Improving Investors' Judgments with Market Benchmarks

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ABSTRACT

I use an experiment to examine when past market returns cause individual investors to become overconfident and test whether providing investors with a salient market benchmark reduces overconfidence and improves their judgments. Participants are experienced investors who make simulated trades on a virtual stock exchange and estimate their future relative investing performance. I document that positive past market returns lead investors to become more overconfident. However, I find that presenting investors with a salient market benchmark reduces their overconfidence and helps investors make judgments consistent with prescriptive investing advice. Thus, my findings suggest salient market benchmarks can serve as a relatively simple and implementable visual cue that can reduce investor overconfidence and its consequences. My findings address concerns among regulators about how to best protect investors and contribute to growing research in accounting on the judgments and behaviors of individual investors in capital markets.

Keywords: Investor judgments, overconfidence, performance benchmarks, digital engagement practices, experimental design

I. INTRODUCTION

Prior work suggests that individual investors are overconfident, as evidenced by their tendency to trade excessively, hold under-diversified portfolios, and earn lower returns than the market (Odean 1998; Barber and Odean 2000, 2001; Goetzmann and Kumar 2008). Further, positive past portfolio returns have been linked to increased overconfidence among investors (Gervais and Odean 2001; Barber and Odean 2002; Glaser and Weber 2009), and several cognitive biases could hinder investors from disentangling the extent to which their returns were driven by ability or general market trends (Tversky and Kahneman 1974; Miller and Ross 1975; Camerer and Lovallo 1999). Because personal portfolio returns conflate overall market returns with individuals' abnormal returns, individual investors might unknowingly take credit for positive past *market* returns. In this paper, I provide causal evidence on the effect of past market returns on individual investor overconfidence and test whether providing investors with a salient market benchmark reduces their overconfidence and improves their investing judgments.

Overconfidence is a multi-dimensional construct that has been used to describe a large set of related phenomena, including overestimating one's absolute ability, overestimating one's ability relative to others, and overestimating the precision of one's private information (Moore and Healy 2008; Skala 2008). Further, overconfidence has been used to describe both a stable individual trait (e.g., Schrand and Zechman 2012; Hribar and Yang 2015) and a dynamic attribute that varies based on environmental factors (e.g., Gervais and Odean 2001; Hales and Kachelmeier 2008; Libby and Rennekamp 2012; Asay 2018). I focus on a fundamental feature of the market setting – past positive market returns – that could lead investors to overestimate their ability relative to other market participants (i.e., over-optimism, the better-than-average effect). I use the term "overconfidence" throughout the paper for parsimony and to be consistent with language used in prior research (Barber and Odean 2000, 2001; Hilary and Menzly 2006; Glaser and Weber 2007a; Libby and Rennekamp 2012).

Understanding factors that contribute to investor overconfidence and testing interventions that might help them make better judgments is important for improving investor welfare. Over the past decade, access to financial markets has increased with the growth of digital trading platforms offering zero-commission trades and no-minimum investment accounts. As a result, individual investors have become increasingly active in the stock market (Deloitte 2021; Fitzgerald 2021). However, evidence suggests that investors either disregard or fail to make full use of publicly available information (Elliott 2006; Blankespoor, deHaan, Wertz, and Zhu 2019), and systematically underperform the market (for a review, see Barber and Odean 2013). Further, regulators tasked with protecting individual investors are increasingly expressing concern about digital engagement practices by online brokerages that might induce overconfidence, excessive trading, and poor performance (SEC 2021a). I address these social issues by examining a visual cue that increases the salience of market benchmark performance and is targeted at correcting one cause of investor overconfidence.

Why might increasing the salience of a market benchmark, such as the return of a market index like the S&P 500, improve investor judgments after periods of positive market returns? First, research highlights the importance of accurate, timely, and precise feedback in helping individuals remedy overconfidence (Arkes, Christensen, Lai, and Blumer 1987; Russo and Schoemaker 1992; Rose and Windschitl 2008). Increasing market benchmark salience could serve as an information signal to help investors evaluate the extent to which their personal portfolio returns were driven by general market trends. Second, market benchmarks could serve as a useful parameter for comparing individual performance against other market participants. If market returns are viewed as the aggregate performance of all market participants, increasing the salience of market returns could help investors consider the performance of other investors and make better inferences about their relative performance. Therefore, I predict that increasing the salience of market benchmark returns will reduce investor overconfidence induced by positive market returns and help investors make better investing judgments.

To test my predictions, I combine an experiment administered on a virtual stock exchange with survey data obtained directly from experimental participants. I vary investors' *Market Return* by manipulating trading start dates and test the effect of *Benchmark Salience* by manipulating whether the return of the S&P 500 is displayed while participants make judgments related to their future performance and decisions. Each participant is randomly assigned to an online trading game with different start times and has one week to build a portfolio (the 'trading period') that they believe will perform best over a four-week period starting at the beginning of the trading period and ending three weeks after the trading period ends. Participants complete two surveys, one before their trading period begins and one at the end of their trading period. In both surveys, I measure investor overconfidence by asking participants to estimate in percentile terms how well they will perform in the game relative to other participants. Measuring overconfidence in this way is consistent with research in psychology (Kruger and Dunning 1999) and provides an objective benchmark (i.e., actual relative performance in percentile terms) for assessing the extent to which participants overestimate their performance relative to other investors. In the second survey, I also ask participants to make attributions for their first-week performance and indicate how likely they would be to reallocate their portfolio to an index fund that tracks the performance of the S&P 500.

Results are based on market returns experienced by participants across eight different trading periods.[1] Consistent with predictions, investors overestimate their relative future performance after periods of higher market returns. Further, I provide evidence that increasing market benchmark salience improves investors' relative performance estimates and investing judgments. Specifically, I find that investors who experience higher past market returns reduce their relative future performance estimates more when the return of the S&P 500 is displayed. Further, these same investors indicate that they are significantly more likely to re-invest their portfolio in an index fund that tracks the S&P 500. These findings suggest that presenting investors with a salient market benchmark can reduce overconfidence and help investors make decisions consistent with prescriptive investing advice (i.e., invest in a well-diversified index fund).

My study makes several contributions to both literature and practice. First, I capitalize on the comparative advantage of experiments (Libby, Bloomfield, and Nelson 2002) to provide *causal* evidence of the effects of past market returns and salient market benchmarks on investors' estimates of their relative future performance and investing judgments. My research design allows me to manipulate past returns independent of investors' ability, directly measure investors' beliefs about their expected future performance, and test whether past market returns bias investors' beliefs. My findings complement a large literature that seeks to understand the behavior of individual investors and whether they learn over time to make better decisions (Gervais and Odean 2001; Feng and Seasholes 2005; Glaser and Weber 2007b; Nicolosi, Peng, and Zhu 2009; Seru, Shumway, and Stoffman 2010; Barber, Lee, Liu, Odean, and Zhang 2020). I

[1] Because my experimental sessions took place during the bear market in the Spring and Summer of 2022, only one of eight groups experienced a positive market return during the trading period. I run a simulation that performs one million random draws of eight weekly S&P 500 returns since 1990. I find that only 1.53 percent of these random draws obtain zero or one positive market return weeks. As a result, I plan to collect four more weeks of data and have an *ex ante* expectation of obtaining more trading periods that result in positive market returns. Regardless, I find strong results that support my hypotheses.

also extend this literature by testing an intervention based on research on effective feedback (Arkes et al. 1987; Russo and Schoemaker 1992; Rose and Windschitl 2008). I show that providing investors with a salient market benchmark helps them to better estimate their relative future performance and make better decisions.

Second, the effects of increasing market benchmark salience may be of interest to regulators who seek to protect individual investors and brokerages who wish to help their customers. SEC Chair Gary Gensler has expressed concern over digital engagement practices used by online brokerages that, in many cases "may encourage investors to trade more often, invest in different products, or change their investment strategy" (SEC 2021a). As a result, in August 2021 the SEC released a request for comment on digital engagement practices. At the time of the release, SEC Chair Gary Gensler stated that he was "particularly focused on policy questions about how we protect investors engaging with technologies that use digital engagement practices" (SEC 2021a). My research contributes to recent literature on digital engagement practices (Elliott, Gale, and Hobson 2021; Grant, Hobson, and Sinha 2022; Moss 2022) and shows that increasing market benchmark salience can serve as a relatively simple and implementable visual cue that can help investors adopt investment strategies that are more consistent with prescriptive norms. As a result, regulators and brokerages might consider ways of implementing my proposed intervention as a type of visual cue for their customers when they log into their accounts. Brokerages already display investors' performance over different time horizons. It would be relatively simple for brokerages to also display the returns of market indices over the same time horizons so that investors can more easily benchmark their performance.

Finally, I make a methodological contribution for researchers interested in experimental methods. To the best of my knowledge, I am the first to conduct an experiment using a virtual stock exchange. As described by Bloomfield, Nelson, and Soltes (2016), all research methods have relative strengths. The virtual stock exchange setting allows for relatively unobtrusive measurement of investors' judgments, given that the researcher can view investors' buy and sell behavior without specifically prompting investors to indicate whether they would engage in such behavior. Additionally, outcomes resulting from investors' judgments can be estimated since portfolios and returns are observable, which helps us better understand how investors' judgments influence downstream effects on investor welfare (Asay, Hales, Hinds, and Rupar 2022). The virtual stock exchange also allows the researcher to randomly assign participants to different experimental conditions while maintaining reasonable degrees of control over the environment. Last, the virtual stock exchange allows participants to hypothetically trade real stocks with real asset prices connected to the natural information environment. As a result, the virtual stock exchange helps at least partially bridge the gaps among the natural trading environment, laboratory experiments, and experimental markets.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Capital Market Participation by Individual Investors

In 2013, Robinhood began offering zero-commission trades and no-minimum investment accounts to investors. This caused a fundamental shift in how digital trading platforms operate, with Charles Schwab eliminating commissions for online trades in October 2019, and other large online brokerages following suit shortly after. These changes have significantly increased access to financial markets, and the gamification of trading and the rise of investing-focused social media platforms have significantly increased interest in investing. As a result, individual investors have become increasingly active in the stock market. For example, in 2020 over ten million Americans opened new brokerage accounts (Deloitte 2021). Further, in January 2021, six million people downloaded trading applications to their phones and at multiple times throughout 2021 individual investors made up a third of all stock market trading in the United States (Deloitte 2021).

These shocks to the online brokerage industry also caused a shift in investor demographics. As a group, investors now have less investing experience, have lower levels of institutional knowledge, are more likely to take large risks, and are less likely to seek advice from financial professionals (Deloitte 2021; United Fintech 2021). These trends are concerning when coupled with prior research showing that investors either disregard or fail to make full use of information available in firm disclosures (Lee 1992; Maines and Hand 1996; Elliott 2006; Hirshleifer, Myers, Myers, and Teoh 2008; Blankespoor et al. 2019), rely more on simple, heuristic-based processes for valuing stocks (Frederickson and Miller 2004), trade excessively (Odean 1998; Barber and Odean 2000, 2001), hold under-diversified portfolios (Goetzmann and Kumar 2008), and systematically earn returns that underperform relative to market benchmarks (for a review, see Barber and Odean 2013). These results provide robust evidence that individual investors make poor judgments, and their financial welfare suffers as a result.

While it is apparent that individual investors make poor judgments, these findings also suggest that more research is needed on how to help individual investors make better judgments. To this end, recent academic research seeks to understand the motives and behaviors of individual investors (e.g., Barber, Huang, Odean, and Schwarz 2021; Bauer, Ruof, and Smeets 2021; Ozik, Sadka, and Shen 2021; Eaton, Green, Roseman, and Wu 2022; Moss 2022; Moss, Naughton, and Wang 2022; Welch 2022). I add to this burgeoning area of research by providing causal evidence on the effect of past market returns on investor overconfidence and testing whether providing investors with a salient market benchmark reduces their overconfidence and improves their investing judgments.

Investor Overconfidence and Past Market Returns

Why might past market returns lead to overconfidence among investors? To the extent that past market returns drive at least a portion of personal portfolio returns, several cognitive biases might hinder investors from determining whether their personal portfolio returns were driven by general market trends, individual ability, or a combination of these factors. For example, individuals tend to make biased self-serving attributions (Miller and Ross 1975). As a result, investors are more likely to overattribute their past success to themselves, underweight the effect of the market, and view themselves better, on average, than other investors. Second, psychology research suggests that when making relative performance assessments, individuals anchor too heavily on their own perceived ability, and fail to adequately adjust their assessments for the ability of others (Klar and Giladi 1999; Kruger 1999; Klar 2002; Moore and Kim 2003). Therefore, investors might anchor too heavily on their personal portfolio returns and fail to consider what information about market returns might mean for the performance of other investors. This myopic focus on self has been termed "reference group neglect" and has been shown to influence the relative performance estimates and decisions of investors (Camerer and Lovallo 1999; Hales and Kachelmeier 2008; Hales 2009).

Each of the above cognitive biases predict that individual investors might unknowingly take credit for positive past *market* returns. Thus, theoretical models often predict that overconfidence will be higher after positive market returns and lower after negative market returns (Gervais and Odean 2001). Consistent with these ideas, prior research has linked positive past market returns to increased overconfidence among investors.[2] For example, Statman, Thorley, and Vorkink (2006) provide evidence that past market returns are positively associated with market-wide trading volume. Further, Griffin, Nardari, and Stulz (2007) examine the relationships between market returns and trading activity in 46 countries and find a positive correlation between past market returns and turnover in many stock markets. However, these studies do not link past market returns to overconfidence directly, but rather draw inferences about overconfidence based on changes in trading volume. I provide a more direct test by using a more direct measure of investor overconfidence. This approach helps rule out alternative explanations for variation in trading volume in response to past market returns (e.g., disposition effect, momentum investing).

The effect of past market returns on overconfidence is not without tension. Glaser and Weber (2009) dispute whether past market returns lead to overconfidence among investors. While they find a positive association between past market returns and trading volume, they do not find evidence of increased risk-taking or under-diversification after periods of higher past market returns. Glaser and Weber (2007b) find that investors have a hard time estimating past returns and suggest that "future research should further investigate why people have problems dealing with returns and how these problems can be mitigated" (pg. 215). These studies suggest that the effect of past market returns on investors' judgments is worth further exploration.

Figure 1 depicts the theoretical process model underlying my experimental design and predicts that market returns affect investor overconfidence through personal portfolio returns. However, because personal portfolio returns conflate investor ability and past market returns, it is difficult to attribute any association between personal portfolio returns and overconfidence to a

[2] Prior research has also examined the relationship between past success and overconfidence among analysts (Hilary and Menzly 2006) and financial managers (Libby and Rennekamp 2012).

bias. Thus, my focus is on market returns because individual investors cannot meaningfully affect the market return and should not allow past market returns to influence their level of overconfidence. Further, a major strength of my experimental approach is that I can rule out confounding factors (e.g., investor ability) because I manipulate past returns independent of participant characteristics or any selection effects.

[INSERT FIGURE 1]

Improving Judgments with Salient Market Benchmarks

Assuming that investors' judgments are biased after experiencing positive past market returns, a natural question that arises is whether anything can be done to alleviate the bias and help investors make wiser investment decisions. Given all the evidence that investors underperform market benchmarks, prescriptive investing advice typically recommends that investors buy and hold low-fee, well-diversified index funds. To this end, the Securities and Exchange Commission's (SEC) Office of Investor Education and Advocacy provides resources to inform investors about different investment products and their associated fees and risks, as well as the benefits of diversification. Recently, SEC Chair Gary Gensler has expressed concern with digital engagement practices employed by online brokerages, suggesting that these practices may harm investors by "[encouraging] investors to trade more often, invest in different products, or change their investment strategy" (SEC 2021a).[3] However, if digital engagement practices used by online brokerages can cause investors to trade in ways that put them at risk, it seems that digital engagement practices may also have the ability to encourage investors to make wise investments.

[3] The SEC groups digital engagement practices into the following nine categories: (1) social networking tools, (2) games, streaks, and other contests with prizes, (3) points, badges, and leaderboards, (4) notifications, (5) celebrations for trading, (6) visual cues, (7) ideas presented at order placement and other curated lists or features, (8) subscriptions and membership tiers, and (9) chatbots (SEC 2021b).

To determine a potential intervention (i.e., a type of digital engagement practice) to reduce investor overconfidence, I rely on research that links different facets of overconfidence to excessive trading and research that highlights the importance of accurate, timely, and precise feedback in helping individuals remedy overconfidence (Arkes et al. 1987; Russo and Schoemaker 1992; Rose and Windschitl 2008). Overconfidence is a multi-faceted construct that includes overestimating one's ability relative to others, overestimating one's absolute ability, and overestimating the precision of one's private information (Moore and Healy 2008). Prior research has linked excessive trading to investors' tendency to overestimate their relative performance (Glaser and Weber 2007a; Glaser and Weber 2009) and suggests that increasing the salience of the reference group can moderate overestimation in relative performance evaluations (Sanbonmatsu, Shavitt, and Gibson 1994; Sanbonmatsu, Shavitt, Sherman, and Roskos-Ewoldsen 1987; Hales 2009).

I hypothesize that increasing market benchmark salience can help investors reduce overconfidence in at least two ways. First, increasing market benchmark salience can serve as a visual cue that provides feedback to investors about their investment returns relative to the market benchmark returns over the same investment period. This can help investors evaluate the extent to which their personal portfolio returns were driven by general market trends and potentially reduce their tendency to make biased self-serving attributions. Second, market benchmarks can serve as a useful parameter for comparing individual performance against other market participants. If market returns are viewed as the aggregate performance of all market participants, increasing the salience of market returns can help investors consider the performance of other investors and make better inferences about their relative performance. Altogether, my predictions are formalized in the following hypotheses:

Hypothesis 1a (H1a): Higher past market returns increase investors' overconfidence.

Hypothesis 1b (H1b): Increasing the salience of a market benchmark alleviates overconfidence induced by higher past market returns.

Hypothesis 2 (H2): Increasing the salience of a market benchmark increases investor propensity to reallocate their portfolio to an index fund that tracks the S&P 500 following higher past market returns.

III. EXPERIMENTAL METHODOLOGY

Experiment Design and Procedures

To test the effects of past market returns and market benchmark salience on investors' judgments, I use an experiment in which participants play an online trading game and complete two surveys.[4] In the upcoming section, I first provide information about participants. Next, I describe the experimental procedures. A summary of experimental procedures is provided in Figure 2, Panel A, and the timeline in which participants complete each task is summarized in Figure 2, Panel B.

[INSERT FIGURE 2]

Participants

Participants are 105 investors recruited from two different sources. First, 69 participants are members of the Investor Insights Research Panel recruited by the Financial Judgments Research Group (FJRG). The FJRG placed advertisements on Seeking Alpha seeking investors interested in supporting academic research.[5] Interested investors were directed to the FJRG

[4] Approval to conduct the experiment was granted by the Institutional Review Board of the author's institution.
[5] Seeking Alpha is a crowd-sourced content service providing articles and research covering a broad range of stocks, asset classes, exchange-traded funds, and investment strategies.

website (https://www.fjrg.johnson.cornell.edu) where they could register as a member of the Investor Insights Research Panel. At the time this study was conducted, the Investor Insights Research Panel had 576 members. I invited all 576 members to participate in the main study, and 69 (12.0 percent) completed all study tasks.

The remaining 36 participants are accounting alumni of a U.S. business school. I sent an initial screening survey to 3,629 accounting alumni to identify investors with interest in participating in the study. For alumni to qualify as investors, they must indicate that they manage investments for themselves or immediate family members. To determine their interest in participating, the study's tasks were described in the screening survey and participants were asked to indicate if they would be interested in participating. This resulted in 62 accounting alumni who completed the screening survey and passed the initial screening requirements. I invited these 62 accounting alumni to participate in the main study, and 36 (58.1 percent) completed all study tasks. Full participant demographics and other information for both participant groups are reported in Table 1.

[INSERT TABLE 1]

Survey one

Prior to completing any tasks, FJRG and alumni participants were each separately assigned at random to one of four online trading game start dates (eight trading game start dates total). Survey one is then delivered via email on the Friday before participants' assigned game start date after the stock market closes at 4:00 PM EST and must be completed by market open at 9:30 AM EST the following Tuesday. In survey one, participants are provided instructions for joining their online trading game and provide an initial assessment of how well they think they will perform in the online trading game relative to other participants. Additionally, participants describe the typical strategies they employ and information sources they seek out when making trading decisions.

Online Trading Game

Participants' primary task is to participate in an online trading game hosted on a third-party virtual stock exchange that allows individuals to make simulated trades of real securities.[6] The setting provides several unique advantages. First, the platform allows participants to play in custom games created by an administrator. The game administrator chooses a start and end date for the game, sets the amount of virtual dollars available for investing, selects a list of tickers that can (and cannot) be traded, and chooses whether to allow short selling, margin trading, or the purchase of fractional shares. From an experimental perspective, this offers greater control over the environment than can be achieved in an archival setting.[7] Second, the virtual stock exchange syncs with the real stock market and updates in real-time. As a result, real-world economic events and market forces influence stock prices and investors' trading behavior, increasing the external validity of the study. Finally, combining individual-level trading data from the platform with matched survey data provides a unique opportunity to answer questions that would otherwise be difficult to test.

As part of the first survey, participants receive instructions for creating a free account with the third-party provider of the virtual stock exchange and joining their online trading game. The parameters for each game are the same for each participant. That is, all games have a four-week duration beginning on a Monday. Participants receive $10,000 virtual dollars to build a

[6] I use the Virtual Stock Exchange created by MarketWatch, a website that provides financial information, business news, analysis, and stock market data (see https://www.marketwatch.com/games).
[7] However, the virtual stock exchange provides less experimental control than a traditional experimental market study. I use the virtual stock exchange setting because its features allow for a more realistic trading experience (e.g., real securities, real asset prices, realistic trading platform, etc.), increasing my ability to capture the real effect of past market returns on investor overconfidence.

portfolio that will earn the best return over the four-week period. Participants are only able to trade during the first week of the game (hereafter, "the trading period").[8] While participants must execute at least one trade, they are otherwise free to trade as often as they wish during the trading period. When the stock market closes at 4:00 PM EST on the Friday at the end of the trading period, participants' portfolios are set, and no additional trading is allowed. Participants can invest in any types of securities available on the virtual stock exchange, including individual stocks, index and mutual funds, and ETFs. However, I do not allow short selling, margin trading, or the purchase of fractional shares.[9] At the end of the four-week period, participants' portfolio returns are calculated, and participants are paid $10 for completing the study plus a bonus between $0 and $30 depending on the performance of their portfolio relative to other participants.[10] Appendix A shows screenshots of the virtual stock exchange interface and game settings.

Survey two

Survey two is sent at the end of the trading period, one week after the first survey is sent. Survey two is delivered via email after the stock market closes at 4:00 PM EST on Friday and must be completed by market open at 9:30 AM EST the following Tuesday.[11] Prior to completing survey two, participants are randomly assigned to one of two market benchmark salience conditions (described below). Participants then provide an updated estimate of how well

[8] As noted by Libby, Bloomfield, and Nelson (2002), experimental studies involving financial markets can be costly in terms of participants' time and researchers' funds. I limit trading to one week to try and keep these costs low. I implement a three-week holding period so that participants must estimate their relative future performance, but also do not have to wait too long to receive compensation.

[9] These limitations are implemented so that a borrowing rate does not need to be implemented and to facilitate comparison between portfolio returns and market returns.

[10] The average bonus is $15, bringing the average total compensation for the study to $25. I compensate participants with an Amazon gift card delivered directly to participants via email.

[11] Two of the 105 participants failed to complete survey two before the deadline. One participant completed survey two at 9:57 AM EST on the following Tuesday and the other completed survey two at 5:44 PM EST the following Wednesday. Results are robust to removing these two participants.

they think they will perform in the online trading game relative to other participants and make attributions regarding their initial performance. Additionally, participants rate how likely they would be to reallocate their game portfolio to an index fund that tracks the S&P 500 benchmark, respond to other post-experiment questions, and provide demographic information.

Independent Variables

The 8 × 2 between-participants design randomly assigns participants to eight levels of *Market Return* and two levels of *Benchmark Salience*. I vary investors' *Market Return* by manipulating online trading game start dates. Because of random assignment of participants to different start dates, the average effect of first week market returns on investor overconfidence, as a group, cannot be explained by extraneous variables, such as individual differences in investors' ability. As a result, my design allows me to draw stronger causal inferences about the effect of past market returns on investor overconfidence than could otherwise be achieved in an archival setting.

Additionally, I manipulate *Benchmark Salience* by showing participants in the 'No Benchmark' condition their portfolio return for the first week of the online trading game while they provide responses to survey two. In the 'Benchmark' condition, in addition to being shown their portfolio return for the first week of the online trading game, participants are also shown the performance of the S&P 500 index over the same period while they provide responses to survey two. I use the S&P 500 index (~$31.7T market capitalization) as the benchmark because it is popular and largely considered to be a better representation of the performance of the overall U.S. stock market (~46.5T market capitalization) than other popular benchmarks such as the

Dow Jones Industrial Average (~9.0T market capitalization).[12]

Dependent Variables

Overconfidence

The primary dependent variable of interest at a theoretical level is investors' overconfidence, and specifically the extent to which they overestimate their performance relative to others. Consistent with prior research in psychology, I use participants' percentile estimates of their future relative performance to measure participants' overconfidence at an operational level (Kruger and Dunning 1999). Specifically, I ask participants the following question: "Like you, participants in this study are investors and [accounting alumni or FJRG members]. In percentile terms, where do you believe your overall returns at the end of the four-week period will rank in comparison to other participants in the study?" Participants respond using a 100-point scale (0 = my overall returns will be at the very bottom; 50 = my overall returns will be exactly average; 99 = my overall returns will be at the very top). First, participants provide an initial response to this question in survey one. Then, participants provide an updated response in survey two, either without the market benchmark provided ('No Benchmark' condition) or with the market benchmark provided ('Benchmark' condition), after one week of trading. I examine participants' updated percentile estimates as my primary dependent variable.

Investing Judgments

To test whether providing investors with a salient market benchmark helps them to be more likely to make investment decisions in line with prescriptive investing advice, I ask participants during survey two to indicate on a 7-point fully labeled Likert scale how likely they

[12] I retrieved market capitalization for the S&P 500 and the Dow Jones Industrial Average from Factsheets published by S&P Global Inc. on their website (https://www.spglobal.com/en/). I retrieved the overall stock market capitalization from the website of Siblis Research Ltd. (https://siblisresearch.com/data/us-stock-market-value/). All market capitalization is as of September 30, 2022.

would be to reallocate their portfolio to an index fund that tracks the performance of the S&P 500.[13] When responding to this question, participants in the 'No Benchmark' condition only see the return they earned over the first week, while participants in the 'Benchmark" condition see both the return they earned and the return of the S&P 500 index over the first week.

IV. RESULTS AND DISCUSSION

Participants make trades on the virtual stock exchange during the first week of their online trading game. Table 2 reports descriptive statistics related to the average trading behavior and performance of each group, including the average portfolio return and market return during the first week of trading and the four-week period. Additionally, Table 2 includes information about the average number of trades executed, the types of assets traded, and the average portfolio allocations (in percentage terms) to cash, individual stocks, and ETFs/index funds.

[INSERT TABLE 2]

Before testing my hypotheses, I examine the effect of *Market Return* and *Benchmark Salience* on participants' *Initial Percentile Estimate* provided in survey one.[14] Given the continuous nature of *Market Return*, I conduct all my analyses using regression.[15] Because I am interested in *over*confidence, I control for participants' *Actual Percentile* (the actual percentile

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[13] The 7-point Likert scale is labeled as follows: 1 = Extremely unlikely; 2 = Unlikely; 3 = Somewhat unlikely; 4 = Neutral; 5 = Somewhat likely; 6 = Likely; 7 = Extremely likely.

[14] I do not make predictions regarding participants' initial level of overconfidence. While participants in my study are not professional investors, they are experienced investors and therefore may be initially overconfident in their ability. However, there are several plausible explanations as to why I may not find overestimation in participants' initial percentile estimates. First, prior research suggests that experience helps individuals better assess their relative performance (Gervais and Odean 2001; Nicolosi et al. 2009). As a result, prior investing experience may help participants make more accurate initial estimates. Second, my study took place during a bear market when overall confidence is likely to be lower among investors.

[15] ANOVA and ANCOVA are special cases of regression. With ANOVA, independent variables must be exclusively categorical variables, while ANCOVA allows for a mix of both categorical independent variables and continuous covariates to be included in the model. All results are robust if I run my analyses as a 1×2 ANCOVA with *Market Return* included as a continuous covariate.

rank of participants' returns relative to other participants assigned to the same online trading game start date) to condition my analyses on participants' actual performance.[16] All reported p-values are two-tailed unless otherwise indicated. In untabulated results, and consistent with effective randomization, I find no main effect of *Market Return* (t_{100} = 1.17; p-value = 0.224) and no significant interaction between *Market Return* × *Benchmark Salience* (t_{100} = -1.27; p-value = 0.207) on *Initial Percentile Estimate*. However, I do find a significant main effect of *Benchmark Salience* (t_{100} = -2.25; p-value = 0.026), which suggests that there are between-group differences in participants' initial overconfidence. Importantly, subsequent analyses are robust to including *Initial Percentile Estimate* as a control.[17]

Primary Analyses

Overconfidence

My primary analyses examine how participants' *Updated Percentile Estimate* changes in response to my manipulations of *Market Return* and *Benchmark Salience*. The regression model underlying my design is:

$$\text{(1)}\quad \textit{Updated Percentile Estimate} = \alpha + \beta_1\, \textit{Market Return} + \beta_2\, \textit{Benchmark Salience} + \beta_3\, \textit{Market Return} \times \textit{Benchmark Salience} + \varepsilon$$

The dependent variable is participants' *Updated Percentile Estimate* provided in survey two.[18] The independent variables of interest are *Market Return* (a continuous variable defined as

[16] As a robustness test, I also define *Actual Percentile* as the actual percentile rank of participants' returns relative to all other participants of the same type (FJRG or accounting alumni). To do so, I calculate participants' market adjusted returns and then calculate their percentile rank. This creates a smoother distribution of percentiles than is achieved when percentiles are calculated within online trading game start date. Results reported are robust to using this alternative definition of *Actual Percentile*.

[17] Following Yzerbyt, Muller, and Judd (2004), results are also robust to controlling for the interaction between *Initial Percentile Estimate* and the confounded independent variable (*Benchmark Salience*).

[18] I use *Updated Percentile Estimate* as my primary dependent variable rather than [*Updated Percentile Estimate* – *Actual Percentile*] because difference measures have statistical properties that make them less reliable (DeVellis

the first-week market return associated with different online trading game start dates), *Benchmark Salience* (an indicator variable equal to '1' if participants are provided the return of the S&P 500 and '0' otherwise), and their interaction. For my primary analyses, I examine three specifications. Specification (1) is the baseline model shown in equation (1) and includes a control for *Actual Percentile*.[19] Specification (2) adds a control for *Initial Percentile Estimate* (as discussed above).[20] Specification (3) adds a control for *Participant Type* (an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant) to control for any differences between FJRG and accounting alumni participants.

H1a predicts that higher past market returns will increase investors' overconfidence, and H1b predicts that increasing the salience of a market benchmark alleviates overconfidence induced by higher past market returns. To test these hypotheses, Table 3 reports the results of the regression model in equation (1). To support H1a, I would expect to find a positive and statistically significant coefficient on *Market Return*, and to support H1b I would expect to find a negative and statistically significant coefficient on the *Market Return* × *Benchmark Salience* interaction. Consistent with H1a, model specification (1) shows a positive and statistically significant coefficient (p-value < 0.05) on *Market Return*. Additionally, model specifications (2) and (3) show that when controls are included for *Initial Percentile Estimate* and *Participant Type*, the coefficient on *Market Return* remains positive and moderately significant (p-values < 0.10 in each specification). Further, I provide evidence consistent with H1b. In model

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2016). Inferences for these two alternative dependent measures are identical when *Actual Percentile* is included as a covariate to control for negative correlation between difference scores and earlier estimates (Darlington and Hayes 2017).

[19] Results are robust to excluding *Actual Percentile* as a control in all models.

[20] In experimental designs that involve repeated measures, adding a covariate for earlier measurements is also consistent with best practice when models use later measurements as the dependent variable (Valente and MacKinnon 2017; Hayes 2018).

specification (1), I find a negative coefficient on the *Market Return* × *Benchmark Salience* interaction that is statistically significant (p-value < 0.01). Results on the interaction are robust (p-value < 0.05) to adding controls for *Initial Percentile Estimate* and *Participant Type* (specifications 2 and 3). Additionally, in all models the coefficient on *Actual Percentile* is insignificant, suggesting that participants' estimates are not predictive of actual performance. These results are consistent with past market returns causing investor overconfidence, and with market benchmark salience being an effective visual cue that can reduce overconfidence.

[INSERT TABLE 3]

Investing Judgments

I also examine how participants' investing judgments are affected by my manipulations of *Market Return* and *Benchmark Salience*. To do so, I run a regression of the following form:

$$(2)\ S\&P500 = \alpha + \beta_1\ Market\ Return + \beta_2\ Benchmark\ Salience + \beta_3\ Market\ Return \times Benchmark\ Salience + \varepsilon$$

The dependent variable is *S&P500*, which is defined as participants' response to a 7-point fully labeled Likert scale question asking how likely they would be to reallocate their portfolio to an index fund that tracks the performance of the S&P 500. As discussed in Section 3, participants respond to this question at the end of the trading period as part of survey two. The independent variables of interest are *Market Return*, *Benchmark Salience*, and their interaction. Each regression is run with and without controls as described previously.

H2 predicts that increasing the salience of a market benchmark increases investor propensity to reallocate their portfolio to an index fund that tracks the S&P 500 following higher past market returns. To test this hypothesis, Table 4 reports the results of the regression model in equation (2). To support H2, I would expect to find a positive and statistically significant coefficient on the *Market Return* × *Benchmark Salience* interaction. Consistent with H2, model specification (1) shows a positive coefficient on the *Market Return* × *Benchmark Salience* interaction that is statistically significant (p-value < 0.01). Results are robust to adding controls for *Initial Percentile Estimate* and *Participant Type*. This suggests that presenting investors with a salient market benchmark can help them make judgments consistent with prescriptive investing advice.

[INSERT TABLE 4]

Additional Analyses

Process Model

As previously discussed, theory predicts that cognitive biases prevent individual investors from disentangling the extent to which their returns were driven by ability or general market trends. As a result, individual investors who focus on personal portfolio returns might unknowingly take credit for positive past *market* returns. Further, I predict that the effect of past market returns on investor overconfidence will be alleviated by increasing the salience of market benchmark returns. This conceptual process model is depicted in Figure 1. Additionally, I test the process model (i.e., Model 14 from Hayes 2018) empirically by testing the conditional indirect effects of past market returns on investor overconfidence for both the 'No Benchmark' (see Figure 3, Panel A) and 'Benchmark' (see Figure 3, Panel B) groups.

[INSERT FIGURE 3]

Consistent with my theory, I find that when no benchmark is provided, past market returns are positively associated with personal portfolio returns ($p < 0.001$) and that personal portfolio returns increase overconfidence ($p = 0.010$). However, I find that the effect of personal portfolio returns on overconfidence ($p = 0.124$) is alleviated by providing a salient market benchmark. To test the conditional indirect effects and establish moderated mediation, I construct 90% bias-corrected confidence intervals with 10,000 bootstrapped resamples of data with replacement (Preacher, Rucker, and Hayes 2007; Preacher and Hayes 2008; Hayes 2018). A statistically significant indirect effect requires that zero not appear within the confidence interval. Consistent with benchmark salience moderating the indirect effect of past market returns on investor overconfidence, I find a statistically significant indirect effect in the 'No Benchmark' group (90% bias-corrected confidence interval: [0.066, 2.119]) but do not find a statistically significant indirect effect in the 'Benchmark' group (90% bias-corrected confidence interval: [-1.240, 0.045]). Additionally, the index of moderated mediation indicates that the difference between the conditional indirect effects for the 'No Benchmark' and 'Benchmark' groups is significant (untabulated 90% bias-corrected confidence interval: [-2.702, -0.434]). Finally, I also find that past market returns do not have a direct effect on investor overconfidence ($p = 0.679$). These results support the theory that past market returns effect investor overconfidence through their effect on investors portfolio returns, and that this bias can be alleviated by increasing benchmark salience.

Unsigned Estimation Error

I repeat the analyses reported in Table 3 but instead examine investors' unsigned estimation error. Specifically, I take the absolute value of the difference between participants' updated percentile estimates and actual percentile (i.e., unsigned updated estimation error). Examining unsigned estimation error allows me to test whether increasing market benchmark salience helps investors make more accurate relative performance estimates, regardless of whether their initial estimates overestimate or underestimate their actual performance. In untabulated results, I find a positive and statistically significant coefficient ($t_{100} = 3.05$; p-value = 0.003) on *Market Return*. Additionally, I find a negative and statistically significant coefficient on the *Market Return* ×

Benchmark Salience interaction (t_{100} = -3.87; p-value = < 0.001). Results are robust to adding controls for *Initial Percentile Estimate* and *Participant Type*. These results provide further evidence that investors' relative performance estimates improve when market benchmark salience increases.

Positive Versus Negative Past Market Returns

Overconfidence is likely to be greater after periods of positive past market returns as opposed to periods of negative past market returns. As discussed in Section 3, my experimental design varies *Market Return* by randomly assigning participants to one of eight different online trading game start dates. I also conduct my analyses as a 2 × 2 experiment by collapsing conditions based on whether *Market Return* is negative or positive. I then perform a two-way between-participants ANCOVA to test the effect of *Market Return* and *Benchmark Salience* on participants' *Updated Percentile Estimate* while controlling for participants' *Actual Percentile, Initial Percentile Estimate,* and *Participant Type*. Table 5, Panel A presents unadjusted means and standard deviations by condition for participants' *Updated Percentile Estimate,* while Figure 4, Panel A presents the ANCOVA adjusted means in an interaction plot. Table 5, Panel B reports the ANCOVA results, which show a significant *Market Return* × *Benchmark Salience* interaction on investors' *Updated Percentile Estimate* (p = 0.012).[21]

Given the significant *Market Return* × *Benchmark Salience* interaction, I also examine the follow-up simple effects to better understand the form of this interaction, which are reported in Table 5, Panel C. I find a significant simple effect of *Market Return* given no benchmark (p = 0.010, one-tailed). That is, consistent with H1a, investors' percentile estimates of their relative performance increase after they experience positive past returns. I also find a significant simple

[21] Consistent with alternative specifications discussed in previous analyses, results are robust to including and excluding covariates.

effect of *Benchmark Salience* given positive past market returns (p = 0.035, one-tailed). This result supports H1b, which predicts that increasing the salience of a market benchmark alleviates overconfidence induced by positive past market returns.

[INSERT TABLE 5]

[INSERT FIGURE 4]

For completeness, I also provide in Figure 4, Panel B the ANCOVA adjusted means in an interaction plot for participants' *S&P500* ratings by positive versus negative past market returns. In untabulated analyses, the *Market Return* × *Benchmark Salience* interaction is statistically significant ($F_{1,97}$ = 9.159; p-value = 0.003). Further, follow-up simple effects reveal a significant simple effect of *Market Return* given the benchmark is provided ($F_{1,45}$ = 10.361; p-value = 0.002) and a significant simple effect of *Benchmark Salience* given positive past market returns ($F_{1,12}$ = 5.202; p-value = 0.042). These results support H2, which predicts that increasing the salience of a market benchmark increases investor propensity to reallocate their portfolio to an index fund that tracks the S&P 500 following higher past market returns.

Taken together, these results suggest that the effect of past market returns on investor overconfidence may be driven by positive versus negative past market returns. A limitation of my experimental design is that by leveraging natural variation in market returns I do not have full experimental control over the realized past market returns. Consequently, because my experimental sessions took place during the bear market in the Spring and Summer of 2022, only one of eight groups realized a positive market return in the first week of trading. Because theory suggests that overconfidence is most likely to be induced by past success, oversampling from negative past market returns likely biases against finding support for my hypotheses. However, despite the relatively small number of participants in the positive *Market Return* condition (*n* =

17), I find a highly significant interaction in all my analyses. Further, the direction of the effects is consistent with theory and my predictions. As a result, while I suspect that these effects would only be stronger if I my experiment had been conducted during a bull market with more positive market return weeks, I plan to collect more data to provide additional assurance.

Self-Serving Attributions

The theory I rely on when forming my hypotheses predicts that investors may become overconfident after experiencing higher past market returns because of several cognitive biases, including the tendency to make self-serving attributions for past performance. As a result, investors are more likely to overattribute their past success to themselves, underweight the effect of the market, and view themselves better, on average, than other investors. In addition to my main hypotheses, I also investigate the effect of past market returns and market benchmark salience on investors' attributions.

To do so, I ask participants in survey two to use a free-response text box to provide attributions for their returns earned in the first week of the online trading game.[22] When making their attributions, participants in the 'No Benchmark' condition only see the return they earned over the first week, while participants in the 'Benchmark' condition see both the return they earned and the return of the S&P 500 index over the first week. Then, blind to condition, two coders code 104 participant *Attributions* by assigning a value of '1' to responses with mostly internal attributions, '-1' to responses with mostly external attributions, and '0' to responses with relatively equal internal and external attributions. Coders initial agreement was 84.6 percent. The

[22] I collect participants attributions for their first week returns with a free-response text box (as opposed to a scale that explicitly asks about internal or external causes for performance) because prior research in psychology suggests that free-response questions allow for better identification of the psychological mechanism behind causal attributions (Malle 2011a, 2011b; Böhm and Pfister 2015).

coders met to resolve any coding differences, and I use their resolved coding in my analyses.[23]

To conduct my analyses, I use regression and replace *Updated Percentile Estimate* in equation (1) with participants' *Attributions*. In untabulated analyses, I find a positive and moderately significant coefficient (t_{99} = 1.59; p-value = 0.058, one-tailed) on *Market Return*, consistent with participants making more internal attributions after experiencing higher past market returns.[24] However, I do not find a statistically significant effect of *Benchmark Salience* or the *Market Return* × *Benchmark Salience* interaction, providing no evidence that increasing market benchmark salience corrects investors' biased self-serving attributions. One explanation for this null result is that the effects of increasing benchmark salience may be operating through another mechanism in helping investors better assess their relative performance and make wiser investing decisions, such as reducing the effects of other cognitive biases (e.g., reference group neglect) (Camerer and Lovallo 1999; Hales and Kachelmeier 2008 Hales 2009).

V. CONCLUSION

Prior research suggests that overconfidence among investors leads them to trade excessively and hold under-diversified portfolios, resulting in lower returns than the market (Odean 1998; Barber and Odean 2000, 2001; Goetzmann and Kumar 2008). As a result, identifying factors that drive investor overconfidence and finding ways to alleviate investor overconfidence are important for improving investors' judgments and welfare. In this study, I provide causal evidence that positive past market returns increase investor overconfidence, and that increasing market benchmark salience alleviates overconfidence induced by past market

[23] Results are robust to using the average rating in cases where coders disagree.
[24] Consistent with alternative specifications discussed in previous analyses, results are robust to adding controls for *Initial Percentile Estimate* and *Participant Type*.

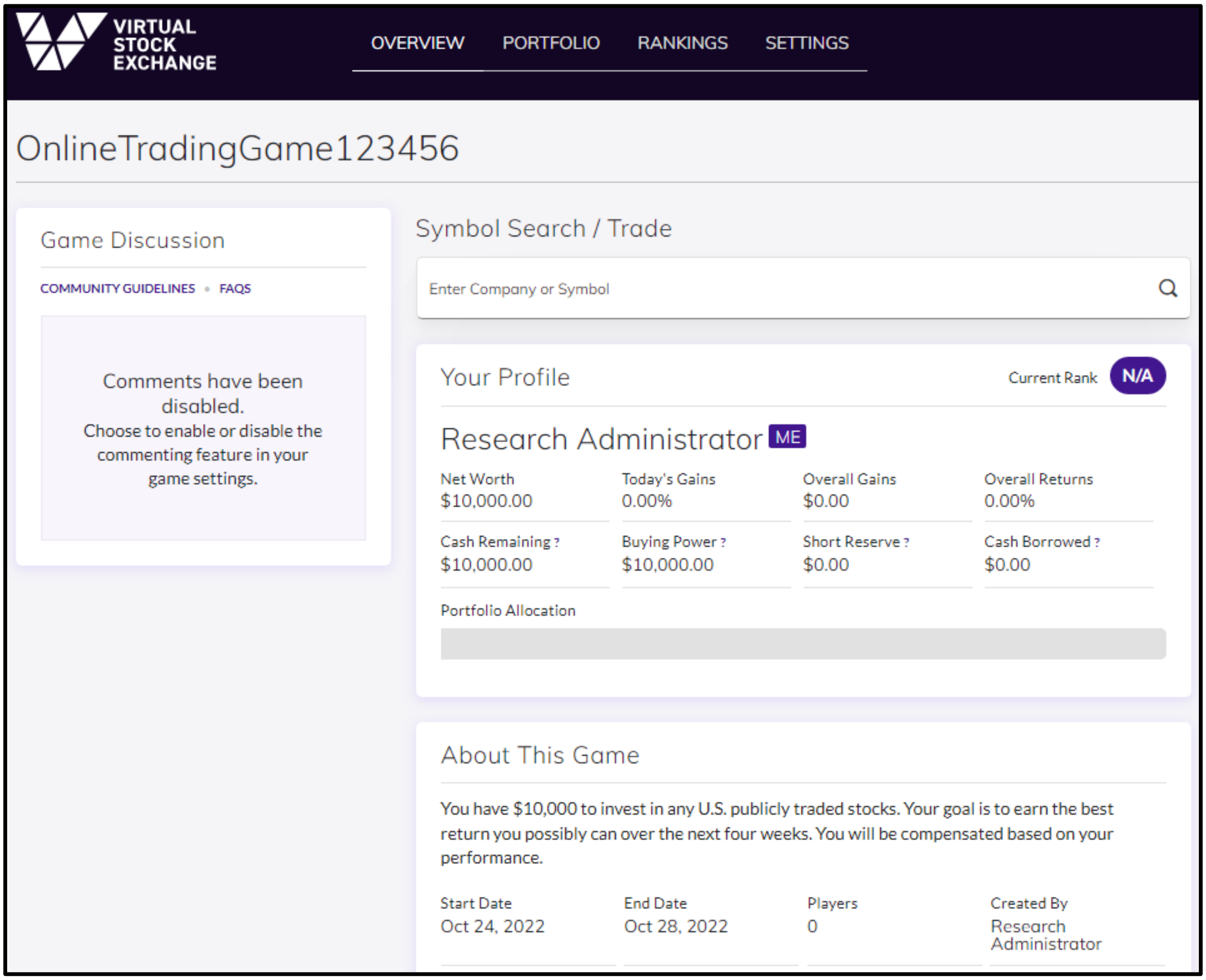
returns. Further, I find that increasing market benchmark salience increases investors' propensity to reallocate their portfolio to an index fund that tracks the S&P 500 following higher past market returns. Thus, my findings suggest salient market benchmarks can serve as a relatively simple and implementable visual cue that can reduce investor overconfidence and its consequences by helping investors' make judgments consistent with prescriptive investing advice.

This study makes important contributions to the growing literature examining the motives and behaviors of individual investors. While investor overconfidence and its consequences are well documented (Odean 1998; Barber and Odean 2000; Glaser and Weber 2007a), less has been done to show causal determinants of investor overconfidence. For example, Barber and Odean (2001) use gender as a proxy for overconfidence to identify the effects of overconfidence on trading. Further, theoretical studies suggest that investors learn to be overconfident from past success (Gervais and Odean 2001) and some studies find positive correlations between past portfolio and market returns and excessive trading (Statman et al. 2006; Griffin et al. 2007). I build on these prior studies by using an experiment to independently vary investor participants' past market returns to provide causal evidence of the effect of past market returns on investor overconfidence.

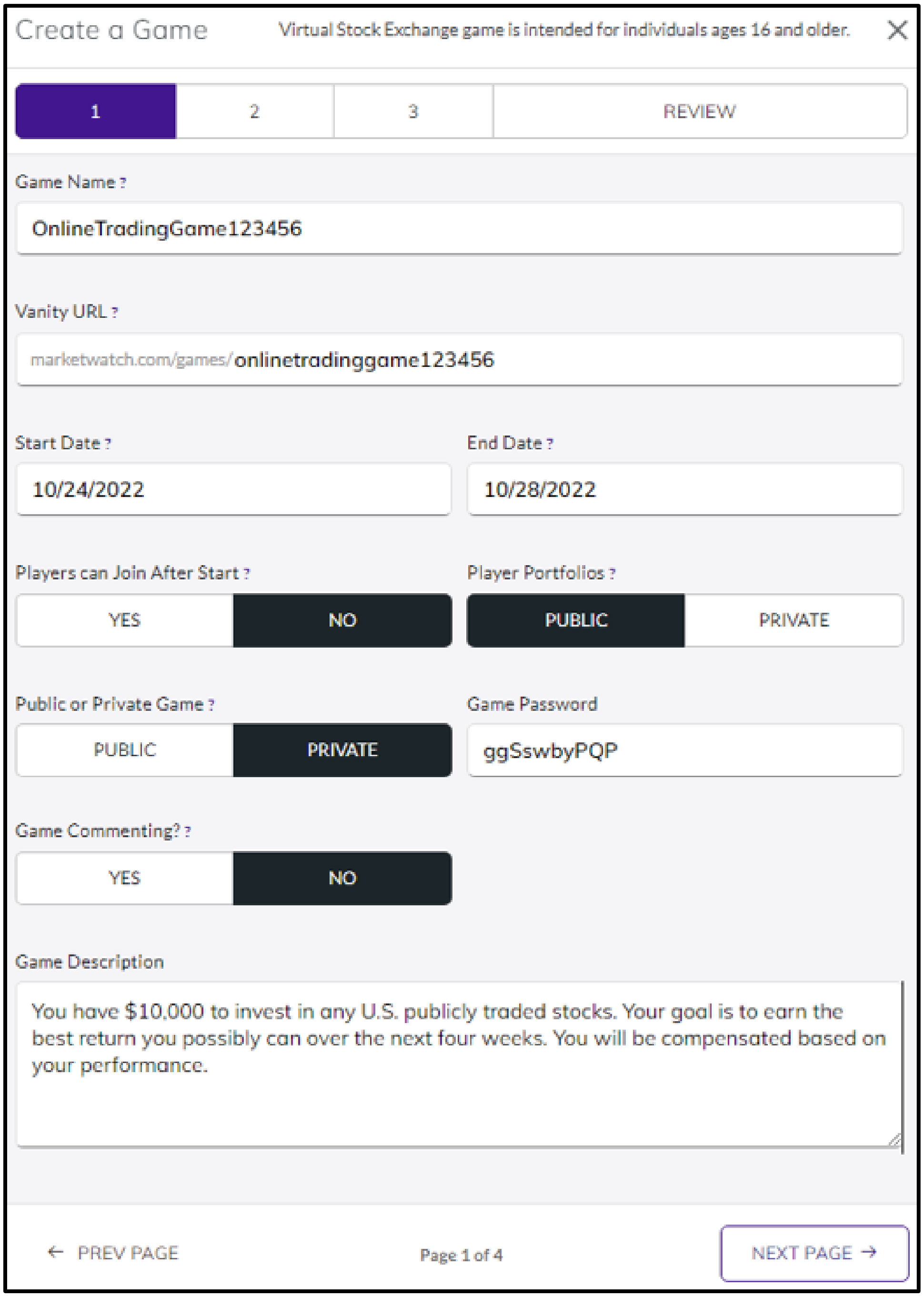
I also provide evidence that may be of interest to regulators tasked with protecting individual investors. The SEC has increasingly expressed concern regarding the digital engagement practices used by online brokerages that, in many cases "may encourage investors to trade more often, invest in different products, or change their investment strategy" (SEC 2021a). Recent research has examined the effects of certain digital engagement practices, such as push notifications (Elliott, Gale, and Hobson 2021; Moss 2022) and visual cues such as color (Grant, Hobson, and Sinha 2022) on investor judgments. I suggest that digital engagement practices can be used for good. Specifically, while market benchmark returns are readily available, my results suggest that increasing market benchmark return salience can improve investor judgments. Brokerages could use push notifications, visual cues, and other digital engagement practices to increase benchmark return salience and help investors consider alternative investment options that are more in line with prescriptive investing advice to buy and hold low-fee, well-diversified index funds.

Of course, my study is not without limitations. First, I examine hypothetical trading decisions made by investor participants on a virtual stock exchange over a short time horizon and do not observe trading decisions in investors' actual portfolios. Future research could design a field experiment to examine the effect of increasing market benchmark salience on investors' judgments in the real trading environment over a longer time horizon. Second, I focus on the presence of a market benchmark presented once at the end of a one-week period, but do not examine other aspects of effective feedback that could make the benchmark intervention more effective. Future research could manipulate the frequency with which investors receive feedback regarding market benchmark returns, the period over which past market returns are calculated, and whether certain market benchmarks are more effective than others in improving investors' judgments. Finally, I do not provide evidence of the precise cognitive process through which increased market benchmark salience operates to reduce overconfidence. Future studies that shed light on the mechanism can improve our ability to identify alternative interventions for reducing investor overconfidence and improving their welfare.

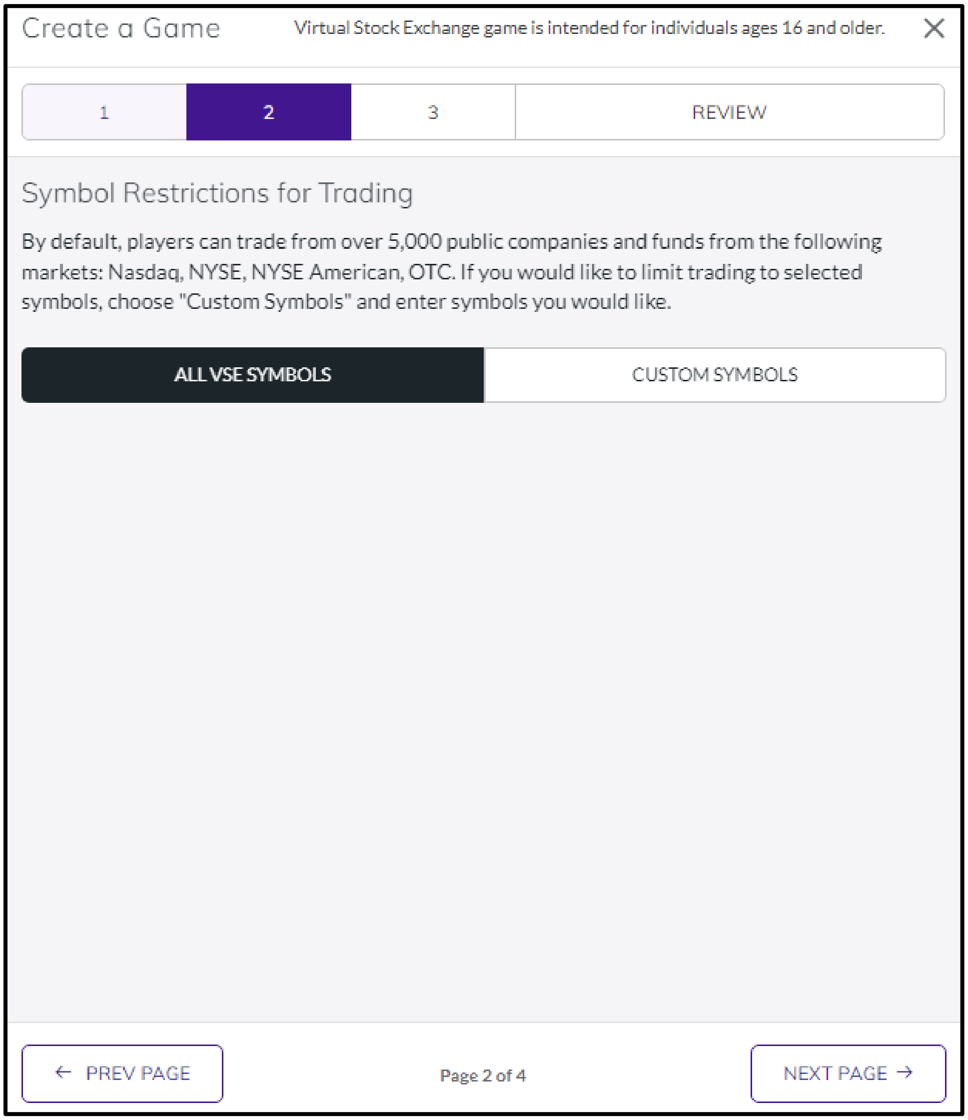
APPENDIX A. VIRTUAL STOCK EXCHANGE INTERFACE AND GAME SETTINGS



APPENDIX A (CONT). VIRTUAL STOCK EXCHANGE INTERFACE AND GAME SETTINGS



APPENDIX A (CONT). VIRTUAL STOCK EXCHANGE INTERFACE AND GAME SETTINGS



APPENDIX A (CONT). VIRTUAL STOCK EXCHANGE INTERFACE AND GAME SETTINGS

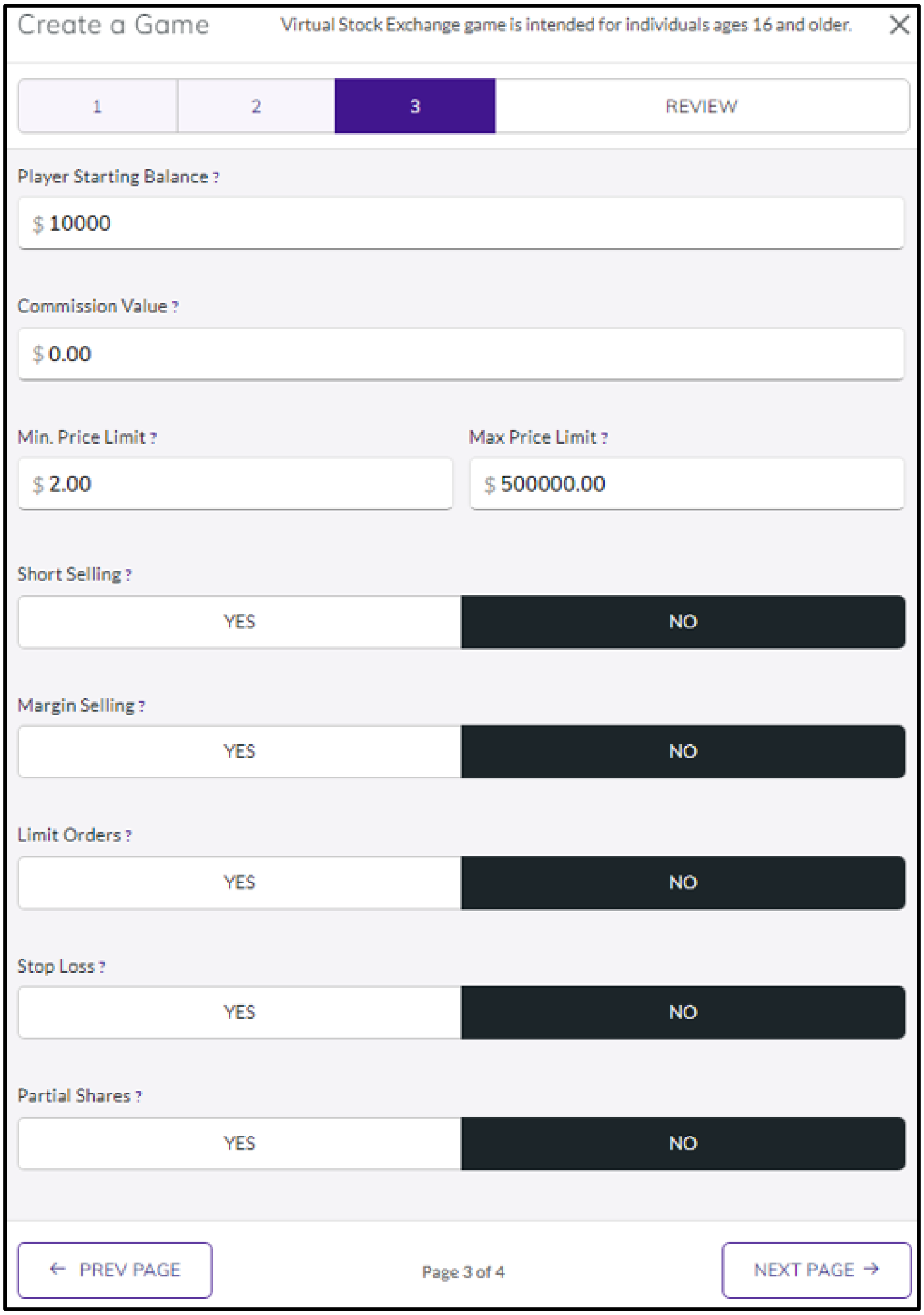


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FIGURE 1. DEPICTION OF CONCEPTUAL PROCESS MODEL

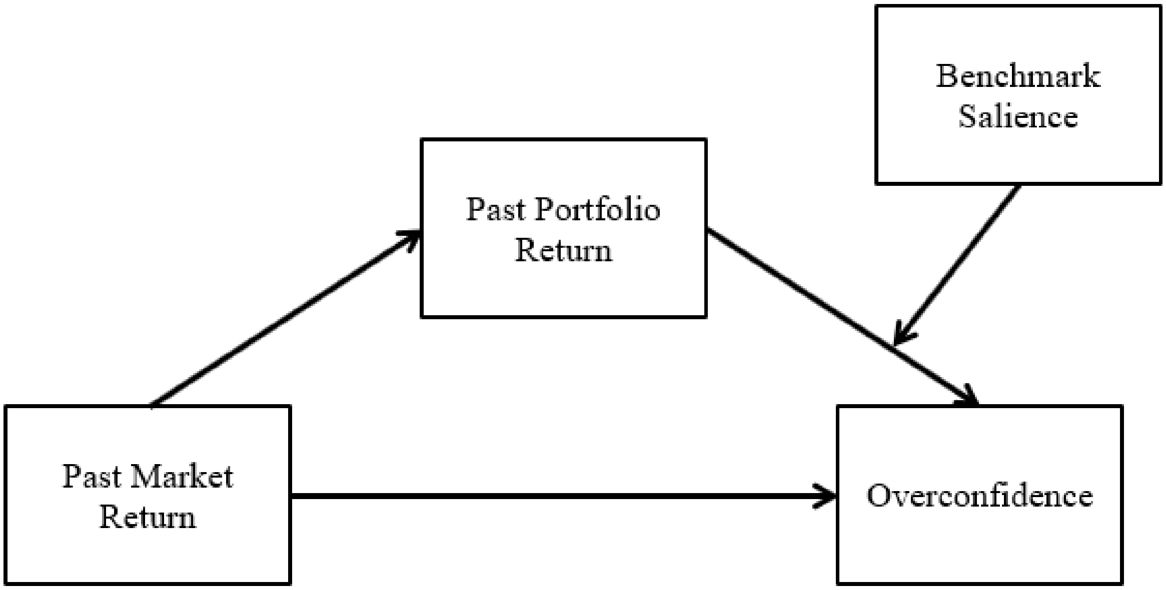

Figure 1 graphically depicts the conceptual process model (i.e., Model 14, Hayes 2018) underlying the experimental design and predicts that past market returns (the predictor) affect investor overconfidence (the dependent variable) through their effect on personal portfolio returns (the mediator). I propose that increasing benchmark return salience (the moderator) can reduce investor overconfidence induced by past market returns.

FIGURE 2, PANEL A. EXPERIMENTAL PROCEDURES

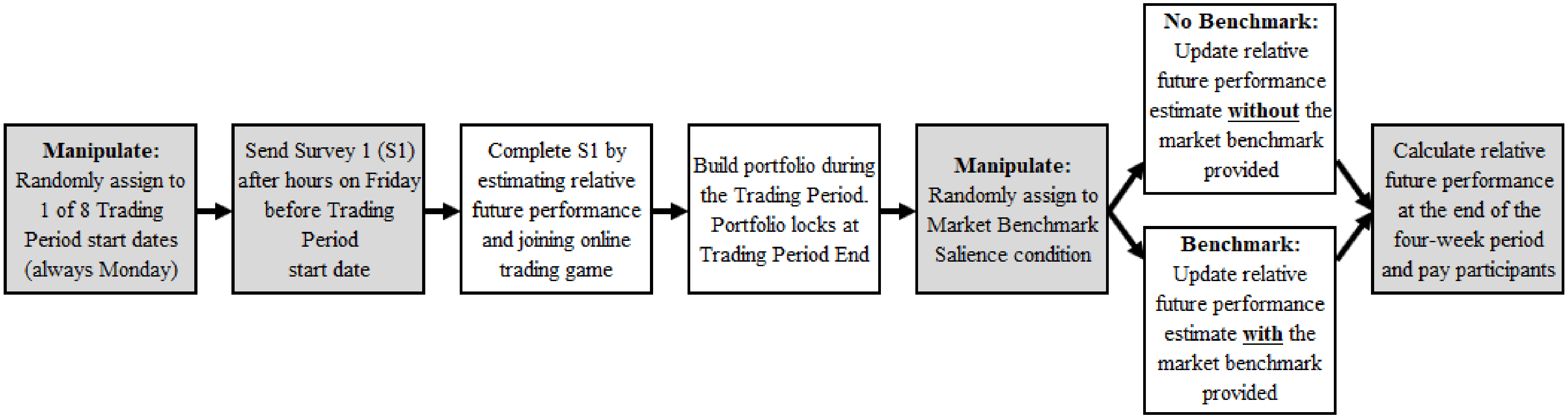

FIGURE 2, PANEL B. EXPERIMENTAL PROCEDURES TIMELINE FOR PARTICIPANTS

	Trading Period					Holding Period														
Pre	**Week 1**					**Week 2**					**Week 3**					**Week 4**				
Fri	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
S1	Start				S2															End

Figure 2, **Panel A** depicts the experimental procedures of the 8 × 2 experiment. Shaded boxes describe actions taken by the researcher, while unshaded boxes describe actions taken by participants.

Figure 2, Panel B depicts the timeline for participants from the time survey one is sent to the time the online trading game ends. '**S1**' refers to survey one, which is sent after the market closes on the Friday before the online trading game begins and includes instructions for joining the online trading game. '**Start**' refers to the start of the four-week online trading game, which always occurs on a Monday. The '**Trading Period**' is shaded and is the period where participants can make changes to their portfolio as often as they wish. The '**Holding Period**' is unshaded and is the period where participants are unable to make any changes to their portfolio. '**S2**' refers to survey two, which is sent after the market closes on the Friday at the end of the Trading Period. '**End**' refers to the end of the four-week online trading game, which always occurs on a Friday.

FIGURE 3, PANEL A. PROCESS MODEL OBSERVED EFFECTS FOR ‘NO BENCHMARK’ GROUP

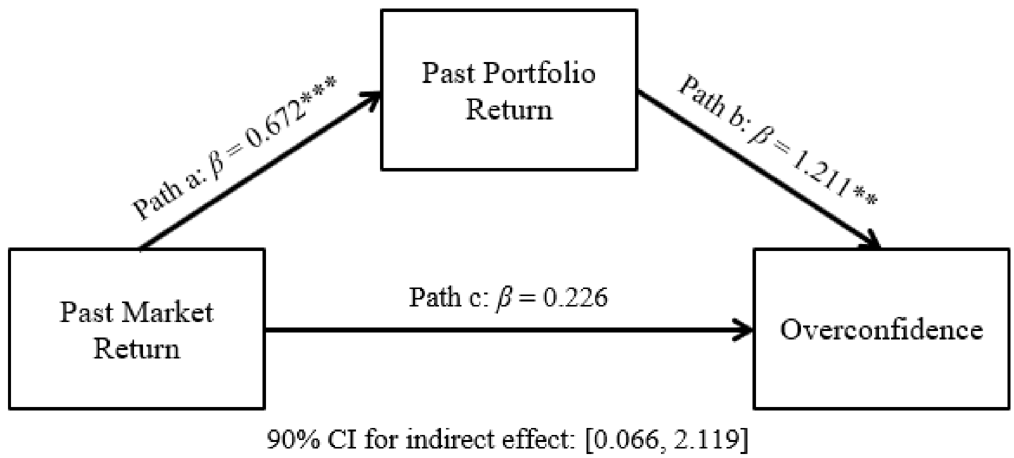

FIGURE 3, PANEL B. PROCESS MODEL OBSERVED EFFECTS FOR ‘BENCHMARK’ GROUP

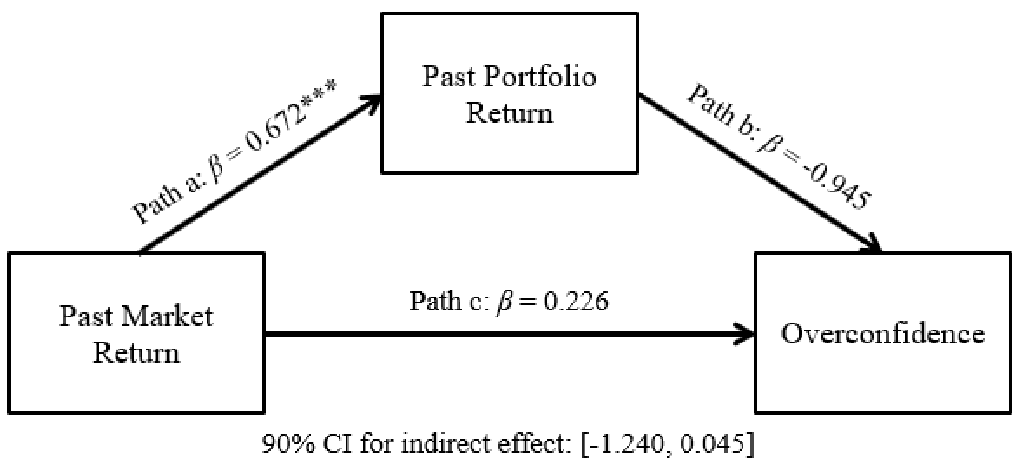

Figure 3 presents the empirical test of the conceptual process model presented in Figure 2. For simplicity, I present results separately for the ‘No Benchmark’ (**Panel A**) and ‘Benchmark’ (**Panel B**) conditions separately, even though the model is calculated simultaneously for all conditions. ***Past Market Return*** is a manipulated continuous variable defined as the first-week market return associated with different online trading game start dates. ***Past Portfolio Return*** is a measured continuous variable defined as the first-week portfolio return earned by participants in the online trading game. ***Benchmark Salience*** is a manipulated dichotomous variable set to ‘0’ if participants estimate their relative future performance without the return of the S&P 500 provided (‘No Benchmark’ condition) or set to ‘1’ if the return of the S&P 500 is provided (‘Benchmark’ condition). ***Overconfidence*** is the updated percentile estimates provided by experimental participants after one week of trading. I test for conditional indirect effects by using a bootstrapping procedure separately for the ‘No Benchmark’ and ‘Benchmark’ groups. Significant indirect effects are indicated by bias-corrected 90 percent confidence intervals that do not include zero. *, **, and *** represent significance (two-tailed) at the 10%, 5%, and 1% levels, respectively.

FIGURE 4, PANEL A. INTERACTION PLOT – UPDATED PERCENTILE ESTIMATE

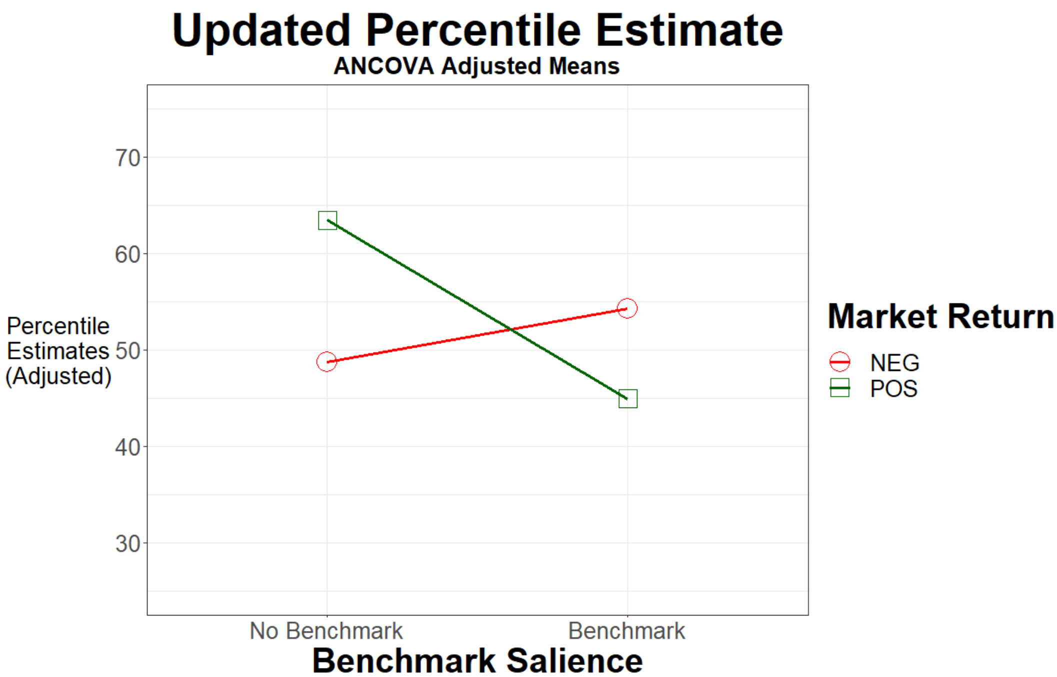

Figure 4, **Panel A** presents the effects of past market returns and market benchmark salience on investors' relative performance estimates. Results are from an experiment that asks participants to play an online trading game and predict their relative performance in percentile terms. The first independent variable is ***Market Return***, which is manipulated by randomly assigning participants to one of eight online trading game start dates. ***Market Return*** is then collapsed to two conditions ('Negative' or 'Positive') based on whether the first-week market return for the online trading game is negative or positive. The second independent variable is ***Benchmark Salience***, which is manipulated by randomly assigning participants to estimate their relative future performance without the return of the S&P 500 provided ('No Benchmark' condition) or with the return of the S&P 500 provided ('Benchmark' condition). The dependent variable is ***Updated Percentile Estimate***, which is the updated percentile estimates provided by experimental participants after one week of trading. The means presented above are adjusted for the following covariates: ***Initial Percentile Estimate***, ***Participant Type***, and ***Actual Percentile***. ***Initial Percentile Estimate*** is the initial percentile estimates provided by experimental participants prior to starting their online trading game. ***Participant Type*** is an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant. ***Actual Percentile*** is the actual percentile rank of participants' returns relative to other participants assigned to the same online trading game start date.

FIGURE 4, PANEL B. INTERACTION PLOT – LIKELIHOOD OF REALLOCATING PORTFOLIO TO A S&P 500 INDEX FUND

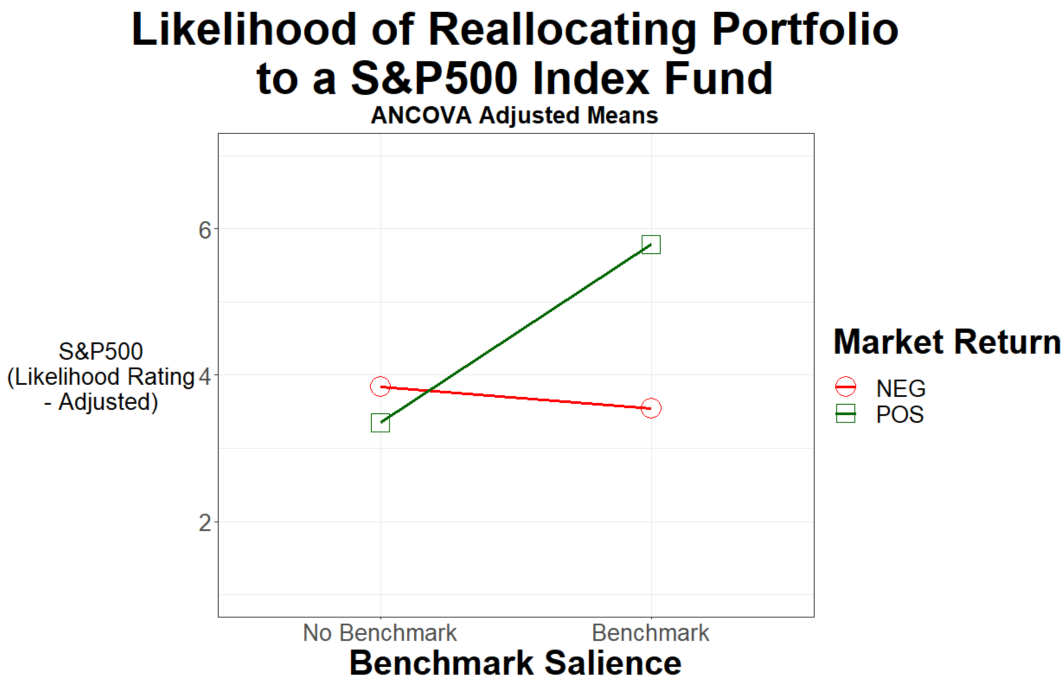

Figure 4, **Panel B** presents the effects of past market returns and market benchmark salience on investors' likelihood of reallocating their portfolio to a S&P 500 index fund. Results are from an experiment that asks participants to play an online trading game and predict their relative performance in percentile terms. The first independent variable is ***Market Return***, which is manipulated by randomly assigning participants to one of eight online trading game start dates. ***Market Return*** is then collapsed to two conditions ('Negative' or 'Positive') based on whether the first-week market return for the online trading game is negative or positive. The second independent variable is ***Benchmark Salience***, which is manipulated by randomly assigning participants to estimate their relative future performance without the return of the S&P 500 provided ('No Benchmark' condition) or with the return of the S&P 500 provided ('Benchmark' condition). The dependent variable is ***S&P500***, which is defined as participants' response to a 7-point fully labeled Likert scale question asking how likely they would be to reallocate their portfolio to an index fund that tracks the performance of the S&P 500. The means presented above are adjusted for the following covariates: ***Initial Percentile Estimate***, ***Participant Type***, and ***Actual Percentile***. ***Initial Percentile Estimate*** is the initial percentile estimates provided by experimental participants prior to starting their online trading game. ***Participant Type*** is an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant. ***Actual Percentile*** is the actual percentile rank of participants' returns relative to other participants assigned to the same online trading game start date.

TABLE 1

Participant demographics and other information

	(1) FJRG	(2) Alumni	(3) Total
Gender	**%**	**%**	**%**
Male	75.0	86.1	78.8
Female	20.6	13.9	18.3
Prefer not to respond/Self-identified	4.4	0.0	2.9
Age	**%**	**%**	**%**
18 — 34	20.6	38.9	26.9
35 — 54	23.5	52.8	33.7
55 — 74	51.5	8.3	36.5
Over 75	4.4	0.0	2.9
Current Residence	**%**	**%**	**%**
United States	82.4	100.0	88.4
Canada	8.8	0.0	5.8
Other/Did not answer	8.8	0.0	5.8
Years of Investing Experience	**%**	**%**	**%**
Less than 1 year	0.0	5.5	1.9
1 — 5 years	17.6	16.7	17.3
5 — 10 years	20.6	25.0	22.1
10 — 20 years	16.2	22.2	18.3
More than 20 years	45.6	30.6	40.4
Time Spent on Tasks	**Mins.**	**Mins.**	**Mins.**
Median for survey one	20.0	5.7	12.4
Median for survey two	4.3	5.3	4.7
Median for playing the trading game	45.0	20.0	30.0

Table 1 presents participant demographics and other information for 104 study participants (one participant did not respond to the demographic questions). Column (1) presents information related to 68 investor participants recruited by the Financial Judgments Research Group (FJRG). Column (2) presents information related to 36 investor participants who are accounting alumni of a nationally recognized business school in the Midwest. Column (3) presents information for both FJRG and alumni participants combined. The FJRG participants registered for a MarketWatch account as part of survey one, while alumni participants registered for a MarketWatch account as part of the screening process. This change explains the larger median time spent on survey one for the FJRG participants.

TABLE 2

Performance and Trading Behavior Statistics by Participant Type and Trading Period

Panel A: Financial Judgment Research Group Participants

Game Statistics	**Group 1**	**Group 2**	**Group 3**	**Group 4**
First week market return (%)	-3.05	6.58	-5.05	-5.79
Mean return for group – first week (%)	-1.96	3.48	-4.82	-5.77
Four-week market return (%)	-3.06	-5.81	-6.89	-0.04
Mean return for group – four weeks (%)	-0.16	-5.94	-7.90	-6.56
Avg. number of trades per participant	9.0	6.9	6.2	4.8
Avg. number of buys per participant	8.3	6.3	5.6	4.8
Avg. number of sells per participant	0.7	0.6	0.6	0.0
Avg. % of portfolio held in cash	7.8	14.5	8.5	16.0
Avg. % of portfolio held in individual stocks	78.0	59.3	63.9	54.9
Avg. % of portfolio held in ETF/index funds	14.2	26.2	27.6	29.1
Avg. number of unique individual stocks traded	6.2	4.7	3.9	3.3
Avg. number of unique ETF/index funds traded	1.1	0.8	1.4	0.9

Panel B: Accounting Alumni Participants

Game Statistics	**Group 1**	**Group 2**	**Group 3**	**Group 4**
First week market return (%)	-4.04	-3.29	-4.77	-4.65
Mean return for group – first week (%)	-2.19	-3.96	-3.25	-2.06
Four-week market return (%)	-8.40	-8.98	-10.50	-7.49
Mean return for group – four weeks (%)	-6.01	-9.53	-3.05	-0.17
Avg. number of trades per participant	9.8	5.7	7.0	4.2
Avg. number of buys per participant	9.3	5.2	6.8	4.2
Avg. number of sells per participant	0.5	0.5	0.2	0.0
Avg. % of portfolio held in cash	12.3	8.6	8.8	5.3
Avg. % of portfolio held in individual stocks	55.4	71.6	66.3	46.6
Avg. % of portfolio held in ETF/index funds	32.3	19.8	24.9	48.1
Avg. number of unique individual stocks traded	8.0	4.6	5.5	3.2
Avg. number of unique ETF/index funds traded	0.9	0.5	0.7	1.0

TABLE 2 (CONTINUED)

Table 2 presents performance and trading behavior statistics by participant type and trading period for 105 investor participants who participated in an online stock trading simulation game during one of eight different weeks. **Panel A** presents statistics for 69 investor participants recruited by the Financial Judgments Research Group who participated across four different weeks, while **Panel B** presents statistics for 36 accounting alumni participants who participants across four different weeks.

TABLE 3

Primary experiment regression results: Updated Percentile Estimate

	(1) *Updated Percentile Estimate*	(2) *Updated Percentile Estimate*	(3) *Updated Percentile Estimate*
Market Return	1.351**	1.033*	1.064*
	(2.10)	(1.75)	(1.75)
Benchmark Salience	-7.881*	-3.594	-3.539
	(-1.75)	(-0.86)	(-0.84)
Market Return × Benchmark Salience	-2.526***	-2.026**	-2.036**
	(-2.72)	(-2.37)	(-2.37)
Actual Percentile	0.065	0.020	0.020
	(0.91)	(0.31)	(0.31)
Initial Percentile Estimate		0.471***	0.472***
		(4.65)	(4.63)
Participant Type			0.877
			(0.23)
N	105	105	105
Adjusted R-Squared	20.8%	20.0%	20.7%

Table 3 presents regressions results of the effects of past market returns and market benchmark salience on investors' relative performance estimates. Results are from an experiment that asks participants to play an online trading game and predict their relative performance in percentile terms. The first independent variable is ***Market Return***, which is manipulated by randomly assigning participants to one of eight online trading game start dates. ***Market Return*** is a continuous variable defined as the first-week market return associated with different online trading game start dates. The second independent variable is ***Benchmark Salience***, which is manipulated by randomly assigning participants to estimate their relative future performance without the return of the S&P 500 provided ('No Benchmark' condition) or with the return of the S&P 500 provided ('Benchmark' condition). The dependent variable is ***Updated Percentile Estimate***, which is the updated percentile estimate provided by experimental participants after one week of trading. Additional covariates include ***Initial Percentile Estimate*** (the initial percentile estimate provided by experimental participants prior to starting their online trading game), ***Participant Type*** (an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant, and ***Actual Percentile*** (the actual percentile rank of participants' returns relative to other participants assigned to the same online trading game start date). I report *t*-statistics in parentheses. *, **, and *** represent significance (two-tailed) at the 10%, 5%, and 1% levels, respectively.

TABLE 4

Primary experiment regression results: Likelihood of reallocating portfolio to a S&P 500 index fund

	(1) *S&P500*	(2) *S&P500*	(3) *S&P500*
Market Return	-0.074	-0.074	-0.025
	(-1.20)	(-1.20)	(-0.43)
Benchmark Salience	0.588	0.599	0.690*
	(1.41)	(1.40)	(1.72)
Market Return × *Benchmark Salience*	0.230***	0.231***	0.216***
	(2.65)	(2.64)	(2.63)
Actual Percentile	0.006	0.006	0.006
	(0.86)	(0.83)	(0.89)
Initial Percentile Estimate		0.001	0.003
		(0.13)	(0.28)
Participant Type			1.411***
			(3.95)
N	104	104	104
Adjusted R-Squared	4.2%	3.2%	15.8%

Table 4 presents regressions results of the effects of past market returns and market benchmark salience on investors' relative performance estimates. Results are from an experiment that asks participants to play an online trading game and predict their relative performance in percentile terms. The first independent variable is ***Market Return***, which is manipulated by randomly assigning participants to one of eight online trading game start dates. ***Market Return*** is a continuous variable defined as the first-week market return associated with different online trading game start dates. The second independent variable is ***Benchmark Salience***, which is manipulated by randomly assigning participants to estimate their relative future performance without the return of the S&P 500 provided ('No Benchmark' condition) or with the return of the S&P 500 provided ('Benchmark' condition). The dependent variable is ***S&P500***, which is defined as participants' response to a 7-point fully labeled Likert scale question asking how likely they would be to reallocate their portfolio to an index fund that tracks the performance of the S&P 500. Additional covariates include ***Initial Percentile Estimate*** (the initial percentile estimate provided by experimental participants prior to starting their online trading game), ***Participant Type*** (an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant, and ***Actual Percentile*** (the actual percentile rank of participants' returns relative to other participants assigned to the same online trading game start date). I report *t*-statistics in parentheses. *, **, and *** represent significance (two-tailed) at the 10%, 5%, and 1% levels, respectively.

TABLE 5

Primary experiment descriptive statistics and analysis of covariance: Updated Percentile Estimate

Panel A. Descriptive statistics – mean, (standard deviation), and number of participants

	Benchmark Salience		
	No Benchmark	*Benchmark*	Overall
Market Return	49.93	52.69	51.25
Negative	(19.91)	(18.06)	(18.99)
	n = 46	n = 42	n = 88
Market Return	67.33	41.50	55.18
Positive	(25.86)	(14.64)	(24.59)
	n = 9	n = 8	n = 17
Overall	52.78	50.90	51.89
	(21.72)	(17.91)	(19.92)
	n = 55	n = 50	n = 105

Panel B. Results of analysis of covariance (ANCOVA)

Source	S.S.	d.f.	M.S.	F-statistic	p-value
Market Return	93.19	1	93.19	0.30	0.587
Benchmark Salience	566.49	1	566.49	1.81	0.182
Market Return × Benchmark Salience	2031.70	1	2031.70	6.48	0.012
Actual Percentile	32.92	1	32.92	0.11	0.747
Initial Percentile Estimate	6977.79	1	6977.79	22.25	< 0.001
Participant Type	41.62	1	41.62	0.13	0.716

Panel C. Follow-up simple effects tests

Source	F-statistic	p-value
No Benchmark v. Benchmark given *Negative* Market Return	2.37	0.127
No Benchmark > *Benchmark* given *Positive* Market Return	3.91	0.035†
Positive > *Negative* given *No Benchmark*	5.74	0.010†
Positive v. Negative given *Benchmark*	3.21	0.080

† = one-tailed equivalent given directional prediction (all other p-values are two-tailed)

Table 5, Panel A presents descriptive statistics for participants' ***Updated Percentile Estimate*** from an experiment that asks participants to play an online trading game and predict their relative performance in percentile terms. The first independent variable is ***Market Return***, which is manipulated by randomly assigning participants to one of eight online trading game start dates. ***Market Return*** is then collapsed to two conditions ('Negative' or 'Positive') based on whether the first-week market return for the online trading game is negative or positive. The second independent variable is ***Benchmark Salience***, which is manipulated by randomly assigning participants to estimate their relative future performance without the return of the S&P 500 provided ('No Benchmark' condition) or with the return of the S&P 500 provided ('Benchmark' condition).

TABLE 5 (CONTINUED)

Table 5, Panel B presents ANCOVA results investigating whether ***Market Return*** and ***Benchmark Salience*** affect participants' ***Updated Percentile Estimate***, and includes covariates for ***Initial Percentile Estimate*** (the initial percentile estimate provided by experimental participants prior to starting their online trading game), ***Participant Type*** (an indicator variable equal to '1' if the participant is an accounting alumni participant and '0' if the participant is a FJRG participant, and ***Actual Percentile*** (the actual percentile rank of participants' returns relative to other participants assigned to the same online trading game start date).

Table 5, Panel C presents follow-up simple effects tests for ***Market Return*** and ***Benchmark Salience*** on participants' ***Updated Percentile Estimate***.