# The Effects of the Presentation of Asset Price Information on Investor Biases

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by

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## ABSTRACT

Financial decisions are a ubiquitous aspect of life, yet retail investors exhibit a large number of biases when making decisions about how to allocate their assets. A thorough understanding of what causes these biases is still lacking. Most retail investors view very similar asset price information formats, and asset price information, across retail investor platforms, raising the question as to whether this presentation format of asset price information could contribute to the perennial biases displayed by retail investors: over-trading, under diversification, the disposition effect, and over-confidence. In two papers I explore the effects of information presentation on investor behavior. In the first paper, I investigate the effects of merely adding price level graphs to summary statistics on trading, diversification and the disposition effect. I observe decisions about buying, selling, and holding assets, and find that the addition of price level graphs does not increase trading, reduce diversification or affect the disposition effect. In the second paper, collaborators and I show how price level graphs, compared to graphs of relative price changes, lead to perceptions that uncertainty is epistemic (knowable) rather than aleatory (unknowable), and this in turn increases the tendency for participants to predict stock price trends to continue. We show that these results are confined to simulated trending graphs and do not generalize to randomly drawn S&P 500 stocks. Further, three experiments demonstrate that price level graphs, compared to relative price graphs, do not increase investor confidence.

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# Introduction

Even experienced decision makers often demonstrate poor performance. The decision biases displayed in financial asset trading provide a relevant high-stakes example. Financial models such as the Capital Asset Pricing Model (CAPM) make clear predictions about what investors should be doing with their assets: for example, hold well-diversified portfolios. Researchers in the finance literature have tested whether predictions from prescriptive financial models bear out in financial markets, and they have documented several investor biases such as the widespread under-diversification of retail investor portfolios (Blume and Friend, 1975; Goetzmann and Kumar, 2008; Fuertes, Muradoglu, and Ozturkkal, 2014), the disposition effect (Shefrin and Statman, 1985; Weber and Hsee, 1998; Odean, 1998a; Weber and Camerer, 1998) and over-trading (Odean, 1999; French, 2008; Barber, Lee, Liu, and Odean, 2009). These perennial biases and others, have led retail investors to lose money relative to average market returns (Odean and Barber, 2000), and researchers have tried to better understand the drivers of the biases and the heterogeneous effects in an effort to correct them. However, so far, little is known about the contextual factors that lead investors to be over-confident and consequently trade too much, diversify too little, and fall prey to the disposition effect.

In order to better understand why retail investors are exhibiting these behavioral biases, it is important to examine how asset price information is presented to them. A large literature in behavioral economics has demonstrated that the manner in which information is presented can significantly impact people's decision making. Retail investors face very similar asset price information formats across different retail investor platforms such as Yahoo Finance, Bloomberg, Marketwatch, or Morningstar. Most platforms include some combination of summary statistics and price graphs. This raises the question as to whether particular numerical and visual presentation of asset price information can contribute to the perennial biases displayed by retail investors: over-trading, under-diversification, the disposition effect, and over-confidence.

In the first paper I investigate the effects of merely adding price level graphs to summary statistics on trading, diversification and the disposition effect (tendency to sell winners and hold losers). Currently there is very little understanding about the effects of price level graphs on investor performance. Specifically, price level graphs could be exacerbating the perception of trends and decreasing the perception of risk for an asset. Investors' perceptions of risk directly influence the degree to which investors will trade, diversify, and exhibit the disposition effect, ultimately affecting their wealth. In three experiments I tested whether price graphs have these effects on investor behavior but find no evidence to support this hypothesis.

In the second paper I examine more closely the driving mechanisms of investor over-confidence. Specifically, while in the first paper I focused on how the price graphs that are currently used affect investor performance, in the second paper my collaborators and I tested how different price graph formats affect investor confidence by way of changing participants' perceptions of uncertainty. There are two common ways of displaying price information:price level graphs and price return graphs. How each price graph affects investor confidence, and through which mechanism, is unknown. We predicted that price level graphs increase the difference in perceptions of epistemic and aleatory uncertainty which in turn exacerbates investor confidence. We found that price level graphs did not affect investor confidence; however, we did find that price level graphs increased the likelihood with which participants predicted trends to continue, because they perceived stock prices to be more predictable with price level compared to relative price graphs.

Together, these two papers tested the effects of the current asset price information format on retail investor investment decisions and examined the effect of perceptions of uncertainty on investor confidence. This research demonstrated that price level graphs do not have significant effects on retail investor behavior; specifically, over-trading, diversification, the disposition effect, and over-confidence. However, the second paper showed that price graphs increase the belief that price trends will continue because participant's perceptions of predictability were higher. In doing so, this research sheds light on fundamental questions about the role of information presentation on financial decision making.

# Paper 1

## The Effects of Price Level Graphs on Over-trading, Diversification, and the Disposition Effect.


### ABSTRACT

This paper investigates the effects of merely adding price level graphs to summary statistics on trading, diversification and the disposition effect (tendency to sell winners and hold losers). Because price level graphs accentuate trends and diminish perceptions of risk, we predicted that adding standard price level graphs to summary statistics would result in poorer performance in terms of higher trading (punished by transaction fees), less diversification, but also a lower disposition effect, resulting in overall lower wealth. We tested whether the addition of price levels graphs would result in worse financial performance across three different experiments, but found no support for this hypothesis.

Financial models such as the Capital Asset Pricing Model (CAPM) make clear predictions about what investors should be doing with their assets. One such prediction is that investors should hold well diversified portfolios. Researchers in the finance literature have tested whether predictions from different financial models bear out in financial markets, and, they have studied investment decisions of retail investors more generally. This research has uncovered several investor biases, with one of the earliest being the widespread under-diversification of retail investor portfolios (Blume and Friend, 1975; Goetzmann and Kumar, 2008; Fuertes et al., 2014). Other important biases followed such as the disposition effect (Shefrin and Statman, 1985; Weber and Hsee, 1998; Odean, 1998a; Weber and Camerer, 1998) and over-trading (Odean, 1999; French, 2008; Barber et al., 2009). Retail investor under-diversification, susceptibility to the disposition effect, over-trading, and other behavioral biases consistently lead retail investors to lose money relative to average market returns (Odean and Barber, 2000). In trying to better understand the causes of these biases, the heterogeneous prevalence of these biases across populations, as well as the driving factors, have received considerable attention. For example, in an attempt to better understand the origins of under-diversification, Fuertes et al. (2014) show that diversification is more pronounced in wealthier and more educated individuals. Over-trading has been most robustly linked to traders' biased perceptions of their investment skills and ability to predict future stock prices, in other words, over-confidence (Odean, 1999; Grinblatt and Keloharju, 2009; Glaser and Weber, 2007; Statman, Thorley, and Vorkink, 2006). Research has devoted less attention to the contextual features that lead investors to trade more, or under-diversify, or exhibit the disposition effect. The manner in which investors process information may be key to understanding these biases.

In making investment decisions, retail investors largely rely on asset information presented on retail investor sites such as Yahoo Finance, Bloomberg, Marketwatch, or Morningstar. The most prominent and salient information is usually a set of summary statistics and a graphical depiction of how the price of a stock or fund has moved over a given time horizon. The summary statistics often consist of the last closing price, the average year-to-date (YTD) return, the past 1-year return, a 52-week price range and the current price. To the right of these summary statistics investors often find a price graph, depicting price on the y-axis and time on the x-axis. An option to more closely inspect the price graphs is usually readily available and the immediate tendency of anyone visiting a retail investor website. Figure 1 depicts sample price graphs from Fidelity, Bloomberg and Yahoo Finance respectively and makes apparent the clear similarities of price graphs used across different investment platforms. Agents have to make investment decisions largely relying on summary statistics and price graphs analogous to those presented in Figure 1 to make financial decisions.

Could the numerical and visual presentation of asset price information be contributing to the perennial biases displayed by retail investors: overtrading, under-diversification, and the disposition effect, which ultimately result in lower returns than the market? The presentation format of stock price information could impact the degree to which investors extrapolate trends, the extent to which they perceive an asset as risky or not, and their confidence in their own ability to predict stock price movements. Substantial research has shown that how graphs are presented significantly impacts how people make interpretations and predictions about the information in the graph. Lawrence and O'Connor (1993) show that forecasts of time series data are highly influenced by how the y-axis is scaled. Specifically, they find that confidence intervals around forecasts are calibrated better when participant's view a y-axis with a "medium" range, compared to participants who view a y-axis with a wide or narrow range. In addition, the authors show that adding salient horizontal gridlines significantly improves participant's calibration. Huber and Huber (2019) find that making the y-axis range more narrow, increases perceptions of risk of the asset. Further, the format in which price graphs are displayed can have significant market impacts; Huber, Bindra, and Kleinlercher (2019) show that asset bubbles in experimental asset markets are significantly less likely to form when the price line (the line connecting all (x - time, y - price) points) is displayed at the top of the y-axis (for example, the y-axis ranges from 0 to 100 but the price line


(a) Fidelity


(b) Bloomberg




(c) Yahoo Finance

**Figure 1.** Sample price graphs on retail investor sites.

*Note:* All price graphs show a salient price line with otherwise hard to read information (e.g. axes labels, tick marks, information below price graph) only fluctuates between the 80 and 100 price range). The current format of price graphs being used on retail investor websites, whether intentional or not, are very similar (Figure 1) across several important dimensions: a narrow y-axis range, non-salient horizontal gridlines, relatively short time horizons and a generally very salient price line. If the format of price graphs can have such big effects on judgments and behavior, depending on how the graphs are presented, the current format of price graphs being used by retail investor websites could exacerbate the behavioral biases exhibited by retail investors, compared to different price graph formats or no price graph at all. Furthermore, alternative price graph formats could potentially improve retail investor decision making by alleviating some of these biases. We predicted that the default price graph format used by retail investor websites worsens retail investor decision making, compared to having just summary statistics. In particular, if default price graph formats make trends in prices salient and diminish the perceived volatility of an asset's price changes, presentation of such graphs could lead to an increase in trading, a decrease in diversification, a decrease in the disposition effect, and ultimately to overall lower wealth, compared to investors with no price graph at all. In addition, price graphs that diminish the salience of trends and increase the perceptions of risk, could improve portfolio returns by decreasing trading and increasing diversification.

In the current paper we present three experiments that test for the adverse effects price level graphs could have on financial decision making[1]. In particular, in all three experiments, we tested whether adding price level graphs would worsen financial decision making and financial performance. In the first experiment subjects participated in 12 investing rounds ($t \in \{1, 2, ..., 12\}$). In each round participants saw 6 assets - randomly drawn from the S&P 500 - with daily prices displayed for the first month at $t = 1$,

[1]None of the studies in this chapter were pre-registered because these studies were tests of the predictions outlined in the dissertation proposal that price-level graphs would produce adverse effects on financial decision making. Once we found compelling evidence for the original predictions, we had planned to run pre-registered versions of the studies. Because we conclusively found that the studies did not produce our predicted results, we decided not to run any pre-registered replications.

the first and second month for $t = 2$ and so forth. In each round participants could choose to buy, sell or hold assets they currently own. For each transaction, participants paid a 2.5% transaction fee. Participants were randomly assigned to one of two conditions: (1) summary statistics or (2) price level graph. In the former, participant's saw summary statistics about each asset and in the latter participant's saw the summary statistics and a corresponding price level graph, for each asset. We predicted that participants in the price level graph condition would trade more, diversify less, have a lower disposition effect, and overall have less wealth, compared to participants in the summary statistics condition. Our hypotheses were not supported, but, we found suggestive evidence that differences in diversification may emerge if we added more rounds and extended the duration of the asset trading experiment. Thus, in Experiment 2, we added 12 non-trading rounds and 12 trading rounds; a total of 36 rounds with non-trading rounds followed by trading rounds. We did not find support for our main hypotheses. Interesting post-hoc analyses revealed that in the price level graph condition women, compared to men, traded less, incurred lower fees, but did not have higher wealth. In Experiment 3 we changed the trading fee structure to strengthen these findings and find evidence that wealth would be higher for women who traded less (as a result of lower trading fees). Experiment 3 did not replicate the gender effects from Experiment 2. Further, we did not find any evidence supporting our main prediction. All three experiments are consistent with the conclusion that participants in the price level graph condition, compared to the summary statistics condition, do not trade more, diversify less, nor have a lower disposition effect or lower wealth.

The rest of this paper is organized as follows: in the first section we review the relevant literature, in the second, third and fourth section we explain the details of experiments 1, 2 and 3 respectively. In the fifth section, we conclude with a general discussion.

# I. Literature Review

The current work speaks to the literature on portfolio diversification by exploring the effects of price graphs on diversification. The work by Blume and Friend (1975) was one of the first fundamental papers on diversification that demonstrated the wide-spread under-diversified portfolios that retail investors hold. Specifically, using tax data from 17,056 individual income tax forms in 1971, the authors found that 50.9% of forms listed no more than two different dividend payers. These stark findings sparked a literature on diversification to address the asset price theory assumptions which implied that investors should hold diversified portfolios. In addition further empirical work shed light on the heterogeneity and drivers of investor diversification. Existing research has shown that people who are financially sophisticated on average diversify more (Von Gaudecker, 2015; Guiso and Jappelli, 2008). Interestingly Dorn and Huberman (2005) show that self reported risk aversion is the highest predictor of diversification; specifically, people who are more risk tolerant have less diversified portfolios. Beyond that, however, little evidence exists on the drivers of under-diversified portfolios. We add to this literature by testing whether the addition of price graphs on retail investor cites could be contributing to under-diversification.

In addition our work relates to the extant literature on over-trading. Anderson (2013) found a positive correlation between trading and under-diversification. Over-trading may be the second most important behavioral bias in the finance literature, first documented by Odean (1999); Odean and Barber (2000). Specifically, using discount broker data Odean and Barber (2000) finds that retail investors actively trade high-beta, small, value stocks, with 75% of portfolios being turned over on a yearly basis. The poor portfolio performance from over-trading has been attributed to the transaction costs associated with trading (Odean, 1999; French, 2008; Barber et al., 2009). While other mechanisms for over-trading exist (e.g. enjoying trading (Dorn and Sengmueller, 2009; Gao and Lin, 2014) and learning (Linnainmaa, 2011)), one of the main reasons that researchers stipulate why traders trade too much is over-confidence (Odean, 1999; Grinblatt and Keloharju, 2009; Glaser and Weber, 2007; Statman et al., 2006; Graham, Harvey, and Huang, 2009; Moore and Healy, 2008). More specifically, most theories in finance focus on the facet "miscalibration" and model agents as having confidence intervals around future price predictions that are too narrow (Benos, 1998; Caballé and Sákovics, 2003; Kyle and Wang, 1997; Odean, 1998b). However, Glaser and Weber (2007) and Graham et al. (2009) show that a "better-than-average" effect (investors perceive their own investment skills to be better than average) is driving trading frequency of retail investors. In the current paper, we focused on how price graphs could impact trading behavior.

The last main behavior we will be measuring in our experiment is the degree of disposition effect exhibited by investors–the tendency to sell winners and hold losers. The disposition effect has been studied for a long time (Shefrin and Statman, 1985; Weber and Hsee, 1998; Odean, 1998a; Weber and Camerer, 1998), and potential explanations of what is driving people to exhibit the disposition effect have been uncovered since (Heimer and Imas, 2019; Imas, 2016; Barberis and Xiong, 2012; Kumar and Lim, 2008). One explanation for the disposition effect is self-justification (Lehenkari, 2012; Heimer, 2016; Chang, Solomon, and Westerfield, 2016). In other words, people have a hard time selling losing stocks because they justified to themselves that buying the stock was the right choice. Now that the stock is losing value, they don't want to sell the stock and accept that their initial decision to buy was wrong. In line with this explanation, Chang et al. (2016); Lehenkari (2012) show that when investors are not personally responsible for their investment decisions the disposition effect is less strong, and, Heimer (2016) shows that entering a social network exacerbates the disposition effect. Not contradictory, theoretical and empirical work has also extensively attributed the disposition effect to the reluctance to realize losses (Heimer and Imas, 2019; Imas, 2016; Barberis and Xiong, 2012), in other words, investors hold onto losers too long because they don't want to realize the loss on their investment. Many of these explanations could be contributing to the overall disposition effect in the market; our study gives further insight into what may be driving the disposition effect. We tested whether the price level graphs retail investors use to trade non-delegated stocks reduces the overall disposition effect displayed by retail investors. In particular, price level graphs could increase perceptions of stock trends and therefore lead people to believe that stocks will continue trending up or down, making them more likely to want to hold onto winners and sell losers.

For all the behavioral biases we measured in our experiment, we predicted each to be affected by whether or not investors see a standard price level graph. In particular, price graphs may affect financial decisions by way of changing perceptions of the asset's risk and stock price trends. Evidence has shown that higher perceptions of risk of investing in the stock market increases trading and decreases buy-sell ratios (Hoffmann, Post, and Pennings, 2015). Further, the finance literature has documented that investors "chase trends". Specifically, "trend chasing" refers to investors believing that past returns predict future returns (Vissing-Jørgensen, 2003; De Bondt, 1993; Andreassen and Kraus, 1990; Fisher and Statman, 2000), in addition, these beliefs seem to be driven by behavioral biases as opposed to rational inferences from past managerial skill (Bailey, Kumar, and Ng, 2011).

However, the work on perceptions of risk and trend chasing behavior, and their relation to the presentation format of information, have received little attention in the literature. Nevertheless, some research exists and Weber, Siebenmorgen, and Weber (2005) showed that providing an assets name decreases perceptions of risk. Diacon and Hasseldine (2007) conducted an experiment that manipulated whether (i) price or returns were presented and (ii) the length of the time horizon. The authors found that differences in the length of the time horizon did not affect perceptions of risk but when assets were displayed using return graphs, compared to price level graphs, they were perceived as riskier. Most related to the current work is that of Huber and Huber (2019) who find that participants who view assets with a narrow y-axis range perceive them to have more risk compared to participants viewing the same asset with a wider y-axis range. The current research adds to this literature by showing that price level graphs ultimately do not affect behavioral finance biases in the current asset trading paradigm. Similarly thus, any differences in perceptions of risk and trend chasing behavior that may have resulted from the addition of price level graphs, did not result in meaningful changes in behavioral biases exhibited by participants.

# II. Experiment 1: Effect of graph presentation on trading behavior

In the first experiment we tested the effects of adding price level graphs to summary statistics on investment decisions. Specifically, we predicted that adding price level graphs to summary statistics information about assets would worsen retail investor decision making.

## *A. Methods*

We recruited 121 participants from Amazon Mechnical Turk (MTurk). For participating in the experiment, we gave participants a $0.50 show up fee and a $\omega = \$1.00$ investment endowment that they could invest. Specifically, subjects participated in 12 investment periods. In each period they observed 6 different assets with updated asset price information. Each asset was a randomly selected stock from the S&P 500 with monthly asset price information over a 1-year period (from 11/01/2016 until 10/31/2017). Participants traded any of the 6 assets by buying more shares, selling existing shares, or holding onto shares they bought in previous rounds. However, for each transaction (buying or selling) participants incurred a 2.5% (of the price) transaction fee. Before starting the experiment, we gave detailed instructions about the asset price information (minimum price, maximum price, beta, and average return) they were seeing, as well as asking a series of comprehension check questions (see Appendix A).

Participants were randomly assigned to one of two conditions: (1) summary statistics or (2) price level graph. Participants in the second condition were given all the same summary asset price information as those in the first condition were, but in addition, were also given a graph displaying the prices in a price level graph, where price is on the y-axis and time is on the x-axis. An example is given in Figure 2. These graphs were intended to mimic the format of price level graphs on retail investor sites.

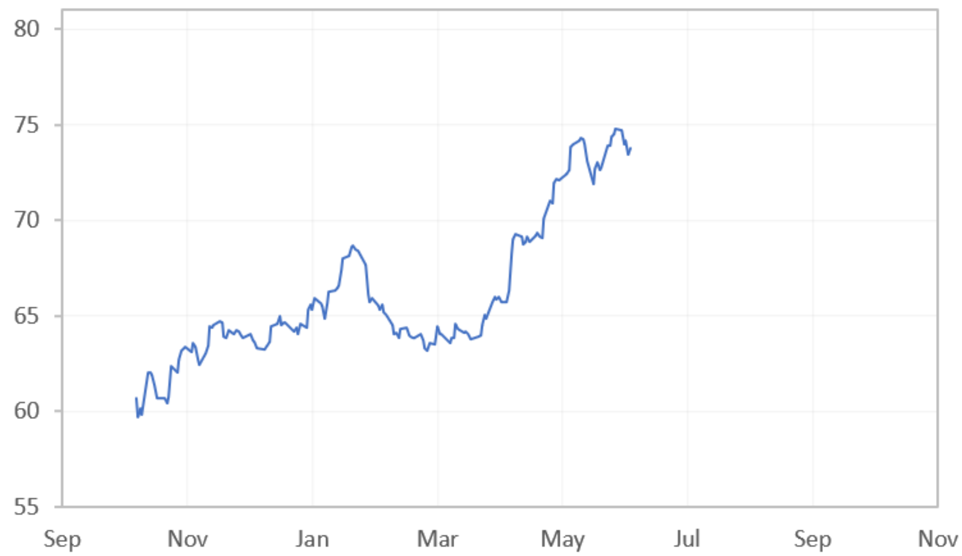



**Figure 2.** Example Price Level Graph

Using this experimental set up, we constructed four dependent variables. The first dependent variable measured the total number of shares a participant bought or sold for each asset in a given period. We will denote the total number of shares a participant holds for an asset $j$ as $N_j$. Specifically, for participant $i$,

$$Trading_{i,t} = \sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Buy or Sell})_{i,t,j,s},$$

where $\mathbb{1}(\cdot)$ is the indicator function, i.e.,

$$\mathbb{1}(\text{Condition}) = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$$

In addition, we measured how diversified a participant's portfolio is on average across the 12 periods. For participant $i$ we measured this as:

$$Diversification_{i,t} = \sum_{j=1}^{6} \left( \frac{\sum_{s=1}^{N_j} \mathbb{1}(\text{Buy or Hold})_{i,t,j,s}}{\sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Buy or Hold})_{i,t,j,s}} \right)^2 .$$

Notice that $Diversification_{i,t} = 1$ means an agent invested their whole portfolio in one asset, and a value of 1/6 means they invested uniformly in all 6 assets. The disposition effect stipulates that participants sell increasing stocks and hold onto losing stocks. We define a stock as a "winner" in period $t$ if the price $p_t > p_{t-1}$, conversely for a "loser", and neither if $p_t = p_{t-1}$. Then, the average disposition effect displayed by participant $i$ across all 12 periods is given by

$$Disposition_{i,t} = \left[ \frac{\sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Sell Winner})_{i,t,j,s}}{\sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Winner})_{i,t,j,s}} - \frac{\sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Sell Loser})_{i,t,j,s}}{\sum_{j=1}^{6} \sum_{s=1}^{N_j} \mathbb{1}(\text{Loser})_{i,t,j,s}} \right].$$

In other words, the difference between the number of winners and losers a participant holds in proportion to the total number of winners and losers they hold, respectively. Further $Disposition_{i,t} \in [-1, 1]$ where a $Disposition_{i,t} = 1$ corresponds to an extreme disposition effect (selling winners and keeping losers) and $Disposition_{i,t} = -1$ corresponds to a reverse disposition effect. Lastly, we measured the overall wealth of a participant in a given round.

$$\begin{aligned} Wealth_{i,t} = \omega_{i,t} &+ \sum_{j=1}^{6} \sum_{s=1}^{N_j} p_{j,t} \mathbb{1}(\text{Hold or Buy})_{i,t,j,s} - \sum_{j=1}^{6} \sum_{s=1}^{N_j} p_{j,t} \mathbb{1}(\text{Sold})_{i,t,j,s} \\ &- \sum_{j=1}^{6} \sum_{s=1}^{N_j} 0.025 \times p_{j,t} \mathbb{1}(\text{Buy or Sold})_{i,t,j,s} \end{aligned}$$

where $\omega_{i,t}$ is a participant's current endowment ("money in the bank") in period $t$.

Now that we have laid out the experimental design and defined our dependent variables[2], we can define our hypotheses. The first hypothesis

[2]Normatively, participants want to maximize their wealth, diversify uniformly across all assets, trade minimally and have a disposition score near 0.

made predictions about $Trades_{i,t}$:

HYPOTHESIS 1: *Participants in the price level graph condition will trade (buy or sell) more compared to participants in the summary statistics condition.*

Further we predicted that $Diversification_{i,t}$ would yield the following results:

HYPOTHESIS 2: *Participants in the price level graph condition will have a lower diversification score compared to participants in the summary statistics condition.*

In addition, we predicted that for $Disposition_{i,t}$:

HYPOTHESIS 3: *Participants in the price level graph condition will have a lower disposition score compared to participants in the summary statistics condition.*

Lastly, we predicted that for $Wealth_{i,t}$:

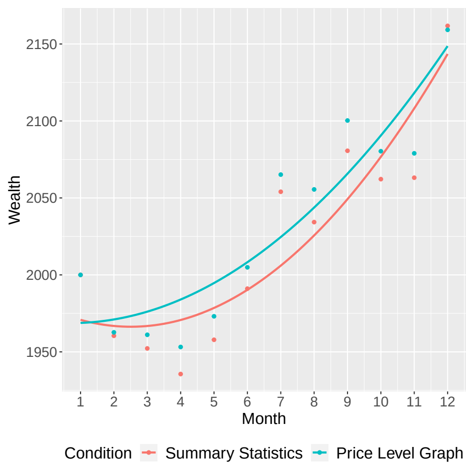
HYPOTHESIS 4: *Participants in the price level graph condition would have lower wealth compared to participants in the summary statistics condition.*

### ***B. Results***

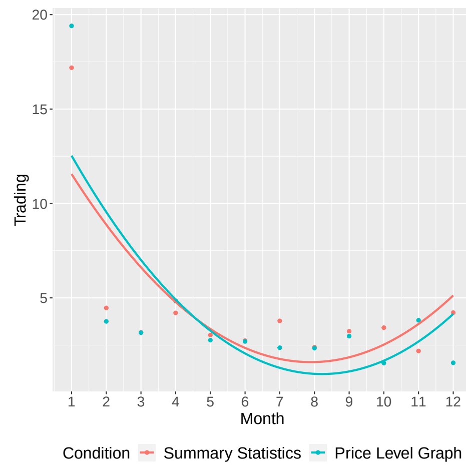
First, we present a series of graphs depicting the differences between the two conditions for each of our 4 main dependent variables across the 12 months (see Figure 3). As can be seen from the graphs, there are no discernible differences across the conditions for all four of our main dependent variables. Diversification shows minor differences in the later periods, however, regressions demonstrate that these differences are statistically minute (Appendix B).

To test hypotheses 1 through 4, the final model we estimate is an OLS regression with the following specifications:

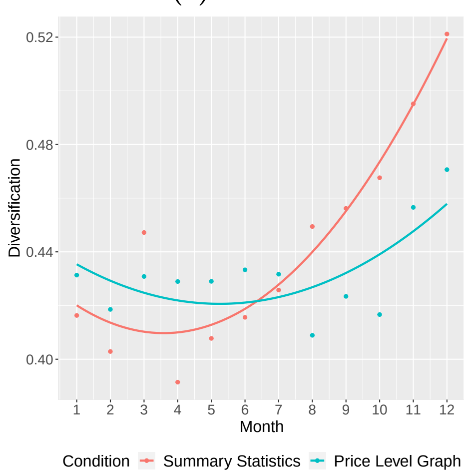
$$y_{i,t} = \alpha_{i,t} + \beta_1 graph_i + \sum_{j=2}^{6} \beta_j X_{i,j} + \epsilon_{i,t} \tag{1}$$



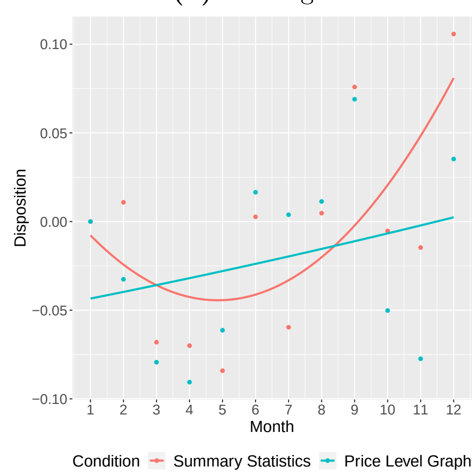

**(a)** Wealth




**(b)** Trading




**(c)** Diversification




**(d)** Disposition

**Figure 3.** Main DV's by Month.
*Note:* Graphs illustrate how means vary across periods. Quadratic functions were fitted for each condition.

for participant $i$ in period $t \in \{1, ..., 12\}$ with errors clustered at the individual level and where

- $y_{it}$ is the dependent variable Trading, Diversification, Disposition, or Wealth defined above.
- $graph_i$ is 1 if participant $i$ was in the price level graph condition and 0 if they were in the summary statistics condition,
- $X_{i,j}$ is a series of controls for participant $i$, including: gender, age, education, and race.

Hypothesis 1 predicted that $\beta_1$ would be significantly positive when $y_{i,t} = Trades_{i,t}$. Hypothesis 2 predicted that $\beta_1$ would be significantly negative when $y_{i,t} = Diversification_{i,t}$. Hypothesis 3 predicted that $\beta_1$ would be significantly negative when $y_{i,t} = Disposition_{i,t}$. Lastly, Hypothesis 4 predicted that $\beta_1$ would be significantly negative when $y_{i,t} = Wealth_{i,t}$. Table I presents the main results and shows that there are no significant differences between the two conditions across our main dependent variables.

### *C. Discussion*

In this experiment we tested the effect adding price graphs to summary statistics has on investment decisions. Specifically, we tested whether there would be differences in trading, diversification, the disposition effect and wealth. As shown in Table I, the results demonstrated that there were no differences between the two conditions for our main dependent variables. One reason for these null-findings may be that the effects in investment behavior only appear after several rounds of trading or observing the asset price information evolve. In particular, we found some suggestive evidence of this for diversification; differences in the level of diversification between the price level graph and summary statistics condition only started to emerge in later periods. To this end, in experiment 2, we decided to extend the number of periods in the asset price experiment to test whether the diversification effect would continue to diverge once we added more periods.

**Table I** Within-subject regression results for main DVs.
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Wealth | Trading | Diversification | Disposition |
| | (1) | (2) | (3) | (4) |
| graph | 8.731 | −0.313 | −0.048 | −0.009 |
| | (27.503) | (0.720) | (0.040) | (0.016) |
| gender | 10.324 | $-1.648^{**}$ | −0.040 | −0.003 |
| | (26.914) | (0.655) | (0.041) | (0.019) |
| age | 0.609 | 0.033 | $0.008^{***}$ | 0.0001 |
| | (1.084) | (0.037) | (0.002) | (0.001) |
| education | 18.872 | −0.831 | $-0.084^{***}$ | 0.015 |
| | (11.498) | (0.539) | (0.024) | (0.011) |
| caucasian | 41.070 | −0.451 | −0.027 | $-0.029^{*}$ |
| | (31.938) | (1.197) | (0.056) | (0.016) |
| Constant | $1{,}884.397^{***}$ | $8.823^{***}$ | $0.534^{***}$ | −0.036 |
| | (67.029) | (2.984) | (0.113) | (0.059) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,452 | 1,452 | 1,452 | 1,452 |
| $R^2$ | 0.020 | 0.009 | 0.147 | 0.006 |
| Adjusted $R^2$ | 0.016 | 0.005 | 0.144 | 0.002 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

## III. Experiment 2: Extending the time-frame

Experiment 2 had the exact same experimental design as Experiment 1, apart from two distinct features: (1) we added 12 periods before participants started trading, where they would just observe stock price information evolve and change over time, and (2) we added 12 additional periods of trading assets, so that there were a total of 24 periods (vs 12 in Experiment 1) of trading. Thus, the experiment was now 36 periods, compared to 12 periods in Experiment 1. In Experiment 1, the addition of price level graphs to summary statistics seemed to be creating a diverging effect on diversification in later periods (although only very slightly so). In Experiment 2, we wanted to test whether this divergent effect would continue if we added more periods to the asset price experiment.

### *A. Methods*

We recruited 103 participants to participate in Experiment 2. The design of Experiment 2 was analogous to that of Experiment 1. However, we added 24 additional periods: (1) 12 non-trading periods that occurred before the trading periods, and (2) 12 additional periods of trading, now a total of 24 periods. Thus, there were now a total of 36 periods: 12 non-trading periods followed by 24 trading periods. To properly compensate participants for the extended length of the experiment, participants' base pay was now \$1.50 and their bonus payment, i.e. their endowment for trading during the 24 trading periods, was $\omega = \$2.00$.

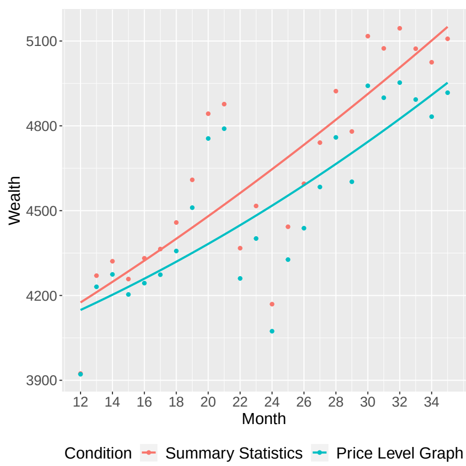
In the 12 non-trading periods, participants watched the price information evolve from period to period and were forced to stay on the screen until all information had loaded. In the price level graph condition, in addition to seeing the summary statistics change (as participants in the summary statistics condition did), they also saw prices being added to the price level graph of each asset. In period 12, all participants could start using their endowment $\omega$ to buy (sell or hold onto) assets. In the final period (as in Experiment 1) all their holdings were sold, to calculate their final wealth. The instructions to Experiment 2 were minimally but carefully modified to reflect the changes to the experimental design.

The main hypotheses we tested in Experiment 2 were analogous to those in Experiment 1 (i.e., hypotheses 1 to 4).

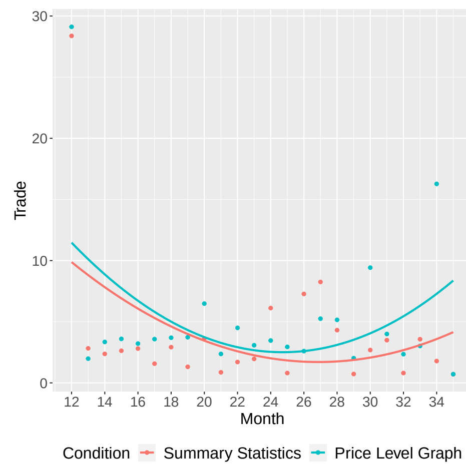
### *B. Results*

Figure 4 depicts the differences between the price level graph and summary statistics conditions for each of our 4 main dependent variables for the trading months (12-35). We use the same regression specification as in equation 1. The regression results are shown in Table II and on aggregate, there are no significant differences between the two conditions for our 4 main dependent variables. In supplementary analysis we investigated a potential interaction of condition and month on diversification. In particular, from inspection of (c) in Figure 4, there may be significant differences in the earlier and later months for diversification levels between the price level graph and summary statistics condition, but not in the middle months. Supplementary analysis in Appendix C shows that this was in fact not the case.

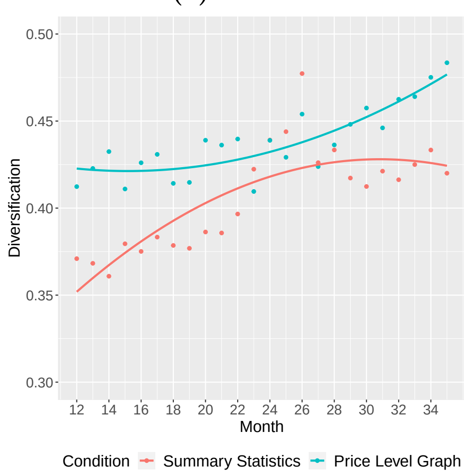
Lastly, we also investigated a potential interaction of condition and gender on trading. In appendix D we conduct a series of regressions to highlight that there is suggestive evidence that women trade less in the price level graph condition, compared to men, but not in the summary statistics condition. Concretely, when conducting separate regressions for each condition, regressing gender on trading, we find that women trade significantly less compared to men in the price level graph condition but not in the summary statistics condition (Table D.I). However, these effects don't yield a significant interaction (Table D.II). Further, we find that the differences in trading behavior for women translates to lower fees in the price level graph condition for women (Table D.III). Nevertheless, the differences in trading and fees in the price level graph condition for women, did not yield higher wealth for women (Table D.IV).



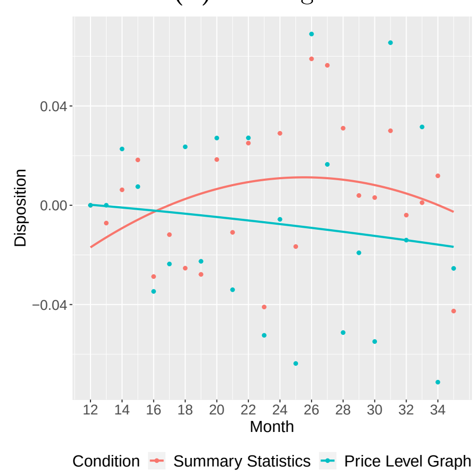

**(a)** Wealth




**(b)** Trading




**(c)** Diversification




**(d)** Disposition

**Figure 4.** Main DV's by Month
*Note:* Graphs illustrate how means vary across periods. Quadratic functions were fitted for each condition.

**Table II** Within-Subject Regression Results for Main DVs with Controls
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Wealth | Trading | Diversification | Disposition |
| | (1) | (2) | (3) | (4) |
| graph | −107.687 | 1.022 | 0.033 | −0.011 |
| | (87.323) | (1.374) | (0.045) | (0.009) |
| gender | −24.274 | −0.257 | −0.003 | $-0.017^{**}$ |
| | (72.504) | (1.852) | (0.054) | (0.007) |
| age | 3.515 | −0.054 | −0.001 | −0.0001 |
| | (3.477) | (0.065) | (0.002) | (0.0004) |
| education | 16.678 | 0.953 | −0.034 | −0.001 |
| | (53.043) | (0.897) | (0.033) | (0.006) |
| caucasian | −97.192 | 0.434 | 0.020 | −0.001 |
| | (109.467) | (1.559) | (0.071) | (0.017) |
| Constant | $4{,}528.274^{***}$ | 2.654 | $0.537^{***}$ | 0.035 |
| | (276.230) | (5.106) | (0.161) | (0.040) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 2,575 | 2,472 | 2,575 | 2,472 |
| $R^2$ | 0.016 | 0.003 | 0.015 | 0.004 |
| Adjusted $R^2$ | 0.014 | 0.001 | 0.013 | 0.002 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

### C. *Discussion*

In the second experiment we tested whether price level graphs in addition to summary statistics information would, across 12 non-trading periods and 24 trading periods, yield higher trading, lower diversification, a smaller disposition effect and overall lower wealth. We found that there were no aggregate difference on these four outcomes between our price level graph and summary statistics condition.

From Experiment 1, because participants in later periods (9-12) in the summary statistics condition, compared to the price level condition, started to diversify less, we stipulated that adding additional trading and non-trading periods may lead to this trend continuing and overall leading to aggregate differences in diversification between the price level graph and summary statistics condition. To the contrary, we did not find that the trend continued and diversification levels were not significantly different between the price level graph and summary statistics condition.

However, we did find significant differences in trading and trading fees accrued by women, compared to men, in the price level graph condition (but not in the summary statistics condition). Nevertheless, these differences did not translate into meaningful interactions of condition and gender on trading or trading fees, or overall lower wealth for women due to the increased trading fees. In Experiment 3 we wanted to pursue these interesting exploratory results further and identify whether we could replicate these results and find significant effects of gender on wealth in the price level graph condition.

## IV. Experiment 3: Fixed trading fee

In Experiment 3 we wanted to test whether the gender effects from Experiment 2 would get stronger and, whether we could find an effect of gender on wealth in the price level graph condition. To this end, we changed the trading fee structure such that over-trading would result in adverse effects on wealth. We opted for a fixed trading fee instead of a percentage based fee structure, mainly because they are the most common alternative trading fee structure to a percentage based trading fee structure[3].

### A. Methods

In Experiment 3 we kept everything the same as in Experiment 2, apart from changing the trading fee structure. Prior to conducting the study, we investigated several different trading fee structures and ran simulations to better understand how different trading fee structures would impact trading, trading fees and overall wealth accrued by participants. We decided on using a fixed trading fee of \$5 for any transaction because fixed trading fees are most common on retail investor sites.

We recruited 91 participants to participate in Experiment 3. Each participant, as in Experiment 2, was given a base payment of \$1.50 and an endowment to trade with of \$2.00. Instructions were altered slightly to reflect the change in trading fee structure.

The main hypotheses we tested in Experiment 3 were analogous to those in Experiment 1 (i.e., hypotheses 1 to 4).

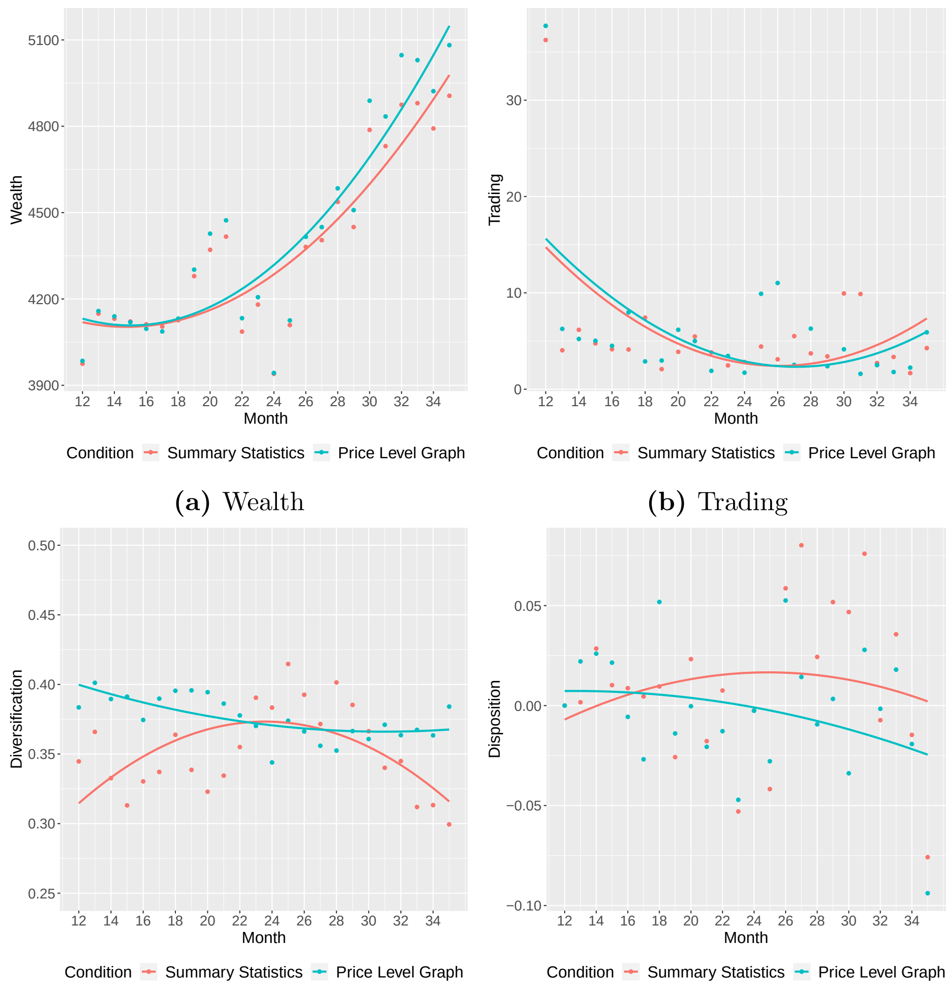
### B. Results

Figure 5 depicts the differences between the price level graph and summary statistics conditions for each of our 4 main dependent variables for the trading months (12-35). We use the same regression specification as in equation 1. The regression results are shown in Table III and on aggregate, there are no significant differences between the two conditions for our 4 main dependent variables.

In addition, as in Experiment 2, we analyzed the effect of gender on trading, trading fees and wealth between the price level graph and summary statistics condition. We did not find any moderation by gender of the effect of price graph (see Appendix E[4]).

[3] See this link [here] for a summary of trading fees across common retail investor sites.

[4] The positive coefficient on gender results from women trading in more rounds, even though they are not trading more shares, compared to men




**(a)** Wealth

**(b)** Trading

**(c)** Diversification

**(d)** Disposition

**Figure 5.** Main DV's by Month
*Note:* Graphs illustrate how means vary across periods. Quadratic functions were fitted for each condition.

**Table III** Within-Subject Regression Results for Main DVs
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Wealth | Trading | Diversification | Disposition |
| | (1) | (2) | (3) | (4) |
| graph | 44.066 | −0.569 | −0.0001 | −0.012 |
| | (73.001) | (1.360) | (0.044) | (0.009) |
| gender | −64.109 | 0.111 | 0.020 | 0.002 |
| | (80.056) | (1.115) | (0.046) | (0.010) |
| age | −1.280 | −0.042 | −0.004* | 0.001 |
| | (2.873) | (0.050) | (0.002) | (0.0004) |
| education | −20.256 | −1.991 | −0.041* | −0.002 |
| | (38.391) | (1.218) | (0.024) | (0.005) |
| caucasian | 84.782 | −0.991 | −0.001 | −0.010 |
| | (70.855) | (1.739) | (0.060) | (0.012) |
| Constant | 4,504.832*** | 15.770*** | 0.623*** | −0.001 |
| | (167.050) | (5.380) | (0.117) | (0.027) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 2,275 | 2,184 | 2,275 | 2,184 |
| $R^2$ | 0.013 | 0.009 | 0.051 | 0.003 |
| Adjusted $R^2$ | 0.011 | 0.007 | 0.049 | 0.001 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | |

### *C. Discussion*

In this final experiment we tested for (1) the main effects as predicted in hypotheses 1 to 4 and (2) an interaction with gender. Unfortunately, we did not find support for the hypotheses outlined and the gender effects suggested in Experiment 2 did not manifest with an alternative trading fee structure. These results now demonstrate for the 3rd time that we were not able to find support for our main hypotheses.

## V. General Discussion

We conducted 3 experiments to test four hypotheses centered around the prediction that financial decision making will be worse when adding price level graphs to mere summary statistics in an asset trading experiment. Across all three experiments we were not able to find any support for hypotheses 1 to 4. In some experiments (1 and 2) we found interesting post-hoc results which we pursued by changing various aspects of the design of Experiment 1. None of these changes affected the overall qualitative results, further substantiating that hypotheses 1 to 4 do not bare out in the experimental paradigm used here. Taking the results together from Experiments 1, 2 and 3, we can conclusively reject hypotheses 1 to 4.

The current paper contributes to existing literature on retail investor behavior and further informs what drives retail investor decision making. In particular, this paper contributes to the extant literature on under-diversification, over-trading and the disposition effect and demonstrated that price level graphs are likely not drivers for these financial biases observed in the literature.

Nevertheless, even if price level graphs do affect financial decision making, there are several reasons we may have found null results. In particular, participants may not have understood the experimental setup and therefore not been able to properly discern and dissect the information presented to them. This seems highly unlikely given the series of attention check questions participants had to pass to continue onto the actual task (see Appendix

A for details).

Further, there are numerous aspects of the current experiments that are pivotal reasons why the current experimental paradigm does not mimic the real world environment, where lay investors make financial decisions; this may be contributing to why we didn't observe any effects of price level graphs on financial decision making. In this asset trading experiment we studied a population of MTurk participants who are not necessarily representative of lay retail investors. Further, these participants were instructed in great detail about the asset price information with which they were presented and how to interpret the statistics. Most retail investors likely have very little understanding of the statistics they are seeing on retail investor sites. In addition, the statistics chosen were key statistics in determining stock price movements and investment decisions, which on retail investors sites are often clouded by a whole mix of statistics. The experimental paradigm tried to mimic 1-3 year investing time horizons with real stock price information. Needless to say, trading in a stylized market for 10-20min is vastly different from actually trading over a 1-3 year time horizon, even if the price movements mimic those seen over 1-3 year time horizons. Participants also did not use their own money, but rather traded using an endowment we provided them. Using one's own money at much higher stakes might result in completely different behaviors of lay investors trading on retail investor sites compared to their trading behaviors in this asset price experiment. Lastly, participants only had to trade 6 different assets. In reality, investors are confronted with a plethora of options to invest their money in and this immense number of options could drastically change decisions investors make.

On the other hand, one can move far away from a realistic experimental design and instead set up an environment in which it is theoretically most likely our hypotheses would bear out. This would be a scenario where there is some combination of trending and non-trending stocks for participants to trade, such that participants first buy non-trending stocks and later want to switch to trending stocks. We would hypothesize that these trends would be more salient with price level graphs than without, thus leading more people to switch and trade their assets in the price level graph condition compared to the summary statistics condition. However, this would be a highly stylized environment, and any results found in this environment would lack external validity. Hence, we did not pursue an experimental paradigm grounded in the most stylized environment that could bring our hypotheses to bear out.

Ultimately, the best way to test the effects of price level graphs as they are currently presented on retail investor sites, would be to run experiments on retail investor sites. This is an avenue that would have been worth exploring if the current results on MTurk would have shown that price level graphs do impact investor decision making. Nevertheless, future researchers should strongly consider the findings uncovered in these MTurk studies as well as their inability to truly mirror investor experiences on retail investor sites. The current results build on the existing literature and should inform future research avenues trying to uncover what drives investor behavior, and in particular, what drives financial biases and how we can best alleviate them.

# Paper 2

## Absolute versus Relative Price Movements, Epistemic versus Aleatory Uncertainty, and their Impact on Stock Price Predictions.


**ABSTRACT**

A significant proportion of retail investors trade too much, and the predominant explanation for this behavior is investor over-confidence. We demonstrate that price level graphs, compared to price difference graphs, increase perceptions of stock price predictability and the likelihood with which participants predict price trends to continue. In three follow up experiments we tested whether price level graphs, compared to price difference graphs, increase investor confidence. Across all three experiments we find no support for our prediction.

A crucial aspect of investing is forming expectations about future stock prices. Such expectations inherently represent the uncertainty investors perceive about the possible future prices of the stock. Depending on how stock information is presented, however, the same historic stock prices and information may lead to systematically different perceptions about a stock's future price uncertainty. Prior research has extensively examined how differences in perceptions of uncertainty can affect decision making. In particular, the literature has distinguished between epistemic and aleatory perceptions of uncertainty. Epistemic uncertainty is uncertainty that is resolvable (and thus predictable) given enough information or skill (for example, answering trivia questions), whereas, aleatory uncertainty describes stochastic events that are inherently unknowable even with all possible information about the state of the world (for example, predicting the outcome of a coin flip that hasn't happened yet). Perceptions of uncertainty along these two dimensions have been found to impact judgments of probabilities (Tannenbaum, Fox, and Ülkümen, 2017) and betting decisions (Fox, Tannenbaum, Ülkümen, Walters, and Erner, 2019b) and may also impact investment decisions by retail investors.

A well known result from the literature on retail investors is that their investments on average lose money, relative to the market return (Odean and Barber, 2000). These low returns are not due to systematically picking sub-optimal stocks, but rather due to high turn-over of their portfolio. In short, lay investors trade too frequently (~75% of their portfolio is turned over each year), incurring high transaction costs (Odean, 1999; French, 2008; Barber et al., 2009) with no better returns than a buy-and-hold strategy. This "over-trading" has been attributed to investor over-confidence (Odean, 1999; Grinblatt and Keloharju, 2009; Glaser and Weber, 2007; Statman et al., 2006). That is, investors overstate their own ability to predict how individual stock prices will change in the near future. The reason for this over-confidence, however, has remained elusive.

Could perceptions of uncertainty explain retail investor over-confidence? The way information is displayed could affect people's perceptions of uncertainty. For stock prices, some price graph formats could highlight the predictability of future stock prices while other price graph formats could highlight the randomness inherent in predicting future stock prices. Retail investors frequently view stock price graphs that show how the stock price changes over time (which we will refer to as an absolute or price level graph). For example, on Fidelity, Yahoo Finance, and TD Ameritrade, the default view of stock price charts shows how absolute prices change over time. In contrast, it is less common to view the stock prices as percentage changes (returns) or the differences in prices between successive periods (both of which we will define as relative price graphs). Table 1 in Glaser, Iliewa, and Weber (2019) shows that many online sources for retail investors do not even give investors the option for stock prices to be displayed as returns. If retail investors viewing absolute stock price graphs, compared to relative stock price graphs, perceive future stock price changes to be more predictable, then the predominant use of price level graphs in the market could exacerbate investor over-confidence. The perception of a stock's predictability is a key facet contributing to the confidence retail investors have in their ability to forecast future price movements of that stock. Specifically, we would expect perceptions of stock predictability to increase investor confidence and, as per the existing literature, increase their trading frequency. Thus, the use of price level graphs could exacerbate perceptions of stock predictability and therefore investor confidence. This relationship could be a fundamental factor that creates retail investor over-confidence and over-trading. We hypothesized that absolute price graphs exacerbate perceptions of stock predictability and significantly affect investors' stock price predictions.

In the first experiment, we showed that participants perceive absolute price graphs to be more predictable (epistemic) compared to relative price graphs, resulting in a significantly higher likelihood of predicting price trend movements to continue. In Experiments 2-4, we tested (a) whether the findings of experiment 1 generalize to randomly picked S&P 500 stocks and (b) whether the effect of price level graphs on perceptions of epistemic uncertainty increase investor confidence; thus, testing for a direct link between perceptions of uncertainty and confidence. Across all 3 experiments we find no support for (a) or (b), however, we replicate the findings of the first experiment in Experiment 4.

In the first experiment, half the participants saw simulated stock price data presented as absolute prices $(p_0, p_1, p_2, ..., p_{23})$ and the other half of participants saw simulated stock price data presented as price changes $(p_1 - p_0, p_2 - p_1, ..., p_{23} - p_{22})$. For each of 10 stock price graphs, participants predicted whether the price in the next period would be higher, lower, or the same as the price in the last period shown. Participants also rated each of the two types of price charts on different types of uncertainty. That is, they rated the degree to which they perceived each price graph to have epistemic uncertainty and aleatory uncertainty. Participants shown the absolute price graphs perceived absolute price graphs to be significantly more epistemic and less aleatory compared to relative price graphs and were significantly more likely to predict prices to continue trending. Further, the effect price graph format had on trend predictions was mainly driven by differences in participants' perceptions of the epistemic uncertainty of the price graphs. Specifically, participants who viewed price graphs to be more predictable (epistemic) were more likely to predict price trends to continue. In other words, we found that absolute price graphs induced higher perceptions of predictability. These higher perceptions of predictability could lead to an increase in participants' confidence in their ability to forecast future price movements, a hallmark of over-confidence. In the second experiment we tested for this link between perceptions of predictability and confidence. In Experiment 2 we used an analogous design as Experiment 1 but employed more realistic stock prices, added comprehension check questions to ensure that participants understood the price graphs, and added two measures of confidence. Specifically, we asked participants to give a price point prediction and a 50% confidence interval for each future stock price prediction (a measure of miscalibration). Further, participants answered how many, out of 10, future directional stock price predictions they thought they predicted correctly (a measure of performance). We tested whether participants in the absolute price graph condition had higher perceptions of predictability and whether these higher perceptions of predictability lead to increases in confidence as measured by narrower confidence intervals and higher expected performance. We were not able to find support for this hypothesis and did not replicate the results from Experiment 1 when using randomly drawn S&P 500 stocks. Nevertheless, we found that participants understood the price graphs well and were able to make accurate numeric calculations using them. That being said, detecting trends was remarkably easier using absolute compared to relative price graphs; we attribute this to a tendency of using a heuristic approach to evaluate trends, compared to an analytical approach. In Experiment 3 we asked participants to make directional price predictions (i.e. the future price will increase, decrease, or stay the same) as in Experiment 1, because price point predictions (i.e. predicting the exact closing price) are a lot harder in the absolute price graph condition, compared to directional price predictions, and may therefore diminish confidence. Experiment 3 also revealed no effect of price graph condition on confidence judgments. Lastly, in Experiment 4, we returned to using simulated stock prices as in Experiment 1. We replicated the results from Experiment 1 in Experiment 4, but did not find any evidence that price level graphs, compared to relative price graphs, increased confidence.

Experiments 1 and 4 were pre-registered studies using simulated stock prices that robustly established the significant effect price level graphs have on increasing participants' likelihood of predicting trends to continue. Experiments 2 and 3 were pilot tests using real stock prices which did not find that the results from Experiment 1 and 4 generalized to randomly drawn S&P 500 stocks, nor that there is a direct link between price graphs and confidence.

The remainder of this paper is structured as follows: in the first section we review the relevant literature and how our results speak to that literature; in the second through fifth section we outline our experiments and their corresponding designs, results and a brief discussion; in the sixth section we discuss the results of the paper overall.

# I. Literature Review

The current research sheds light on two fundamental questions addressed by previous literature; it illuminates the process by which lay investors evaluate stocks and make investment decisions, and it also builds on work exploring how predictions are affected by the nature of uncertainty.

Household investor strategies have been considered adequate on average (Campbell, 2006; Schlarbaum, Lewellen, and Lease, 1978a,b). Using discount broker data Odean and Barber (2000) found that retail investors actively trade high-beta, small, value stocks, with 75% of portfolios being turned over. Researchers argue that excessive trading has led to the poor performance of household investors due to the transaction costs associated with trading (Odean, 1999; French, 2008; Barber et al., 2009). Further, over-confidence has repeatedly been argued to be the reason traders trade too much (Odean, 1999; Grinblatt and Keloharju, 2009; Glaser and Weber, 2007; Statman et al., 2006). Over-confident investors are optimistic about their ability to predict future events, perceive their prediction accuracy to be better than average, and are miscalibrated (Kahneman and Tversky, 1973; Grether, 1980; Weinstein, 1980; Moore and Healy, 2008). The finance literature has specifically modeled over-confidence as miscalibration (Benos, 1998; Caballé and Sákovics, 2003; Kyle and Wang, 1997; Odean, 1998b). In particular, agents underestimate the variance of a risky asset and are over-precise in their future stock price estimates. In other words, the confidence intervals agents have around future stock prices are too narrow. We demonstrate that absolute price graphs used on retail investor sites are likely not a driver of miscalibrated over-confidence (or performance over-confidence).

In addition our research speaks to previous research on differences in future price forecasts across return and price movements. Research on this topic was first initiated by Glaser, Langer, Reynders, and Weber (2007), and Diacon and Hasseldine (2007). The literature has focused on manipulating price level forecasts and returns on two dimensions: graph format and response mode. For example, Glaser et al. (2007) manipulate the response mode (whether participants are asked to forecast the return of a stock compared to the price level of a stock), while fixing the graphs to depict price levels. The authors found that asking participants to predict the future stock return significantly increases the likelihood with which participants predict trends to continue compared to asking participants for the future price level. Diacon and Hasseldine (2007) did not find significant effects of manipulating chart format (while fixing response mode) on investment decisions, but Stössel and Meier (2015) found significantly more optimistic forecasts for return compared to price level charts. Glaser et al. (2019) reconcile these findings by eliminating confounds that could have explained previous discrepancies in the literature. The authors show that asking participants to predict returns compared to price movements (while fixing graph format) results in higher expected returns whereas showing return graphs as opposed to price level graphs (while fixing response mode) results in lower expected returns. Glaser et al. (2019) tested several different explanations of their treatment effect - higher expected returns when the response mode is to give a returns estimate but lower expected returns when viewing return graphs - and show that responses to the cognitive reflection task are correlated with expected returns (even after controlling for mathematical ability) and partially explain their treatment effect. The literature so far has focused on the effect of different graphs on predictions of returns or prices. We investigate a novel reason for why price graphs affect return/price predictions: perceptions of stock price predictability.

A central focus of the current paper is the manner in which conceptualizations of uncertainty affect price predictions and investor confidence. Previous work has indicated that people perceive and treat epistemic and aleatory uncertainty differently. The distinction between epistemic and aleatory uncertainty was first made in modern probability theory (Hacking, 2006). However, only recently have psychologists looked at the psychological differences between these dimensions of uncertainty (Fox and Ülkümen, 2011). Specifically, researchers have explored how these two types of uncertainty affect: language used to express uncertainty (Ülkümen, Fox, and Malle, 2016), judgments of probabilities (Tannenbaum et al., 2017), betting decisions (Fox, Goedde-Menke, and Tannenbaum, 2019a) and assignments of blame (Fox et al., 2019b). Most relevant to the current work is a paper exploring how epistemic and aleatory perceptions of uncertainty affect investment decisions (Walters, Ülkümen, Erner, Tannenbaum, and Fox, 2019). The authors show that people who view the stock market as more epistemic are more sensitive to available information and are more likely to seek guidance from experts, while people who view the stock market as higher in aleatory uncertainty are more sensitive to their risk preferences when picking stocks and, when trying to reduce risk, are more likely to diversify. Most relevant to the current work are findings from a study manipulating how price charts are displayed. In this study, Walters et al. (2019) randomly assigned half of the participants to see an analyst's past stock price forecasts and outcomes (on the same graph) in absolute price levels and the other half of participants to see an analyst's past stock price forecasts and outcomes as percentage changes between two period prices. In the absolute condition participants were more likely to view the stock market as epistemic compared to the percentage change condition. In the percentage change (relative) condition participants were more likely to view the stock market as aleatory compared to the absolute price graph condition. Further, participants reported higher willingness to pay for expert advice in the absolute price graph condition compared to the relative price graph condition; this effect was mediated by perceptions of epistemic uncertainty. However, to the best of our knowledge, our paper is the first to study how these price graph changes affect investor confidence and forecasts of future stock prices.

## II. Experiment 1: Initial Evidence

In the first experiment we generated stock prices with distinct trends. Participants who viewed price level graphs compared to price difference graphs, were more likely to predict trends to continue, and these differential predictions were driven by changes in perceptions of uncertainty. Specifically, participants who perceived the stock prices as knowable were more likely to predict trends to continue compared to participants who perceived the stock prices as less knowable and more random.

### *A. Methods*

We recruited 402 participants from an online labor market (MTurk) and asked them to participate in a 10-minute survey[5] for a payment of \$0.50. Participants could earn additional payments based on their decisions during the study. We excluded 4 participants because they reported having technical problems with the survey. The final sample consisted of 398 participants whose average age was 39 and 46% of whom were male. The complete summary statistics can be found in Appendix F.

Participants were randomly assigned to either the absolute or relative price graph condition and asked to make 10 stock price predictions. Participants were paid a bonus based on one randomly drawn stock price prediction. If participants correctly predicted the direction of the future price movement of that stock, they received an additional \$0.30 as a bonus payment. In the absolute price graph condition, for all 10 stock predictions, participants saw historical prices as absolute prices ($p_0, p_1, p_2, ..., p_{23}$; Figure 1). However, in the relative price graph condition, participants saw price movements as price differences compared to the previous period ($p_1 - p_0, p_2 - p_1, ..., p_{23} - p_{22}$; Figure 2)[6]. Participants in both conditions were informed that the starting price ($p_0$) was \$50. We generated stock prices using the following self-generated formula[7]:

$$p_{t+1} = \mu_{t-2,t}(0.5 - r)\sigma + p_t(1 + ppt)$$

where $p$ denotes the stock price, $\mu$ the average of a series of stock prices, $r$ a pseudorandom number generated using the Mersenne Twister algorithm, $\sigma$ the variance, and $ppt$ the per period trend. The initial three period (-2, -1, 0) prices were \$50.

By manipulating the variance and per-period trend, we created 4 different types of stocks: linear positive, linear negative, quadratic positive, and quadratic negative. We distinguished between different types of price

[5]The study was was pre-registered on OSF and can be viewed at `osf.io/k526m`.
[6]A manipulation inspired by Walters et al. (2019)
[7]Kindly provided to us by Dan Walters.

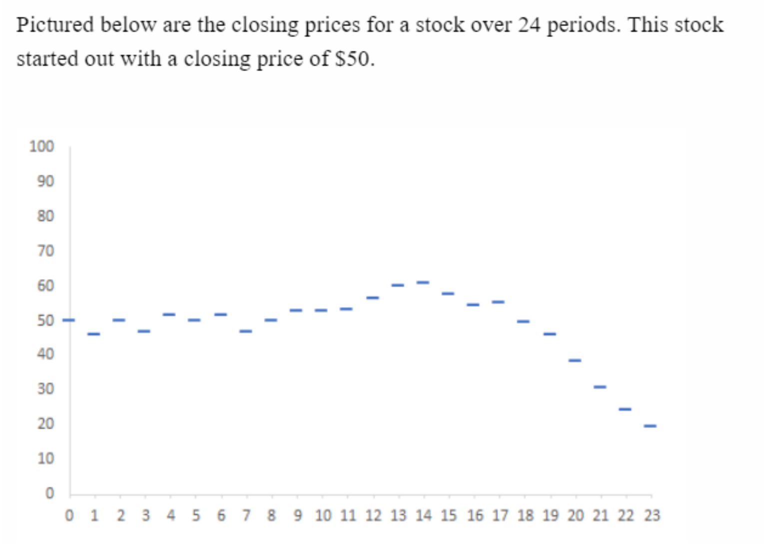



**Figure 1.** Absolute Condition. Note that the graphs presented to participants did not contain axis labels. Participants needed to read the text above the graph to know what each axis represented.

graphs as positive compared to negative price movements as well as linear compared to quadratic price movements because these price graph characteristics could have different effects on trend predictions (which we control for in our analyses).

In total we generated 10 independent stock price movements: 5 linear positive price movements and 5 quadratic positive price movements. The linear negative and quadratic negative price movements were created by taking the inverse of their positive counterparts. This resulted in a total of 20 stock price graphs (5 of each type), which were either displayed as relative or absolute prices changes. Right below the price graph participants made their stock prediction by answering the following question: “For the stock above, do you think its next closing price will increase, stay exactly the same, or decrease?” After completing the 10 price predictions, participants filled out an Epistemic and Aleatory Rating Scale (EARS).

The EARS scale (Figure 3) consisted of an explanation, an absolute and relative price graph, and two questions; one question pertaining to the

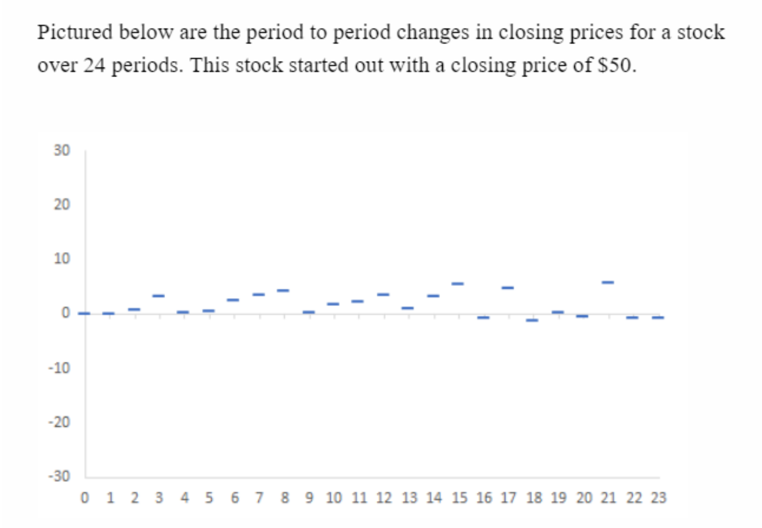



**Figure 2.** Relative Condition. Note that the graphs presented to participants did not contain axis labels. Participants needed to read the text above the graph to know what each axis

absolute price graph and one question pertaining to the relative price graph, but otherwise identical questions. Each question started with "For Graph X, predicting the future stock price is...", where X referred to the specific graph. The rest of the question was then filled in with one of three aleatory or epistemic items. Participants responded to each item on a 7 point scale ranging from "not at all" to "very much". Figure 3 illustrates an example of an epistemic measure item. (Note that in order to know which graph was absolute and which was relative, participants needed to read the very tiny font text printed above the graphs, as the graphs themselves contained no axis labels.) A complete list of all 6 items as well as validity and reliability results of the scale can be found in Appendix G. In all of our analyses, and concretely in order to do our mediation analysis, we only used responses to the questions participants' answered that corresponded to the graph of their condition. Specifically, if participants were in the absolute condition, we only used the EARS responses for the absolute graph and vice versa for the relative graph condition.

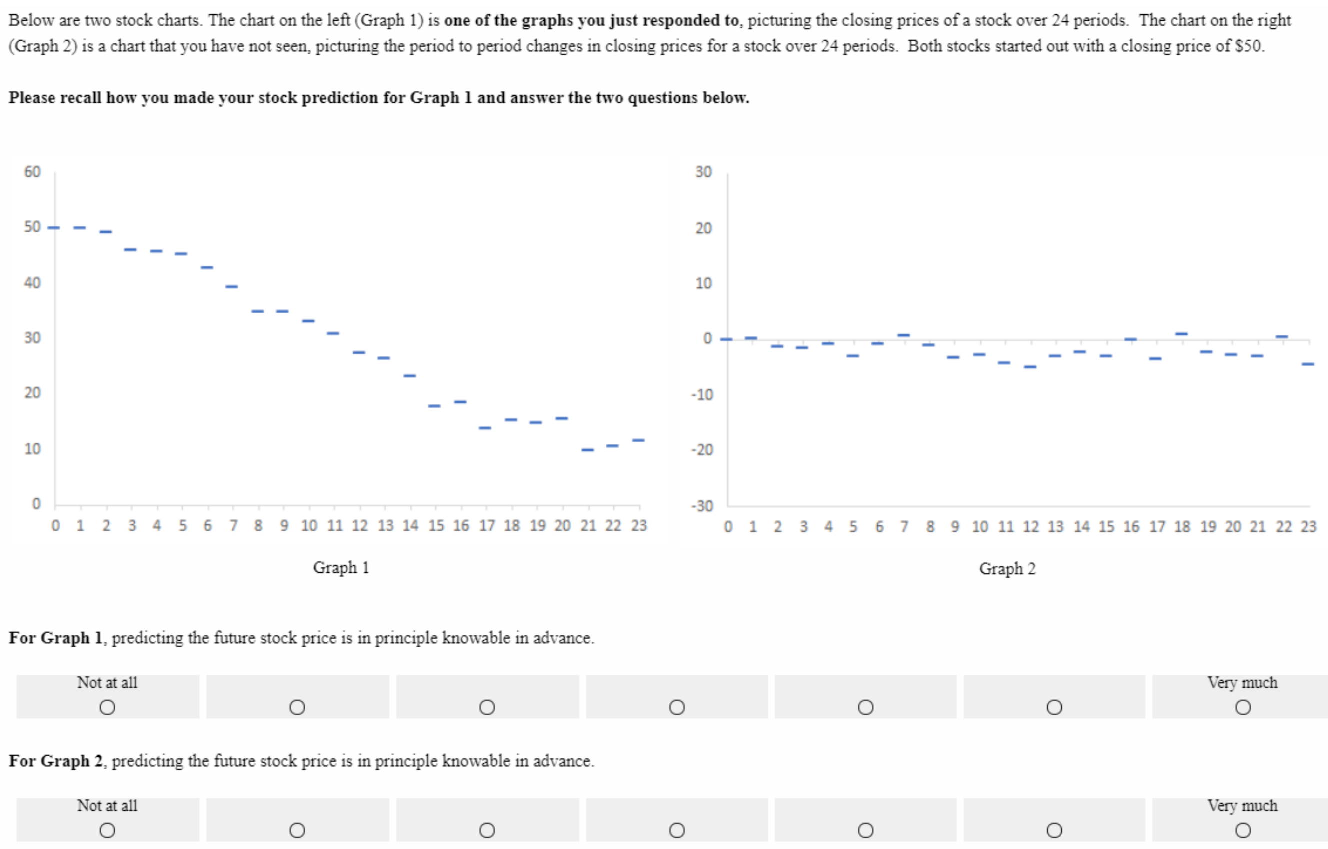



**Figure 3. EARS.**

The main dependent variable (*ptrend*) measures whether participants predict the stock price to continue trending, reverse its trend, or stay constant, coded as 1, -1 and 0 respectively (a trinary variable). Given our price graph manipulations and main dependent variable, we posit the following first hypothesis.

HYPOTHESIS 1: *Participants will be more likely to predict prices to continue trending ($ptrend = 1$) in the absolute price condition compared to the relative price condition.*

One of our main covariates is a difference measure of participants' EARS responses to the graph of their condition. Specifically, for individual $i$ we will construct a difference measure $diff_i$ such that:

$$diff_i = \frac{1}{3}\sum_{k=1}^{3} epistemic_{k,i} - \frac{1}{3}\sum_{l=1}^{3} aleatory_{l,i}.$$

In other words, we will subtract the average of the responses participants gave to the aleatory items from the average of the responses participants gave to the epistemic items. This "diff" covariate measures the difference in perceptions of predictability and randomness for the stock graph of their condition. Thus, higher diff values correspond to higher epistemic (predictability) ratings or lower aleatory (randomness) ratings, or both.

We predict that different presentation formats will affect perceptions of uncertainty. Specifically, we hypothesize that participants in the relative condition will view relative price graphs as less epistemic and more aleatory compared to participants in the absolute condition. Hence, we arrive at the following hypothesis.

HYPOTHESIS 2: *Participants in the relative price graph condition will perceive the graphs to be less epistemic and more aleatory (lower diff values) compared to those in the absolute price graph condition.*

Lastly, we also predict that participants who perceive the stock graphs to be more epistemic and less aleatory, will be more likely to predict the stock price trends to continue. Thus, our final hypothesis is stated below.

HYPOTHESIS 3: *Participants who perceive the stock graphs to be more epistemic and less aleatory (higher diff values) will be more likely to predict stock trends to continue.*

Taking hypotheses 1 – 3 together, we predict a statistical attenuation of our treatment effect after adding $diff$ to our main bivariate regression and a mediation of $diff$ between our treatment dummy and our main dependent variable $ptrend$.

### *B. Results*

To test hypothesis 1 and 3, the final model we estimate is an OLS regression with the following specifications:

$$ptrend_{it} = \alpha_{it} + \beta_1 rel_i + \beta_2 diff_i + \beta_3 pos_{it} + \beta_4 quad_{it} + \beta_5 order_i + \sum_{j=6}^{10} \beta_j X_{ij} + \epsilon_{it} \tag{2}$$

with errors clustered at the individual level and where

- $ptrend_{it}$ is 1 if participant $i$ for prediction $t$ predicted the stock price to continue trending, 0 if they predicted the stock price to stay exactly the same, and -1 if they predicted the stock price trend to reverse,
- $rel_i$ is 1 if participant $i$ was in the relative condition and 0 if they were in the absolute condition,
- $diff_i$ is the average of participant $i$'s epistemic ratings minus the average of participant $i$'s aleatory ratings,
- $pos_{it}$ is 1 if the stock price for participant $i$ at prediction $t$ was positively trending and 0 if it was negatively trending,
- $quad_{it}$ is 1 if the price trend for participant $i$ at prediction $t$ was quadratic and 0 if it was linear,
- $order_i$ is a dummy for the order of the EARS scale graphs for participant $i$,
- $X_{ij}$ is a series of controls for participant $i$, including: gender, age, education, race and income.

We build up to this final regression in Table I. Column 1 indicates a coefficient of -0.328 on the rel condition dummy. This means that participants in the relative condition were significantly less likely to predict trends to continue compared to the absolute condition. This coefficient decreased to -0.289 once we added our $diff_i$ covariate, demonstrating that part of the treatment effect is explained by our EARS measure. In column (4) the difference measure is significant at the 1% level with a coefficient of 0.034. Thus, participants who thought the difference in epistemic and aleatoriness was larger, were more likely to predict trends to continue. We replicate these effects using an ordered logistic regression in Appendix H and show that the mediation effects of $diff$ are driven by changes in the epistemic (predictability) perceptions of participants. Specifically, after adding controls in column (4) of Table H.II and H.III in Appendix H, only the epistemic ratings, and not the aleatory ratings, are significantly correlated with participant stock price predictions. The positive coefficient on epistemic indicates that participants who viewed the stock prices as more predictable were more likely to predict trends to continue. In the joint mediation model in Appendix H we find similar effects.

To test hypothesis 2 we ran the following regression model:

$$diff_i = \alpha_{it} + \beta_1 rel_i + \beta_2 pos_{it} + \beta_3 quad_{it} + \beta_4 order_i + \sum_{j=5}^{9} \beta_j X_{ij} + \epsilon_{it} \quad (3)$$

with errors clustered at the individual level. The results are displayed in Table II. With a highly significant negative coefficient of -1.171 on the $rel$ dummy, the results support our hypothesis and demonstrate that participants in the relative price graph condition were more likely than those in the absolute price graph condition to have a lower diff score. Further, in Appendix H Table H.IV we show that the epistemic ratings were significantly lower in the relative price graph condition and the aleatory ratings were significantly higher in the relative price graph condition. Thus, participants in the relative price graph condition perceived the stock prices to be less predictable and more random compared to participants in the absolute price graph condition.

In Appendix I we present the results of a complete bootstrapped mediation model with clustered standard errors and 1,000 iterations. The mediation analysis is further evidence showing that the EARS diff measure significantly mediates the effect of graph format on trend prediction. We calculated the cronbach alpha's for our epistemic and aleatory items and found alphas of 0.786 and 0.728 respectively. In addition, we conducted a component-factor analysis and found two factors with inter-item correlations of 0.7 or greater for each item within their respective factor.

**Table I** The Effect of Price Graph Display on Stock Price Predictions
*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| DV: | ptrend | ptrend | ptrend | ptrend |
| rel | -0.328*** | -0.289*** | -0.283*** | -0.283*** |
| | (0.041) | (0.043) | (0.043) | (0.043) |
| diff | | 0.033*** | 0.033*** | 0.034*** |
| | | (0.010) | (0.010) | (0.010) |
| pos | | | 0.179*** | 0.178*** |
| | | | (0.025) | (0.025) |
| quad | | | -0.070** | -0.069** |
| | | | (0.029) | (0.029) |
| order | | | -0.060 | -0.063 |
| | | | (0.041) | (0.041) |
| Constant | 0.344*** | 0.352*** | 0.324*** | 0.279** |
| | (0.031) | (0.031) | (0.040) | (0.115) |
| Controls: | | | | |
| Demographic | | | | Y |
| *N* | 3980 | 3980 | 3980 | 3980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. None of the demographic variables are correlated with predictions at the 5% level.

### *C. Discussion*

The results presented in the previous section show that participants view absolute price graphs as more predictable compared to relative price graphs. Further, this increase in perceptions of predictability increases the likelihood with which participants predict prices to continue trending. The design we

**Table II** Price Graph Display Manipulates Perceptions of EARS

*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) | (2) | (3) |
|---|---|---|---|
| DV: | diff | diff | diff |
| rel | -1.171*** | -1.162*** | -1.145*** |
| | (0.202) | (0.205) | (0.202) |
| pos | | -0.009 | -0.015 |
| | | (0.047) | (0.047) |
| quad | | -0.025 | -0.025 |
| | | (0.045) | (0.044) |
| order | | -0.076 | -0.066 |
| | | (0.205) | (0.203) |
| Constant | -0.239 | -0.189 | 1.249* |
| | (0.152) | (0.173) | (0.646) |
| Controls: | | | |
| Demographic | | | Y |
| *N* | 3980 | 3980 | 3980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Being caucasian is significantly ($p < 0.05$) related to predictions with a coefficient of -0.573.

used to demonstrate this result relied on simulated price data. We specifically used these simulations to create price charts that exhibit positive or negative and linear or quadratic price movements.

Interpretability of the results in Experiment 1 depends critically on participants' understanding of the two types of graphs. If, for example, some participants in the relative graph condition mistook the graphs to be showing price levels rather than price changes, that would explain why they failed to predict that trends would continue and why they viewed the graphs as unpredictable. Further adding to this concern, the lack of axis labels in the graphs presented to participants may have made it particularly challenging for participants to correctly interpret the relative price graphs. Experiment 1 did not include any comprehension checks to confirm that participants correctly interpreted the graphs. Consequently, caution is advised in drawing conclusions from the Experiment 1 results. Experiment 2 addressed this limitation.

## III. Experiment 2: Real stock prices and confidence measures

In Experiment 2 we made two changes to the design of Experiment 1: (i) we used more realistic stock prices, randomly selected S&P 500 stocks, to assess the generalizability of the Experiment 1 findings (ii) we measured confidence, and (iii) we assessed participants' understanding of the price graphs. The predictions we made included those of Experiment 1, even though the stock prices are very different (the details of which are explained in the next sub-section). In addition, we predicted that perceptions of uncertainty would significantly mediate an effect of price graph condition on confidence. Thus, we tested whether a direct link between perceptions of uncertainty and confidence exists.

### *A. Methods*

For Experiment 2, we recruited 95 participants from Prolific. Participants were paid \$1.90 for participating in the experiment and awarded a \$1.00 bonus for correctly predicting the next directional stock price movement. The design of Experiment 2 was similar to that of Experiment 1. That being said, compared to Experiment 1, in this experiment, we used real stock price data and added multiple confidence measures.

In the second experiment we changed the stock prices used to test whether our effects from Experiment 1 were robust to non-trending and representative stock prices that retail investors are confronted with on online retail investor sites. Hence, in Experiment 2, we randomly drew stocks from the S&P 500 to be used in the experiment. For each stock we used 24 monthly prices spanning across a 2 year interval. Figure 4 and Figure 5 show sample graphs for the absolute and relative price graph conditions respectively.

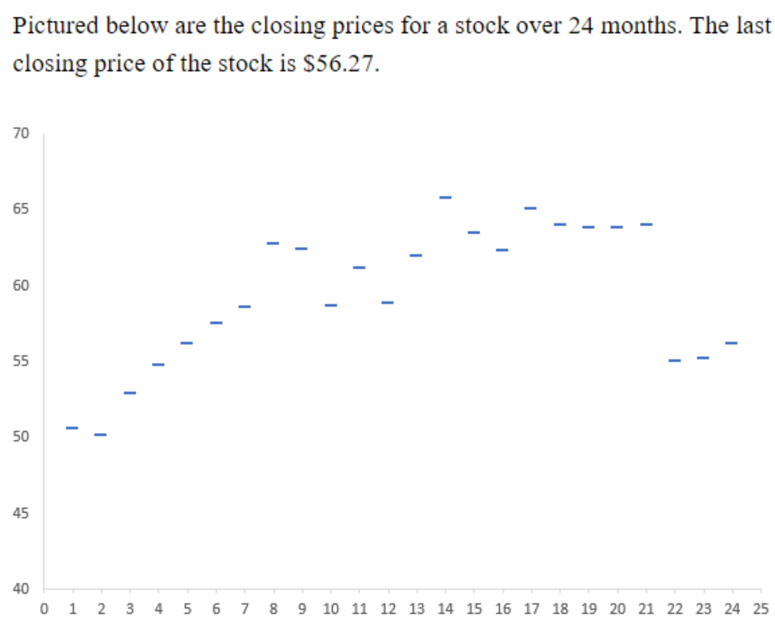



**Figure 4.** Real stock price graph for the absolute condition

Several changes to the design were made to add two different confidence

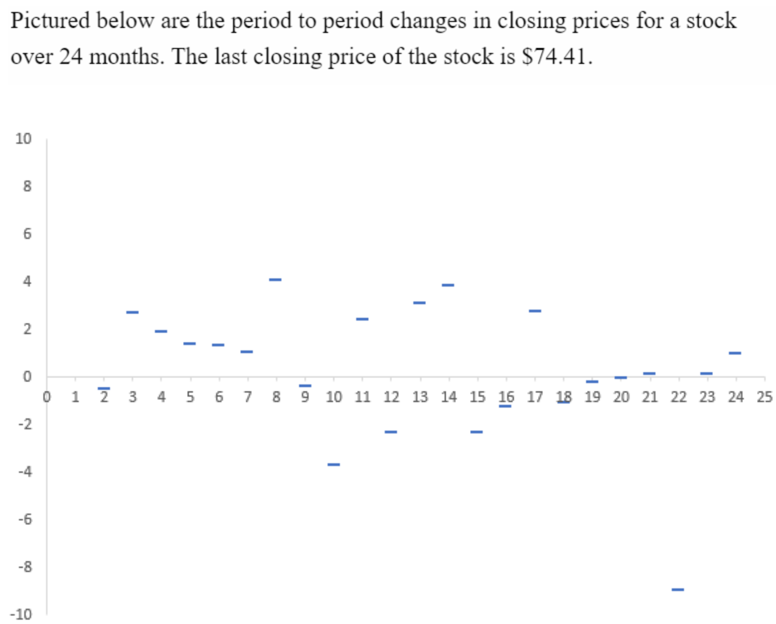



**Figure 5.** Real stock price graph for the relative condition

measures: miscalibration and performance. In the relative price graph condition, instead of giving participants the first price ($p_0$), we gave participants the final price ($p_{23}$). Further, we asked participants to make specific price point predictions, in addition to providing their 50% confidence intervals around said price predictions. In other words, we asked participants to provide a price range within which they believe the future price should be 50% of the time. Using these CI's, we measured the degree to which participants were over-confident in their calibration of future stock prices (or the degree of miscalibration). Concretely, if the true price $p_t$ lies outside the stated 50% CI, then we coded the response as a surprise. The total number of surprises ($surprises_i$) across the 10 predictions, if a participant is well calibrated, should be 5. Further, the finance literature has modeled over-confidence as people having CI's that are too narrow, in other words people are overprecise. We measured the degree of over and under-precision as $precision_i = 5 - surprises_i$, where $precision_i < 0$ means a participant was overprecise, and conversely for under-precision; $precision_i$ is our main variable measuring the degree of miscalibration by participant $i$.

At the end of the experiment, we measured participant's over-confidence in performance. Participants were asked how many of the 10 stock price predictions they believed they got correct. We define a prediction as correct if the price point prediction is in the right direction of the future price. In other words, if the future price increased, a participant correctly predicted ($corr_{i,t} = 1$, and 0 if incorrect) the future stock price if their price point prediction also predicted the future price to increase, and conversely for a price decrease. If the stock price stayed the same, a participant correctly predicted the future stock price if their predicted price point was exactly the same as the future price. The total number of times a participant correctly predicted the future price is $corr_i = \sum_{t=1}^{10} corr_{i,t} \in [0, 10]$; $corr_i$ measures the degree of over-confidence in absolute performance. Thus, we have now defined our two new measures of confidence: $precision_i$ and $corr_i$, each corresponding to measuring over-confidence in calibration and over-confidence in performance, respectively.

The final change to Experiment 2 was that before participants completed demographics, and after they finished the performance measure of over-confidence, participants were asked comprehension check questions about the absolute and relative price graphs (see Appendix J for question wording). Participants answered three questions for each a relative and absolute price graph: (1) they had to estimate the price change between two periods, (2) they were asked whether the price would generally keep increasing, decreasing or stay the same (i.e. estimate the price trend), and (3) estimate whether the price in a given month was higher than the previous month. If participants could not answer question (1) and (3) correctly, this would indicate that participants do not understand the price graphs. These two questions test participants' ability to numerically calculate price changes and differences in the graphs. However, question (2) does not ask participants for precise numeric evaluations but rather a general trend, and therefore induces participants to use a heuristic approach to answer question 2. It could be that participants know how make the numeric price change calculations in the relative and absolute price graphs, but resort to inaccurate heuristics when answering question (2).

To replicate hypotheses 1 - 3 from Experiment 1, we needed to create *ptrend* using our new price point prediction elicitation. To create *ptrend*, we created a variable called *pred* first. Let $p(i)_t$ be the point prediction participant $i$ made in period $t$ and $p_t$ the current period price. Then, when participant $i$ is predicting the price $p_{t+1}$ in period $t$,

$$pred_{i,t} = \begin{cases} 1 & \text{if } p(i)_t > p_t \\ 0 & \text{if } p(i)_t = p_t \\ -1 & \text{if } p(i)_t < p_t \end{cases}$$

Using *pred*, we can constructed *ptrend* as in Experiment 1. Using *ptrend* we also predicted the same three hypotheses from Experiment 1 (hypotheses 1 - 3). In addition to these hypotheses, we also had the following hypotheses about confidence:

HYPOTHESIS 4: *Participants in the absolute price graph condition compared to the relative price graph condition will be more over-precise (higher values of* $precision_i$*) and have higher values of* $correct_i$*.*

HYPOTHESIS 5: *Participants who perceive stocks to be more knowable will be more over-precise (higher values of* $precision_i$*) and have higher values of* $correct_i$*.*

Notice that hypotheses 2, 4, and 5 imply that the effect of price graph on confidence will be mediated by participants' perceptions of uncertainty (as measured by EARS).

### *B. Results*

To test hypotheses 1 - 3 we slightly changed the model specifications defined in section II.B, the results section of Experiment 1 of this paper. Specifically, we ran the following two models, with all the variables as defined previously in section II.B:

$$ptrend_{it} = \alpha_{it} + \beta_1 rel_i + \beta_2 diff_i + \beta_3 order_i + \sum_{j=4}^{8} \beta_j X_{ij} + \epsilon_{it} \tag{4}$$

and

$$diff_i = \alpha_i + \beta_1 rel_i + \beta_2 order_i + \sum_{j=3}^{7} \beta_j X_{ij} + \epsilon_i. \tag{5}$$

The results for each can be found in Table III and Table IV, respectively.

In addition, we ran the following model to address the predictions outlined in hypotheses 4 and 5:

$$confidence_i = \alpha_i + \beta_1 rel_i + \beta_2 diff_i + \beta_5 order_i + \sum_{j=6}^{10} \beta_j X_{ij} + \epsilon_i \tag{6}$$

where $confidence_i \in \{precision_i, corr_i\}$. Thus, the model was run twice for each confidence measure. The results for $precision_i$ and $corr_i$ can be seen, respectively, in Tables VI and V.

For all four main dependent variables we find no significant effects apart from in Table IV, which replicates our results from Experiment 1 and demonstrates that participants in the relative price graph condition have lower $diff_i$ scores compared to participants in the absolute price graph condition. In addition, in Appendix K we show that condition significantly affects epistemic and aleatory ratings. In particular, in the relative price graph condition, compared to the absolute price graph condition, participants perceive epistemic uncertainty to be lower and aleatory uncertainty to be higher.

**Table III** Within-Subject Regression Results for ptrend

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | 0.030 | 0.048 | 0.058 |
| | (0.036) | (0.040) | (0.043) |
| diff | | 0.008 | 0.009 |
| | | (0.009) | (0.009) |
| order | | | −0.045 |
| | | | (0.039) |
| gender | | | −0.030 |
| | | | (0.032) |
| age | | | −0.0003 |
| | | | (0.001) |
| education | | | 0.013 |
| | | | (0.021) |
| income | | | 0.007 |
| | | | (0.005) |
| Constant | 0.223*** | 0.221*** | 0.205** |
| | (0.025) | (0.025) | (0.083) |
| Clustered SE: | Y | Y | Y |
| Observations | 950 | 950 | 950 |
| $R^2$ | 0.001 | 0.003 | 0.013 |
| Adjusted $R^2$ | 0.0002 | 0.001 | 0.006 |

**Table IV** Within-Subject Regression Results for diff

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | |
|---|---|---|
| | diff | |
| | (1) | (2) |
| rel | $-2.209^{***}$ | $-2.074^{***}$ |
| | (0.433) | (0.436) |
| order | | $-0.270$ |
| | | (0.450) |
| gender | | $-0.108$ |
| | | (0.372) |
| age | | $-0.012$ |
| | | (0.021) |
| education | | $-0.097$ |
| | | (0.233) |
| income | | $-0.034$ |
| | | (0.064) |
| Constant | 0.201 | 1.406 |
| | (0.318) | (1.201) |
| Clustered SE: | Y | Y |
| Observations | 950 | 950 |
| $R^2$ | 0.210 | 0.225 |
| Adjusted $R^2$ | 0.209 | 0.220 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

**Table V** Within-Subject Regression Results for corr

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | corr | | |
| | (1) | (2) | (3) |
| rel | −0.465 | −0.127 | −0.270 |
| | (0.467) | (0.538) | (0.536) |
| diff | | 0.153 | 0.172 |
| | | (0.121) | (0.114) |
| order | | | −0.010 |
| | | | (0.481) |
| gender | | | −0.454 |
| | | | (0.392) |
| age | | | −0.002 |
| | | | (0.021) |
| education | | | $0.463^{**}$ |
| | | | (0.195) |
| income | | | 0.053 |
| | | | (0.068) |
| Constant | $5.226^{***}$ | $5.196^{***}$ | $4.020^{***}$ |
| | (0.282) | (0.284) | (0.926) |
| Clustered SE: | Y | Y | Y |
| Observations | 950 | 950 | 950 |
| $R^2$ | 0.011 | 0.032 | 0.099 |
| Adjusted $R^2$ | 0.010 | 0.030 | 0.092 |

**Table VI** Within-Subject Regression Results for precision

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | precision | | |
| | (1) | (2) | (3) |
| rel | −0.342 | −0.173 | 0.014 |
| | (0.507) | (0.611) | (0.614) |
| diff | | 0.070 | 0.058 |
| | | (0.126) | (0.123) |
| order | | | −0.276 |
| | | | (0.542) |
| gender | | | 0.285 |
| | | | (0.369) |
| age | | | −0.021 |
| | | | (0.019) |
| education | | | −0.124 |
| | | | (0.228) |
| income | | | 0.029 |
| | | | (0.062) |
| Constant | 0.547** | 0.533** | 1.100 |
| | (0.260) | (0.262) | (1.284) |
| Clustered SE: | Y | Y | Y |
| Observations | 920 | 920 | 920 |
| $R^2$ | 0.006 | 0.010 | 0.031 |
| Adjusted $R^2$ | 0.004 | 0.008 | 0.023 |

We also ran a series of analysis to asses the degree to which participants understood the comprehension check questions (see Appendix J for question wording). Table VII and Table VIII present the results for the absolute and relative price graph participants. Each participant answered three comprehension check questions for both relative and absolute price graphs. First, there are no differences in participant's ability to answer the comprehension check questions based on the condition they are in. In other words, participants in the absolute and relative price graph condition did not get better at answering comprehension check questions for the absolute and relative price graph condition, respectively. Second, apart from detecting trends, participants are equally good at answering the comprehension check questions for the absolute and relative price graphs. That being said, participants in both conditions were significantly better at detecting trends for the absolute price graphs compared to the relative price graphs. Third, in supplementary analysis in Appendix L we found that responses to the comprehension check questions did not relate to trend predictions ($ptrend$), however, they did predict EARS ratings ($diff$). In particular, we matched participants' EARS ratings and trend prediction answers for each the relative and absolute price graphs. We found that participants who got the trend prediction question correct for the relative price graph, had a significantly higher difference between their epistemic and aleatory ratings for the relative graph than participants who got the trend prediction wrong for the relative graph. This difference did not exist for the absolute price graph and did not explain the effect $rel$ had on $diff$ in Table IV.

### *C. Discussion*

Experiment 2 addressed three main concerns from Experiment 1: (i) the stock prices that we used weren't representative of real stock prices, (ii) we did not test for a direct link between confidence and price level graphs, and (iii) we did not ensure that participants understood the price graphs. Therefore, in Experiment 2 we addressed these concerns by: (i) randomly picking stocks from the S&P 500, (ii) asking participants a series of questions

**Table VII** Responses to comprehension check questions for absolute price graph condition

| Question | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Higher price (Rel) | 53 | 0.774 | 0.423 | 0 | 1 | 1 |
| Higher price (Abs) | 53 | 0.849 | 0.361 | 0 | 1 | 1 |
| Trend direction (Rel) | 53 | 0.321 | 0.471 | 0 | 0 | 1 |
| Trend direction (Abs) | 53 | 0.943 | 0.233 | 0 | 1 | 1 |
| Price change (Rel) | 53 | 17.811 | 14.225 | 0.240 | 12.760 | 42.700 |
| Price change (Abs) | 53 | 18.057 | 11.027 | 0.810 | 16.660 | 38.810 |

**Table VIII** Responses to comprehension check questions for relative price graph condition

| Question | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Higher price (Rel) | 42 | 0.738 | 0.445 | 0 | 1 | 1 |
| Higher price (Abs) | 42 | 0.762 | 0.431 | 0 | 1 | 1 |
| Trend direction (Rel) | 42 | 0.405 | 0.497 | 0 | 0 | 1 |
| Trend direction (Abs) | 42 | 0.857 | 0.354 | 0 | 1 | 1 |
| Price change (Rel) | 42 | 19.330 | 13.116 | 0.240 | 18.040 | 41.660 |
| Price change (Abs) | 42 | 19.878 | 11.617 | 0.420 | 23.020 | 40.020 |

about their confidence in their stock price predictions and (iii) asking a series of comprehension check questions about the graphs.

The main focus of this paper, and Experiment 2, was to test the effect of price graphs on investor confidence, and the degree to which investor confidence is driven by perceptions of uncertainty. We found no support for this main hypothesis. Further, we did not replicate the results from Experiment 1 completely. More concretely, we found that price levels increase differences in epistemic and aleatory uncertainty, however, we did not find that participants viewing relative price graphs were less likely to predict trends to continue. These results imply that the results from Experiment 1 may be isolated to specific simulated graphs and not real stock prices.

That being said, it could be that participants did not fully understand the graphs we presented them. We found that participants were equally effective at calculating price changes and whether a price is higher or lower, compared to the price in the previous period, for absolute and relative price graphs. However, participants were better at detecting trends for relative price graphs compared to absolute price graphs; but, this did not explain the effect $rel$ had on $ptrend$ or $diff$. We don't believe these results, in particular that participants were better at detecting trends for absolute compared to relative price graphs, suggest that participants cannot understand the relative price graphs. Instead, we believe that participants have the necessary skills to estimate the trends for both price graphs, because they can calculate price changes for both types of graphs equally effectively, but, when asked what the trend is in the graphs, participants use a heuristic approach, rather than calculating each of the price changes to estimate the overall price trend. Hence, we do believe participants understood the different price graphs in our experiment.

# IV. Experiment 3: Directional price predictions and confidence

In Experiment 1, compared to Experiment 2, we asked participants for price point predictions compared to directional price predictions. Price point predictions, compared to directional price predictions, are significantly harder for both the relative and absolute price graphs, but especially for the absolute price graphs. In order to test whether switching from directional price predictions to price point predictions eliminated the difference in confidence between the price level graph condition and relative price graph condition; in Experiment 3 we eliminated the price point predictions and only asked directional price predictions. We predicted that participants in the absolute price graph condition would be more confident compared to participants in the relative price graph condition, and that this difference would driven be differences in perceptions of uncertainty.

## *A. Methods*

We recruited 92 participants from MTurk and paid participants \$1.00 for completing the study and \$0.30 for correctly predicting the directional stock price movement. The design of Experiment 3 was similar to that of Experiment 2.

We made three changes to Experiment 3: (1) instead of asking participants to make price point predictions, we asked participants to make directional stock price predictions, (2) we eliminated the comprehension check questions, and (3) we added attention check questions (the specific question wording can be found in Appendix M). We eliminated the comprehension check questions because this (a) would reduce survey fatigue and (b) we had established what participant's understanding of the price graphs were in Experiment 2. We added attention check questions to test whether our intent-to-treat analysis would be affected by only including participants who paid attention. In particular, it could be that participants in Experiment 2 were not attentive enough to create differences across the two conditions.

In the current experiment we wanted to test whether attentive participants behaved differently compared to participants in our intent-to-treat sample.

Our main predictions were analogous to those in Experiment 2: hypotheses 1 - 5.

### *B. Results*

We tested our hypotheses using the same regressions specifications as in Experiment 2. In particular, we ran model 4, 5, and 6 to test our predictions for $ptrend$, $diff$, and $corr$ and $precision$, respectively. Tables IX, X, XI, and XII present the results respectively.

Table IX shows that participants in the relative price graph condition are significantly less likely to predict trends to continue. Nevertheless, the coefficient on $diff$ in column (2) is small and insignificant, demonstrating that this effect is not attenuated or mediated by perceptions of uncertainty. In Table X we find that participants in the relative price graph condition have significantly lower $diff$ scores. In Appendix O we replicate these findings using individual aleatory ratings, and find strongly suggestive evidence for the epistemic ratings. The aleatory ratings are significantly higher in the relative price graph condition compared to the absolute price graph condition, and robust after adding demographic controls.

We also analyzed how confidence was affected by the relative price graphs. We found no significant effects of price graph on both $corr$ and $precision$ (Table XI and Table XII). However, we did find that perceptions of uncertainty significantly affected the number of correct predictions participants thought they had made. In particular, as the difference in epistemic and aleatory uncertainty increased, and more concretely perceptions of epistemic uncertainty (see Table O.IV in Appendix O), participants believed they made more correct directional price predictions.

Lastly, only 7 participants failed our attention check questions. Naturally, including or excluding these participants did not significantly alter our results.

**Table IX** Within-Subject Regression Results for ptrend

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | $-0.453^{***}$ | $-0.444^{***}$ | $-0.396^{***}$ |
| | (0.093) | (0.096) | (0.098) |
| diff | | 0.007 | 0.008 |
| | | (0.019) | (0.021) |
| order | | | 0.043 |
| | | | (0.092) |
| gender | | | $-0.004$ |
| | | | (0.089) |
| age | | | $-0.001$ |
| | | | (0.005) |
| education | | | $0.099^{**}$ |
| | | | (0.048) |
| income | | | $-0.035^{**}$ |
| | | | (0.016) |
| Constant | $0.496^{***}$ | $0.494^{***}$ | 0.334 |
| | (0.060) | (0.059) | (0.282) |
| Clustered SE: | Y | Y | Y |
| Observations | 920 | 920 | 920 |
| $R^2$ | 0.067 | 0.067 | 0.085 |
| Adjusted $R^2$ | 0.066 | 0.065 | 0.078 |

**Table X** Within-Subject Regression Results for diff

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | |
|---|---|---|
| | diff | |
| | (1) | (2) |
| rel | −1.189*** | −0.982** |
| | (0.432) | (0.439) |
| order | | −0.560 |
| | | (0.371) |
| gender | | 0.058 |
| | | (0.411) |
| age | | −0.056*** |
| | | (0.017) |
| education | | −0.089 |
| | | (0.212) |
| income | | −0.037 |
| | | (0.078) |
| Constant | 0.258 | 3.033** |
| | (0.235) | (1.215) |
| Clustered SE: | Y | Y |
| Observations | 920 | 920 |
| $R^2$ | 0.083 | 0.174 |
| Adjusted $R^2$ | 0.082 | 0.169 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

**Table XI** Within-Subject Regression Results for corr
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | corr | | |
| | (1) | (2) | (3) |
| rel | −0.643 | −0.256 | −0.177 |
| | (0.452) | (0.479) | (0.504) |
| diff | | 0.326*** | 0.350*** |
| | | (0.107) | (0.104) |
| order | | | 0.029 |
| | | | (0.425) |
| gender | | | 0.120 |
| | | | (0.434) |
| age | | | 0.013 |
| | | | (0.020) |
| education | | | 0.576*** |
| | | | (0.219) |
| income | | | −0.027 |
| | | | (0.087) |
| Constant | 6.566*** | 6.482*** | 3.777*** |
| | (0.320) | (0.318) | (1.278) |
| Clustered SE: | Y | Y | Y |
| Observations | 920 | 920 | 920 |
| $R^2$ | 0.021 | 0.104 | 0.160 |
| Adjusted $R^2$ | 0.020 | 0.102 | 0.154 |

**Table XII** Within-Subject Regression Results for precision
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | precision | | |
| | (1) | (2) | (3) |
| rel | 0.185 | 0.185 | 0.318 |
| | (0.476) | (0.510) | (0.512) |
| diff | | −0.0004 | 0.007 |
| | | (0.136) | (0.142) |
| order | | | 0.579 |
| | | | (0.446) |
| gender | | | 0.634 |
| | | | (0.470) |
| age | | | −0.007 |
| | | | (0.026) |
| education | | | −0.221 |
| | | | (0.288) |
| income | | | −0.126* |
| | | | (0.076) |
| Constant | −2.596*** | −2.596*** | −2.034 |
| | (0.282) | (0.285) | (1.639) |
| Clustered SE: | Y | Y | Y |
| Observations | 860 | 860 | 860 |
| $R^2$ | 0.002 | 0.002 | 0.071 |
| Adjusted $R^2$ | 0.001 | −0.0005 | 0.063 |

### *C. Discussion*

In Experiment 3, compared to Experiment 2, we made one significant change to our experimental design: instead of asking participants to make price point predictions, we asked them to make directional price predictions. We found that this did not change the effect price graphs had on overall confidence, measured by both *corr* and *precision*. We did find that switching to directional price predictions resulted in participants in the relative price graph condition being less likely to expect trends to continue, compared to participants in the absolute price graph condition. Even though this result replicates our findings from Experiment 1, we did not find that the main effect of condition on predicting trends to continue was mediated by perceptions of uncertainty.

We also added attention check questions and found that most participants passed these attention check questions, and therefore excluding participants who failed our attention check questions, did not meaningfully alter our results. This highlights that the pool of participants we are recruiting from is at the very least paying attention, and the results cannot be dismissed due to inattentiveness by participants.

In Experiment 4 we returned to the simulated stock graphs from Experiment 1, to test whether confidence in predicting simulated stock prices, compared to real stock prices, would be higher and more pronounced in absolute price graphs compared to relative price graphs.

## V. Experiment 4: Confidence with simulated stock prices

The design of Experiment 4 was analogous to that of Experiment 3. However, instead of using real stock price data from stocks randomly drawn from the S&P 500, we returned to using simulated stocks used in Experiment 1.

### *A. Methods*

As in Experiment 3, we asked participants to make directional price predictions, state their 50% confidence interval for the future price range, guess how many directional stock price predictions they got correct, and fill out an EARS scale. Instead of using real stocks, we used simulated stock graphs and prices, an example of which can be seen in Figure 1 and 2.

We recruited 400 participants from MTurk[8] to participate in Experiment 4. Participants had to pass attention check questions to participate (the same questions used in Experiment 3, the specific wording of which can be found in Appendix M). Our final sample included 369 participants after eliminating participants who reported issues with the survey (15 participants), duplicate MTurkers, and MTurkers who did not enter correct completion codes.

As in prior experiments, our main predictions were hypotheses 1 - 5.

### *B. Results*

We tested our hypotheses using the same regression specifications as in Experiment 2. In particular, we ran model 4, 5, and 6 to test our predictions for *ptrend*, $diff$, and *corr* and *precision*, respectively. Tables XIII, XIV, XV, and XVI present the results.

Table XIII shows that participants in the relative price graph condition are significantly less likely to predict trends to continue. Further, this effect is attenuated (column (2) of Table XIII) by $diff$. We replicate these findings using Ordered Logistic Regressions in Appendix P. In Table XIV we show that our condition dummy also significantly predicts $diff$. In particular, we estimate a negative coefficient with a near zero constant, which indicates that participants in the relative price graph condition perceive the difference between epistemic and aleatory uncertainty to be negative (i.e. aleatory uncertainty is > than epistemic uncertainty), and that the difference in epistemic and aleatory uncertainty is significantly smaller in the relative price graph condition compared to the price level graph condition.

[8]Pre-registration can be found here: https://osf.io/a5d6z

Taken together, Tables XIII and XIV demonstrate a baron-kenny mediation of *rel* on *ptrend*, mediated by $diff$. We replicate these results using a bootstrapped mediation model in Appendix Q and using individual EARS in Appendix R.

Lastly, we analyze the effects of *rel* on *corr* and *precision* in Tables XV and XVI. We find no significant main effects. Although, as in Experiment 2, differences in perceptions of uncertainty significantly predict the number of price predictions participants thought they got correct. In particular, as the difference in epistemic and aleatory uncertainty increases, participants believe they got more directional stock price predictions correct.

**Table XIII** Within-Subject Regression Results for ptrend

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | $-0.350^{***}$ | $-0.316^{***}$ | $-0.325^{***}$ |
| | (0.041) | (0.044) | (0.044) |
| diff | | $0.035^{***}$ | $0.034^{***}$ |
| | | (0.011) | (0.011) |
| order | | | 0.039 |
| | | | (0.041) |
| gender | | | 0.005 |
| | | | (0.037) |
| age | | | $-0.004^{**}$ |
| | | | (0.002) |
| education | | | $0.047^{**}$ |
| | | | (0.023) |
| income | | | 0.0003 |
| | | | (0.007) |
| Constant | $0.474^{***}$ | $0.473^{***}$ | $0.425^{***}$ |
| | (0.030) | (0.029) | (0.130) |
| Clustered SE: | Y | Y | Y |
| Observations | 3,690 | 3,690 | 3,690 |
| $R^2$ | 0.043 | 0.048 | 0.054 |
| Adjusted $R^2$ | 0.042 | 0.048 | 0.052 |

**Table XIV** Within-Subject Regression Results for diff

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | |
|---|---|---|
| | diff | |
| | (1) | (2) |
| rel | −0.978*** | −1.001*** |
| | (0.195) | (0.192) |
| order | | 0.199 |
| | | (0.196) |
| gender | | −0.071 |
| | | (0.194) |
| age | | −0.004 |
| | | (0.011) |
| education | | 0.020 |
| | | (0.123) |
| income | | −0.079** |
| | | (0.037) |
| Constant | 0.026 | 0.590 |
| | (0.141) | (0.783) |
| Clustered SE: | Y | Y |
| Observations | 3,690 | 3,690 |
| $R^2$ | 0.064 | 0.080 |
| Adjusted $R^2$ | 0.063 | 0.078 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

**Table XV** Within-Subject Regression Results for corr

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | corr | | |
| | (1) | (2) | (3) |
| rel | −0.088 | 0.104 | 0.009 |
| | (0.242) | (0.245) | (0.236) |
| diff | | 0.197*** | 0.194*** |
| | | (0.062) | (0.061) |
| order | | | −0.099 |
| | | | (0.233) |
| gender | | | −0.630*** |
| | | | (0.240) |
| age | | | 0.012 |
| | | | (0.012) |
| education | | | 0.592*** |
| | | | (0.139) |
| income | | | −0.027 |
| | | | (0.045) |
| Constant | 6.016*** | 6.011*** | 4.475*** |
| | (0.164) | (0.163) | (0.755) |
| Clustered SE: | Y | Y | Y |
| Observations | 3,690 | 3,690 | 3,690 |
| $R^2$ | 0.0004 | 0.026 | 0.088 |
| Adjusted $R^2$ | 0.0001 | 0.025 | 0.087 |

**Table XVI** Within-Subject Regression Results for precision
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | precision | | |
| | (1) | (2) | (3) |
| rel | −0.342 | −0.413* | −0.300 |
| | (0.251) | (0.249) | (0.243) |
| diff | | −0.072 | −0.057 |
| | | (0.075) | (0.074) |
| order | | | 0.156 |
| | | | (0.244) |
| gender | | | 0.462** |
| | | | (0.234) |
| age | | | −0.008 |
| | | | (0.013) |
| education | | | −0.562*** |
| | | | (0.142) |
| income | | | 0.108** |
| | | | (0.044) |
| Constant | −2.231*** | −2.231*** | −1.269 |
| | (0.180) | (0.181) | (0.869) |
| Clustered SE: | Y | Y | Y |
| Observations | 3,530 | 3,530 | 3,530 |
| $R^2$ | 0.005 | 0.009 | 0.066 |
| Adjusted $R^2$ | 0.005 | 0.008 | 0.065 |

### C. *Discussion*

In Experiment 4, we returned to simulated stock price graphs and asked participants for their 50% confidence intervals around the future price and how many directional stock price predictions they think they got correct. We found that even with simulated stock price graphs that look extremely trending, participant's confidence in correctly predicting the direction of future stock prices, and correctly predicting the range of the future stock prices, did not increase with absolute price graphs compared to relative price graphs. However, we were able to replicate our results from Experiment 1, further substantiating that absolute compared to relative price graphs increase the number of trends participants predict with simulated stock prices, which is mediated by perceptions of uncertainty.

The culmination of Experiments 2-4 leads us to conclude that absolute price graphs do not affect confidence in stock price predictions.

## VI. General Discussion

In this paper, we conducted a series of experiments to investigate the effects of absolute price graphs, compared to relative price graphs, on participants' ability to predict trends and confidence. We randomly assigned participants to view price graphs as either absolute period to period prices or differences between period to period prices. We found that participants were more likely to predict trends to continue in the absolute price graph condition compared to the relative price graph condition. Further, we showed that this main treatment effect of price graph display on likelihood of predicting a trend to continue is partially explained by the degree to which participants view the stock prices as being epistemic (predictable). Nevertheless, we did not find that these findings generalized to randomly selected S&P 500 stocks, but remained robust across other experiments using simulated stock prices. In follow-up experiments we also tested whether price level graphs, compared to relative price graphs, increase confidence by increasing perceptions of predictability. We measured confidence as confidence in predicting future price ranges and confidence in predicting the direction of the future stock price. We did not find that absolute price graphs increased confidence compared to relative price graphs.

It is possible that our confidence measures were not sensitive enough. However, both of our measures of confidence (i.e., asking participants to estimate their performance and confidence intervals around future prices) are common confidence measures in the literature (Moore and Healy, 2008; Glaser and Weber, 2009). Further, in Experiment 3 and 4 (Tables XI and XV, respectively) we found that participants' EARS ratings predicted the number of correct directional price predictions participants thought they had made. Thus, it is unlikely that the measures themselves were insensitive.

As in Paper 1, there is also a chance that participants did not understand the experiment and task. Given the results from Experiment 2 (for details see section III.B) where we ask a series of comprehension questions (discussed elaborately in section III.C), we believe it is unlikely participants did not understand the graphs and the task at hand. Hence, we believe the results explained in the first paragraph have a lot of important implications for existing research, retail investor sites, and lay investors.

In particular, Glaser et al. (2019) manipulated graph format and price elicitation method to disentangle the mixed results that were present in the literature at the time. However, the current study demonstrates that a third factor: perceptions of uncertainty, may significantly impact the effect of graph format on price movement predictions. Specifically, Experiment 1 and Experiment 4 show that perceptions of predictability significantly explain the impact price graph format has on directional stock price movement predictions. The effects that Glaser et al. (2019); Diacon and Hasseldine (2007); Stössel and Meier (2015) find are likely to a great extent explained by the effects perceptions of predictability have on participants completing their task.

Our work also speaks to the existing literature on institutional investor trading. Recently there has been a shift by institutional investors to use factor investing strategies – a factor being a type of asset you tilt your portfolio selection towards – focusing on factors that have been found to perform well outside of the market. Institutional investors construct funds that focus on, usually, a combination of these factors, often referred to as "smart beta" investing (Malkiel, 2014). Factors that have more recently gained traction are focusing on value (Fama and French, 1998; Dodd and Graham, 1934; Fama and French, 1992), small firms (Kleim, 1983), momentum and mean reversion (Jegadeesh and Titman, 1993, 2001), and low volatility stocks (Frazzini and Pedersen, 2014; Asness, Frazzini, and Pedersen, 2012). More concretely, the literature on momentum finds that stock prices reflect positive serial correlations in the short to medium term (3 - 12 months) (Jegadeesh and Titman, 1993; Cutler, Poterba, and Summers, 1991) but stock prices over the long horizon (∼5 years) exhibit negative auto-correlations (De Bondt and Thaler, 1985; Chopra, Lakonishok, and Ritter, 1992). The research presented here directly speaks to investors' ability to asses and interpret performance measures. Specifically, we show that assessing the momentum of a stock may be more difficult when investors are interpreting stock performance measures relatively compared to in an absolute sense. Future research could investigate the degree to which investors use relative versus absolute stock performance measures and the impact this has on their ability and willingness to use momentum trading strategies. Investors who use absolute price graphs may more easily detect underlying trends and momentum, and may also be more willing to engage in momentum trading strategies. The effects that absolute price graphs have on portfolio performance of professional investors, and on performance of momentum trading could be both negative or positive. Given the effects of price graph format in our study, the effects on performance for institutional investors could be substantial.

In addition, professional investors can use the price graph display format to their advantage. Walters et al. (2019) show that investors pay twice as much for expert advice when the past performance of financial advisors is displayed using price level graphs than when it is displayed using relative price graphs. Indeed, investors are more responsive to expert advice when past performance is displayed in absolute price level graphs as compared to relative price graphs. Our current research shows that presenting stock performance as price level graphs increases perceptions of predictability.

Thus, investors might not only present price level graphs to argue for their investment skills, they might also use similar price level graphs to convince clients to turnover their portfolio, directly increasing management fees and transaction costs. Our research suggests why most online retail investor sources would want to present price level graphs instead of price returns: the increased perception of predictability by retail investors could increase trade and fees collected by the platform. While this hypothesis is plausible when taking this paper in isolation. The first paper in this dissertation demonstrates that this hypothesis is false (See Paper 1 for details).

Most importantly our work speaks to the behavior of lay investors. The existing literature on lay investors has established that a significant proportion have poor investing strategies. Specifically, they are turning over their portfolio too often, which has been attributed to over-confidence. Our results demonstrate that over-confidence is not exacerbated by absolute price graphs and the use of absolute price graphs on online retail investor sites is likely not a reason for trading and high turn-overs on retail investor sites. Nevertheless, retail investors likely believe they can more accurately predict future stock prices because absolute price graphs, compared to relative price graphs, increase perceptions of predictability.

# Conclusion

The two papers presented in my dissertation proposal focus on better understanding the effects of default stock price information used on retail investor sites. There is a clear pattern of how asset price information is displayed to retail investors with respect to both summary statistics and price graphs; a few specific summary statistics and price level graph formats are used. The effects of presenting asset price information in this specific and near uniform way across investor sites has not been studied. In my dissertation I tested the effects of specific price graphs on investor decision making and how price graphs are affecting perceptions of uncertainty and investor confidence. We did not find that the addition of price level graphs affected trading, diversification, the disposition effect, and overall wealth in an asset price experiment. In comparison to relative price graphs, we found that price level graphs increase the likelihood with which participants predict trends to continue, and this is driven by an increase in perceptions of predictability. However, price level graphs, compared to relative price graphs did not increase investor confidence.

These results inform the vast literature that exists on the drivers of and potential avenues for improving retail investor trading behavior, diversification strategies and susceptibility to the disposition effect. A better understanding of retail investor behavior informs future theories and models of over-confidence, trading, diversification and the disposition effect in finance. For example, the current models of over-confidence focus on miscalibration, however, more work is needed to better understand which facets of investor confidence drive investment decision making. Important work by Glaser and Weber (2007) has shown that miscalibration may not be the facet of confidence impacting investor financial decision making. In addition, no one has explored the underlying process that drives different levels of confidence in investment decision making, a question that Paper 2 addresses. The pervasive use of graphs to display asset information to investors has remained largely unquestioned, and the general idea of thinking about how asset price information is communicated has only recently gained traction with work such as Shue and Townsend (2019); Shue and Townsend (2019) show that the effects of using nominal prices instead of returns to communicate and present asset price information can have significant economic effects. My work contributes to the growing literature on thinking about how the specific communication of asset information is impacting investor decision making and potentially exacerbating pervasive biases among retail investors. While my work suggests that the specific use of price level graphs does not exacerbate retail investor biases, they do alter investor beliefs about stock price trends continuing.

My work and other work on the communication of asset price information can inform future policies to improve financial decision making by retail investors, but also raises important questions such as "Would retail investor sites be willing to change their asset price information format to improve investor decision making?", if not, "How can we push retail investors to think about price returns (as the research by Shue and Townsend (2019) would suggest), or otherwise helpful ways to process asset price information?"

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# Appendices

# Paper 1

## Appendix A. Experiment 1: Asset Price Information Instructions

Participants received lengthy instructions to clarify how the asset price trading experiment worked and what all the asset price information they were seeing meant. Below are the instructions:

Welcome to today's experiment.

In today's experiment, you will be participating in 12 rounds of investing, each round representing a month (referred to as trading months). In each trading month, you can buy and sell shares of 6 different stocks. For each share that you buy or sell in a month, you will incur a 2.5% transaction fee of the price. In addition, you can choose not to invest any money in any of the stocks, and instead just hold onto the money as cash. In each trading month, you will see stock information updated to include one additional month of daily stock prices; thus, in the first month you will see stock price information based on 1 month of daily stock prices, in the second month you will see stock price information based on two months of stock price information: the first and second month of daily stock price data, and so forth.

In the final month (month 13), you will not be able to buy/sell shares. In this month, we will sell all the shares you own of each stock, at month 13 stock prices, to determine your bonus payment. All the stocks presented in this study are real, and you will see their real stock price information from the period 11/01/2016 until 10/31/2017 for months 1-12. Finally, the month 13 stock prices are taken from the following month, November 2017.

Thus, your final payment will depend on how you perform in the stock trading task. In particular your bonus payment will be calculated by dividing your final total wealth in the stock trading task by 2000 and rounding it to the nearest cent. **Thus, please pay careful attention to these instructions and those to follow, as your final payment will depend on it.**

*** New Page ***

Let's take a look at the kinds of stock information you will be shown in this study. Below is an example of the type of stock price information that you will receive. Each column represents a stock, and each row shows a different piece of stock information.

Let's walk through what each row means:

- Minimum Price: the minimum stock price during the relevant period.*
- Maximum Price: the maximum stock price during the relevant period.
- Beta: A measure of how much the daily stock prices fluctuated, relative to the S&P 500. A value greater (less) than 1 indicates the stock price fluctuated more (less) than the S&P 500.
- Average Return: the average percentage change in stock price for the respective period, calculated using daily prices. A positive percentage means the stock gained in value, while a negative percentage means the stock lost value.

*Note that “relevant period” means the first month for month 1, the first and second month for month 2, etc.

| | Stock 1 | Stock 2 | Stock 3 | Stock 4 | Stock 5 | Stock 6 |
|---|---|---|---|---|---|---|
| Minimum Price | $719.07 | $11.90 | $71.29 | $59.70 | $44.10 | $66.53 |
| Maximum Price | $787.75 | $12.50 | $81.80 | $63.54 | $48.20 | $78.61 |
| Beta | 1.83 | 0.94 | 0.71 | 0.97 | 1.06 | 0.53 |
| Average Return | -0.21% | -0.18% | 0.53% | 0.22% | 0.28% | 0.67% |

*** New Page ***

Let’s continue walking through what each row means. The table shown at the bottom of this page is a continuation of the one on the previous page. In this part of the table, you will be deciding how many shares of each stock to buy or sell.

- (Closing) Price: the price of the stock on the last day of the current period.
- Current Number of Shares: the number of shares you currently own for that respective stock.
- Buy/Sell Shares: this is a box where you can change the number of shares you own of a stock by buying (positive numbers) or selling (negative numbers) shares.
- New Number of Shares: the new number of shares you own after incorporating the number of shares you will buy/sell this round.
- Total Cost: the total cost, i.e. the Price of the stock times the New Number of Shares you own of that stock.

Note the information shown below the Table:

- Current Cash Holdings: the amount of cash you have that is not invested in stocks or spent on transaction fees.
- New Cash Holdings: automatically calculated to be any leftover cash from your Current Total Wealth that is not invested in stocks or spent on transaction fees.
- Current Total Wealth: the total amount of wealth you have in the current period, i.e. the amount of money you would have if you sold all the Current Number of Shares of stocks you own at the current Price, plus the Current Cash Holdings.

It is important to highlight that the New Number of Shares and New Cash Holdings are numbers currently given in green. This is because they are positive numbers. **You cannot hold a negative amount of New Number of Shares or New Cash Holdings**, if this happens these numbers will turn red and you will not be able to advance. Thus, please make sure that you hold a positive Number of Shares and New Cash Holdings, before trying to advance.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Closing) Price | $750.57 | $11.95 | $80.25 | $63.39 | $47.35 | $77.24 |
| Curent Number of Shares | 0 | 0 | 0 | 0 | 0 | 0 |
| Buy/Sell Shares | 0 | 0 | 0 | 0 | 0 | 0 |
| New Number of Shares | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total Cost** | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 |

Curent Cash Holdings: $2000.00

New Cash Holdings: $2000.00

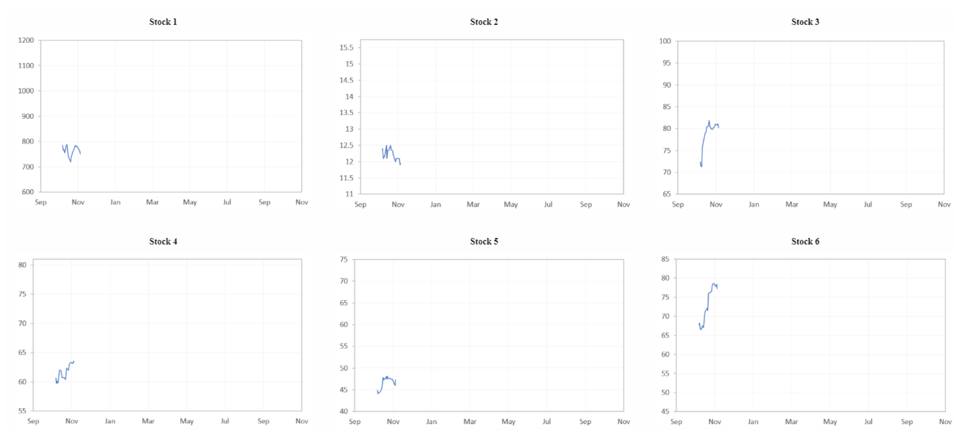
**Current Total Wealth : $2000.00**

*** New Page ***

**All of the information given** in the rows of the table called Minimum Price, Maximum Price, Beta, Average Return and (Closing) Price, **will be updated every month.** Further, this updated stock price information will come in sequentially and **you will not be able to advance until all the stock price information on the page has loaded.**

*** IF participants were in the Price Level Graph Condition ***

Lastly, above the table, you will also see a series of graphs depicting the stock prices. In particular, on the vertical axis you will see the price and on the horizontal axis the dates. One graph will be depicted for each stock and will load sequentially with the other stock price information. An example is given below.




*** New Page ***

You will receive \$0.50 as a base payment just for completing this study. In addition, you will receive a bonus payment of \$1 that you can use in the stock trading task. This bonus payment is converted to your initial Cash Holdings by a 2000:1 ratio. In other words, you will start the stock trading experiment with \$2000. **The bonus payment you will actually receive at the end of the study will be your Final Total Wealth, divided by 2000, rounded to the nearest cent.**

Your Final Total Wealth will be calculated by summing your New Cash Holdings (which includes transaction fees paid) in month 12, with, the New Number of Shares you own at the end of month 12 multiplied by the month 13 stock price. If you want to be sure you will receive a \$1 bonus payment at the end of the study, you should keep your \$2000 in your Cash Holdings throughout the 12 trading months. If you invest any or all of your Cash Holdings, you could lose your whole bonus payment, or you could make significantly more than \$1 as your final bonus payment. It is completely up to you how much and whether you want to invest your bonus payment in the stock trading task.

*** New Page: Comprehension check questions ***

What is the benchmark used for Beta?

- S&P 500
- NASDAQ
- Dow 30
- Crude Oil

What does a Beta value greater than 1 mean?

- The stock price varies more than the benchmark

- The stock price varies less than the benchmark
- The stock price varies to the same degree as the benchmark
- Not enough information

What is the return of a stock?

- The percentage change in price between two time periods
- The difference in price between two time periods
- The average change in price of a stock across the time period
- The ratio of two prices

Can you own a negative number of shares of a stock?

- Yes
- No

Can you hold a negative amount of cash?

- Yes
- No

How is your bonus payment determined?

- My New Number of Shares in Month 12, multiplied by Month 13 prices, plus my New Cash Holdings in Month 12
- My New Number of Shares in Month 12, multiplied by Month 12 prices, plus my New Cash Holdings in Month 12
- My New Number of Shares in Month 12, multiplied by Month 13 prices, plus my New Cash Holdings in Month 13
- My New Number of Shares in Month 11, multiplied by Month 13 prices, plus my New Cash Holdings in Month 12

In the trading task, you will incur a 2.5% transaction fee of the stock price for each share that you trade of that stock. Suppose you bought 2 shares of a stock that is priced at $10. How much will your transaction fees be?

- $0.25
- $0.50
- $1.00
- $1.25

# Appendix B. Experiment 1: Per period diversification effects

**Table B.I** Diversification for Months 1-6

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Diversification | | | | | |
| | Month 1 | Month 2 | Month 3 | Month 4 | Month 5 | Month 6 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| graph | −0.025 | −0.033 | −0.051 | 0.005 | −0.018 | −0.016 |
| | (0.052) | (0.046) | (0.051) | (0.043) | (0.042) | (0.044) |
| gender | 0.058 | 0.026 | −0.004 | −0.051 | −0.038 | −0.066 |
| | (0.055) | (0.048) | (0.054) | (0.046) | (0.045) | (0.046) |
| age | 0.007*** | 0.009*** | 0.007*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| education | −0.068** | −0.077*** | −0.056* | −0.045* | −0.062** | −0.057** |
| | (0.031) | (0.027) | (0.030) | (0.026) | (0.025) | (0.026) |
| caucasian | −0.046 | 0.006 | 0.008 | 0.007 | 0.014 | 0.019 |
| | (0.072) | (0.063) | (0.070) | (0.060) | (0.058) | (0.061) |
| Constant | 0.371** | 0.322** | 0.409** | 0.338** | 0.370*** | 0.419*** |
| | (0.164) | (0.144) | (0.160) | (0.137) | (0.133) | (0.138) |
| Observations | 121 | 121 | 121 | 121 | 121 | 121 |
| $R^2$ | 0.112 | 0.186 | 0.091 | 0.141 | 0.175 | 0.150 |
| Adjusted $R^2$ | 0.074 | 0.150 | 0.051 | 0.104 | 0.139 | 0.113 |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table B.II** Diversification for Months 7-12

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Diversification | | | | | |
| | Month 7 | Month 8 | Month 9 | Month 10 | Month 11 | Month 12 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| graph | −0.030 | −0.087* | −0.067 | −0.086* | −0.082 | −0.086 |
| | (0.045) | (0.046) | (0.048) | (0.050) | (0.051) | (0.055) |
| gender | −0.049 | −0.026 | −0.114** | −0.059 | −0.049 | −0.106* |
| | (0.048) | (0.049) | (0.051) | (0.053) | (0.053) | (0.058) |
| age | 0.007*** | 0.009*** | 0.008*** | 0.008*** | 0.009*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) |
| education | −0.079*** | −0.099*** | −0.123*** | −0.093*** | −0.121*** | −0.133*** |
| | (0.026) | (0.027) | (0.028) | (0.030) | (0.030) | (0.032) |
| caucasian | 0.009 | −0.010 | −0.073 | −0.096 | −0.103 | −0.056 |
| | (0.062) | (0.064) | (0.066) | (0.070) | (0.070) | (0.076) |
| Constant | 0.506*** | 0.524*** | 0.829*** | 0.662*** | 0.743*** | 0.918*** |
| | (0.142) | (0.145) | (0.151) | (0.159) | (0.159) | (0.174) |
| Observations | 121 | 121 | 121 | 121 | 121 | 121 |
| $R^2$ | 0.151 | 0.206 | 0.221 | 0.164 | 0.215 | 0.184 |
| Adjusted $R^2$ | 0.114 | 0.172 | 0.187 | 0.128 | 0.181 | 0.149 |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

# Appendix C. Experiment 2: Diversification across months

**Table C.I** Within-Subject Regression Results for Diversification interacted with Month

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Diversification | | |
| | (1) | (2) | (3) |
| graph | 0.033 | 0.033 | 0.043 |
| | (0.045) | (0.045) | (0.061) |
| Month | | $0.006^{***}$ | $0.007^{***}$ |
| | | (0.001) | (0.002) |
| gender | −0.003 | −0.003 | −0.003 |
| | (0.054) | (0.054) | (0.054) |
| age | −0.001 | −0.001 | −0.001 |
| | (0.002) | (0.002) | (0.002) |
| education | −0.034 | −0.034 | −0.034 |
| | (0.033) | (0.033) | (0.033) |
| caucasian | 0.020 | 0.020 | 0.020 |
| | (0.071) | (0.071) | (0.071) |
| graph:Month | | | −0.0004 |
| | | | (0.002) |
| Constant | $0.537^{***}$ | $0.391^{**}$ | $0.387^{**}$ |
| | (0.161) | (0.157) | (0.159) |
| Clustered SE: | Y | Y | Y |
| Observations | 2,575 | 2,575 | 2,575 |
| $R^2$ | 0.015 | 0.041 | 0.041 |
| Adjusted $R^2$ | 0.013 | 0.039 | 0.039 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

# Appendix D. Experiment 2: Gender effects

**Table D.I** Within-Subject Regression Results for Gender on Trading
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Trade | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | $-1.121$ | $-1.267$ | $-4.606^{***}$ | $-4.247^{***}$ |
| | (1.695) | (1.434) | (1.524) | (1.322) |
| age | | $-0.002$ | | $-0.049$ |
| | | (0.092) | | (0.065) |
| education | | 0.576 | | $-0.393$ |
| | | (0.713) | | (1.166) |
| caucasian | | $2.371^{**}$ | | 1.612 |
| | | (1.170) | | (1.405) |
| Constant | $4.357^{***}$ | 0.312 | $6.518^{***}$ | 8.280 |
| | (1.239) | (5.190) | (1.507) | (6.022) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,224 | 1,224 | 1,224 | 1,224 |
| $R^2$ | 0.001 | 0.003 | 0.012 | 0.014 |
| Adjusted $R^2$ | 0.00004 | $-0.0002$ | 0.011 | 0.011 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

**Table D.II** Within-Subject Regression Results for Gender interaction with Trading

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Trade | | |
| | Whole Sample | | |
| | (1) | (2) | (3) |
| gender | $-2.832^{**}$ | $-1.121$ | $-1.189$ |
| | (1.152) | (1.687) | (1.548) |
| graph | 0.796 | 2.161 | 1.901 |
| | (1.278) | (1.941) | (1.958) |
| age | | | $-0.030$ |
| | | | (0.059) |
| education | | | 0.079 |
| | | | (0.645) |
| caucasian | | | $1.820^{**}$ |
| | | | (0.833) |
| gender × graph | | $-3.485$ | $-3.081$ |
| | | (2.269) | (2.192) |
| Constant | $5.062^{***}$ | $4.357^{***}$ | 3.721 |
| | (1.064) | (1.233) | (3.768) |
| Clustered SE: | Y | Y | Y |
| Observations | 2,448 | 2,448 | 2,448 |
| $R^2$ | 0.006 | 0.007 | 0.009 |
| Adjusted $R^2$ | 0.005 | 0.006 | 0.006 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

**Table D.III** Within-Subject Regression Results for Gender on Fees
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | fees | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | −0.805 | −1.131 | −5.382* | −4.332* |
| | (2.110) | (2.247) | (2.869) | (2.445) |
| age | | −0.083 | | −0.157 |
| | | (0.078) | | (0.110) |
| education | | −1.340 | | −1.824 |
| | | (1.311) | | (2.245) |
| caucasian | | 3.303* | | 4.423 |
| | | (1.694) | | (2.920) |
| Constant | 7.798*** | 13.287** | 12.481*** | 20.943* |
| | (1.589) | (5.928) | (2.630) | (10.803) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,224 | 1,224 | 1,224 | 1,224 |
| $R^2$ | 0.0003 | 0.008 | 0.008 | 0.017 |
| Adjusted $R^2$ | −0.0005 | 0.004 | 0.007 | 0.014 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table D.IV** Within-Subject Regression Results for Gender on Wealth
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Wealth | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | 0.951 | 24.518 | 4.762 | 28.637 |
| | (137.699) | (133.915) | (108.097) | (108.433) |
| age | | 3.211 | | 0.308 |
| | | (5.198) | | (4.357) |
| education | | −66.193 | | 118.666 |
| | | (73.222) | | (75.048) |
| caucasian | | −441.349*** | | 180.590* |
| | | (142.711) | | (94.147) |
| Constant | 4,612.915*** | 5,099.106*** | 4,498.042*** | 3,876.034*** |
| | (90.028) | (416.808) | (73.139) | (268.952) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,275 | 1,275 | 1,275 | 1,275 |
| $R^2$ | 0.00000 | 0.055 | 0.00002 | 0.042 |
| Adjusted $R^2$ | −0.001 | 0.052 | −0.001 | 0.039 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

# Appendix E. Experiment 3: Gender effects

**Table E.I** Within-Subject Regression Results for Gender on Trade
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Trade | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | −1.274 | −0.126 | −0.566 | 0.763 |
| | (1.904) | (1.827) | (1.412) | (1.129) |
| age | | −0.066 | | −0.071 |
| | | (0.071) | | (0.067) |
| education | | −2.718 | | −0.887 |
| | | (1.868) | | (0.737) |
| caucasian | | 1.645 | | −4.747 |
| | | (2.019) | | (2.895) |
| Constant | 6.199*** | 17.765** | 6.134*** | 15.243*** |
| | (1.204) | (8.514) | (1.222) | (4.611) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,176 | 1,176 | 1,008 | 1,008 |
| $R^2$ | 0.001 | 0.019 | 0.0002 | 0.012 |
| Adjusted $R^2$ | −0.00002 | 0.016 | −0.001 | 0.008 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table E.II** Within-Subject Regression Results for Gender interaction on Trade

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Trade | | |
| | Whole Sample | | |
| | (1) | (2) | (3) |
| gender | −0.920 | −1.274 | −0.230 |
| | (1.180) | (1.895) | (1.672) |
| graph | 0.204 | −0.064 | −0.824 |
| | (1.226) | (1.706) | (1.761) |
| age | | | −0.044 |
| | | | (0.049) |
| education | | | −1.979 |
| | | | (1.212) |
| caucasian | | | −0.992 |
| | | | (1.746) |
| gender × graph | | 0.707 | 0.677 |
| | | (2.358) | (2.144) |
| Constant | 6.090*** | 6.199*** | 16.008*** |
| | (1.062) | (1.199) | (5.624) |
| Clustered SE: | Y | Y | Y |
| Observations | 2,184 | 2,184 | 2,184 |
| $R^2$ | 0.001 | 0.001 | 0.009 |
| Adjusted $R^2$ | −0.0004 | −0.001 | 0.007 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table E.III** Within-Subject Regression Results for Gender on Fees
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | fees | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | −0.071 | −0.751 | 3.962** | 4.584** |
| | (2.780) | (2.723) | (1.772) | (2.116) |
| age | | −0.113 | | −0.060 |
| | | (0.089) | | (0.059) |
| education | | 1.023 | | −0.096 |
| | | (0.988) | | (0.886) |
| caucasian | | 1.111 | | −2.245 |
| | | (2.670) | | (2.705) |
| Constant | 5.668*** | 5.654 | 3.351*** | 7.518** |
| | (1.307) | (3.717) | (0.619) | (3.645) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,176 | 1,176 | 1,008 | 1,008 |
| $R^2$ | 0.00001 | 0.020 | 0.058 | 0.075 |
| Adjusted $R^2$ | −0.001 | 0.016 | 0.057 | 0.071 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table E.IV** Within-Subject Regression Results for Gender on Wealth
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Wealth | | | |
| | Summary Statistics Condition Only | | Price Level Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| gender | 13.320 | 20.638 | −141.723 | −121.064 |
| | (101.759) | (107.649) | (98.697) | (122.190) |
| age | | 2.114 | | −6.332 |
| | | (3.518) | | (5.203) |
| education | | −33.102 | | 3.088 |
| | | (50.394) | | (58.836) |
| caucasian | | 109.949 | | 22.967 |
| | | (84.860) | | (118.362) |
| Constant | 4,349.755*** | 4,309.521*** | 4,467.653*** | 4,671.187*** |
| | (41.608) | (239.302) | (73.869) | (308.288) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 1,225 | 1,225 | 1,050 | 1,050 |
| $R^2$ | 0.0002 | 0.021 | 0.017 | 0.030 |
| Adjusted $R^2$ | −0.001 | 0.018 | 0.016 | 0.026 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

# Paper 2

## Appendix F. Experiment 1: Summary Statistics

Below is a description of all the variables. See Appendix G for details on each of the EARS items (A1-A3 and E1-E3).

aleatory: average of the three aleatory items.
epistemic: average of the three epistemic items.
Male: 1 if male, 0 otherwise.
Age: numeric age.
Education: 1 less than HS, 2 HS graduate, 3 some college, 4 Bachelors, 5 Graduate.
Caucasian: 1 if Caucasian, 0 otherwise.
Income: income level, every increment (income = 1 - 11) translates to a \$10k increase in household income starting from 0 - \$10k until \$150k or more (income = 12).

**Table F.V: Aggregate Summary Statistics**

| | Count | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| A1 | 398 | 4.621 | 1.592 | 1 | 7 |
| A2 | 398 | 4.535 | 1.593 | 1 | 7 |
| A3 | 398 | 5.181 | 1.395 | 1 | 7 |
| E1 | 398 | 3.668 | 1.586 | 1 | 7 |
| E2 | 398 | 3.882 | 1.546 | 1 | 7 |
| E3 | 398 | 4.304 | 1.497 | 1 | 7 |
| aleatory | 398 | 4.779 | 1.231 | 1.333333 | 7 |
| epistemic | 398 | 3.951 | 1.291 | 1 | 7 |
| male | 398 | 0.455 | 0.499 | 0 | 1 |
| age | 398 | 39.088 | 11.645 | 18 | 72 |
| educ | 398 | 3.613 | 0.867 | 1 | 6 |
| caucasian | 398 | 0.796 | 0.403 | 0 | 1 |
| income | 398 | 6.442 | 2.944 | 1 | 12 |
| *N* | 398 | | | | |

**Table F.VI: Means Between Relative and Absolute Condition**

| | Count | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Absolute | | | | | |
| ptrend | 198 | 0.344 | 0.438 | -1.00 | 1.00 |
| aleatory | 198 | 4.478 | 1.262 | 1.33 | 7.00 |
| epistemic | 198 | 4.239 | 1.313 | 1.00 | 7.00 |
| diff | 198 | -0.239 | 2.138 | -6.00 | 5.00 |
| Relative | | | | | |
| ptrend | 200 | 0.016 | 0.377 | -0.80 | 1.00 |
| aleatory | 200 | 5.077 | 1.126 | 1.67 | 7.00 |
| epistemic | 200 | 3.667 | 1.207 | 1.00 | 7.00 |
| diff | 200 | -1.410 | 1.880 | -6.00 | 4.00 |
| *N* | 398 | | | | |

# Appendix G. Experiment 1: EARS Reliability and Validity

All epistemic and aleatory items started with "For Graph X, predicting the future stock price is..." The epistemic items we included were:

E1 ... in principle knowable in advance.
E2 ... knowable in advance, given enough information.
E3 ... something that well-informed people would agree on.

and the aleatory items we included were:

A1 ... something that has an element of randomness.
A2 ... unpredictable.
A3 ... something that could play out in different ways on similar occasions.

We tested the reliability of this scale by calculating the cronbach alpha's for each the epistemic and aleatory subscale. The epistemic subscale cronbachs alpha is 0.786 and the aleatory subscale cronbachs alpha is 0.728. Further, we conducted a component-factor analysis. We found two factors and the following results for each:

**Table G.I: Component-Factor Results**

| Item | Factor 1 | Factor 2 |
|---|---|---|
| A1 | -0.1253 | 0.8371 |
| A2 | -0.3176 | 0.7181 |
| A3 | -0.0783 | 0.7999 |
| E1 | 0.8337 | -0.1666 |
| E2 | 0.8414 | -0.1919 |
| E3 | 0.7901 | -0.0676 |

# Appendix H. Experiment 1: Robustness and Individual EARS Results

**Table H.I: Ordered Logistic Regression of the Effect of Price Graph Display on Stock Price Predictions Using Diff EARS.**

| | (1) ptrend | (2) ptrend | (3) ptrend | (4) ptrend |
|---|---|---|---|---|
| rel | -0.689*** | -0.610*** | -0.605*** | -0.605*** |
| | (0.090) | (0.094) | (0.096) | (0.096) |
| diff | | 0.070*** | 0.070*** | 0.072*** |
| | | (0.023) | (0.023) | (0.023) |
| pos | | | 0.394*** | 0.393*** |
| | | | (0.056) | (0.056) |
| quad | | | -0.164** | -0.164** |
| | | | (0.065) | (0.065) |
| order | | | -0.138 | -0.146 |
| | | | (0.091) | (0.092) |
| cut1 | -1.123*** | -1.142*** | -1.100*** | -0.996*** |
| | (0.074) | (0.073) | (0.092) | (0.258) |
| cut2 | -0.327*** | -0.343*** | -0.291*** | -0.186 |
| | (0.071) | (0.071) | (0.091) | (0.256) |
| Controls: | | | | |
| Demographic | | | | Y |
| $N$ | 3980 | 3980 | 3980 | 3980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. No demographic characteristics were significant at the 5% level.

**Table H.II: OLS Regression of the Effect of Price Graph Display on Stock Price Predictions Using Individual EARS.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| DV: | ptrend | ptrend | ptrend | ptrend |
| rel | -0.328*** | -0.291*** | -0.286*** | -0.286*** |
| | (0.041) | (0.043) | (0.043) | (0.043) |
| aleatory | | -0.003 | -0.003 | -0.002 |
| | | (0.019) | (0.019) | (0.019) |
| epistemic | | 0.061*** | 0.060*** | 0.064*** |
| | | (0.018) | (0.018) | (0.019) |
| pos | | | 0.179*** | 0.179*** |
| | | | (0.025) | (0.025) |
| quad | | | -0.070** | -0.070** |
| | | | (0.029) | (0.029) |
| order | | | -0.055 | -0.059 |
| | | | (0.041) | (0.041) |
| Constant | 0.344*** | 0.098 | 0.073 | -0.016 |
| | (0.031) | (0.137) | (0.138) | (0.189) |
| Controls: | | | | |
| Demographic | | | | Y |
| *N* | 3980 | 3980 | 3980 | 3980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. No demographic characteristics were significant at the 5% level.

**Table H.III: Ordered Logistic Regression of the Effect of Price Graph Display on Stock Price Predictions Using Individual EARS.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ptrend | ptrend | ptrend | ptrend |
| rel | -0.689*** | -0.618*** | -0.615*** | -0.614*** |
| | (0.090) | (0.094) | (0.096) | (0.096) |
| aleatory | | 0.000 | -0.000 | 0.002 |
| | | (0.043) | (0.043) | (0.043) |
| epistemic | | 0.135*** | 0.134*** | 0.142*** |
| | | (0.041) | (0.040) | (0.042) |
| pos | | | 0.395*** | 0.394*** |
| | | | (0.056) | (0.056) |
| quad | | | -0.165** | -0.166** |
| | | | (0.065) | (0.065) |
| order | | | -0.127 | -0.136 |
| | | | (0.091) | (0.092) |
| cut1 | -1.123*** | -0.554* | -0.517* | -0.321 |
| | (0.074) | (0.304) | (0.308) | (0.416) |
| cut2 | -0.327*** | 0.247 | 0.293 | 0.490 |
| | (0.071) | (0.305) | (0.309) | (0.416) |
| Controls: | | | | |
| Demographic | | | | Y |
| $N$ | 3980 | 3980 | 3980 | 3980 |

* p < 0.10, ** p < 0.05, *** p < 0.01. No demographic characteristics were significant at the 5% level.

**Table H.IV: Price Graph Display Manipulates Perceptions of EARS**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| DV: | epistemic | epistemic | epistemic | aleatory | aleatory | aleatory |
| rel | -0.572*** | -0.559*** | -0.550*** | 0.599*** | 0.604*** | 0.594*** |
| | (0.126) | (0.127) | (0.124) | (0.120) | (0.121) | (0.120) |
| pos | | -0.014 | -0.018 | | -0.005 | -0.002 |
| | | (0.029) | (0.029) | | (0.028) | (0.027) |
| quad | | -0.002 | -0.002 | | 0.023 | 0.023 |
| | | (0.027) | (0.027) | | (0.028) | (0.028) |
| order | | -0.129 | -0.105 | | -0.053 | -0.039 |
| | | (0.127) | (0.125) | | (0.121) | (0.120) |
| Constant | 4.239*** | 4.304*** | 5.397*** | 4.478*** | 4.493*** | 4.148*** |
| | (0.093) | (0.109) | (0.378) | (0.090) | (0.104) | (0.378) |
| Controls: | | | | | | |
| Demographic | | | Y | | | Y |
| *N* | 3980 | 3980 | 3980 | 3980 | 3980 | 3980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In Column 3, being caucasian ($p = 0.012$) is significantly related to predictions with a coefficient of -0.424. In Column 6, higher levels of education ($p = 0.045$) are significantly related to predictions with a coefficient of 0.166.

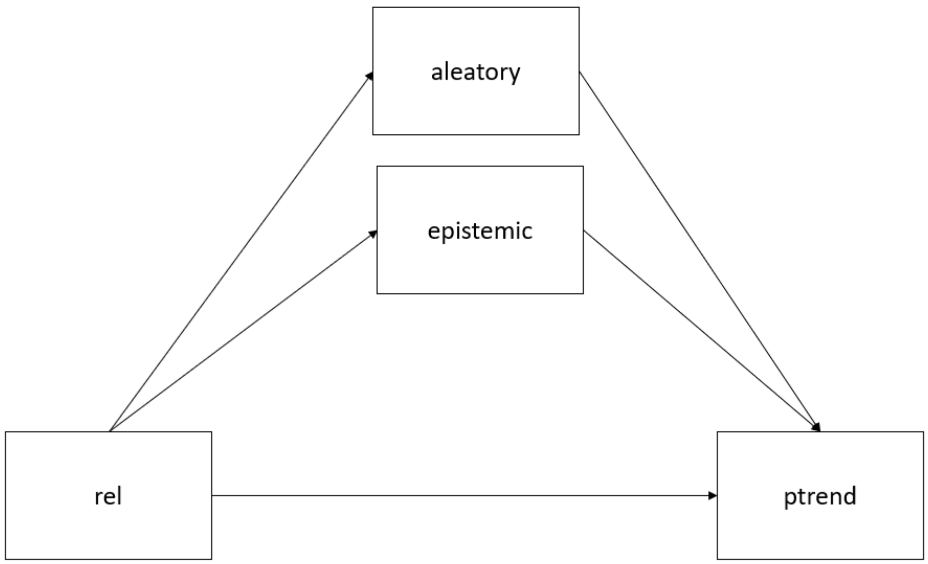



**Figure H.1. Joint Mediation Model**

```
Bootstrap results                               Number of obs     =      3,980
                                                Replications      =       1000

------------------------------------------------------------------------------
             |    Observed               Bootstrap
             |       Coef.       Bias    Std. Err.  [95% Conf. Interval]
-------------+----------------------------------------------------------------
Indirect E   |  -.03506197  -.0001903   .00689385  -.0485527  -.0220866   (P)
             |                                     -.0484897  -.0217448  (BC)
Indirect A   |  -.00178966  -.0004031   .00696021   -.015759   .0114759   (P)
             |                                     -.0146049   .0122053  (BC)
Indirect E&A |  -.03685163  -.0005934   .00830067  -.0539805   -.022469   (P)
             |                                     -.0530673  -.0214343  (BC)
Direct       |  -.29109281   .0015265   .02763405  -.3422706  -.2369497   (P)
             |                                     -.3471941  -.2383176  (BC)
Total        |  -.32794444   .0009331   .02659292  -.3780088   -.277076   (P)
             |                                     -.3802339  -.2781028  (BC)
------------------------------------------------------------------------------
(P)    percentile confidence interval
(BC)   bias-corrected confidence interval
```

**Figure H.2. Joint Mediation Results**

# Appendix I. Experiment 1: diff Mediation Results

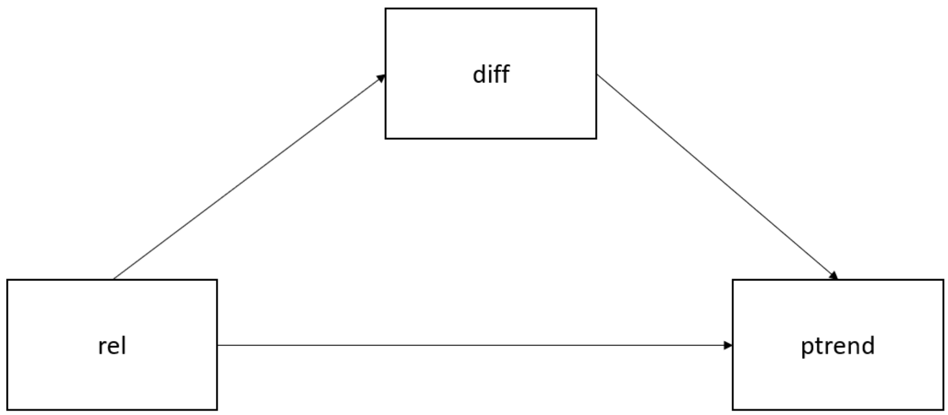



**Figure I.1. Mediation Model**

Bootstrap results — Number of obs = 3,980; Replications = 1000

| | Observed Coef. | Bias | Bootstrap Std. Err. | [95% Conf. | Interval] | |
|---|---|---|---|---|---|---|
| Indirect | -.03896042 | -.0005212 | .0082225 | -.0563567 | -.0247361 | (P) |
| | | | | -.0560198 | -.0240133 | (BC) |
| Direct | -.28898402 | .0014543 | .02763475 | -.3407933 | -.2346304 | (P) |
| | | | | -.3452221 | -.2366074 | (BC) |
| Total | -.32794444 | .0009331 | .02659292 | -.3780088 | -.277076 | (P) |
| | | | | -.3802339 | -.2781028 | (BC) |

(P) percentile confidence interval
(BC) bias-corrected confidence interval

**Figure I.2. Mediation Results**

# Appendix J. Experiment 2: Comprehension check questions

All participants answered a set of comprehension check questions about both the relative and absolute price graphs. In particular, the following three questions were asked for an absolute and relative price graph for each subject:

1. **Price change**: Pictured below are the period to period changes in closing prices for a stock over 24 months. The last closing price of the stock was XX.

   ** Insert absolute or relative price graph **

   For the above price graph, what is your best estimate of the change in price from month 11 to month 12? (indicate a decrease with negative numbers and an increase with positive numbers)

2. **Trend direction**: ** Insert absolute or relative price graph **

   For the above price graph, is the price generally increasing, decreasing or staying constant? The price is generally...

   - Increasing
   - Decreasing
   - Staying constant

3. **Higher price**: ** Insert absolute or relative price graph **

   For the above price graph, is the price in month 21 higher than in month 20?

   - Yes
   - No

# Appendix K. Experiment 2: Individual EARS results

**Table K.I** Within-Subject Regression Results for individual EARS
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | epistemic | | aleatory | |
| | (1) | (2) | (3) | (4) |
| Relative | $-1.235^{***}$ | $-1.177^{***}$ | $0.975^{***}$ | $0.897^{***}$ |
| | (0.288) | (0.303) | (0.242) | (0.252) |
| order | | $-0.138$ | | 0.132 |
| | | (0.289) | | (0.269) |
| gender | | 0.004 | | 0.112 |
| | | (0.241) | | (0.234) |
| age | | $-0.011$ | | 0.001 |
| | | (0.013) | | (0.010) |
| education | | 0.011 | | 0.108 |
| | | (0.147) | | (0.147) |
| income | | $-0.021$ | | 0.013 |
| | | (0.042) | | (0.036) |
| Constant | $4.528^{***}$ | $5.028^{***}$ | $4.327^{***}$ | $3.622^{***}$ |
| | (0.210) | (0.739) | (0.177) | (0.648) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 950 | 950 | 950 | 950 |
| $R^2$ | 0.158 | 0.170 | 0.142 | 0.158 |
| Adjusted $R^2$ | 0.157 | 0.165 | 0.141 | 0.153 |

# Appendix L. Experiment 2: Additional comprehension check analysis

We use two different data sets in the analysis presented below. In Tables L.I and L.IV we use the data frame that has been used throughout all previous analysis. In particular, it has 10 rows per subject and estimates variables clustered at the individual level. On the other hand, because participants filled out EARS ratings for both relative and absolute graphs and completed all comprehension check questions for the relative and absolute graph, we created a second data frame that is two rows per subject. Each row has the subject's EARS and comprehension check question responses for the relative and absolute price graph, respectively. We use the two rows per subject data frame in Tables L.III and L.II.

There were several new variables we created in both data frames. In the 10 rows per subject data frame we created:

- corr_direction_rel: a dummy variable indicating whether the participant got the trend comprehension check question correct (corr_direction_rel = 1) or wrong (= 0) for the relative graph.

Further, in the two rows per subject data frame we created three new variables. For each variable defined below, each subject had a row with the subject's response to the relative graph and a row with the subject's response to the absolute graph:

- diff_graph: epistemic minus aleatory ratings matched on response to the relative and absolute price graph.
- corr_direction: a dummy variable indicating whether the participant got the trend comprehension check question correct (corr_direction = 1) or wrong (= 0).
- rel_graph: a dummy variable indicating whether the response was for the relative (= 1) or absolute (= 0) price graph.

**Table L.I** Within-Subject Regression Results for ptrend and comprehension questions

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | 0.030 | 0.023 | 0.033 |
| | (0.036) | (0.047) | (0.046) |
| corr_direction_rel | 0.001 | −0.007 | −0.021 |
| | (0.037) | (0.051) | (0.054) |
| order | | | −0.047 |
| | | | (0.039) |
| gender | | | −0.032 |
| | | | (0.033) |
| age | | | −0.0004 |
| | | | (0.001) |
| education | | | 0.012 |
| | | | (0.021) |
| income | | | 0.006 |
| | | | (0.005) |
| rel × corr_direction_rel | | 0.018 | 0.021 |
| | | (0.074) | (0.076) |
| Constant | 0.222*** | 0.225*** | 0.223** |
| | (0.029) | (0.032) | (0.090) |
| Clustered SE: | Y | Y | Y |

**Table L.II** Within-Subject Regression Results for $diff$ and comprehension questions
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | diff | | |
| | (1) | (2) | (3) |
| corr_direction | 0.421 | −0.749 | −0.764 |
| | (0.344) | (0.622) | (0.637) |
| rel_graph | −2.247*** | −3.463*** | −3.510*** |
| | (0.342) | (0.679) | (0.692) |
| order | | | −0.011 |
| | | | (0.283) |
| gender | | | 0.135 |
| | | | (0.230) |
| age | | | −0.003 |
| | | | (0.014) |
| education | | | −0.187 |
| | | | (0.171) |
| income | | | −0.031 |
| | | | (0.041) |
| corr_direction × rel_graph | | 1.607** | 1.718** |
| | | (0.736) | (0.773) |
| Constant | −0.171 | 0.889 | 1.687* |
| | (0.351) | (0.574) | (0.920) |
| Clustered SE: | Y | Y | Y |

**Table L.III** Within-Subject Regression Results for $diff$ and comprehension questions
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | diff | | | |
| | Absolute Price Graph Condition Only | | Relative Price Graph Condition Only | |
| | (1) | (2) | (3) | (4) |
| corr_direction | −0.749 | −0.803 | 0.858** | 0.843** |
| | (0.620) | (0.626) | (0.393) | (0.418) |
| order | | 0.017 | | −0.035 |
| | | (0.458) | | (0.418) |
| gender | | 0.072 | | 0.192 |
| | | (0.392) | | (0.324) |
| age | | −0.014 | | 0.008 |
| | | (0.021) | | (0.018) |
| education | | −0.349 | | −0.019 |
| | | (0.248) | | (0.221) |
| income | | −0.085 | | 0.024 |
| | | (0.065) | | (0.057) |
| Constant | 0.889 | 3.124** | −2.574*** | −3.209*** |
| | (0.573) | (1.284) | (0.237) | (0.973) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 95 | 95 | 95 | 95 |
| $R^2$ | 0.010 | 0.089 | 0.049 | 0.058 |
| Adjusted $R^2$ | −0.0003 | 0.027 | 0.038 | −0.006 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

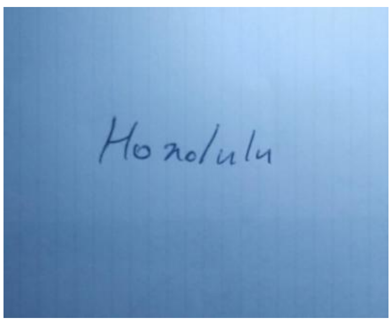
**Table L.IV** Within-Subject Regression Results for $diff$ and comprehension questions
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | diff | | |
| | (1) | (2) | (3) |
| rel | $-2.222^{***}$ | $-2.689^{***}$ | $-2.560^{***}$ |
| | (0.433) | (0.561) | (0.581) |
| corr_direction_rel | 0.156 | −0.441 | −0.399 |
| | (0.440) | (0.640) | (0.638) |
| order | | | −0.250 |
| | | | (0.447) |
| gender | | | −0.117 |
| | | | (0.362) |
| age | | | −0.008 |
| | | | (0.021) |
| education | | | −0.173 |
| | | | (0.225) |
| income | | | −0.030 |
| | | | (0.061) |
| rel × corr_direction_rel | | 1.277 | 1.329 |
| | | (0.859) | (0.853) |
| Constant | 0.151 | 0.343 | 1.661 |
| | (0.362) | (0.403) | (1.156) |
| Clustered SE: | Y | Y | Y |

# Appendix M. Experiment 3: Attention check questions

We asked participants a series of attention check questions.

1. A captcha question, i.e. checking a box and identifying elements in a picture to ensure participants aren't bots.

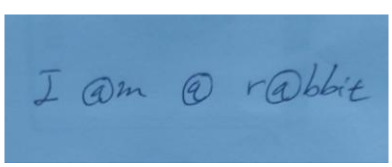
2. 


   Please type the word above into the space below.

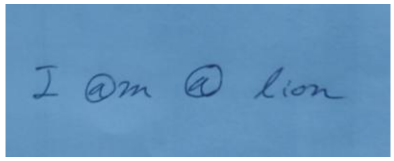
3. 

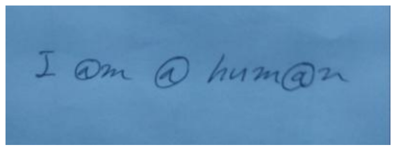

   Please type the letter that is written on the picture of the apple.

4. Which of the following sentences most accurately describes you?

   - 

   -


I @m @ lion

- 
I @m @ hum@n

# Appendix N. Experiment 3: Ordered logistic regression

**Table N.I** Within-Subject Ordered Logistic Regression Results for ptrend
*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) ptrend | (2) ptrend | (3) ptrend |
|---|---|---|---|
| rel | -1.028*** | -1.014*** | -0.922*** |
| | (0.221) | (0.223) | (0.225) |
| diff | | 0.012 | 0.018 |
| | | (0.046) | (0.049) |
| order | | | 0.128 |
| | | | (0.230) |
| gender | | | 0.045 |
| | | | (0.219) |
| age | | | -0.001 |
| | | | (0.012) |
| education | | | 0.237** |
| | | | (0.110) |
| income | | | -0.083** |
| | | | (0.039) |
| cut1 | -1.505*** | -1.502*** | -0.972 |
| | (0.178) | (0.177) | (0.650) |
| cut2 | -0.732*** | -0.729*** | -0.186 |
| | (0.158) | (0.157) | (0.667) |
| *N* | 920 | 920 | 920 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# Appendix O. Experiment 3: Individual EARS results

**Table O.I** Within-Subject Regression Results for ptrend
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | $-0.453^{***}$ | $-0.449^{***}$ | $-0.410^{***}$ |
| | (0.093) | (0.095) | (0.096) |
| aleatory | | $0.060^{*}$ | $0.063^{*}$ |
| | | (0.033) | (0.034) |
| epistemic | | $0.050^{**}$ | $0.064^{**}$ |
| | | (0.024) | (0.029) |
| order | | | 0.094 |
| | | | (0.090) |
| gender | | | $-0.046$ |
| | | | (0.090) |
| age | | | 0.003 |
| | | | (0.005) |
| education | | | 0.079 |
| | | | (0.049) |
| income | | | $-0.032^{**}$ |
| | | | (0.016) |
| Constant | $0.496^{***}$ | $-0.019$ | $-0.310$ |
| | (0.060) | (0.202) | (0.389) |
| Clustered SE: | Y | Y | Y |

**Table O.II** Within-Subject Ordered Logistic Regression Results for ptrend with individual EARS

*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ptrend | ptrend | ptrend |
| rel | -1.028*** | -1.074*** | -1.013*** |
| | (0.221) | (0.228) | (0.233) |
| aleatory | | 0.182** | 0.203** |
| | | (0.088) | (0.093) |
| epistemic | | (0.063) | (0.077) |
| order | | | 0.248 |
| | | | (0.226) |
| gender | | | -0.081 |
| | | | (0.223) |
| age | | | 0.010 |
| | | | (0.015) |
| education | | | 0.190* |
| | | | (0.111) |
| income | | | -0.079** |
| | | | (0.039) |
| cut1 | -1.505*** | -0.072 | 0.929 |
| | (0.178) | (0.550) | (0.987) |
| cut2 | -0.732*** | 0.711 | 1.727* |
| | (0.158) | (0.542) | (0.998) |
| *N* | 920 | 920 | 920 |

* p < 0.10, ** p < 0.05, *** p < 0.01.

**Table O.III** Within-Subject Regression Results for individual EARS
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | epistemic | | aleatory | |
| | (1) | (2) | (3) | (4) |
| rel | $-0.685^{**}$ | $-0.438$ | $0.505^{**}$ | $0.544^{**}$ |
| | (0.321) | (0.303) | (0.242) | (0.245) |
| order | | $-0.712^{***}$ | | $-0.152$ |
| | | (0.266) | | (0.237) |
| gender | | 0.363 | | 0.306 |
| | | (0.292) | | (0.266) |
| age | | $-0.061^{***}$ | | $-0.005$ |
| | | (0.014) | | (0.010) |
| education | | 0.108 | | 0.197 |
| | | (0.153) | | (0.128) |
| income | | $-0.044$ | | $-0.006$ |
| | | (0.052) | | (0.046) |
| Constant | $4.830^{***}$ | $6.740^{***}$ | $4.572^{***}$ | $3.707^{***}$ |
| | (0.194) | (0.824) | (0.170) | (0.785) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 920 | 920 | 920 | 920 |
| $R^2$ | 0.049 | 0.282 | 0.044 | 0.095 |
| Adjusted $R^2$ | 0.048 | 0.277 | 0.043 | 0.090 |
| *Note:* | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ | | |

**Table O.IV** Within-Subject Regression Results for corr with individual EARS
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | corr | | |
| | (1) | (2) | (3) |
| rel | −0.643 | −0.288 | −0.273 |
| | (0.452) | (0.454) | (0.475) |
| aleatory | | 0.149 | 0.144 |
| | | (0.136) | (0.136) |
| epistemic | | 0.628*** | 0.745*** |
| | | (0.153) | (0.157) |
| order | | | 0.386 |
| | | | (0.404) |
| gender | | | −0.174 |
| | | | (0.409) |
| age | | | 0.040** |
| | | | (0.019) |
| education | | | 0.436** |
| | | | (0.213) |
| income | | | −0.007 |
| | | | (0.082) |
| Constant | 6.566*** | 2.853*** | −0.716 |
| | (0.320) | (1.054) | (1.721) |
| Clustered SE: | Y | Y | Y |

# Appendix P. Experiment 4: Ordered logistic regression

**Table P.I** Within-Subject Ordered Logistic Regression Results for ptrend
*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ptrend | ptrend | ptrend |
| rel | -0.818*** | -0.744*** | -0.774*** |
| | (0.099) | (0.105) | (0.106) |
| diff | | 0.082*** | 0.079*** |
| | | (0.027) | (0.027) |
| order | | | 0.099 |
| | | | (0.098) |
| gender | | | 0.016 |
| | | | (0.089) |
| age | | | -0.011** |
| | | | (0.005) |
| education | | | 0.113** |
| | | | (0.055) |
| income | | | 0.003 |
| | | | (0.017) |
| cut1 | -1.517*** | -1.521*** | -1.438*** |
| | (0.088) | (0.086) | (0.319) |
| cut2 | -0.642*** | -0.642*** | -0.554* |
| | (0.079) | (0.077) | (0.312) |
| $N$ | 3690 | 3690 | 3690 |

* p < 0.10, ** p < 0.05, *** p < 0.01.

# Appendix Q. Experiment 4: Bootstrapped mediation

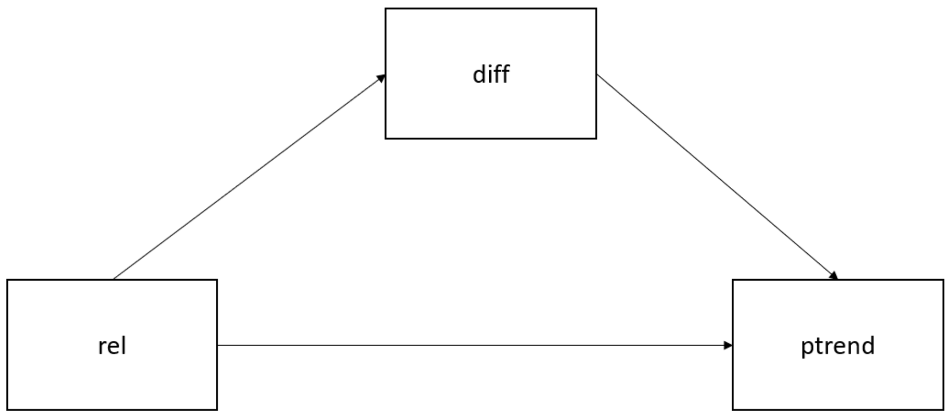



**Figure Q.1. Mediation Model**

```
Bootstrap results                              Number of obs     =      3,690
                                               Replications      =       1000

------------------------------------------------------------------------------
             |    Observed               Bootstrap
             |       Coef.       Bias    Std. Err.  [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Indirect |  -.03388329   .0002448    .0077924   -.0494897  -.0190096   (P)
             |                                      -.0512615  -.0200706  (BC)
    Direct   |  -.31630489 -.0002144   .02833455   -.3722042  -.2630329   (P)
             |                                      -.3739252  -.2643771  (BC)
    Total    |  -.35018818   .0000304   .02675433   -.4030074  -.2998907   (P)
             |                                      -.4039891  -.3011855  (BC)
------------------------------------------------------------------------------
(P)    percentile confidence interval
(BC)   bias-corrected confidence interval
```

**Figure Q.2. Mediation Results**

# Appendix R. Experiment 4: Individual EARS results

**Table R.I** Within-Subject Regression Results for ptrend

*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ptrend | | |
| | (1) | (2) | (3) |
| rel | $-0.350^{***}$ | $-0.316^{***}$ | $-0.325^{***}$ |
| | (0.041) | (0.044) | (0.044) |
| aleatory | | $-0.026$ | $-0.032^{**}$ |
| | | (0.016) | (0.016) |
| epistemic | | $0.042^{***}$ | $0.035^{**}$ |
| | | (0.015) | (0.015) |
| order | | | 0.039 |
| | | | (0.041) |
| gender | | | 0.006 |
| | | | (0.038) |
| age | | | $-0.004^{**}$ |
| | | | (0.002) |
| education | | | $0.046^{**}$ |
| | | | (0.023) |
| income | | | 0.0003 |
| | | | (0.007) |
| Constant | $0.474^{***}$ | $0.400^{***}$ | $0.413^{**}$ |
| | (0.030) | (0.104) | (0.163) |
| Clustered SE: | Y | Y | Y |

**Table R.II** Within-Subject Ordered Logisitc Regression Results for ptrend

*Note:* Regression coefficients are displayed with clustered standard errors in parentheses.

| | (1) | (2) | (3) |
|---|---|---|---|
| | ptrend | ptrend | ptrend |
| rel | -0.818*** | -0.746*** | -0.774*** |
| | (0.099) | (0.105) | (0.106) |
| aleatory | | -0.060 | -0.074* |
| | | (0.040) | (0.040) |
| epistemic | | 0.099*** | 0.083** |
| | | (0.034) | (0.035) |
| order | | | 0.099 |
| | | | (0.098) |
| gender | | | 0.018 |
| | | | (0.090) |
| age | | | -0.011** |
| | | | (0.005) |
| education | | | 0.111** |
| | | | (0.054) |
| income | | | 0.003 |
| | | | (0.017) |
| cut1 | -1.517*** | -1.341*** | -1.399*** |
| | (0.088) | (0.248) | (0.394) |
| cut2 | -0.642*** | -0.462* | -0.515 |
| | (0.079) | (0.246) | (0.389) |
| *N* | 3690 | 3690 | 3690 |

* p < 0.10, ** p < 0.05, *** p < 0.01.

**Table R.III** Within-Subject Regression Results for individual EARS
*Note:* Regression coefficients are displayed with standard errors in parentheses.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | epistemic | | aleatory | |
| | (1) | (2) | (3) | (4) |
| rel | $-0.531^{***}$ | $-0.589^{***}$ | $0.447^{***}$ | $0.413^{***}$ |
| | (0.141) | (0.137) | (0.129) | (0.127) |
| order | | 0.065 | | $-0.134$ |
| | | (0.139) | | (0.128) |
| gender | | $-0.224^{*}$ | | $-0.153$ |
| | | (0.135) | | (0.125) |
| age | | $-0.009$ | | $-0.005$ |
| | | (0.007) | | (0.007) |
| education | | $0.250^{***}$ | | $0.230^{***}$ |
| | | (0.077) | | (0.078) |
| income | | $-0.062^{**}$ | | 0.017 |
| | | (0.026) | | (0.023) |
| Constant | $4.695^{***}$ | $4.780^{***}$ | $4.668^{***}$ | $4.190^{***}$ |
| | (0.097) | (0.466) | (0.098) | (0.465) |
| Clustered SE: | Y | Y | Y | Y |
| Observations | 3,690 | 3,690 | 3,690 | 3,690 |
| $R^2$ | 0.037 | 0.084 | 0.031 | 0.066 |
| Adjusted $R^2$ | 0.037 | 0.082 | 0.031 | 0.064 |
| *Note:* | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ | | |

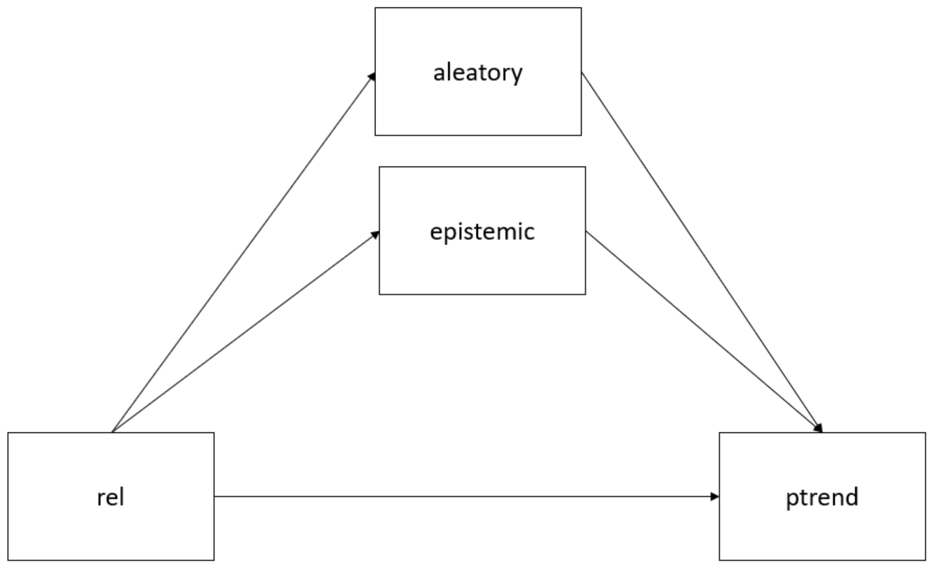



**Figure R.1. Joint Mediation Model**

```
Bootstrap results                                Number of obs     =      3,690
                                                 Replications      =       1000

------------------------------------------------------------------------------
             |    Observed               Bootstrap
             |       Coef.       Bias    Std. Err.  [95% Conf. Interval]
-------------+----------------------------------------------------------------
Indirect E   |  -.02221502  -.0001047    .0058265   -.0345353  -.0114253   (P)
             |                                      -.0348203  -.0116153  (BC)
Indirect A   |  -.01171047     .00031   .00496711   -.0216353  -.0018013   (P)
             |                                      -.0223895  -.0027011  (BC)
Indirect E&A |  -.03392549   .0002054   .00784636   -.0491655  -.0190283   (P)
             |                                      -.0514348   -.019744  (BC)
Direct       |  -.31626269   -.000175   .02834837   -.3719489  -.2629019   (P)
             |                                       -.374794  -.2638307  (BC)
Total        |  -.35018818   .0000304   .02675433   -.4030074  -.2998907   (P)
             |                                      -.4039891  -.3011855  (BC)
------------------------------------------------------------------------------
(P)    percentile confidence interval
(BC)   bias-corrected confidence interval
```

**Figure R.2. Joint Mediation Results**