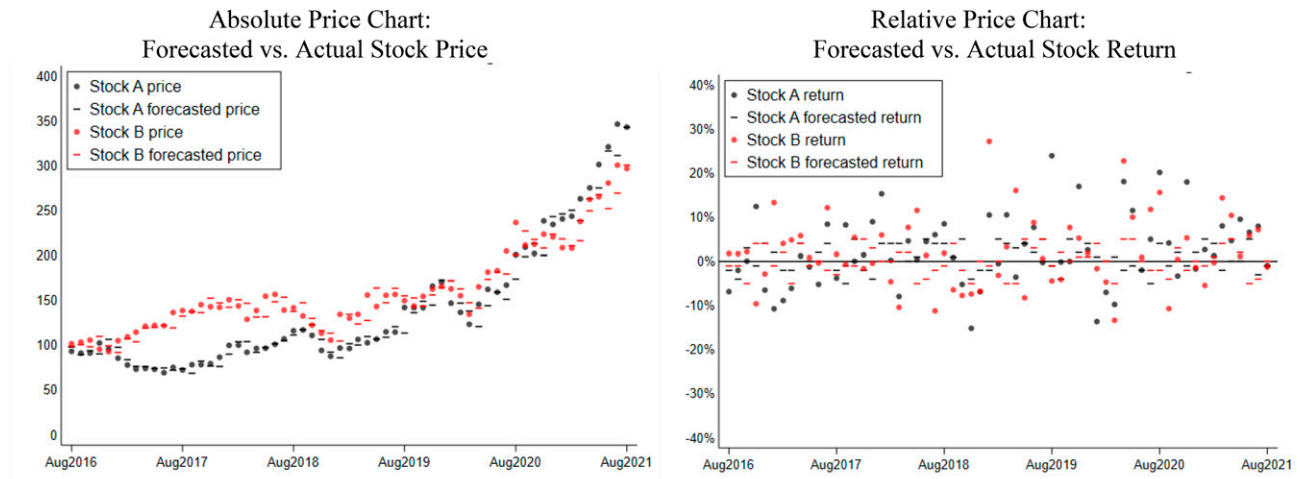
**Table 2.** Study 1 Regression Estimates

	DV: Financial advisor		DV: Diversification	
	(1)	(2)	(3)	(4)
Epistemicness	0.346*** (0.093)	0.321*** (0.097)	0.877 (0.694)	0.739 (0.725)
Aleatoriness	0.014 (0.113)	0.028 (0.117)	2.801*** (0.834)	3.100*** (0.885)
Risk perception (DOSPRT)		0.083 (0.093)		-1.491 (0.891)
Net investment value		0.097 (0.094)		2.703** (0.881)
Other assets		-0.041 (0.099)		-1.290 (0.879)
Number of stocks held		-0.006 (0.006)		
Financial literacy		-0.091 (0.200)		-0.268 (1.976)
Observations	354	354	354	354

Notes. Robust standard errors in parentheses. For the "financial advisor" columns, estimates represent the log odds coefficients from a logit model (0 = no, 1 = yes). For the "diversification" columns, estimates represent OLS coefficients. Diversification was coded as the number of stocks held (winsorized at 100 stocks). Epistemicness and aleatoriness are coded on seven-point scales; risk perception is coded on a seven-point scale (1 = not at all risky, 7 = extremely risky); net investment value and other assets coded on a seven-point scale (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); number of stocks is coded as before when used as our measure of diversification; financial literacy as the number of questions answered correctly (zero to three).

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Figure 2. Absolute and Relative Price Charts Used in Study 2



illustrated in Figure 2, even when forecasted and realized price changes are virtually uncorrelated ( $r = -0.04$  for stock A,  $r = 0.00$  for stock B), forecasted and realized absolute prices can be highly correlated ( $r = 0.99$  for stock A,  $r = 0.96$  for stock B). The seemingly high correlation in absolute price charts 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 eliminates spurious correlations between forecasts and outcomes, but also draws attention to short-term fluctuations in prices and variability in the direction of those changes. Thus, relative price charts should convey the impression of greater randomness in stock prices compared with absolute price charts.

In Study 2, we focus on the relationship between (1) perceptions of epistemicness and willingness to pay for financial advice and (2) perceptions of aleatoriness and diversification. We predicted that participants are willing to pay more for a second analyst's advice after they view forecasts from a first analyst that are presented in an absolute rather than a relative price chart. We emphasize here that we asked about willingness to pay for stock advice from a *different* analyst to ensure the effect is not driven by perceptions of the first analyst's expertise. Additionally, we predicted that participants diversify more after they view forecasts that are presented in a relative rather than an absolute price chart.

## Method

We recruited participants from a QuestionPro panel to complete a survey in exchange for \$5.00. The QuestionPro panel is composed of a subject population with a broad range of professional experience, and

each participant completes a maximum of five studies per month.

Before completing the questionnaire, we screened participants to verify that they met a minimum threshold of investing experience. To be eligible for the study, participants were required to own at least \$1,000 in stock market investments and report making their own investment decisions. A complete list of these questions can be found in our ResearchBox. Of the 717 individuals who responded to the initial screening questions, 350 passed the screening. The final sample was 64% male and had an average age of 47 years (range: 18–88 years), with the median respondent reporting total investment assets in the stock market between \$20,000 and \$50,000.

Participants read that they would make an investment decision after viewing stock recommendations from a professional stock analyst. Next, they 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*) as depicted in Figure 2. Data points in both charts represent monthly intervals from August 2016 to 2021, and participants were told that the analyst made forecasts exactly one month in advance.<sup>6</sup> Participants were also told that stock prices shown in the study came from real companies whose identities were concealed. In fact, stock prices represented the real movement of Target stock (in black) and Facebook stock (in red). We concealed the real stock names in order to reduce variation in behavior because of differences in stock familiarity (e.g., Huberman 2001) or company-specific prior beliefs (e.g., Long et al. 2018). To generate forecasts for each stock analyst, we took the prior period stock price and multiplied it by a growth rate that was randomly



selected from a uniform distribution between 0.95 and 1.05 (i.e., stock price change of –5% to 5%).

**Diversification.** After participants viewed the stock chart, we asked them to imagine having \$1,000 to allocate between the two stocks for the next month. Participants were instructed that they could invest between the two stocks “in any way you see fit, including investing entirely in only one stock.” Participants then entered their allocations for each stock into open text boxes and were required to enter values summing to \$1,000. We operationalized diversification as variance in the amount invested across the two stocks (i.e., average squared deviation from \$500). We then reverse-coded this measure so that higher numbers reflected greater diversification and smaller numbers reflected greater concentration (values could range between 0 and 250,000).<sup>7</sup> We find similar results when using other measures of diversification, such as absolute percentage deviation from even allocation.

**Willingness to Pay for Advice.** On the next page, we showed participants the same chart they viewed before and asked them to imagine investing an additional \$1,000 between the two stocks for a one-month period. They were then asked, “Before you invest, how much would you be willing to pay to see the one-month price forecasts [for stocks A and B] from another five-star rated analyst?” Participants indicated their maximum WTP to view the analyst’s forecast from a list of 11 logarithmically spaced prices ranging from \$0 to \$400. We coded WTP responses as taking a value between 0 and 10 based on the maximum price selected.

**Level of Uncertainty.** As a control measure for perceived level of uncertainty, we asked participants to provide 80% confidence intervals for each stock concerning its next month’s return (Soll and Klayman 2004). In a separate experiment, we verified that this confidence interval measure appropriately tracks level of uncertainty (see Study S1 in the online appendix). In particular, we manipulated stock price volatility (high versus low) as an objective indicator of level of uncertainty and crossed this with chart format (absolute versus relative). We found a significant main effect on confidence interval width of stock volatility but no significant effect of chart format nor a significant interaction between these two factors. Thus, confidence intervals appear to track perceived level but not nature of uncertainty.

We averaged the confidence interval ranges for stocks A and B to compute a measure of overall level of uncertainty (our results do not meaningfully change if we instead use separate confidence interval widths in

the analysis).<sup>8</sup> In accordance with our preregistration plan, we excluded responses from participants who provided confidence interval widths of more than \$2,500 for either stock. We chose this cutoff as it represents approximately 15 times the standard deviation of the monthly returns of the stocks shown in the charts. This resulted in us excluding eight participants.

**EARS Ratings.** We asked participants to rate epistemicness and aleatoriness of the task of forecasting the price of the stock over one month, using the six-item EARS.

## Results and Discussion

For all analyses reported, we implemented robust standard errors to account for arbitrary heteroscedasticity.

**Manipulation Check.** As predicted, participants rated stocks as entailing greater epistemicness when viewing absolute prices ( $M = 5.21$ ,  $SD = 1.06$ ) than relative prices ( $M = 4.75$ ,  $SD = 1.31$ ),  $t(340) = 3.54$ ,  $p < 0.001$ ,  $d = 0.38$ . Participants also rated stocks as entailing greater aleatoriness when viewing relative prices ( $M = 5.69$ ,  $SD = 0.90$ ) than absolute prices ( $M = 5.11$ ,  $SD = 1.14$ ),  $t(340) = 5.24$ ,  $p < 0.001$ ,  $d = 0.57$ . Using simultaneous estimation equations (Zellner 1962), we also conducted a Wald joint hypothesis test and found that epistemicness and aleatoriness ratings reliably differed as a function of chart format,  $\chi^2(1) = 46.13$ ,  $p < 0.001$ .

Similar to the results in our supplemental Study S1, chart format appears to have reliably shifted perceptions of nature of uncertainty (as measured by EARS) although not meaningfully altering subjective level of uncertainty (as measured by confidence interval widths). Confidence intervals of future price movements were not reliably wider in the relative price chart ( $M = 303.61$ ,  $SD = 215.38$ ) than in the absolute price chart ( $M = 317.63$ ,  $SD = 287.46$ ),  $t(340) = 0.51$ ,  $p = 0.610$ .

**Key Results.** Our central findings concern the impact of chart format on advice seeking and diversification. First, as predicted, WTP for financial advice (on a 0–10 scale) was higher when outcomes were presented as absolute prices ( $M = 7.46$ ,  $SD = 2.48$ ) than as relative prices ( $M = 6.13$ ,  $SD = 2.98$ ),  $t(340) = 4.48$ ,  $p < 0.001$ ,  $d = 0.48$ . To provide a sense of the difference in responses between the two conditions, the median scale value for WTP corresponded to \$50 for the absolute price chart and \$25 for the relative price chart. Second, also as predicted, participants engaged in greater diversification when outcomes were presented as relative prices ( $M = 233,304.09$ ,  $SD = 43,543.13$ ) than as absolute prices ( $M = 219,715.80$ ,  $SD = 52,285.73$ ),  $t(340) = 2.61$ ,  $p = 0.009$ ,  $d = 0.28$ . Finally, we conducted a Wald joint hypothesis test and found that investment responses

reliably differed as a function of chart format,  $\chi^2(1) = 6.84$ ,  $p = 0.009$ .

Our key results also hold when controlling for subjective level of uncertainty over stock prices (i.e., confidence interval width). With this measure added as a covariate, participants in the absolute (versus relative) price condition still indicated greater willingness to pay for financial advice,  $b = 1.32$ , 95% CI = [0.74, 1.91],  $p < 0.001$ , and diversified less,  $b = -13,760.20$ , 95% CI = [-24,026.01, -3,494.39],  $p = 0.009$ .

**Mediation Analysis.** To explore the independent contribution of epistemicness and aleatoriness to our key dependent variables (as depicted in Figure 1(A)), we performed Sobel–Goodman tests in which chart format is treated as our independent variable (0 = relative price chart, 1 = absolute price chart) and ratings of epistemicness and aleatoriness as separate mediator variables. Indirect effects are estimated using bootstrapped standard errors based on 10,000 resamples, and confidence intervals are bias corrected (Efron 1987, Shrout and Bolger 2002). Note that, unlike our previous analyses, this analysis treats epistemicness and aleatoriness as variables that causally mediate the effects of chart format on responses rather than as measures of the independent variable (i.e., manipulation checks).

Consistent with our conceptual model, willingness to pay for financial advice was primarily mediated by epistemicness, whereas diversification was primarily mediated by aleatoriness. First, looking at WTP for financial advice, we find that statistically controlling for epistemicness and aleatoriness reduces the effect of chart format by 27.9%,  $b = 0.37$ , 95% CI = [0.03, 0.74],  $p = 0.040$ . This decomposes into a 35.8% indirect effect due to perceptions of epistemicness,  $b = 0.48$ , 95% CI = [0.21, 0.80],  $p = 0.001$ , and a nonsignificant -7.9% indirect effect due to perceptions of aleatoriness,<sup>9</sup>  $b = -0.10$ , 95% CI = [-0.27, 0.02],  $p = 0.151$ . Next, looking at diversification, we find that statistically controlling for epistemicness and aleatoriness reduces the effect of chart format by 91.3%,  $b = -12,404.31$ , 95% CI = [-20,044.14, -7,058.32],  $p < 0.001$ . This decomposes into a 72.5% indirect effect due to perceptions of aleatoriness,  $b = -9,852.22$ , 95% CI = [-16,211.91, -5,379.06],  $p < 0.001$ , and an 18.8% indirect effect due to perceptions of epistemicness,  $b = -2,552.09$ , 95% CI = [-5,907.23, -603.67],  $p = 0.045$ .<sup>10</sup> Furthermore, these results are virtually unchanged when judged level of uncertainty (i.e., confidence interval width) is added as a control variable in the path models, the results of which are provided in the online appendix.

The results of Study 2 demonstrate that participants are willing to pay more for financial advice when stock charts are presented in absolute prices than in relative returns. Our results suggest that this occurs

because chart format influences the perceived nature of uncertainty. Absolute price charts promote the impression that stock prices are more knowable (epistemic), whereas relative price charts promote the impression that stock prices are more random (aleatory). As a result, the heightened epistemicness conveyed by absolute price charts leads to greater WTP for financial advice (Figure 1, path *a*), whereas the heightened aleatoriness conveyed by relative price charts leads to greater diversification (Figure 1, path *b*). In the online appendix, we provide additional data that replicates our pattern of findings using both between-participants and within-participant designs (see Studies S2 and S3 for replications of WTP and Study S4 for an incentive-compatible replication of diversification).

### Study 3: Perceived Epistemicness Amplifies Sensitivity to Expert Advice

Studies 1 and 2 focus on the relationship between the subjective nature of stock market uncertainty and the strategies investors use to manage this uncertainty. Our results thus far suggest that perceptions of epistemicness increase advice seeking (Figure 1, path *a*), and perceptions of aleatoriness increase diversification behavior (path *b*). We next turn to the relationship between the subjective 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 are more responsive to expert investment advice when deciding how to invest (path *e*).

#### Method

We recruited a sample of 195 participants from the United States and United Kingdom using 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 subsequent six months. We told participants that any uninvested amount would be held in cash, which would earn no return over the same period. Participants were informed that one randomly selected respondent would receive the realized value of the respondent's investment (i.e., the market value of stock and cash investments) at the end of the six-month period.

**Round 2: Postinformation Investment.** After completing round 1, participants were presented with a real analyst research report predicting that the Apple stock price would increase in the coming months (for full

details, see our ResearchBox). We then asked participants to complete the same investment task as in 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.

Afterward, participants rated the nature of uncertainty of “the stock price of Apple six months in the future” using the six-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 would be more responsive to expert advice and, therefore, show a greater increase in willingness to invest in Apple stock from round 1 to 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 ratings 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

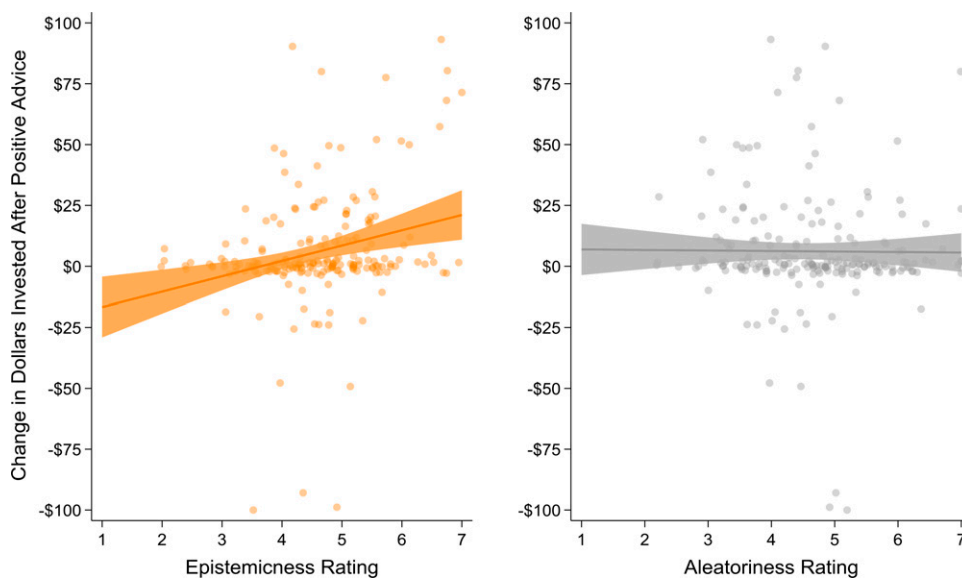
between investment round and ratings of aleatoriness was not significant,  $b = -0.21$ , 95% CI = [-3.09, 2.66],  $p = 0.884$ . Furthermore, using an equality of coefficients test, we find that the investment round  $\times$  epistemicness interaction was reliably larger in magnitude than the investment round  $\times$  aleatoriness interaction,  $t(194) = 3.13$ ,  $p = 0.002$ . Figure 3 plots the change in investments after receiving advice from an analyst as a function of rated epistemicness and aleatoriness.

The results of Study 3 support our prediction that stock advice has a greater influence on investors who view uncertainty in future stock prices as more epistemic in nature (Figure 1, path *e*). Meanwhile, we do not observe a similar effect of expert advice on willingness to invest among those who view the uncertainty in stock prices as more aleatory in nature (path *h*).

## Study 4: Perceived Aleatoriness Amplifies Sensitivity to Risk Preference

In our final study, we test the prediction that perceptions of aleatoriness uniquely moderate the effect of risk preferences on willingness to invest (Figure 1, path *f*). To do this, we recruited three independent samples of participants (Studies 4A–C). All three sub-studies use a correlational design in which participants first make a prediction about the direction of future movement of stocks or stock indices and then are given the opportunity to bet on their prediction by choosing between a larger amount of money that is contingent on their stock prediction being correct or a smaller amount of money that is certain. In order to

Figure 3. Study 3 Results



Notes. The  $y$ -axis represents the difference in dollars invested from investment round 1 to 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.

rule out level of uncertainty as a potential confound, we also control for confidence (e.g., judged probability of one's prediction being correct). Study 4A involves movement of the S&P 500 index, Study 4B involves the movement of individual stocks, and Study 4C involves the movement of a single stock over different time horizons. Studies 4A and 4B employ incentive-compatible designs.

## Method

**Study 4A.** We recruited 564 participants<sup>11</sup> (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 five-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 six-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 is 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 this choice honored for real money. As a control variable, participants assessed the likelihood that their prediction would be correct on a scale from 0% to 100%. Finally, participants provided basic demographic information and were debriefed.

**Study 4B.** 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 five-point scale (1 = low, 5 = high). We then elicited their risk preference using the same procedure as in Study 4A.

Participants next evaluated the returns 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.<sup>12</sup> 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 name] relative to the S&P 500 over the course of one week" using the six-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 is 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 was correct on a scale from 0% to 100%. After completing this task for all eight stocks, participants rated their knowledge of each company (1 = very low, 7 = very high), provided basic demographic information, and were debriefed.

**Study 4C.** 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 five-point scale (1 = low, 5 = high). We then elicited their risk preference using the same procedure as in Study 4A.<sup>13</sup>

Participants then provided several assessments concerning 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 five 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 rated the nature of uncertainty concerning “the return of Apple stock relative to the S&P 500 over the next [time period]” on the 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 seven-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 0% to 100%. Finally, at the end of the study, participants rated their knowledge of Apple stock on a five-point scale (1 = low, 5 = high), provided basic demographic information, and were debriefed.

## 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 4B and 4C 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 = choose certain payout, 1 = bet on their prediction).

For each model, our predictor variables were ratings of aleatoriness, epistemicness, and risk preference as well as interaction terms between risk preference and each dimension of subjective uncertainty. Table 3 provides results for each substudy both with and without additional controls. In all three substudies, we found, as predicted, a significant positive interaction between risk preference and perceived aleatoriness: risk preferences were more predictive of investment decisions for participants who viewed the market as more aleatory in nature (see the shaded rows in Table 3). Figure 4 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.<sup>14</sup> Also consistent with our framework, Table 3 indicates that, for all three studies, there was no significant interaction between risk preference and perceived 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 *f* is stronger than path *g*). Using equality of coefficients tests, we found that the aleatoriness × risk preference interaction on choice was larger than the epistemicness × risk preference interaction in Study 4A (without controls:  $z = 2.95$ ;  $p = 0.003$ ; with controls,  $z = 2.52$ ,  $p = 0.012$ ), in Study 4B (without controls:

**Table 3.** Study 4 Regression Estimates on Investment Decisions

	Study 4A		Study 4B		Study 4C	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk preference	0.793*** (0.087)	0.795*** (0.095)	0.476*** (0.059)	0.555*** (0.068)	0.672*** (0.091)	0.879*** (0.102)
Epistemicness	-0.009 (0.077)	-0.070 (0.086)	0.300*** (0.057)	0.170** (0.060)	0.243*** (0.051)	0.064 (0.061)
Aleatoriness	-0.038 (0.089)	0.031 (0.095)	-0.143** (0.052)	-0.105+ (0.058)	0.046 (0.063)	0.048 (0.073)
Epistemicness × risk preference	-0.097 (0.070)	-0.025 (0.071)	-0.025 (0.045)	-0.028 (0.045)	-0.074 (0.048)	-0.078 (0.053)
Aleatoriness × risk preference	0.216** (0.080)	0.251** (0.086)	0.100* (0.043)	0.122* (0.050)	0.121* (0.058)	0.172** (0.065)
Controls	No	Yes	No	Yes	No	Yes
Participants	564	549	365	361	320	291
Observations	564	549	2,920	2,881	1,834	1,744

*Notes.* Estimates represent log odds coefficients from logistic regression (robust standard errors in parentheses). The outcome variable in all models is whether participants choose the uncertain investment decision (0 = reject, 1 = accept). Risk preference is measured on a four-point scale (1 = strongly risk averse, 4 = risk seeking; mean-centered), and epistemicness and aleatoriness on seven-point scales (both mean centered). Model 2 includes the following controls: participant gender (0 = female, 1 = male), age (in years; mean centered), total investment assets (U.S. dollars; mean-centered), whether participants predicted the market to go up or down in the following six months (0 = down, 1 = up), and likelihood their prediction is correct (0–1; mean-centered), and general investment knowledge (1 = low, 5 = high; mean-centered). Models 4 and 6 include all the previously listed controls plus company specific knowledge (1 = very low, 7 = very high; mean-centered). Model 6 also asks an additional measure of confidence on a seven-point scale (1 = not at all confident, 7 = extremely confident; mean-centered). Company fixed effects are included in Model 4, and time period fixed effects are included in model 6.

<sup>†</sup> $p < 0.10$ ; \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

$z = 1.95$ ;  $p = 0.051$ ; with controls,  $z = 2.19$ ,  $p = 0.029$ , and in Study 4C (without controls:  $z = 3.20$ ;  $p = 0.001$ ; with controls,  $z = 3.75$ ,  $p < 0.001$ ).

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

## General Discussion

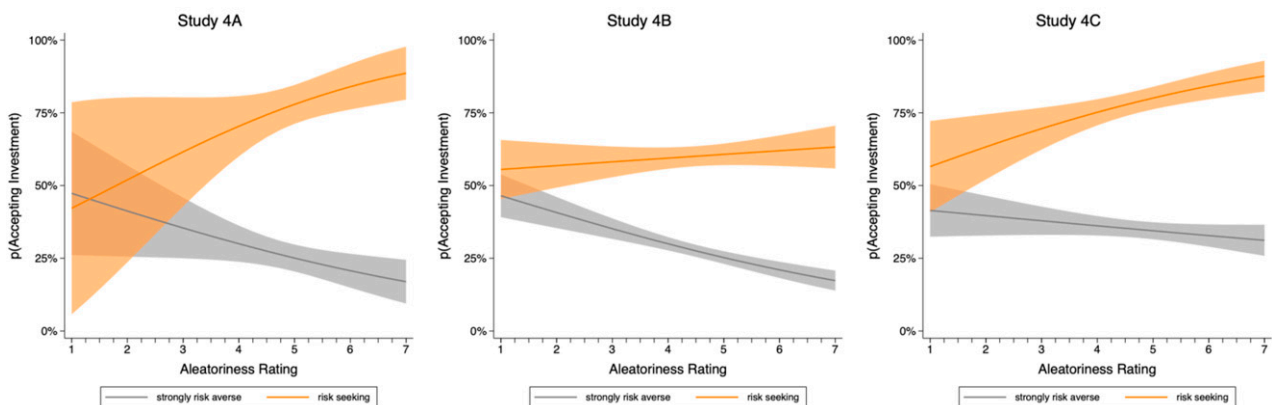
In this paper, we demonstrate that investors differ in their perception of stock market uncertainty along two distinct dimensions: the extent to which they see future movement of stocks and markets as inherently epistemic (knowable) and the extent to which they see future movement as inherently aleatory (random). Second, we provide evidence that these two dimensions of subjective uncertainty are related to distinct actions investors take to manage their uncertainty: those who perceive uncertainty to be more epistemic in nature are more likely to seek information or expertise, while those who perceive uncertainty as more aleatory in nature are more likely to diversify their assets (Studies 1 and 2). Third, we provide evidence that these two dimensions of subjective uncertainty are related to distinct investment behaviors. Investors who perceive market uncertainty to be more epistemic in nature are more responsive to expert advice (Study 3), while investors who perceive market uncertainty to be more aleatory in nature are more likely to act in accordance with their general attitudes toward risk as measured using chance gambles (Study 4).

Our studies also address how investors—at least those in our samples—view the nature of stock market uncertainty. Do investors tend to view stock market uncertainty as relatively high in both epistemicness and aleatoriness, relatively low in both, or as some combination of high and low? Figure 5 displays the joint distribution of rated epistemicness and aleatoriness as scatterplots for all studies. Ratings among our samples of investors in these studies reveal considerable heterogeneity on both dimensions with many respondents seeing the market as moderate to high in both epistemicness and aleatoriness, several respondents seeing uncertainty as high on one dimension and low on another, and relatively few participants viewing stock market uncertainty as 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.

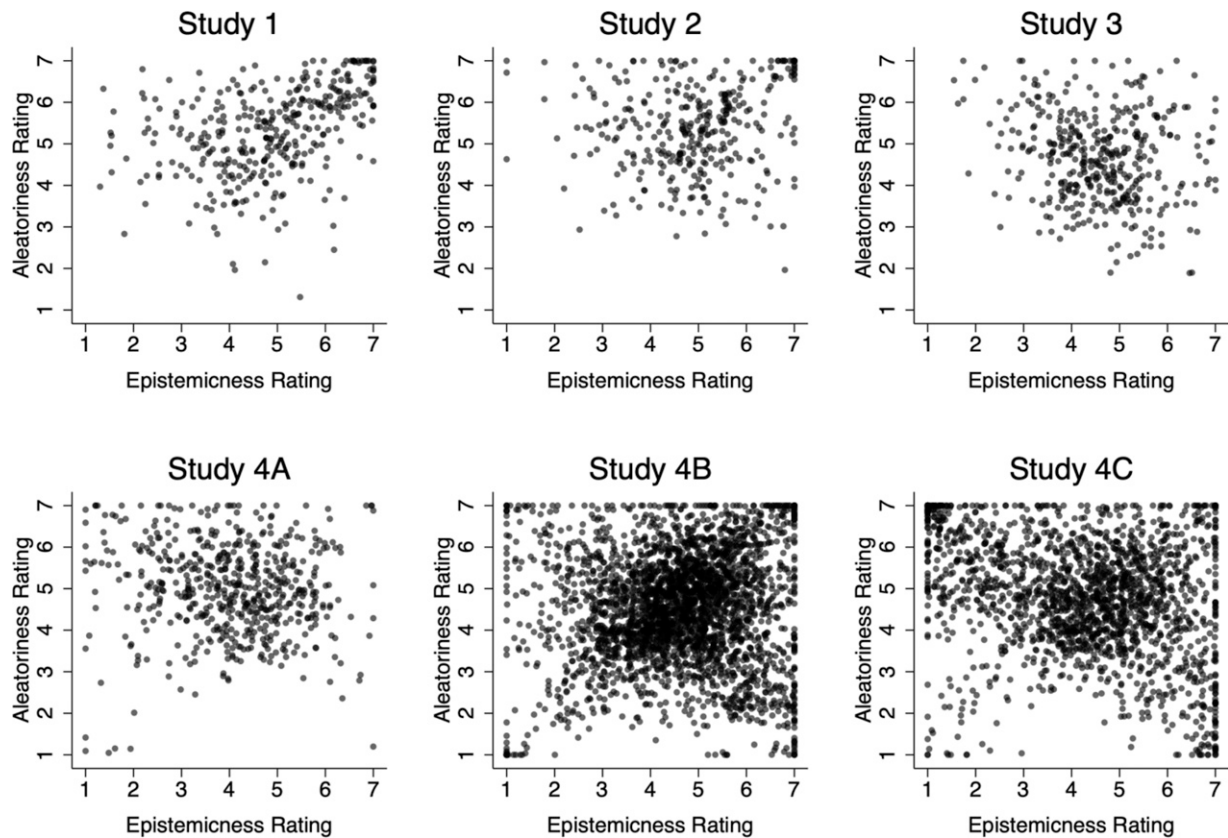
## Related Constructs

Prior research finds that willingness to invest increases with subjective knowledge (Hadar et al. 2013), feelings of competence (Graham et al. 2009), one's sense of understanding (Long et al. 2018), and familiarity with an asset or investment decision (Huberman 2001). We assert that these constructs are associated primarily with the perceived *level* of epistemic uncertainty rather than the perceived *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 uncertainty is seen as epistemic in nature. In our studies, we statistically controlled for level of uncertainty, subjective knowledge of the stock market, and relevant demographic variables, such as financial literacy and investment net worth.

Figure 4. Study 4 Results



Notes. Plots represent the interaction between aleatoriness and risk preferences in Studies 4A–C on the probability of accepting an investment (versus taking a sure payment). Gray lines represent the predicted average marginal effect (based on the logistic regression discussed in the results) for strongly risk-averse participants (risk preference of one out of four), and orange lines represent the average marginal effect for risk-seeking participants (risk preference of four out of four). Error bands represent 95% confidence intervals.

**Figure 5.** Joint Distribution of Epistemicness and Aleatoriness Ratings from All Studies

Notes. Samples include investors with at least \$1,000 in stock market investments in a Qualtrics panel (Study 1) and a QuestionPro Panel (Study 2) and novice participants from Prolific Academic (Study 3) and Amazon Mechanical Turk (Studies 4A–C). Data points have a small amount of jitter added to indicate density. For studies with repeated measures, data points represent observations at the participant–trial level.

Past research also finds that higher risk perceptions are associated with lower willingness to invest in an asset (Weber et al. 2002). One difficulty with interpreting subjective measures of risk perception, however, is that they tend to conflate risk with related constructs (Fox et al. 2015). Notably, risk perception may be associated with both unfamiliarity (Long et al. 2018) and high variance in outcomes (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. 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. Indeed, 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 find that individual investors presented with a stock analyst’s past predictions in an absolute price chart rather than in a relative price chart are willing to pay roughly double the amount for subsequent advice from a new analyst. In this study, financial forecasts were, in fact, uncorrelated with stock movements, but the absolute price chart gives the impression of greater epistemicness than the relative price chart. 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 of 2,429 analyst reports by (Walters et al. 2022) suggests that the overwhelming majority—nearly 99% in their sample—presented past performance in absolute prices rather than relative returns. We note that the two government bodies overseeing 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 they do not specify whether past performance, when disclosed, must be in terms of absolute or relative prices. Our research suggests that the overwhelming majority of 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 are 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 1993). We speculate that consumers may benefit from interventions that dampen perceived epistemicness of the market. Past research suggests that paying a financial advisor is an investment strategy that generally incurs additional costs with no incremental returns (Sharpe 1991, Bender et al. 2013), whereas diversification is the cornerstone of portfolio theory (Markowitz 1952). In addition, the efficient-market hypothesis (Malkiel and Fama 1970, Basu 1977) holds that all publicly available information useful for predicting future stock prices is already incorporated into current stock prices. 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 aleatoriness from the sample of novice investors in Study 1 to a convenience sample of 37 practicing financial advisors who attended an executive education program at the University of California, Los Angeles. 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 nonprofessional investors ( $M = 5.32$ ,  $SD = 1.04$ ),  $t(39.3, \text{unequal variances assumed}) = 1.47$ ,  $p = 0.149$ ,  $d = 0.32$ . In contrast, nonprofessional investors, despite having considerably less experience and less knowledge, perceived much greater epistemicness in

stock market uncertainty ( $M = 4.91$ ,  $SD = 1.32$ ) compared with professional financial advisors ( $M = 3.04$ ,  $SD = 1.29$ ),  $t(42.7) = 8.24$ ,  $p < 0.001$ ,  $d = 1.42$ .

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 (Sharpe 1991, Bender et al. 2013), purchasing overpriced mutual funds (Chen et al. 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 \$4.3 trillion was held in actively managed funds in 2019 (Lauricella and DiBenedetto 2019) 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

<sup>1</sup> 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.

<sup>2</sup> Note that one might also see naïve diversification in situations involving epistemic uncertainty, but only 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, whereas perceived aleatoriness may be a sufficient condition for naïve diversification, perceived epistemicness is not.

<sup>3</sup> We note that these predictions reflect two implicit assumptions: (1) most investors feel they are less knowledgeable than a professional financial advisor and, therefore, can benefit from professional financial advice, and (2) most investors are risk-averse and, therefore, prefer to expose themselves to lower variability over outcomes. A sample drawn from Studies 4A–C, in which we measured risk preference and subjective knowledge on a sample from Amazon.com's Mechanical Turk, supports these assumptions: participants rated their knowledge of investments as relatively low on a



seven-point scale ( $M = 3.17$ ,  $SD = 1.32$ ,  $N = 1,547$ ), and most participants were risk-averse (82% risk-averse,  $N = 1,538$ ).

<sup>4</sup> 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 reran our analysis using 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 perceived aleatoriness and the raw number of stocks an individual holds ( $\rho = 0.18$ ,  $p < 0.001$ ).

<sup>5</sup> We hasten to acknowledge that the interpretation of the equality of coefficients test relies on the assumption that measurement of epistemicness and aleatoriness are comparable. Of course, we cannot rule out the possibility that differences in coefficients predicting whether an investor has a financial advisor (path  $a > d$ ) are partly attributable to differences between epistemicness and aleatoriness in scaling and/or measurement error. This said, scaling differences and measurement error alone cannot simultaneously accommodate the reverse interaction that we observe in coefficients predicting diversification (path  $b > c$ ).

<sup>6</sup> In a supplemental study in the online appendix (Study S3), we scaled the absolute and relative price charts so that the visual magnitude of analyst errors (i.e., the range of values on the vertical axis) was equivalent across presentation formats. This study replicates the major results of WTP in Study 2, suggesting that differences in visual magnitude across chart formats do not explain our results.

<sup>7</sup> Unfortunately, our preregistration for Study 2 contains a small error. We neglected to explicitly specify that our measure of diversification would be reverse coded. Because greater variance implies less diversification, without the reverse-coding our preregistration implies the *opposite* of what we intended to predict for diversification and our joint hypothesis test. As should be apparent from our conceptual model as well as all of our other preregistrations and empirical findings, we expected rated aleatoriness to be associated with *greater*, not less diversification.

<sup>8</sup> We calculated confidence interval width by taking the absolute difference between each participant's high and low estimate. We note that, for 6.6% of trials, participants provided a negative confidence interval (i.e., their low estimate was larger than their high estimate). By taking the absolute difference, we interpret negative confidence intervals as participants providing their honest estimates but mixing up the high and low response options. Our results do not meaningfully change if we instead exclude negative confidence intervals from the analysis.

<sup>9</sup> The negative indirect effect implies that aleatoriness acted as a suppressor variable on the relationship between chart format and WTP; see MacKinnon et al. (2000).

<sup>10</sup> We also compared the size of the indirect effects using equality of coefficients tests. For WTP for financial advice, the indirect effect of epistemicness was reliably larger than the indirect effect of aleatoriness,  $\chi^2(1) = 15.58$ ,  $p < 0.001$ . For diversification, the indirect effect of aleatoriness was reliably larger than the indirect effect of epistemicness,  $\chi^2(1) = 7.18$ ,  $p = 0.007$ .

<sup>11</sup> A number of participants ( $n = 78$ ) started but did not complete the survey, and so we excluded them from analysis as choice data were not recorded for these participants.

<sup>12</sup> We selected these companies because we found in a pretest that they encompassed a wide range on ratings of epistemicness and aleatoriness.

<sup>13</sup> 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.

<sup>14</sup> As a robustness check, we conducted these same regressions in which we interact all control variables with risk preference, and this does not qualitatively change the results. This analysis is included in the online appendix.

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