Expectation Formation from Realized Stock Prices: An Eye-Tracking Study*

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Abstract

Eye movements reflect biases inherent in decision-making. We conduct an eye-tracking experiment to measure how subjects allocate attention over a price chart while predicting future stock returns. We confirm that the attention allocation reflects how subjects form expectations from past price information. The measure of expectation based on eye-tracking quantitatively fits the actual forecasts submitted by subjects. Easily recognizable patterns in data receive disproportionately more attention: Subjects spend much more time reading recent as well as extreme trends and price levels. Such heuristics in information acquisition are heterogeneous across subjects and lead to inferior forecast precision. Overall, the results provide direct evidence for investor beliefs hypothesized by theories of return extrapolation.

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1 Introduction

Expectation formation models based on extrapolative beliefs can explain important facts about asset prices. Recent research provides direct evidence that investors believe an asset's future return is positively correlated with its recent past returns (Vissing-Jorgensen, 2004; Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin, and Shleifer, 2018; Cassella and Gulen, 2018; Da, Huang, and Jin, 2021). However, due to the methodological limitations embodied in price information and surveys, not much is known about the underlying mechanism of the return extrapolation.[1] When different cognitive processes derive the same conclusion, it is often impossible to make inferences about cognitive processes by analyzing the expectation itself. For this reason, the fundamental question about extrapolative beliefs remains unsolved: How do investors relate historical price information to future price movements?

To answer this question, we conduct an experiment through an eye-tracking technique to investigate the computational process of return extrapolation. We set up an experimental version of the gamified investment environment in which unsophisticated investors predict future stock returns based on a price chart. Subjects are asked to read a chart that presents monthly stock prices of the past 18 months as simulated from a random walk while predicting stock prices for the next 1 or 3 months. Subjects are not informed about the true data generating process since the information can influence their behavior. An eye-tracking device records the entire process of information acquisition during experiments, including which parts of the price graph are read and for how long.

Using data on the eye movements of experimental subjects, we then quantify how subjects allocate attention to trends and price levels in past price information. This measure makes it possible to study heuristics in information acquisition during expectation formation by capturing which price information receives excessive attention. The variation of the attention parameter associated with the characteristics of the data is key to understanding heuristics in the information acquisition process. If subjects do not rely on heuristics when inferring future price movements, all data points are equally likely to receive attention regardless of computational capability.[2] In this case, the characteristics of the price

[1] See Barberis (2018) and Choi and Robertson (2020) for further discussion on the methodological limitations of previous studies.

[2] If subjects have infinite computational capability, all data points would receive an equal amount of attention. On the other hand, if subjects have limited computational capability, only a subset of the data will receive attention. Nevertheless, the likelihood of receiving attention will be equal for all data as subjects will randomly select a subset of data to make inferences.

information and the amount of allocated attention will be irrelevant. On the other hand, if heuristics intervene in the expectation formation process, subjects will selectively acquire information with characteristics that are heuristically thought to be more related to future stock prices.

To establish the link between heuristics in information acquisition and biased expectation, we suggest an attention-based framework of extrapolation. This framework extends the extrapolative framework of Greenwood and Shleifer (2014) in two directions. In Greenwood and Shleifer's specification, the expectation is a weighted linear combination of historical returns in which weights placed on historical returns feature a geometric decay. From the attention and information acquisition perspective, the specification can be interpreted as the expectation is formed based on the perceived past information, with more interest in recent returns. Therefore, this paper replaces the weight function of the Greenwood and Shleifer with the attention parameter measured by eye-tracking. No less importantly, we introduce the term related to the average of the past price level. This addition reflects the fact that subjects spend much time reading both level and trend in an experiment. Thus, in the attention-based framework, an investor's expectation of future stock return is the weighted linear combination of past returns and average price levels, whose weight is the allocated attention during the prediction task.

The results provide evidence that heuristics in information acquisition reflect a biased expectation formation process and therefore support the attention-based framework of extrapolation. Non-parametric bootstrap shows that the measure of expectation calculated through the attention framework quantitatively fits the average actual response quite well. In addition, results from the prediction-level regression suggest that the attention-based measure is positively correlated with the actual predictions submitted by subjects. Interestingly, the measure based on attention to trends fits actual predictions better when there is a drift in the data. In contrast, the measure based on attention to price levels fits actual predictions better when volatility is higher. This result suggests that subjects may rely on different computational processes according to the characteristics of price paths.

With the established relationship between the information acquisition process and expectation, we examine how subjects allocate attention to past price information over a price chart. First, we confirm that the weight for each price information is mainly determined by how recent the data is, as predicted by the existing extrapolative framework—-subjects allocated about 40% of their total attention to reading recent data, which comprises of only 12% of overall data. Previous studies have confirmed that there is an overreaction to recent data. This study shows that such overreaction may result from inattention to distant past data

during the information acquisition process. Second, we find that subjects have heuristics to focus more on the tail events. Subjects place more weight on extreme returns and prices than on data in the moderate range, as predicted by the literature on excessive attention to tail events. Subjects mainly focus on extreme negative returns, price peaks, and troughs. Returns with the lowest rank in a price graph receive approximately one percentage point more attention than returns with an average rank.

Next, we quantitatively compare various heuristics that participants have in relation to return extrapolation using an attention parameter. The results provide a few implications for the weight function to the past price information in the existing extrapolative framework. For returns, we find that the concentration of attention in recent data is stronger than the concentration of attention in tail events. For price levels, on the contrary, attention in tail events that occurred in the distant past receives a considerable amount of attention. This finding implies that investors can be excessively affected by past tail events even if they learn about them through a graph, unlike theories based on experience and recalled memory suggest.

Importantly, heuristics in the information acquisition process and errors in expectation formation are correlated. The more concentrated attention is to specific price information that draws attention heuristically, the lower the prediction precision compared to benchmarks. In addition, the amount of data acquired by subjects is also associated with the prediction precision, as thorough investigation of data is likely to involve fewer heuristics. Making accurate predictions is connected with maximizing the payoff in this experiment. Therefore, it is possible that the degree of heuristics in the information acquisition process results in a reduction in investors' utility in real investment situations.

Finally, we confirm that the heuristics of the information acquisition process are diverse at the subject level. Existing evidence focuses on the fact that the heterogeneity comes from a superiority of information or experience. Although theories on extrapolatiion bias assume a cross-sectional difference in the degree of extrapolative bias, not much is known about whether this heterogeneity can result from the difference in the psychological process for expectation formation. Empirical works to date focus on the fact that heterogeneity comes from a superiority of information or experience. This study shows that the heuristics in acquiring past price information are heterogeneous across individuals. Results using post-experimental survey data suggest that the extent to which subjects are affected by heuristics may depend on educational backgrounds. In particular, subjects with science, technology, engineering, or math (STEM) majors and training are less affected by heuristics.

This study builds on the literature that uses process-tracing technologies to investigate the computational process in decision-making. A set of studies investigates the decision-making process in strategic games using a simpler technology called MouseLab (Camerer, Johnson, Rymon, and Sen, 1993; Costa-Gomes, Crawford, and Broseta, 2001; Johnson, Camerer, Sen, and Rymon, 2002; Costa-Gomes and Crawford, 2006). These papers find that the patterns of information search help predict the deviations from the optimal strategy. Some studies explore the role of attention in economic decisions.[3] Lahey and Oxley (2016) use the eye-tracking technique to detect top-down attention discrimination of students while reading a resume. On the other hand, Li and Camerer (2021) study whether bottom-up visual salience in images can predict subjects' economic decisions in games. More closely related to this study, several studies explore the information acquisition process in choice problems to investigate cognitive models with bounded rationality (Gabaix, Laibson, Moloche, and Weinberg, 2006; Caplin, Dean, and Martin, 2011). Using eye-tracking, Reutskaja, Nagel, and Camerer (2010) conduct an experiment similar to the consumer's supermarket problem to investigate computational processes when making choices. Arieli, Ben-Ami, and Rubinstein (2011) study information acquisition in decision-making for choice over lotteries. This paper contributes to this literature by investigating the computational process of making predictions based on historical data.

Next, this paper adds to the literature on the experimental research of expectation formation from a random sequence. De Bondt (1993) documents that non-experts extrapolate past trends but at the same time also are anchored to past prices. Several studies debate over the regime-shifting model of Barberis, Shleifer, and Vishny (1998). Bloomfield and Hales (2002) provide results that support the regime-shifting beliefs using a selection of graphs from a random sequence. However, with modified experimental design, Asparouhova, Hertzel, and Lemmon (2009) find evidence that favors Rabin's (2002) model based on the law of small numbers over regime-shifting beliefs. In addition, Beshears, Choi, Fuster, Laibson, and Madrian (2013) show that subjects are not effective in recognizing the degree of mean reversion of the underlying process, especially when the mean reversion is slow. On the other hand, Frydman and Nave (2017) take an interesting approach by comparing the extrapolative beliefs in perceptional and price predictions. They provide convincing evidence that two different tasks share the same mechanism, supporting the idea that behavioral biases stem from low-level thought processes. Lastly, Afrouzi, Kwon, Landier, Ma, and Thesmar (2021) compare various models of expectation formation and find that commonly-used expectation models do not explain the variation in the overreaction to recent observations across different

[3] See Gabaix (2019) for a comprehensive review of this topic.

treatments.

Finally, this work contributes to the broad literature studying investors' biased beliefs using survey data (Malmendier and Nagel, 2011; Hirshleifer, Li, and Yu, 2015; Amromin and Sharpe, 2016; Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Kuchler and Zafar, 2019; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Choi and Robertson, 2020; Giglio, Maggiori, Stroebel, and Utkus, 2021). This study related specifically to a component of the literature analyzing investor beliefs based on past price information.[4] In particular, Greenwood and Shleifer (2014) suggest that investor expectations can be specified as a linear combination of past returns whose weight is a geometric decay function with regard to time. Based on the survey results of Greenwood and Shleifer (2014), Barberis, Greenwood, Jin, and Shleifer (2015) and Jin and Sui (2021) discuss asset pricing models in which some investors have extrapolative beliefs. Cassella and Gulen (2018) provide evidence of a time-series variation in extrapolative beliefs. They show that the variation is associated with the predictability of stock returns by price-scaled variables. Lastly, this study adds to the active literature that investigates cross-sectional variation in the extrapolative beliefs (Nagel and Xu, 2019; Atmaz, Cassella, Gulen, and Ruan, 2021; Da et al., 2021). The paper contributes to the literature by showing that heuristics in the information acquisition process varies across subjects. Moreover, the utilization of the acquired information varies across the characteristics of the data delivered to subjects.

The remainder of the paper proceeds as follows. Section 4 discusses the experimental design in detail. Section 2 presents the attention-based framework of extrapolation. Section 3 introduces the eye-tracking-based methodology to estimate parameters in the framework and provides examples of attention distribution in the actual experiment. Section 5 explores the main results of the experiment. Section 6 discuss the implications and limitations of the study and suggests potential direction for future research.

2 Attention Framework of Extrapolation

The literature in behavioral finance provides evidence that investors use only a subset of past price changes when predicting future returns. In the case of extrapolative belief, for example, it is assumed that investors overly reflect the most recent trend in their prediction. Motivated by Gabaix (2019)'s model of attention, this paper introduces a framework that describes return prediction as the computational process that investors rely on past price

[4] See Barberis (2018) for a comprehensive review of this topic.

changes with heuristic attention allocation. This framework aims to encompass behavioral biases in asset pricing such as extrapolative belief or distorted probability function toward tail events.

Before introducing the framework, we briefly discuss the specifications of the existing studies that link investor expectations to past returns. First, OLS approach can be written as below:

$$Exp_t = \alpha + \beta_k \sum_{k \in K} \left(\frac{p_{t-k+1}}{p_{t-k}} - 1 \right) \tag{1}$$

Investor expectations are often modeled as the weighted linear combination of past returns in which psychological biases are characterized by an exogenously defined weight function. Greenwood and Shleifer (2014), for example, explicitly model overextrapolative beliefs using the following equation:

$$\begin{aligned} Exp_t &= \alpha + \beta \sum_{k \in K} w_k \left(\frac{p_{t-k+1}}{p_{t-k}} - 1 \right), \\ w_k &= \frac{\lambda^{k-1}}{\sum_{j \in J}}, \quad \text{where } 0 \leq \lambda \leq 1 \end{aligned} \tag{2}$$

In their framework, the key parameter is w_k, the geometric decay function with regard to k. This specification implies that investors not only trend past returns, but also excessively overweight recent returns and underweight distant returns when they predict future returns.[5] Another example is Barberis, Mukherjee, and Wang (2016), in which the weight function is from the cumulative prospect theory (Tversky and Kahneman, 1992).

Instead of using exogenously defined decision weights, this paper proposes a new approach by using attention parameter. In our framework, how investors allocate attention over the historical returns decide the decision weights in the expectation formation. In particular, investors overweight returns that draw their attention when they form expectations:

$$\begin{aligned} Exp_t &= \alpha + \beta \sum_{k \in K} f(m_k^r) \left(\frac{p_{t-k+1}}{p_{t-k}} - 1 \right), \\ \sum_{k \in K} m_k^r &= 1, \quad \text{where } 0 \leq m_k \leq 1 \end{aligned} \tag{3}$$

[5] See Cassella and Gulen (2018); Jin and Sui (2021); Da et al. (2021) for further research using the equation (2) to model extrapolative beliefs.

m_k^r is an attention parameter for return k, p_{t-k} is the price at $t-k$, and f is a continuous and strictly increasing function.

Substantial evidence shows that subjects in our experiment used price levels as an important source of information when making prediction.[6] First, the experiment participants themselves are aware that they are affected by the price levels. Appendix table A.1 shows that approximately 10% of respondents answered that they used peak and trough prices and another 7% of respondents wrote that they predicted future price changes based on average of historical prices. Second, the eye-tracking data indicate that subjects devoted a significant portion of their attention to the behavior of reading price levels. The attention used for level recognition corresponds to 43.7% of the total attention distribution.

Therefore, the model that embraces both historical returns and prices is suitable in our setting. We expand the equation (3) to reflect that investors rely on *price levels* as well as *trends* in historical prices.

$$\begin{gathered} Exp_t = \alpha + \beta \sum_{k \in K} f(m_k^r) \left(\frac{p_{t-k+1}}{p_{t-k}} - 1 \right) + \gamma \sum_{k \in K} g(m_k^p) \left(\left(\frac{p_{t-k}}{p_t} \right)^{\frac{1}{k+1}} - 1 \right), \\ \sum_{k \in K} m_k^r + m_k^p = 1, \quad \text{where } 0 \leq m_k^r \leq 1 \text{ and } 0 \leq m_k^p \leq 1 \end{gathered} \tag{4}$$

m is an attention parameter, r is the past returns, and f and g is a continuous and strictly increasing function. Note that the last term in equation (4) reflects how investors use price averages in forming their expectations. For example, $p_{t-k} > p_t$ then p_{t-k} increases an investor's expectation by the percentage difference between two prices, scaled by the distance. $\frac{1}{k+1}$ is a term to scale this difference on a monthly basis since the adjustment in predicted return should be smaller when reference price is in distant past. [7]

In our framework, investors' expectations are linked to past price information in two folds. The first dimension, represented as β and γ, is whether, and to what degree investors use historical returns and prices when they form expectations. The second dimension, represented as m_k^r and m_k^p, is how investors use historical returns and prices. Previous studies

[6] Evidence in the literature suggests that price levels, as well as returns, play an important role in investor decision making (De Bondt, 1993; George and Chuan-Yang, 2006; Shue and Townsend, 2021). Especially, De Bondt (1993) analyzes the effect of the average past stock prices on predicting future returns.

[7] In our specification, "trend" and "level" have opposite effect on the prediction. If the past price is higher than the current price, then prediction based on trend indicates that the predicted return should be negative, since the slope of the trend line is negative. On the other hand, prediction based on level indicates that the predicted return should be positive, the average of two prices is higher than the current price.

jointly test these separate processes in a single specification, with exogenously defined weight function. Instead, in this study, we study variations in the relative weights without jointly testing two dimensions of beliefs on past price information.

Literature on information search in economic decisions suggests that incomplete search and information processing lead to sub-optimal decisions (Caplin et al., 2011; Caplin and Dean, 2011; Li and Camerer, 2021; Frydman and Jin, 2022). Failure to fully consider available information introduces biases in perceiving the correct distribution of choices or payoffs. We apply this finding to the perception of historical returns and its effect on expectation formation. Specifically, we define biases in attention as deviation from a complete search on the historical price information. A complete search in our framework involves equally distributed attention over all available information. In other words, an investor without heuristics is likely to investigate the data without focusing on the subset of data.

Consider a stock price path following geometric Brownian motion. An investor with the Full Information Rational Expectation (FIRE) knows the true return process and parameter, and therefore would not need to use historical prices to predict future returns. If an investor knows the process but not the parameters, she would use the entire price path to obtain the best available estimate of parameters. The weights on returns, m_k^r, should be same across all available returns. The weights on prices, m_k^p should be zero for all available prices except for p_{t+1}. On the other hand, investors with false beliefs on past price information may overweight some prices that receive more attention when they form expectations. For example, m^r may vary according to how distant the return is from and how extreme the return is in the underlying distribution at the same time. Therefore, in our framework, attention parameter m works as a channel through which biases enter into investor expectations.

Information set I, the recognized subset of all available information, can be useful in summarizing the biases and beliefs of subjects (Masatlioglu and Nakajima, 2013).[8] Specifically, the set I represents to which return or price information a subject has paid attention and how a subject allocated their attention to acquire the necessary information.[9] The elements in the information set I are the parameters from the equation (10) as follows:

$$I = (\mathbf{m^r}, \mathbf{r}, \mathbf{m^p}, \mathbf{p}), \tag{5}$$

[8] The information set only includes information that is visually available to subjects via stimulus in the monitor, and does not include past memories or experience recalled in the thought process.

[9] Unlike the literature in consumer choice that borrows the concept of information set, however, this paper does not address the search process that forms the information set.

where $\mathbf{m^r}$ is a vector of attention parameter for past returns, $\mathbf{r}$ is a vector of past returns, $\mathbf{m}^p$ is a vector of attention parameter for past prices, and $\mathbf{p}$ is a vector of past prices.

If attention is a finite resource and investors can only acquire a limited amount of information, the information set reflects a belief about what past information will be relevant to future returns.[10] First of all, investors cannot reflect any information unless they perceive it by allocating attention. Any information that investors believe irrelevant to future returns will be disregarded and will receive $m = 0$. Moreover, the information set is helpful in distinguishing the beliefs about the stock returns with a limited attention. If investors are subject to the limited attention allowing them access to only a few price information but not to any beliefs, the amount of attention received by returns or prices should not be correlated with any of the characteristics. But rather, the attention should be distributed randomly.

3 Measuring Attention using Eye Tracking

3.1 Gaze Path and Gaze Path Duration

In this section, we explain how data collected from eye-tracking is used to study heuristics in acquiring historical price information during the prediction task. We consider the allocation of visual attention as a proxy for the allocation of mental attention in the computational process.[11] For example, if a subject spends half of round reading r_{t-1}, the latest available return, the interpretation is that she allocated half of her attention to r_{t-1}.

There are several useful metrics provided by the eye-tracking system to study computational process of subjects. First, *fixation* denotes a period where the eyes are locked at a specific location for a certain period of time (Reutskaja et al., 2010).[12] Second, *gaze path* connects fixations in chronological order and measures shift of the gaze from one point to

[10] In an environment where limited time is provided, Li and Camerer (2021) argue visually salient options might shape one's choice (bottom-up approach). On the other hand, in an environment where time is not strictly limited before making a decision, as in our paper, it is more likely that the belief shapes one's allocation of visual attention.

[11] While it is tempting to interpret visual attention as a mental attention, eye-tracking data is a process-tracing data, the pre-decisional observations. Eye-tracking tracks all the visual information acquired during the mental process. Whether such information is actually used by a mental process is a separate question. Proper research design to tightly link the *information acquired* and the *information used* is required (Schulte-Mecklenbeck, Johnson, Böckenholt, Goldstein, Russo, Sullivan, and Willemsen, 2017).

[12] The minimum dwell time to be classified as fixation is 60 ms in this research. Typical criteria in eye-tracking research vary from 60ms to 200ms.

another. Gaze path is useful when the shift of gaze, not the fixation itself, is associated with the underlying thought process of decision making (Arieli et al., 2011). Finally, the *gaze path duration* is measured from the beginning of the first fixation to the end of the second fixation. In this study, we primarily rely on gaze path and gaze path duration to study subjects' extrapolative behaviors. This is because subjects not only read the price itself when reading price paths, but also look at the trend of the price, or the rate of return.

How can gaze paths indicate which *trends* from historical data and which *price levels* are being referenced by subjects? We categorize gaze paths into two groups. First, a gaze path is classified as a trend reading type if the first fixation and the second fixation are located at different prices. Figure 1, Panel A illustrates the examples of a subject's gaze path associated with reading trends. In this example, the subject first read the price of March 1988 ($194) followed by the most recent price of April 1989 ($196). The gaze path can be interpreted as the subject recognizes the returns from the past 13 months, from r_{t-13} to r_{t-1}. Next, the eyes of the subjects shift from the price of April 1989 ($196) to the price of January 1989 ($165). In this case, the subject recognizes returns for the past three months, from r_{t-3} to r_{t-1}.

Further, the gaze path duration for returns can indicate how much attention is allocated to reading specific trends. We denote sum of the duration of gaze paths that cover r_{t-k} as dur_k. For Figure 1, Panel A, let's assume the duration of both gaze paths as 100 ms. Then, returns from r_{t-3} to r_{t-1} are recognized by both gaze paths, with a duration of 100 ms each. Therefore, dur_k^r for $k = 1, 2, 3$ is 200 ms. Next, returns from r_{t-13} to r_{t-3} are recognized by the gaze path with duration of 100 ms. Then dur_k^r for $k = 4, ..., 13$ is 100 ms. Finally, returns from r_{t-14} to r_{t-17} have not been recognized and thus dur_k^r for $k = 14, ..., 17$ is 0 ms.

Next, we discuss gaze paths associated with reading price levels. A gaze path is classified as price reading type if it falls in either of two categories: 1) the first and second fixations are located at the same price, or 2) the first fixation is the price and the second fixation is elsewhere in the screen or vice versa. Figure 1, Panel B illustrates examples of gaze paths associated with reading price levels. In this example, the subject first reads the price of March 1988 ($194) for the duration of two fixations. Next, the subject is fixated at the price of August 1988 ($185) then shifts to the date axis. The interpretation is that a subject is confirming the date of the price that she considers important in predicting future price. Finally, a subject reads the price of January 1989 ($165) then moves to y-axis. Since only one price is perceived in this gaze path, it is likely that a subject is paying attention to the perceived price.

Therefore, the gaze path duration for prices can indicate how much attention is allocated to reading specific price levels. We define sum of the duration of gaze paths that cover p_{t-k} as dur_k. The computation of dur_k^p is straightforward. If the duration of all gaze paths is 100ms in Figure 1, Panel B, then the total duration of gaze paths associated with price reading is 300ms. From the duration of perceived prices, dur_4^p, dur_9^p, dur_{14}^p are all 100 ms. The rest of prices are assigned with the the duration of 0 ms and considered as they are not recognized by subjects.

Figure 1, Panel C shows the gaze paths from the actual experiment. The figure illustrates that actual gaze paths are the mixture of the trending gaze paths and price reading gaze paths. While the example here is relatively simple, there are more complex cases in which the number of gaze path is greater than 100. Examples are available in Figure A.2 in the Appendix. Note that some gaze paths are not associated with both trend and price reading. For example, a gaze path can be formed between two adjacent fixations within data axis. Such gaze paths are difficult to interpret and will be excluded when estimating parameters of equation (10).

3.2 Model Estimation

Using metrics of eye-tracking, this paper takes non-parametric approach to measure decision weights in the attention model of investor expectations, the equation (4). The visual attention allocated to each return and price, or the time spent on reading such information, determines the decision weights. In particular, gaze paths are considered as the unit of information acquisition and gaze path duration determines the attention measure. We estimate an attention parameter allocated to each return as follows:

$$m_k^r = \frac{dur_k^r}{\sum_{i=1}^{n-1} dur_i^r + \sum_{j=0}^{n-1} dur_j^p}, \quad 0 \leq m_k^r \leq 1, \quad k \in [1..n-1] \tag{6}$$

where n represents the total number of prices in a chart, dur_k^r represents the sum of gaze path duration that cover r_{t-k} and dur_j^p represents the sum of gaze path duration that cover p_{t-j} in each round.

Similarly, we use gaze paths associated with reading prices to compute an attention parameter allocated to each price.

$$m_k^p = \frac{dur_k^p}{\sum_{i=0}^{n-1} dur_i^r + \sum_{j=0}^{n} dur_j^p}, \quad 0 \leq m_k^p \leq 1, \quad k \in [0..n-1] \tag{7}$$

where dur_k^p represents the sum of gaze path duration that cover p_{t-k} in each round.

The remaining question is how to link the decision weights to investor expectations. First, we model investor expectations based on with perceived past returns or trends only. In other words, investors do not spend any time reading past prices and thus $m_k^p = 0$ for all k in equation (4). If we posit $f(m_k^r) = m_k^r$, the past trend perceived by investors becomes the weighted linear combination of past returns.[13] *GazeRet(trend)* reflects how subjects use the perceived past trends for prediction and can be defined as follows:

$$GazeRet(trend) = \sum_{k=1}^{n-1} m_k^r \left(\frac{p_{t-k+1}}{p_{t-k}} - 1 \right). \tag{8}$$

Next, we propose a specification for investor expectations associated with price levels. From equation (4), if subjects tend to average past prices to estimate future prices, past prices that are higher (lower) than the current price will increase (decrease) the forecast of future returns. If we assume $m_k^p = 0$ for all k, *GazeRet(level)* is computed as follows:

$$GazeRet(level) = \sum_{k=0}^{n} m_k^p \left[\left(\frac{p_{t-k}}{p_t} \right)^{\frac{1}{k+1}} - 1 \right]. \tag{9}$$

Simply put, the specification of *GazeRet(level)* captures how investors use the weighted average of the price at $t-k$ and the latest price in return prediction. The attention parameter m_k^p represents the attention distributed to past price p_{t-k}.

In our framework, subjects collectively perceive trends and price levels and use both types of information to predict future returns. The expectation based on both types of information is modeled in equation (4). For simplicity, we write equation (4) as a linear combination of *GazeRet(trend)* and *GazeRet(level)*. Specifically, we use the weighted average of equations (8) and (9), with the weights being the respective total durations of the two types of gaze

[13] The literature in vision science shows that the distribution of salience across a visual scene tends to follow an exponential distribution, meaning that a few regions have high salience, while most regions have low salience (Krüger, Tünnermann, and Scharlau, 2017; Moon, Choe, Lee, and Kwon, 2019). Therefore, another possibility to model the mapping function f is to reflect this finding. It would be an interesting future research avenue to study which function f explains the relationship between the computational weight and visual attention well.

paths. From equation (6) and (7), the combined specification can be written as follows:

$$GazeRet = \sum_{k=1}^{n} m_k^r GazeRet(trend) + \sum_{k=0}^{n} m_k^p GazeRet(level), \tag{10}$$

where $\sum m_k^r$ represents the percentage of the total gaze path duration allocated to reading trends, while $\sum m_k^p$ is the corresponding fraction allocated to reading price levels, such that $\sum m_k^p = 1 - \sum m_k^r$.

Finally, if subjects form expectations based on the information perceived from the price path, we expect that there is a positive relationship between *GazeRet* and the subject's actual return predictions. Our empirical specification to test the predictability of *GazeRet* is as follows:

$$Exp_{s,r} = \beta GazeRet_{s,r} + \delta X_{s,r} + \zeta_s + \eta_r + \epsilon_{s,r}, \tag{11}$$

where s indexes subjects, and r indexes rounds. ζ_s and η_r are subject and round fixed effects.

3.3 Saliency Map

Now, we briefly explore the saliency map, the visualized examples of the information set. A saliency map is helpful in understanding how subjects approach to the prediction task overall.[14] Figure 2 provides examples of a saliency map from the actual experiment. The characteristics of attention distribution that can be found in the examples are a) attention is highly concentrated on the subset of data, and b) only some data, rather than the whole, is recognized.

The concentration of attention on several prices can be observed in heatmaps presented in Figure 2, Panel A, and Figure 2, Panel B. The "hotter" colors represent more and longer fixations in one area. In Figure 2A, red colors are focused on the prices of the last four months, while green colors cover the remaining prices. The interpretation is that the subject appears to focus on the prices from last four months while giving some glances to the rest of data. In Figure 2, Panel B, however, red colors cover not only the recent data, but also the peak that occurred about 12 months ago. The subject appears to focus on the peak

[14] The saliency map is based on the fixation duration, meaning that it does not directly represent the distribution of m^r and m^p. But since the attention measures of gaze path are obtained from the fixation duration, saliency maps are helpful in understanding the distribution of visual attention in general.

and the data around it. Overall, heatmaps illustrate that subjects may heuristically allocate attention during the prediction task and that such heuristics can be heterogeneous. More examples of saliency maps are available in Figure A.3 in the Appendix.

Next, the "inattentional blindness" to several prices can be highlighted using the scope maps in Figure 2, Panel C and Figure 2, Panel D. The "brighter" area represents the more and longer fixations. Both figures clearly show that subjects may disregard part of the data during the prediction. In 2, Panel C, only some portion of the screen are bright and subjects do not have fixations for approximately one-third of the graph. In Figure 2, Panel 2D, bright spots are focused on the recent prices only, leaving prices 9 months before or earlier with no attention. Overall, the blind spots in the graph imply that subjects tend to ignore the data with little importance. Even though peripheral vision may mitigate this ignorance, results in vision science imply that complicated thoughts cannot be processed from an object in peripheral vision (Kowler, 2011).

The saliency map also suggests that subjects have a tendency to interpret data through their heuristics rather than reading the data as it is. While a subject *without heuristics* is likely to investigate the data without specifically focusing on the subset of data, eye-ball inspection on the saliency map implies the opposite. While it might be difficult to tell from the small amount of examples presented in the paper, it can be easily noticed that subjects are inattentive to what the entire data is about. Together with the survey result in Table A.1 in the Appendix in which more than 80% of subjects tend to believe there is a trend or pattern in the data, the saliency map suggests that subjects seek patterns from a random walk as the uneven distribution of attention implies.

One might question whether the concentration on specific data points is due to the bounded rationality of subjects, which makes it impossible for subjects to cover all the available data points presented on the screen. If so, instead of considering all the data points, subjects would randomly choose several data points and read trends and prices. On the other hand, if heuristics drive subjects to view only a few data points even with enough computational capability, there should be certain return or price characteristics that draw excessive attention. The evidence presented throughout the following section supports the latter argument.

4 Experimental Design

4.1 Procedures

The purpose of the experiment is to observe how subjects visually acquire information when looking at a price chart to predict a future stock price. The experimental interface is designed to be similar to websites and applications that are easy to use for unsophisticated investors. In each of the 40 rounds, subjects make predictions of the simulated stock prices of 18 months. Specifically, subjects read the stock price graph presented on the computer screen and submit their response.[15] After each round is completed, subjects have the opportunity to learn the prediction precision of the round and the total score accumulated so far. For half of the rounds, subjects make predictions of the stock price 1 month later. For the remaining half, subjects make predictions of the stock price 3 months later. There is a short break between the first half and the second half of the experiment. After the prediction tasks are over, subjects answer a post-experimental survey.[16] There is no time limit for each round, as this experiment does not aim to investigate decision making under time-pressure. Figure 3 shows examples of the one month and three month prediction tasks. The Figure A.1 in the Appendix reports the entire experiment flow.

During each prediction task, movements of subjects' eye pupils are recorded with an eye-tracking device. The eye-tracking model of this study, Smart Eye Aurora, is a screen-based device that records the gazing points for every 15 ms.[17] For the best performance of the device, subjects are required to be seated approximately 63 cm away from the screen. Head movements of approximately 10 cm from the original position are allowed. Subjects are asked to focus on the screen as much as possible while performing the prediction task. Other than these strict restrictions on the sitting posture, subjects performed the experimental tasks without any direct intervention.

[15] Glaser, Iliewa, and Weber (2019) collect and summarize the format of charts available to investors from various sources, including online sources of retail investors, newspapers and magazines, and online sources of professionals. They document that over 90% of data sources present price charts, while less than 10% present return charts.

[16] Questionnaires for Cognitive Reflection Test (CRT) are from Frederick (2005). Questionnaires for statistical background knowledge are from Afrouzi et al. (2021).

[17] The sampling rate from the manufacturer's manual is 60 hz.

4.2 Data

The price path for each round is from the simulated monthly stock prices based on the geometric Brownian motion:

$$p_t = p_{t-1}(1 + \mu + \sigma z_t), \tag{12}$$

where z_t is standard normal random variable. The experiment presents monthly prices in the form of time-series graph. The calendar dates for each t are randomly drawn from the set of monthly date starting from January, 1970 to December, 1999. We excluded years from 2000 to alleviate the concern that subjects may reflect past experience or knowledge in their prediction. (μ, σ) is randomly drawn from the set {(0,0.05), (0,0.10), (0.01,0.05)} and assigned to each subject at the beginning of the experiment.[18]

No identical price paths were presented for each round and each participant. One might claim that employing a carefully designed stimulus is more helpful to study extrapolative behavior than using a randomly generated stimulus. However, when a researcher generates arbitrary data under a condition where the number of samples is limited, the price path may contain excessively many tail events compared to the random walk process. The problem of including excessive tail events is posed by Asparouhova et al. (2009). They argue that when an experiment is conducted with data containing many extreme events, it is impossible to distinguish between subjects' behavioral bias and a rational conclusion that the data is of a regime shifting type.

Subjects are not informed that the price paths follow a random walk process. The ambiguity of the underlying statistical process is important in observing heuristics that subjects typically use to read an actual stock price series. If subjects know that price changes for each month are set randomly, they are likely to make predictions from random guesswork independent from the information acquisition process. Under these circumstances, the correlation between the data acquisition process and subjects' response becomes low, which unnecessarily increases the type II error of the experiment. Instead, subjects are provided ten practice rounds to learn the process governing the price paths before the main prediction task. Practice rounds alleviate the concern that any deviation from the optimal behavior might have resulted from the initial learning process, not the heuristics that participants

[18] For the sample period from 1970 to 2000, average monthly stock returns and volatility of US stock market is about 1.3% and 17%, respectively. Based on these numbers, (μ, σ) are chosen to make sure visual clarity and graphical distinctions between treatments.

have when reading stock price data.

4.3 Payments

The payment function is designed to give subjects financial incentive to exert the best effort to make accurate predictions. This function is built on the experiment conducted by Afrouzi et al. (2021). First, subjects receive \$5 as a base payment, regardless of the completion of the experiment task. Next, subjects receive an incentive payment that is equal to the total score divided by 125. The incentive payment is computed from the total score, the sum of round scores for forty rounds. The round score is computed using the following equation:

$$RS = 100 \times \max\left[0, 1 - \frac{1}{2\sigma_i^k}\left|\frac{p_{t+i} - \widetilde{p_{t+i}}}{p_t}\right|\right] \tag{13}$$

where $\widetilde{p_{t+i}}$ is a predicted price by a subject for i month forecast at time t and σ_i^k is standard deviation of a return distribution for treatment k and forecasting horizon i.[19]

The score function measures the absolute difference between the actual return and the return response, scaled by twice the standard deviation. This specification allows subjects to receive non-zero scores as long as the difference between the actual return and the predicted return does not exceed two standard deviations of the underlying process. This design is to rule out the potential impact of disappointment or anger on the subjects' behavior (Strahilevitz, Odean, and Barber, 2011; Frydman and Camerer, 2016). Given that $E_t[p_{t+1}/p_t] = \mu$, the optimal prediction $\widehat{p_{t+i}}$ that maximizes the expected payoff is $p_t(1+\mu)^i$. For example, if $\mu = 0$ for price paths, the optimal prediction is always p_t for any horizon i. The average payment to subjects is \$21.

4.4 Treatments

The base setup of the experiment is to use $(\mu, \sigma) = (0, 0.05)$ in equation (12) to generate price paths. The first two treatments alter the underlying statistical process. The *High Mu* treatment is to adopt drift in the random walk process ($\mu = 0.01$). This treatment

[19] The standard deviations are computed 10,000 returns from simulating equation (12) 10,000 times. $\sigma_3^{Base} = 0.0865$, $\sigma_3^{High\ Mu} = 0.0885$, $\sigma_3^{High\ Vol} = 0.173$. In signal treatment, we computed σ on the basis of posterior distribution after receiving signal in either direction. $\sigma_1^{Signal} = 0.046$ and $\sigma_3^{Signal} = 0.0796$.

is to analyze the heuristics that investors may have when asset prices are on an upward trend. The second treatment is to use higher volatility ($\sigma = 0.1$). Through The *High Vol* treatment, we examine whether there is a change in the way subjects allocate attention when looking at stock prices with high volatility. Finally, in the *Signal* treatment, we examine the behavioral changes of subjects when there is information other than stock price data, the typical environment situation for most investors. Before each round starts, subjects observe recommendations on whether the stock price will rise or fall for the prediction period, compared to the latest stock price available. The recommendation system is based on the difference between the true price for a given horizon and the most recent available price, $p_{t+i} - p_t$. The recommendation is "Up" ("Down") if $p_{t+i} - p_t$ is positive (negative). In order to minimize the possibility that subjects making simple guesses based on signal without examining the stock price data, the signal is designed to have an accuracy of 75%, not 100%. Yet, subjects have incentives to make a prediction corresponding to the signal since the expected payoff of following the signal is higher than the expected payoff of not following the signal. The *Signal* treatment uses $(\mu, \sigma) = (0, 0.05)$, as in the base setup to correctly gauge the impact of having signal alone.

4.5 Subjects

Subjects (N=175) are students from Purdue University studying various majors. We recruited subjects by email using the Online Recruitment System for Economic Experiments (ORSEE) (Greiner, 2015) from March to May, 2021. No subject participates in the experiment more than once. At the beginning of each session, an experimenter reads instructions aloud and subjects follow through their own copies of the instructions.[20] After subjects sign the consent form, they go through a calibration process provided by the eye-tracking system. Subjects are not allowed to continue the experiment when the system judges a subject's calibration quality to be poor. Further, records are filtered to remove data with insufficient quality from poor calibration or errors.[21] The final sample includes 136 subjects (73 males) with 4,262 rounds.

[20] An exact copy of instructions is available in Appendix B.

[21] First, if the device does not record eye movement at all, the data is excluded from the sample. Next, if the device records data with errors (i.e. continuously vibrating eye movements that are different from the actual eye movements), the data is excluded from the sample. Finally, if data quality reported by eye-tracking system is below 70%, then the round is excluded.

5 Results

5.1 Tests of the Attention Framework

Before analyzing what characteristics of data influence attention allocation, we test the underlying assumption of attention framework: Attention parameters estimated via eye-tracking reflect the actual computational weight in the responses of the experiment subjects. In particular, we confirm the equation (11) with several methodologies. It is important to verify the relationship between visual and mental attention, since this experiment aims to find heuristics in extrapolation by deconstructing how subjects allocate their attention during the prediction task.

Table 1 presents the results of OLS regressions with both subject and round fixed effects. *GazeRet* is the predicted return response based on the attention parameters measured by eye-tracking using equation (10). *GazeRet(trend)* and *GazeRet(level)* are from equations (8) and (9), respectively. We compare the predictability of *GazeRet* with other estimation methodologies used in the literature. *OLSRet* is the predicted return response of each round using the β values calculated by estimating equation (1) for each treatment. Finally, *NLRet* is the predicted return response of each round using the λ and β values calculated by estimating equation (2) for each treatment. Note that *GazeRet* is an ex-ante estimator of subjects' return response in all specifications, since it can be computed using the information acquisition process during the prediction task. On the other hand, *OLSRet* and *NLRet* are the results from the ex-post estimation of specifications (1) to (6). The definitions of other control variables are available in the Appendix table.

First, columns (1) to (3) show that *GazeRet* significantly predicts investors' return predictions at the 1% level. Specifically, a one percentage point increase in *GazeRet* is associated with an increase in return response of 0.27 to 0.42 percentage points. These results hold even after controlling for other variables such as *OLSRet*, *NLRet*, and other control variables. It is important to note that the predictability of *GazeRet* remains robust even after including visually salient returns, *Salient Ret*, *Max Ret*, and *Min Ret* in the price chart as control variables. This implies that the attention parameters measured in our experiment are not entirely driven by visual or bottom-up saliency (Bose, Cordes, Nolte, Schneider, and Camerer, 2020).

Next, the columns (4) to (6) show that the two components of the *GazeRet* also predict the return response at 1% significance level. Interestingly, as much as the *GazeRet* calculated

from the trend, the *GazeRet* calculated from the price level is also a significant predictor of the return response. This supports the observation from our data that subjects use a significant portion of attention to read prices.

Finally, in columns (7) and (8), we estimated *OLSRet* and *NLRet* out of sample. In column (7), we estimated equations (1) and (2) from the first 20 rounds and then used the estimated coefficients to compute return predictions in the latter 20 rounds. In column (8), we estimated equations (1) and (2) from the first 20 subjects of each treatment and then used the estimated coefficients to compute return predictions of the other subjects. There is a noticeable decrease in the size of the coefficient of *OLSRet* by about 0.7, and *GazeRet* outperforms other measures of expectations in all specifications.

Next, we investigate whether the quantitative pattern of the data can be explained within the attention framework. To check the quantitative fit between the actual return response and *GazeRet*, we perform the following non-parametric bootstrap 100 times. First, we create a bootstrapped sample by sampling with replacement as many as the number of rounds included in each treatment. Next, the average of the return response and the *GazeRet* for each treatment is obtained, and then plotted in the figure. The final outcome of the practice is 400 combinations of average *GazeRet* and return response.

Figure 4 shows the results of this simulation exercise by treatments. Figure 4, Panel A presents the quantitative fit between *GazeRet* and the actual response. For all treatments, data points are fairly well clustered. In addition, bootstrapped averages from *Base*, *High Mu* and *Signal* treatments are sorted along the diagonal line. The only exception is the averages from *High Vol* treatment that are located above the line, suggesting that *GazeRet* tend to underestimate the actual response in *High Vol*. Overall, *GazeRet* seems to provide an excellent quantitative fit for the return response data.

It is worth noting the characteristics of the actual response itself. The return response is close to 0, on average, in *Base* and *Signal*, whereas it is approximately 0.5 percentage points in *High Mu* and *High Vol*. Therefore, in *High Mu*, where drift is set to be one percentage point, subjects underestimated μ by 0.5 percentage point. On the other hand, in *High Vol* where no drift exists, subjects overestimated μ by approximately 0.5 percentage points. These results imply that the way subjects predict future prices could vary depending on the characteristics of data.

Figure 4, Panel B and Figure 4, Panel C describe the quantitative fit of each component of *GazeRet*: *GazeRet(trend)* and *GazeRet(level)*. While both figures show somewhat similar performance for *Base* and *Signal* treatments, dramatic contrast exists between the

performance in *High Mu* and *High Vol*. First, in the case of *GazeRet(trend)*, the measure quantitatively fits well with the return response for *High Mu*, but significantly underestimates the response for *High Vol*. On the other hand, in the case of level-based *GazeRet*, it shows relatively good quantitative fit with *High Vol*, while the measure underestimates average response from *High Mu*. The clear distinction in the result of two measures suggests that subjects may rely on different computational process according to the characteristics of price paths. Specifically, the results suggest that subjects seem to depend more on price levels than trends in the reasoning process for data where it is difficult to find a trend.[22]

The results in Panel B and C of Figure 4 also imply that there could be limitations in utilizing visual attention to gauge the actual thought process. For example, while eye-tracking data indicates that subjects read both trend and level information in any of the treatment, results suggest that trending is more dominant computational process when the data has a drift. It is important to bear in mind that there could be discrepancies between the acquired information and the information actually used when interpreting the results on visual attention.

Even so, the results suggest that *GazeRet* can be a reasonable ex-ante estimation of the return prediction. This ex-ante measure can be widely used in an environment where eye-tracking data can be collected.[23] In addition, *GazeRet* has a comparable quantitative fit to the actual response compared to *OLSRet* and *NLRet*. Figure A.4 in the Appendix implies *NLRet* varies too much and the fit is scattered, while *OLSRet* varies too little. Interestingly, Figure 4, Panel B and Figure A.4, Panel B in the Appendix present that *GazeRet(trend)* and *NLRet* have similar fit to the actual response. This result is not surprising, considering that the NL model is designed to catch the return extrapolation behavior of investors. The similarity between the two measures suggests that the attention distribution regarding trending past prices may appear similar to the shape of the weight function.

5.2 Summary of the Information Set

In this section, we first examine the summary statistics of the information set. Table 2 provides several implications for how subjects refer to past price information during the

[22] Such an interpretation is consistent with the result in Da et al. (2021), who use investor level mobile application data.

[23] Note however that the distribution of two measures could be different. Figure A.5 in the Appendix provides evidence that the distributions of the actual response and *GazeRet* are centered around the same mean. But Kolmogorov-Smirnov test rejects that the actual response and *GazeRet* have the same distribution.

prediction tasks. First, there is large variation in the amount of time and effort that subjects used to complete the task. The average time to make a prediction is approximately 14 seconds, but the shortest time reported is just 1.5 seconds, which may not be enough time to fully cover the data in the graph. On the other hand, the longest time reported is longer than 2 minutes. The average number of gaze paths for each round is approximately 38. Together with the average round duration of 14 seconds, this result suggests that subjects read approximately 2.7 gaze paths per second on average. The average number of gaze paths indicate that an average subject reads the price path with enough capability to cover most of the data. When the least effort was exerted, only two gaze paths were used, whereas, when the most effort was exerted, 377 gaze paths were used. Overall, average Subjects exerted enough time and effort to read most of the available data, while some did not read enough to process the entire data presented in the screen.

Subjects may still acquire most of the data in a price path with limited use of time and effort. Suppose a trend is identified through the gaze path from the beginning to the end of the graph. In that case, a subject can minimize blind spots of the graph with only a small number of gaze paths and a short duration. However, the table implies that in most cases, subjects fail to acquire all available data on the screen. The average number of returns recognized by the subject is 11, and the median is 13. In other words, approximately 50% of subjects are unintentionally blind to about 22% of available data. Similarly, the average number of prices perceived by the subject is only four. Moreover, while most of the subjects recognize the latest return available, r_{t-1}, only about 50% of the participants recognized the earliest return available, r_{t-17}. This imbalance suggests that subjects are more likely to be blind to returns from the distant past.

On the other hand, the average return perceived by subjects has a mean close to 0, suggesting that being positive or negative does not trigger more attention. Similarly, subjects do not appear to discriminate between prices above median and prices below median. Note, however, that the results in the summary table is more about overall recognition of the information rather than the attention allocation. Figure 5 is a box plot summarizing the information recognized by subjects by treatment. We can confirm that subjects fail to recognize all available data regardless of the treatment types or the characteristics of the data.

Overall, the summary suggests that while average subjects seem to have capability enough to process entire data, they are blind to a subset of data that does not draw attention. Moreover, some subjects exert insufficient effort to cover the entire data. The limited use of resources may be due to the heuristics that affect which information should be acquired

and disregarded. Specifically, the tendency observed from the summary is that the recent returns or prices are more associated with the future return than the distant past returns. More details of heuristic attention distribution will be discussed in the next section.

5.3 Heuristic Attention Distribution: Extrapolative Bias

In this section, we focus on how subjects allocate attention according to the characteristics of return and price. We first examine whether the attention distribution is affected by extrapolative beliefs: A Belief that recent data is more relevant to future price changes. Specifically, we compare the weight function and λ in equation (2) implied by the attention distribution with the existing results on extrapolative bias using Greenwood and Shleifer's (2014) model.[24]

Figure 6 shows how individual subjects distributed attention, sorted from the earliest to the latest available returns. Each dot represents the average degree of attention, m_k^r, for each k distributed by each subject. For example, the dots located at the rightmost position (time = 1) represent the individual subject's m_1^r values for r_{t-1}. The black dotted line is the average m_k^r from all subjects. Meanwhile, the colored lines depict the weight function with varying λ in the Greenwood and Shleifer's (2014) specification. Smaller λ implies a greater extent of the reaction to the recent return.

The overall trend of the attention parameter indicates that subjects' attention decays monotonically according to how far distant a return is, as the literature on the existing extrapolative bias suggests. On average, 18% of attention is allocated for the most recent return, while approximately 9% is allocated to r_{t-9}, and almost 0 attention is allocated to the most distant return. Compared to the weight when attention is equally distributed to all returns, approximately 5.9%, the figure suggests that subjects are significantly overweighting recent returns. The degree to which the weight decays corresponds to λ of 0.82 in the Greenwood and Shleifer (2014). Although there is no correlation between the simulated returns, the figure suggests subjects are excessively attentive to recent returns.

The finding that attention geometrically decays with regard to time indicates that there are heuristics among subjects that they find recent returns more relevant to future price changes. This is surprising as the true data generating process was a random walk in which the autocorrelation between returns is set to zero. The time-decaying attention implies

[24] Since there is no existing literature on extrapolative beliefs based on price levels, we focus on returns rather than price levels.

that overextrapolation in expectation formation reported in empirical research may stem from investors' heuristics that they are inattentive to what happened in the past. More specifically, the attention channel of overextrapolation presented here suggests that subjects' information sets are distorted toward recent returns, regardless of how predictions are made with the acquired information.

Next, attention distribution for each subject is significantly different from one another. For the subject with the most excessive interest in the recent return, m_1^r is 0.67, whereas, for the subject with the least interest, m_1^r is only 0.006. Specifically, the 10th percentile of m_1^r is 0.07, meaning that approximately 10% of the subjects are underweighting the recent returns. Another interesting result is that the degree of attention for the recent returns has a large variance by subject, while weights for the previous returns are clustered at a certain level. This finding supports the idea of weight function in the Greenwood and Shleifer model: the change in the degree of extrapolation is mainly represented by the change in weight for the most recent return. Overall, the observed heterogeneity across subjects indicates that the heterogeneous extrapolative bias assumed in recent theories may stem from the varying degree of heuristics in the information acquisition process.

Finally, Figure A.6 in the Appendix presents the time decaying attention weight for each treatment. In general, unlike previous results reporting heterogeneity across subjects, attention allocation does not vary significantly across variation in data generating process.[25] This result is surprising, as the result in quantitative fits indicate that *GazeRet* computed from trending is significantly more associated with the actual prediction in *High Mu*. This indicates that there are two separate channels that heuristics affect the computational process of extrapolation. The first channel is the heuristics in the information input process where only a subset of information is perceived while the rest is ignored. The second channel is the heuristics in processing the information where more prevalent information enters into the actual computation.

[25] The slight difference is that *High Mu* and *High Vol* are above the *Base* treatment for most of the recent period, suggesting that subjects overweight recent returns more when there is an obvious trend or when returns are volatile. On the other hand, in *Signal* treatment, subjects overweight recent returns more than in any other treatments. This could be because attention is limited: Subjects do not have enough attention to cover the entire price path because they have to keep thinking about the signal during the prediction task.

5.4 Heuristic Attention Distribution: Tail Events

Next, we investigate a different type of heuristics: Whether subjects have heuristics to pay excessive attention to extreme or rare events. Figure 7 examines the effect of the relative ranking of return and price on the attention distribution. Figure 7, Panel A shows that the relative ranking of the return has a significant effect on the attention weight. In particular, the returns in the lowest ranks (Rank = 1) and the highest ranks (Rank = 9) receive more attention than the returns in the middle rank (Rank = 5) from 0.5 percentage points to 1 percentage point. The U-shaped attention plot supports the empirical finding that investors overweight the events with small probability when forming expectations on stock price (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Barberis et al., 2016). Moreover, lower-ranked returns are overweighted more than higher-ranked returns on average. This imbalance is shared by all but the signal treatment. This suggests that regarding attention, left tail events draw more attention than right tail events.

Figure 7, Panel B shows that the relative ranking of price also has an essential effect on how attention is distributed. In all treatments except for High Mu, subjects allocate much more attention to peak and trough than other prices. The price at both extremes receives approximately two percentage points more weight than the price with median rank. This result implies that subjects are excessively influenced by peaks and troughs when predicting future prices. On the other hand, in the case of High Mu, subjects allocate more attention to the peak compared to the trough. This imbalance seems natural since recent prices tend to have higher prices in High Mu. Interestingly, however, the consequence is that an upward trend in the data could lead to inattention to the trough. The result suggests an interesting mechanism for why left tail risks are often ignored in a bull market: Investors don't remember trough because it occurred in the distant past.

5.5 Two Determinants of Attention

We now investigate whether two determinants of attention, the distance to the current time and the rarity of an event, are robust to the inclusion of a set of controls. Table 3 is the result of logistic and OLS regressions with attention to returns. For a dependent variable, OLS regressions use m_k^r, where as logistic regressions use a dummy variable that equals one

if $m_k^r > 0$.

$$m_{s,r,k} = \alpha_s + \beta Time_{s,r,k} + \delta Abs(Z)_{s,r,k} + \xi Time_{s,r,k} * Treat_s \\ + \phi Abs(Z)_{s,r,k} * Treat_s + \psi Treat_s + \epsilon_{s,r,k} \tag{14}$$

where s indexes subjects, r indexes rounds, and k indexes for time for r_{t-k}.

The results from columns (1) to (3) show the effect of two characteristics of returns and prices on the probability to receive any attention during the prediction task. Column (1) shows the results using the whole sample. The estimated coefficients imply that a unit increase in Time is associated with a 0.788 (21.2%) decrease in the odds ratio of receiving any attention. In addition, a unit increase in Abs(Z) leads to a 1.04 (4%) increase in the odds of receiving attention.[26] These results indicate that both Time and Abs(Z) play an important role in determining which returns are to be included in the information set. Column (2) shows that Time has a larger effect on the probability in *High Mu* and *High Vol* treatments compared to the base treatments. On the other hand, column (3) shows that the effect of Abs(Z) does not differ across the treatments.

The results from columns (4) to (6) shows the effect of two characteristics of return on the attention weight, m_k^r, during the prediction task. The result using the whole sample in column (4) shows that both Time and Abs(Z) affect the size of m_k^r. Specifically, a unit increase in Time is associated with the decrease of m_k^r by 0.837 percentage points. A unit increase in Abs(Z) leads to the increase in the m^r by 0.095 percentage points. Column (5) displays no significant difference in the effect of Time on m_k^r across treatments. Column (6), however, presents that the positive effect of Abs (Z) on m^r does not exist in *High Vol*.

Table 4 presents the logistic and OLS regression results with attention to prices, m_k^p. Rank indicates how close the price is to the median in that price path. For example, if a price is either peak or trough, the value of Rank is 9. On the contrary, median prices have the value of rank of 1. The results are similar to the attention to returns. In logistic regressions from column (1) to (3), a unit increase in Time is associated with an approximate 0.85 (15%) decrease in the odds ratio of receiving positive attention. A unit increase in Rank leads to about 1.05 (5%) increase in the odds ratio. Similarly, in the result from OLS regression, a unit increase in Time is associated with the decrease of m_k^p for -1.383 percentage points. A unit increase in Rank is associated with the increase of m_k^p for 0.466 percentage points.

[26] A unit increase is an approximate 0.80 increase in the absolute value of the standardized returns.

One interesting question could be whether there is a learning effect in subjects' attention allocation. Are subjects less affected by the two determinants when acquiring information for return prediction as they gain experience? To investigate this question, we study whether the degree to which return and price characteristics affect attention allocation differs in the first 20 rounds and the latter 20 rounds. Results in Table A.2 and Table A.3 do not support that learning effects exist in attention allocation: Heuristics in information acquisition do not disappear even though they gain additional experience of 20 rounds. However, these results do not indicate that learning has little effect on how subjects allocate attention for the following two reasons. An additional experience of 20 rounds may not be enough for the learning effect to exist. Next, fatigue may have offset the learning effect, as subjects would be more tired in the 20 rounds than in the first 20 rounds.

The results so far show that the more recent and rare the data are, the more attention the subjects allocated. The natural question by having two determinants of attention is whether there is any interaction between them. In particular, are tail events forgotten less, even after time has passed? To investigate this, we sorted returns and prices into nine groups separately by time and relative ranking within a price path. Then, using the entire sample, we obtained the average of m^r and m^p for each double-sorted group. This exercise examines whether subjects allocate relatively large amounts of attention to tail events in the distant past.

Figure 8 presents the average attention weight of each double sorted group as a heatmap. First, Figure 8, Panel A is the result of return. The attention distribution indicates that the degree of attention change with time is much larger than that of return ranking. In addition, return rank groups do not differ in terms of how fast the attention weight decays. Therefore, it can be concluded that the interaction between the two determinants does not exist in m^r. On the other hand, the results for price in Figure 8, Panel B are quite striking. There is no significant difference in the degree of attention according to the price rank in the most recent data (the right-most column). However, prices with higher ranks tend to receive more weight in the distant past. The decay of the attention weight is much slower for prices with a higher rank. That is, subjects seem to have relatively longer memory for past peaks than other prices. Under the attention framework, longer memory for peaks could lead to optimistic return prediction.

What is the qualitative implication of the results in Figure 8 in the actual investment? Suppose an investor who relies on extrapolation wants to predict the price of a stock. First, the investor will try to reflect recent price movements in future stock prices. Past return fluctuations would not override recent returns, even if extreme price changes were in the

distant past. Nevertheless, the investor also looks at price information, trying to reflect the average of recent prices in future stock prices. In addition, the investor pays considerable attention to past peaks. If a stock has recorded a high stock price in the past, the investor tends to believe in the possibility of recovering to the peak level when the current stock price is lower. This belief could make overly optimistic predictions about future stock prices.

5.6 Attention Distribution and Prediction Error

The results so far suggest that subjects have heuristics to pay more attention to recent data and rare and extreme data during the prediction task. In this section, we study whether such heuristics should be interpreted as cognitive biases that interrupt subjects' utility maximization. Since subjects are incentivized to make as much accurate predictions as possible, the question is whether the heuristics are associated with the poor performance of subjects.

The quality of a decision can be defined as the deviation of response from the optimal prediction that subject can make based on given information. The larger deviation is associated with inferior decision quality. The main measure is a deviation of return response from the overall trend of the sample and is computed as follow:

$$Error(\hat{\mu}) = \frac{1}{\sigma_i}\left|\left(\frac{p_t}{p_{t-17}}\right)^{\frac{1}{17}} - \left(\frac{\widetilde{p_{t+i}}}{p_t}\right)^{\frac{1}{i}}\right|, \tag{15}$$

where σ_i is a true standard deviation of the data generating process for prediction horizon i, and $\widetilde{p_{t+i}}$ is a subjects' prediction for i. This measure is based on the assumption that a subject would use the sample μ, $\hat{\mu}$, as a proxy for true μ, if she knows returns are from a random walk process. The measure can be interpreted as a standardized error whose benchmark is a sample μ. To complement this view about the optimal behavior, we introduce two additional measures of the decision quality. The second measure assumes a subject has full information about the data:

$$Error(\mu) = \frac{1}{\sigma_i}\left|1 + \mu - \left(\frac{\widetilde{p_{t+i}}}{p_t}\right)^{\frac{1}{i}}\right|, \tag{16}$$

where μ is true parameter from the data generating process. The third measure is the actual

performance of a subject in the experiment and measured by the following equation:

$$Error(RS) = \frac{1}{\sigma_i}\left|\left(\frac{p_{t+i}}{p_t}\right)^{\frac{1}{i}} - \left(\frac{\widetilde{p_{t+i}}}{p_t}\right)^{\frac{1}{i}}\right|. \tag{17}$$

Table 5 presents the result of regressing three measures of decision quality on the characteristics of a subject's information set and attention distribution. The first three columns use $Error(\hat{\mu})$ as a dependent variable. Column (1) shows the result using the amount of information acquired as variables of interest. First, the number of gaze paths is negatively related with $Error(\hat{\mu})$. A unit increase in the gaze path is associated with a 0.335 percentage point decrease in the standardized error. The interpretation is that the amount of information acquired is associated with the decision quality, since careful investigation of data involves less heuristics. Note that the round duration is *positively* correlated with $Error(\hat{\mu})$, meaning that the amount of information, not the time spent, matters. Next, a unit increase in the number of returns perceived leads to 0.584 decrease in the standardized error. This result also shows that acquiring information is important in making better decision. On the other hand, the number of prices perceived is positively related with error. The price information is irrelevant in estimating the true μ. We can interpret this result as acquiring noisy information leads to inferior decision quality.

Column (2) shows that heuristic allocation of attention is associated with inferior decision quality. M(Recent), the sum of m^r for the recent three month returns, is positively correlated with the error. Specifically, a ten percentage point increase in the allocated attention to recent returns is associated with a 0.73 increase in the standardized error. The result is striking for M(Rare Z), the sum of m^r for two lowest and two highest returns in a price path. A ten percentage point increase in the allocated attention to extreme returns leads to 1.67 increase in the standardized error. This result clearly shows that excessive attention to rare events could prevent subjects from making accurate predictions. On the other hand, attention to extreme prices is not associated with the decision quality in this experiment.

Column (3) includes all variables of interest in the analysis and shows that all but M(Recent) are robust to the change. The insignificant coefficient of M(Recent) is not a concern, since M(Recent) has a high correlation with the number of returns perceived. Column (4) uses $Error(\mu)$ and column (5) uses $Error(RS)$ as a dependent variable. The previous results are robust to using alternative specification in general, though M(Rare Z) is not significant in column (5).

5.7 Attention Distribution and Demographics

The last analysis investigates the correlation between the attention distribution and demographic characteristics of subjects. We focus on traits including gender, grade point average (GPA), STEM major, the number of statistics and finance courses taken, self-evaluated investment experience, and the score from CRT test from Frederick (2005).[27] Popular demographics including age or income are excluded from our survey since undergraduate subjects are not meaningfully heterogeneous in those characteristics.

Table 6 presents the results. Among demographic characteristics analyzed in this table, *MALE* is positively correlated with the attention allocated to extreme events in columns (5) and (6) at the 5% significance level. Male subjects tend to spend more time reading extreme returns and price peaks and troughs. Furthermore, although insignificant, our results suggest that male subjects acquire less information from the data in general. Our findings are consistent with the literature that indicates gender affects how much an investor is susceptible to behavioral biases (Barber and Odean, 2001). Next, subjects from STEM majors tend to complete 5.015 more gaze paths and read 1.017 more returns on average compared to subjects with non-STEM majors. Further, subjects from STEM majors allocate less attention to the latest two month returns and price peaks and troughs. Finally, high scores in CRT, indicating a subject is a less intuitive thinker, are negatively related to excessive attention to recent returns and price peaks and troughs. The result is consistent with studies showing that CRT score correlates highly with various measures of mental heuristics. (Frederick, 2005; Oechssler, 2009; Hoppe, 2011)

Although the results are not statistically significant, it is worth mentioning that subjects who have taken more courses in statistics and finance tend to perceive more returns and allocate less attention to recent and extreme returns. Together with the results for STEM, our results so far suggest that STEM and training in statistics and finance seem to help in acquiring more information with less reliance on heuristics. Further, coefficients for self-reported investment indicate that being experienced helps alleviate the heuristic attention distribution in general. Being experienced is associated with less attention to recent and extreme returns.

To conclude, results in Table 6 indicate that some of the demographic characteristics from our survey are associated with heuristic attention allocation, although this analysis makes no

[27] The classification to STEM major follows the list published by The U.S. Department of Homeland Security (DHS). The CRT test measures the tendency to stifle intuitive answers and arrive at more thoughtful and accurate answers.

effort to evaluate a causal interpretation. Nevertheless, the influence of educational factors is notable. If a causal relationship could be established, STEM or statistical education can potentially reduce the extent to which heuristics are involved in information acquisition process during investment decision-making. Considering the previous results that heuristic attention allocation negatively affects the decision quality in price prediction, the results in Table 6 imply that minimal education could be a way to protect investors from their own biased decisions.

6 Conclusion

Extant literature studies how investors use past price information to gauge future price changes. Yet, knowledge of the origins and underlying mechanisms of extrapolative behavior remains largely unknown despite its importance. One of the reasons is the limitation of the existing methodology that relies on price information or surveys in which the reason behind the prediction or choice is often unobserved. In this study, we overcome this problem by introducing a new technology to finance literature, eye-tacking, through which we can observe the information acquisition process during expectation formation. In particular, we conduct an experiment during which investors predict future stock prices based on price charts in the gamified investment environment.

In order to learn the information acquisition process, we collect data on which parts of the price chart are read and for how long. We use gaze paths as a unit of acquired information. We conjecture that a trend is read if a gaze path connects two prices in a chart. On the other hand, we assume a price level is read if a gaze path connects a price and a location indicating non-price information. Based on how subjects allocate attention to the past returns and price levels, we closely observe the heuristics in information acquisition and examine their effects on the precision of the prediction.

To provide direct evidence that the heuristics of the information acquisition process are related to the actual prediction, we propose an attention-based framework of extrapolation that generalizes the framework of Greenwood and Shleifer (2014). In this framework, the expectation is modeled as a linear function of past returns and prices with allocated attention as a weight. Gaze paths associated with reading past returns are used to compute attention allocation over past returns. On the other hand, Gaze paths associated with reading past prices are used to compute attention allocation over past prices.

We compare the quantitative fit between a measure of expectation based on attention and the actual prediction through a non-parametric bootstrap. The findings confirm that the eye-tracking-based measure of expectation generally represents the actual prediction well. In particular, trend-based prediction explain the actual prediction well when the random walk process with drift is the data generating process, and level-based prediction explain the actual prediction well, especially when volatility is high. OLS regressions also confirm a positive relationship between the attention-based measure of expectation and the actual prediction.

Subjects pay excessive attention to recent returns and prices. Approximately 40% of attention is allocated to the most recent three-month data, which corresponds to a λ of 0.85 in the Greenwood and Shleifer (2014) Framework. The heuristics of when reading past prices make subjects focus on recent data with high probability and unintentionally blind to distant past data. These results suggest that the overextrapolation bias in expectation formation is reflected in the disproportionate information acquisition of price information. On the other hand, subjects pay significant attention to extreme returns and prices, and show relatively little interest in data in moderate areas. The attention distribution is U-shaped along the relative ranking of prices and returns in the graph. The excessive interest in the tail events that makes subject neglect the base rate of return distribution, is also reflected in the information acquisition process.

When comparing two different types of heuristics using the attention parameter, we find that the degree of attention focused on recent data is relatively larger than the degree of concentration on the tail event. The exception is price peaks. Subjects have a relatively longer memory for price peaks compared to moderate prices. This result supports the idea that extreme events have long lasting effects on investors' expectation, regardless of the effect from memory or experience. Overall, subjects acquire information that draws their attention by heuristics to infer future price changes, while disregarding information that does not attract attention.

In addition, we also confirm that the heuristics reflected in the information acquisition process are heterogeneous across subjects, but no significant differences are observed across treatments. This finding suggests that the heuristics in the information acquisition process are likely to stem from individual-level psychological bias rather than reactions to external conditions. In particular, the subject group that received STEM education or took three or more statistics courses has less attention bias compared to other subjects.

On the other hand, heuristics in information acquisition are associated with a decrease in

the decision quality of subjects. First, the amount of information acquired is associated with the prediction precision. The number of gaze paths, the number of returns seen are positively associated with prediction quality. The number of prices seen is positively related to the negatively associated with prediction quality, as the price information should not be used in the return prediction. Next, the heuristics in attention distribution are also associated with the prediction quality. Specifically, the more focused on recent data and the more focused on extreme return, the lower the prediction accuracy compared to the benchmark.

The findings of this paper have important implications. First, this study sheds light on how investors extrapolate through analyzing the information acquisition process. Observed heuristics in the information acquisition process indicate that subjects fail to recognize the actual distribution of data: They tend to focus more on price information with specific characteristics. Furthermore, the results of this paper indicate that heuristics are directly associated with prediction quality. Therefore, this paper provides a microfoundation of theories of expectation formation based on extrapolative beliefs by documenting the mechanism through which heuristics intervene rational expectation formation.

Second, this study suggests that attention framework can be used as a unifying theme of various behavioral models. This study compares two heuristics through the methodology of using physiological measure of attention. The quantitative comparison between the biases is possible if two psychological biases can be modeled based on the same framework. The comparison between different psychological processes is important to better understand how heuristics affect investors' decision. While this study focuses on the overextrapolation and excessive attention to extreme events, it will be interesting to compare more heuristics using attention framework in future research.

Third, as recent theories on extrapolative bias hypothesize, this study shows that the heuristics of the information acquisition process are heterogeneous. Providing direct evidence on the heterogeneous belief of return extrapolation is difficult due to the methodological limitations of price data. In particular, it is often impossible to know whether the disagreement in expectation stems from different beliefs or different information. This paper provides direct evidence that beliefs can be heterogeneous even among unsophisticated investors relying on the same source of information.

Finally, this study confirms that the actual prediction can be ex-ante measured through the information acquisition process. The results of the paper suggest that heuristics in information acquisition process reflects the biases affecting expectation formation. Therefore, this finding has an important practical implication: By tracking the heuristics of the information

acquisition process in real time while investors trade, the possible error in their subjective expectations can be detected in advance.

In this study, we investigate the mechanism of extrapolative thinking by utilizing the fact that the information acquisition process reflects the computational process of prediction. However, the fact that the information acquisition process is endogenously determined is also the limit of this study: It is impossible to judge whether causality exists between heuristics and biased beliefs in the search process. If the causality can be confirmed, the implication is that it will also be possible to de-bias extrapolative beliefs if the data acquisition process is controlled. Due to the development of technology, many wearable devices can provide physiological data. Based on eye-tracking technology, many attempts have been made to assist decision making in various industries, including aviation, medical services, and sports. Revealing the causality between attention and biased expectations is not only an interesting research avenue, but it can also serve as a cornerstone for practically adopting physiological data in the finance industry.

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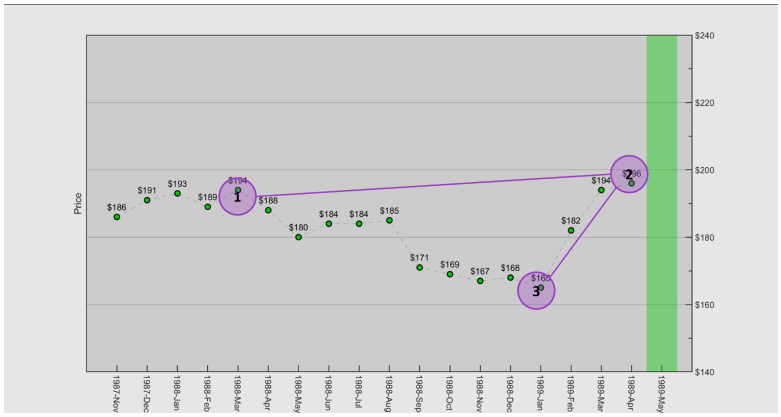
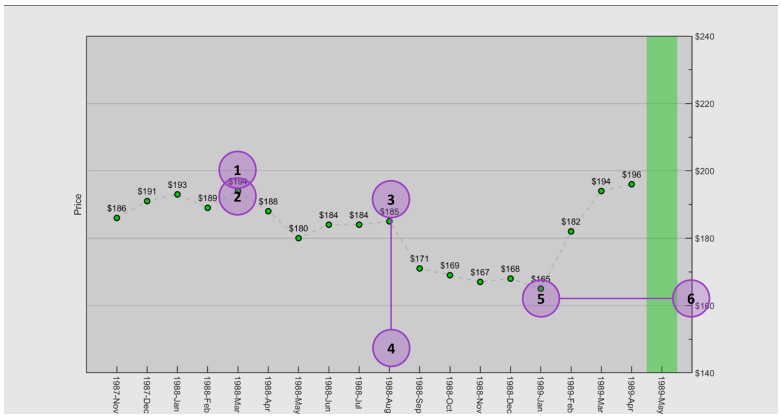
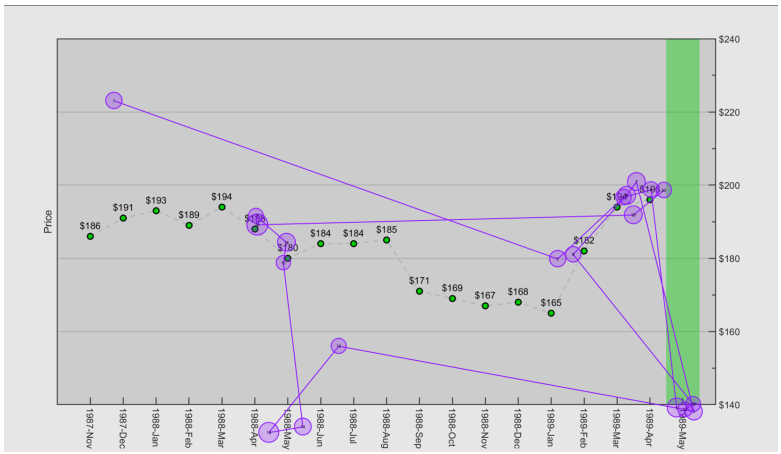


(A) Gaze Path Example: Trend



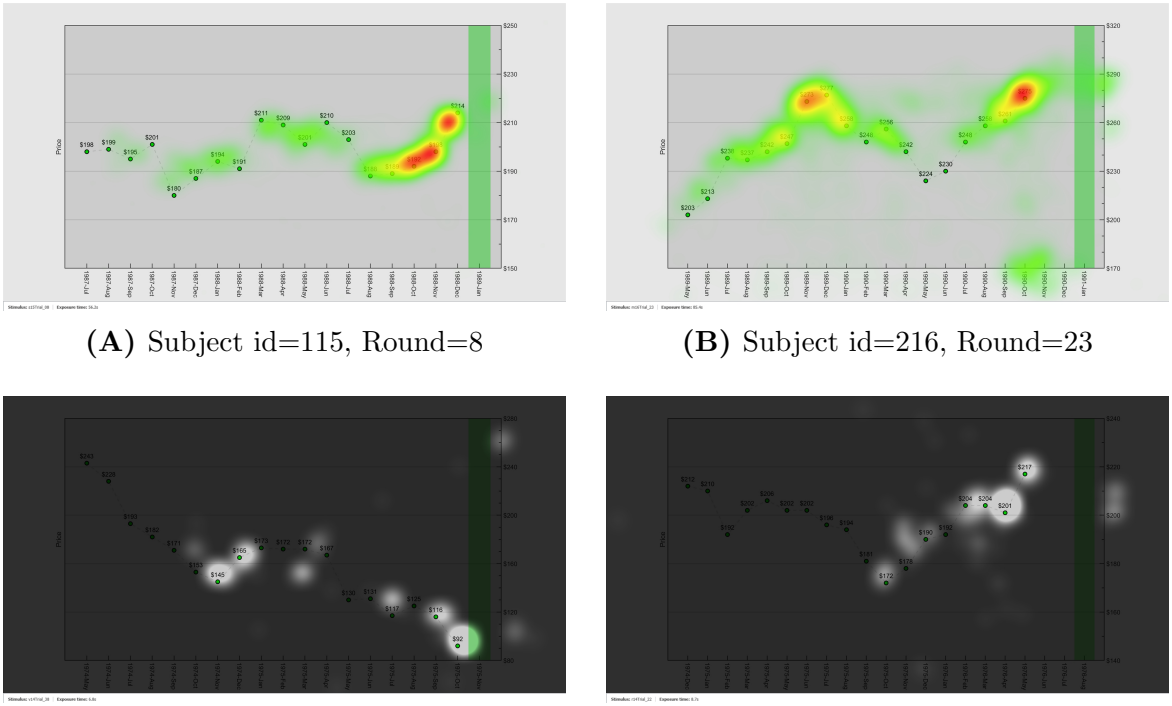
(B) Gaze Path Example: Level



(C) Gaze Path Example: Actual

Figure 1
Examples of Gaze Paths

The figure illustrates how to interpret the gaze paths collected from eye-tracking. Panel A is an example of the gaze paths that represent trend reading. Panel B is an example of gaze paths that represent price level reading. Panel C is the image of gaze paths collected from the actual experiment. Yellow circles represent the fixation points, and lines represent how fixation has shifted from one to another. Numbers in a circle represent the order of fixations.



(A) Subject id=115, Round=8

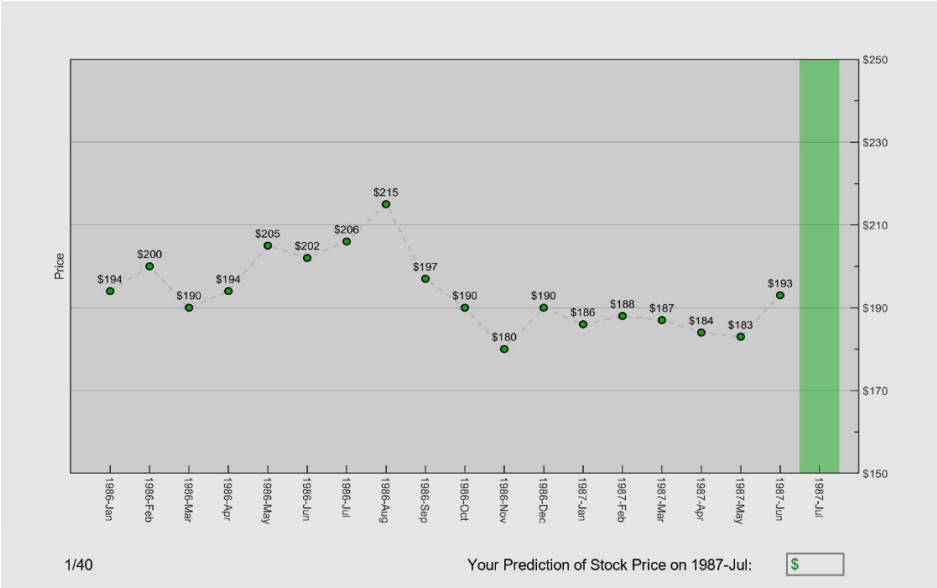
(B) Subject id=216, Round=23

(C) Subject id=314, Round=38

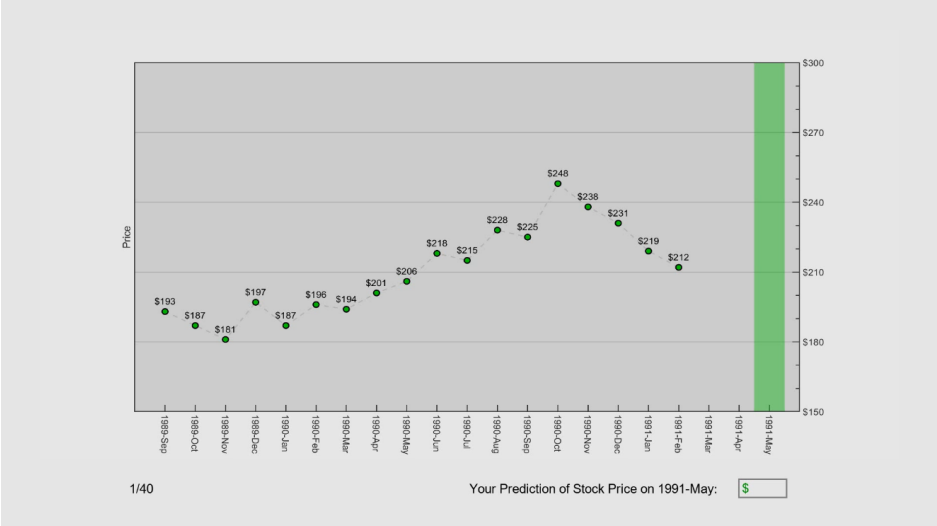
(D) Subject id=414, Round=22

Figure 2
Examples of Saliency Map

The figure offers examples of a saliency map from the actual experiment. Panel A and B are the examples represented in heatmaps. The "hotter" the colors the more and longer fixations are in one area. Panel C and D are the examples represented in scope maps. Scope maps are the inverse of the heatmaps: More and longer fixations lead to a clearer view of the page.



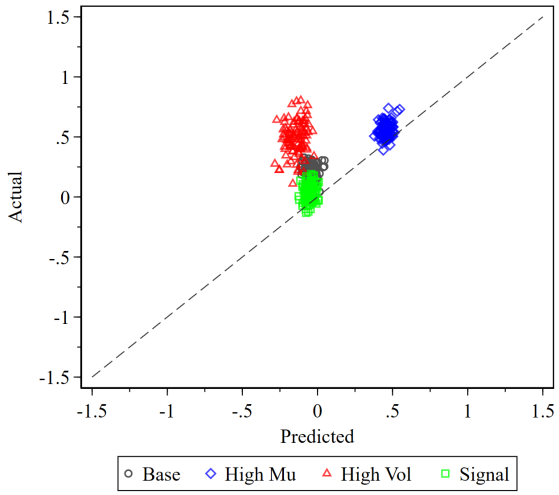
(A) One Month Prediction



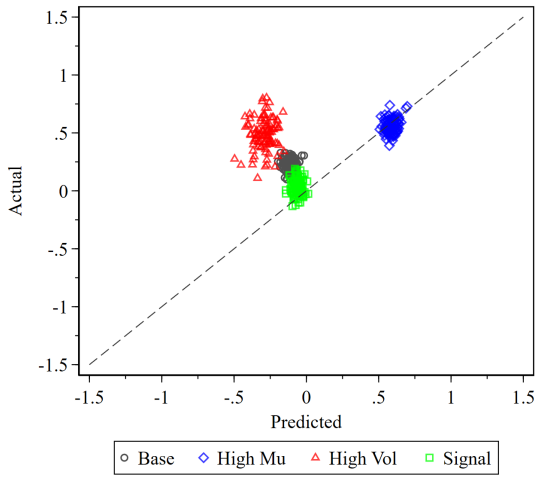
(B) Three Month Prediction

Figure 3
Sample Screen

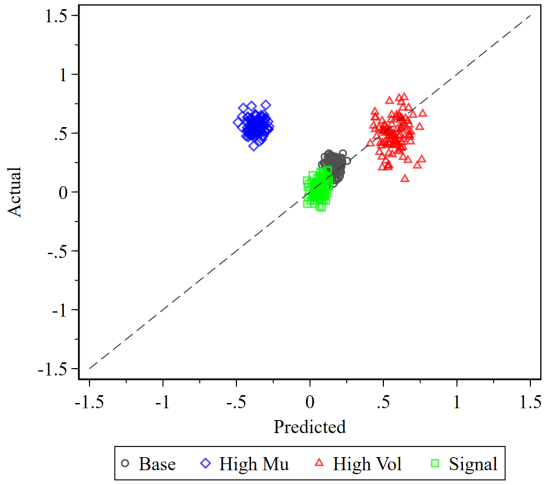
This figure shows the screenshots of the actual experiment. Panel A is an example of a one month prediction task. Panel B is an example of a three month prediction task. The y-axis is the price of a stock denoted in USD, and the x-axis is the date. Each dot represents the stock price at the end of month.



(A) GazeRet: Whole



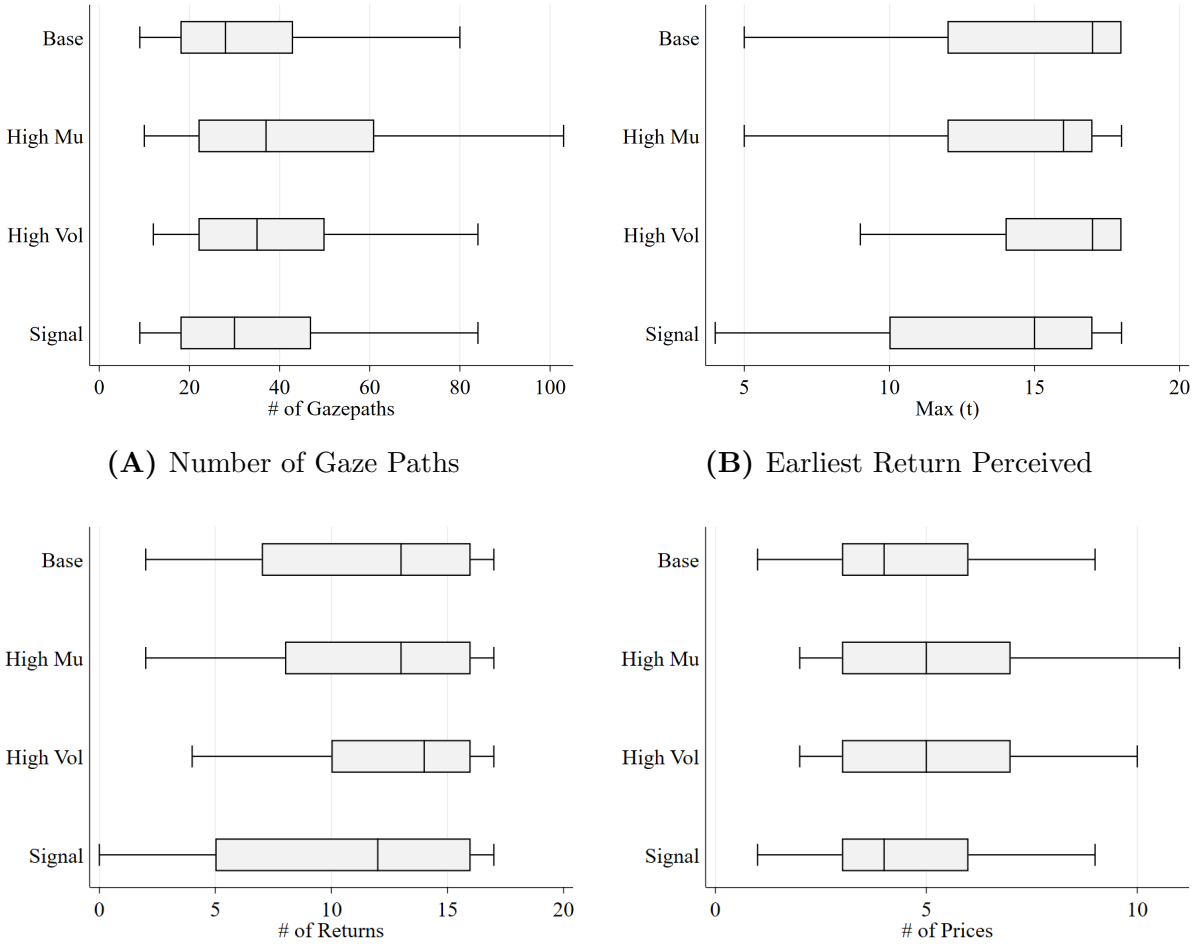
(B) GazeRet: Trend



(C) GazeRet: Level

Figure 4
Quantitative Fits of the Attention Model

The figure depicts the quantitative fit of an attention model using non-parametric bootstrap. First, we create a bootstrapped sample by randomly sampling with replacement for each treatment. Next, the average of the actual return response and predicted response using equation (10) is computed at the treatment level. Then, we repeatedly perform the sampling procedure for a hundred times. Grey colored circles represent the average of samples from the *Base* treatment. Blue colored diamonds represent the average of samples from the *High Mu* treatment. Red colored triangles represent the average of samples from the *High Vol* treatment. Green colored squares represent the average of samples from *Signal* treatment. The Y-axis represents the average of actual response, while the X-axis represents the average of predicted response. Panel A is the result using the combined *GazeRet* as a predictor. Panel B is the result using the *GazeRet* from trend reading. Panel C is the result using the *GazeRet* from price level reading.



(A) Number of Gaze Paths

(B) Earliest Return Perceived

(C) Number of Returns Perceived

(D) Number of Prices Perceived

Figure 5
Effect of Treatments on Information Set

The figure is the summary of information set for each treatment. The right hinge of the box is the 75th percentile and the left hinge is the 25th percentile. *# of Gazepaths* represents how much gaze paths a subject used to read a price path during the prediction task of each round. *Max(t)* is the earliest return seen by a subject each round. *# of Returns* is the number of returns seen by a subject each round. *# of Prices* is the number of returns seen by a subject each round.

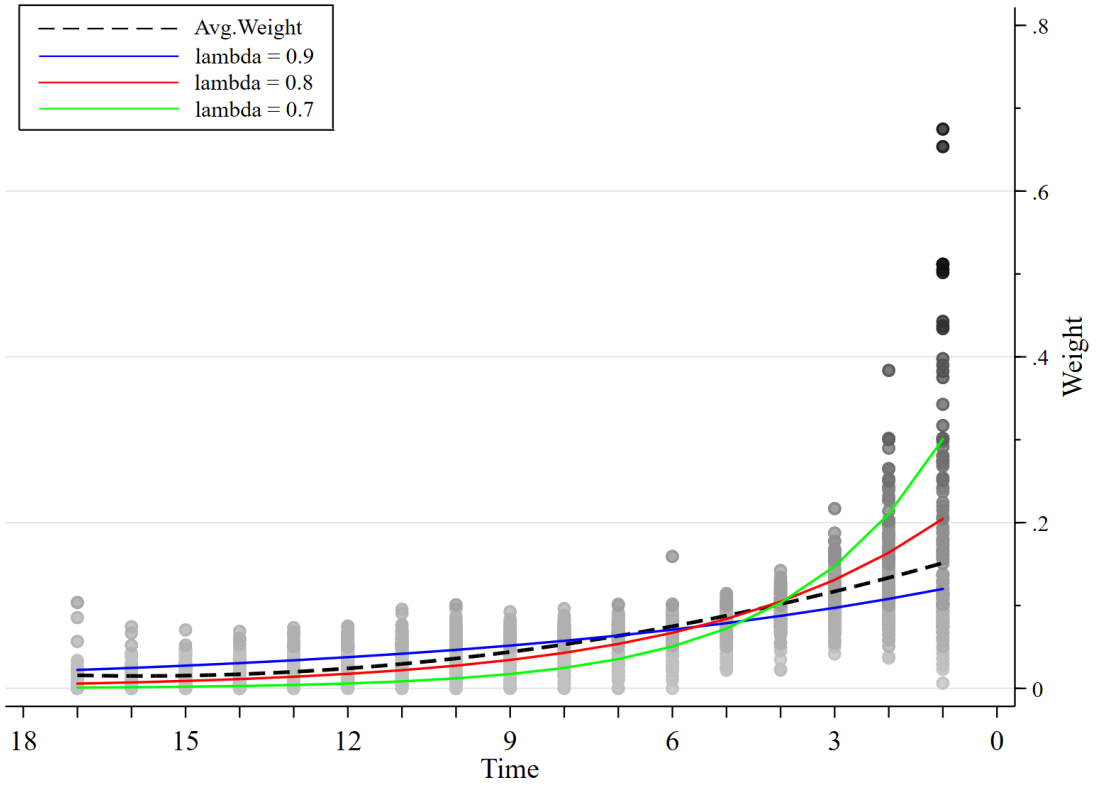
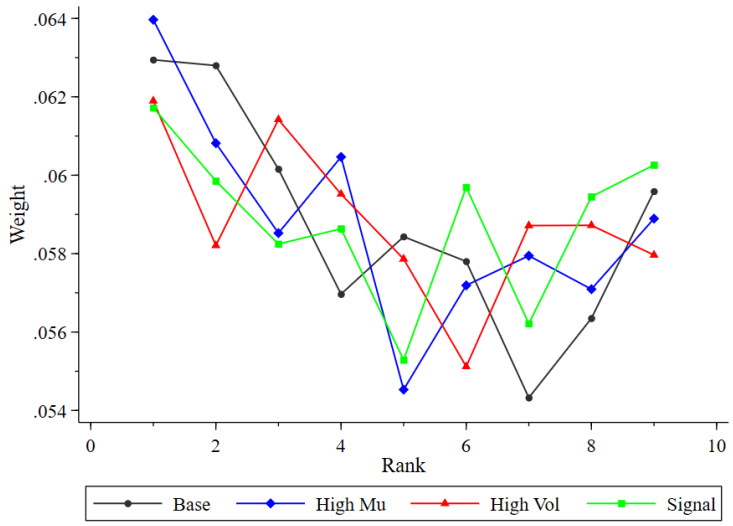
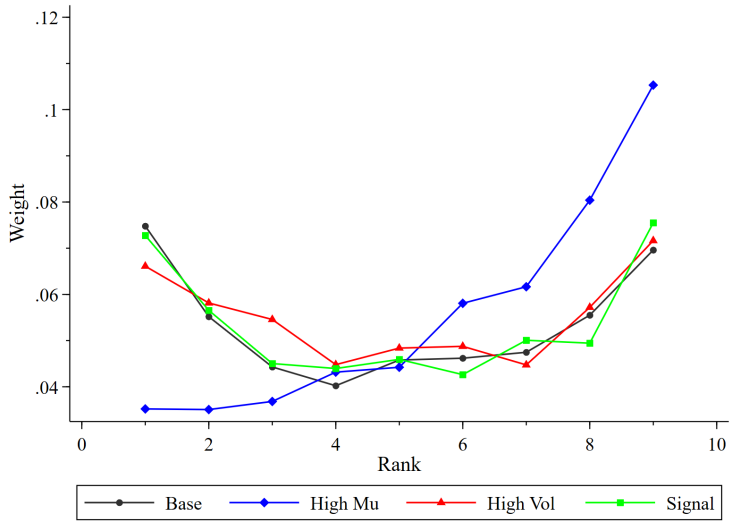


Figure 6
Attention to Past Price Paths: Time

The figure compares the attention allocation with regard to the recency of return with the geometric decay function w from Greenwood and Shleifer (2014). Each dot represents the average m_k^r for r_{t-k} of a subject s. The dotted line is the average m_k^r from the whole sample. Colored lines illustrate the function w obtained from three different λ.



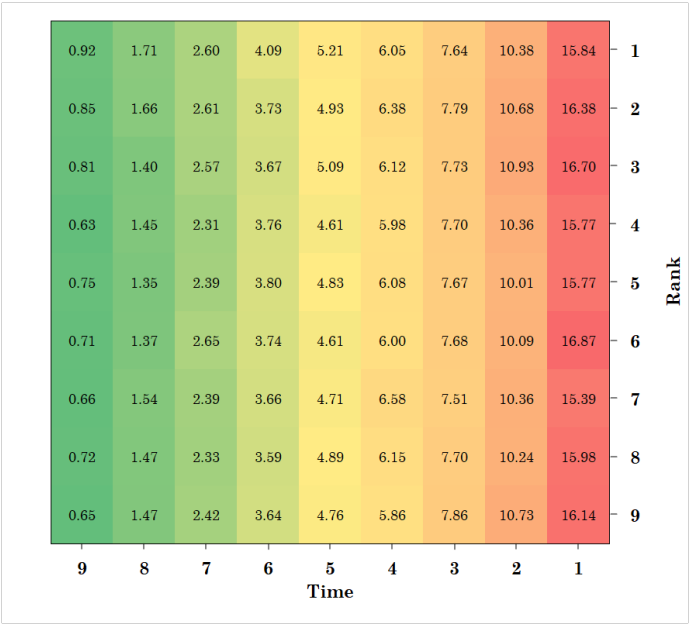
(A) Return Ranking



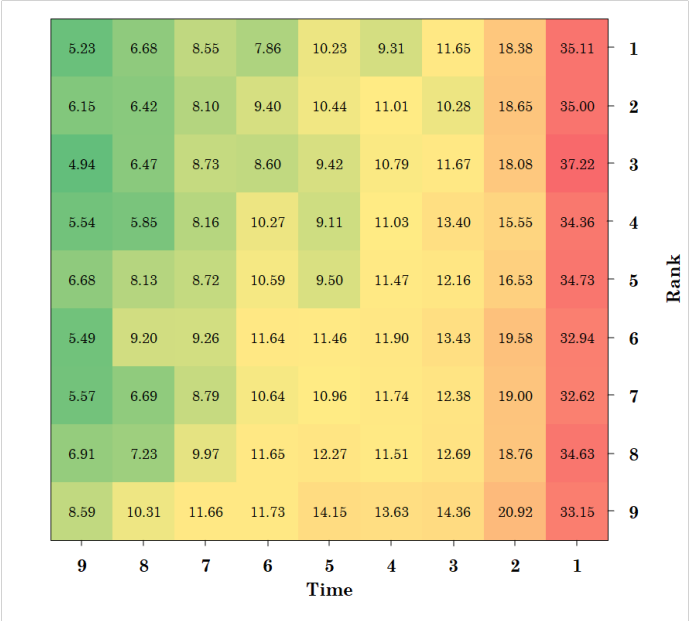
(B) Price Ranking

Figure 7
Attention to Past Price Paths: Ranking

The figure compares the attention allocation with regard to the ranking of returns and prices across treatments. Panel (a) depicts the average attention allocated for each return group. Panel (b) depicts the average attention allocated for each price group. For each round, returns and prices are sorted into nine groups from the lowest (1) to the highest (9) according to their ranking within a price path. The attention parameter m_k^r allocated to r_{t-k} are averaged within each group.



(A) Return Ranking



(B) Price Ranking

Figure 8
Attention to Past Price Path: Time and Ranking

The figure illustrates the attention distribution with regard to both the recency and the ranking of returns and prices. anel (a) depicts the average attention allocated for each return group. Panel (b) depicts the average attention allocated for each price group. For each round, returns and prices are sorted into nine groups according to how recent the return is. At the same time, returns and prices are sorted into nine groups from the lowest (1) to the highest (9) according to their ranking within a price path. The attention parameter m_k^r allocated to r_{t-k} are averaged within each double sorted group.

Table 1
Predictability of Attention Model

The table shows the results of OLS regressions of the actual return response by subjects on the eye-tracking-based measure of expectation:

$$Exp_{s,r} = \beta GazeRet_{s,r} + \delta X_{s,r} + \zeta_s + \eta_r + \epsilon_{s,r}$$

where s indexes subjects, and r indexes rounds. ζ_s and η_r are subject and round fixed effects. *GazeRet* is the eye-tracking based measure of prediction from equation (10). *GazeRet(trend)* is the measure of prediction based on trend-reading gaze paths from equation (8). *GazeRet(level)* is the measure of prediction based on level-reading gaze paths from equation (9). *OLSRet* is the estimated prediction computed from the coefficients obtained from the equation (1). *NLRet* is the estimated prediction computed from the coefficients obtained from the equation (2). *SalientRet* is the average of returns adjacent to a price peak and trough in a price chart. *MaxRet* is the maximum return observed in a price chart. *MinRet* is the minimum return observed in a price chart. *Surprise* is the difference between the return prediction and realized return from a previous round. *Sample* μ is the average slope of a price chart each round. *Sample* σ is the standard deviation of returns each round. Standard errors are clustered at both the subject and round levels in all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GazeRet	0.272***	0.300***	0.309***				0.313***	0.422***
	(0.075)	(0.073)	(0.074)				(0.077)	(0.095)
GazeRet(trend)				0.210***	0.212***	0.214***		
				(0.043)	(0.042)	(0.044)		
GazeRet(level)				0.329***	0.365***	0.345***		
				(0.058)	(0.058)	(0.057)		
OLSRet		1.032***	0.978***		1.051***	0.997***	0.215*	0.347***
		(0.116)	(0.123)		(0.111)	(0.118)	(0.114)	(0.116)
NLRet		-0.025	-0.006		0.024	0.031	-0.037	-0.002
		(0.029)	(0.027)		(0.023)	(0.024)	(0.027)	(0.039)
SalientRet			-0.008			-0.004	0.009	-0.042
			(0.028)			(0.029)	(0.019)	(0.045)
MaxRet			0.000			-0.003	-0.002	-0.033
			(0.026)			(0.025)	(0.020)	(0.035)
MinRet			−0.102***			−0.103***	−0.104**	−0.100***
			(0.030)			(0.031)	(0.041)	(0.026)
Surprise			−0.101***			−0.099***	−0.092***	−0.033
			(0.030)			(0.031)	(0.041)	(0.026)
$\hat{\mu}$			0.000			0.000	0.001	0.001
			(0.001)			(0.001)	(0.001)	(0.001)
$\hat{\sigma}$			-0.001			-0.001	-0.002	-0.001
			(0.001)			(0.001)	(0.002)	(0.001)
Subject FEs	✓	✓	✓	✓	✓	✓	✓	✓
Round FEs	✓	✓	✓	✓	✓	✓	✓	✓
N	4479	4479	4476	4479	4479	4476	2250	2230
R^2	0.064	0.086	0.122	0.080	0.103	0.137	0.146	0.092

Standard errors in parentheses

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

Table 2
Summary Statistics of Information Set

The table reports the summary statistics on the acquired information by subjects each round. *Round Dur* is the average duration of each prediction task in seconds. *Round Dur* is the average duration of each gaze path in seconds. *Ret Response* is the average return response submitted by subjects each round in percentage points. *# Gaze Path* is the average number of gaze path used by subjects to acquire information before prediction each round. *# Ret* is the average number of returns seen by subjects each round. *# Prc* is the average number of prices seen by subjects each round. *Min.t* is the time of latest return available perceived by subjects each round. *Max.t* is the time of earliest return available perceived by subjects each round. *Avg.Ret* is the average of mean return seen by subjects each round in percentage points. *Avg.Z* is the average of mean standardized return seen by subjects each round. *Avg.Rank(Prc)* is the average of rank of price seen by subjects each round, where ranks are from 1(lowest) to 18(highest). $\sum m^r$ is the proportion of attention allocated to read trends of a graph each round. $\sum m^p$ is the proportion of attention allocated to read price-levels of a graph each round.

				Percentile			
	Mean	SD	Min	25th	50th	75th	Max
Round Dur	14.31	9.420	1.470	7.870	11.93	18.02	144.3
Gaze Path Dur	0.594	0.146	0.304	0.496	0.566	0.662	2.553
Ret Response	0.316	3.596	-20.00	-1.778	0.615	2.290	19.05
# Gaze Path	38.20	26.59	2.000	20.00	32.00	49.00	377.0
# Ret	11.87	4.860	1.000	8.000	13.00	16.00	17.00
# Prc	4.355	2.563	1.000	2.000	4.000	6.000	16.00
Min.t	1.016	0.201	1.000	1.000	1.000	1.000	8.000
Max.t	14.37	4.154	2.000	13.00	16.00	18.00	18.00
Avg.Ret	0.201	2.346	-16.24	-0.978	0.199	1.492	13.38
Avg.Z	-0.009	0.370	-2.673	-0.198	-0.005	0.185	2.351
Avg.Rank(Prc)	8.922	4.183	1.000	5.857	8.867	11.75	18.00
Σm^r	0.563	0.189	0.000	0.441	0.579	0.697	1.000
Σm^p	0.437	0.189	0.000	0.303	0.421	0.559	1.000

Table 3
Determinant of Attention: Return

The table reports the results of a return-level linear regression of the attention parameter on the return characteristics and categorical variables for treatments:

$$m_{s,r,k} = \alpha + \beta\, Time_{s,r,k} + \delta\, Abs(Z)_{s,r,k} + \xi\, Time_{s,r,k} * Treat_s + \phi\, Abs(Z)_{s,r,k} * Treat_s + \psi\, Treat_s + \epsilon_{s,r,k}$$

where s indexes subjects, r indexes rounds, and k indexes for time k for r_{t-k}. From column (1) to (3), the dependent variable is the dummy that equals one if the attention parameter m_k is positive. From column (4) to column (6) the dependent variable is the attention parameter m_k. *Time* is a variable that represents the distance to the current time, k, from r_{t-k}. *Abs(Z)* is computed as the absolute value of a standardized return using the true parameters of the data generating process. *High Mu*, *High Vol*, and *Signal* are dummies for each treatment. Standard errors are clustered at the subject level in all specifications.

	(1) Logit	(2) Logit	(3) Logit	(4) OLS	(5) OLS	(6) OLS
Time	-0.238***	-0.204***	-0.238***	-0.837***	-0.781***	-0.837***
	(0.010)	(0.020)	(0.010)	(0.033)	(0.078)	(0.033)
Abs(Z)	0.042***	0.042***	0.054*	0.095**	0.095**	0.207**
	(0.016)	(0.016)	(0.029)	(0.047)	(0.047)	(0.093)
*Time*High Mu*		-0.051*			-0.080	
		(0.030)			(0.102)	
*Time*High Vol*		-0.075***			-0.003	
		(0.028)			(0.092)	
*Time*Signal*		-0.027			-0.150	
		(0.025)			(0.100)	
*Abs(Z)*High Mu*			0.031			-0.147
			(0.047)			(0.136)
*Abs(Z)*High Vol*			-0.029			-0.253**
			(0.041)			(0.119)
*Abs(Z)*Signal*			-0.044			-0.059
			(0.042)			(0.140)
High Mu	0.076	0.628	0.052	0.034	0.749	0.150
	(0.290)	(0.475)	(0.296)	(0.031)	(0.899)	(0.117)
High Vol	0.425*	1.271***	0.448*	0.047*	0.076	0.248**
	(0.249)	(0.384)	(0.249)	(0.025)	(0.820)	(0.102)
Signal	-0.212	0.085	-0.176	-0.028	1.325	0.019
	(0.273)	(0.368)	(0.271)	(0.030)	(0.879)	(0.121)
Constant	3.128***	2.765***	3.119***	13.719***	13.216***	13.630***
	(0.218)	(0.261)	(0.218)	(0.290)	(0.690)	(0.295)
N	72454	72454	72454	72454	72454	72454
R^2 (Pseudo R^2)	0.182	0.184	0.182	0.275	0.277	0.275

Standard errors in parentheses

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

Table 4
Determinant of Attention: Price

The table reports the results of a price-level linear regression of the attention parameter on the return characteristics and categorical variables for treatments:

$$m_{s,r,k} = \alpha_s + \beta\, Time_{s,r,k} + \delta Rank_{s,r,k} + \xi\, Time_{s,r,k} * Treat_s + \phi Abs(Z)_{s,r,k} * Treat_s + \psi\, Treat_s + \epsilon_{s,r,k}$$

where s indexes subjects, r indexes rounds, and k indexes for Prc_{t-k}. From column (1) to (3), the dependent variable is the dummy that equals one if the attention parameter m_k is positive. From column (4) to column (6) the dependent variable is the attention parameter m_k. *Time* is a variable that represents the distance to the current time, k, from Prc_{t-k}. *Rank* is the relative ranking of Prc_{t-k} in a price chart each round. *High Mu*, *High Vol*, and *Signal* are dummies for each treatment. Standard errors are clustered at the subject level in all specifications.

	(1) Logit	(2) Logit	(3) Logit	(4) OLS	(5) OLS	(6) OLS
Time	-0.176***	-0.180***	-0.176***	-1.383***	-1.383***	-1.383***
	(0.009)	(0.016)	(0.009)	(0.057)	(0.099)	(0.057)
Rank	0.053***	0.053***	0.056***	0.406***	0.406***	0.466***
	(0.004)	(0.004)	(0.010)	(0.054)	(0.054)	(0.120)
*Time*High Mu*		0.023			0.088	
		(0.024)			(0.166)	
*Time*High Vol*		0.006			-0.048	
		(0.024)			(0.161)	
*Time*Signal*		-0.014			-0.027	
		(0.024)			(0.142)	
*Rank*High Mu*			-0.006			-0.140
			(0.014)			(0.186)
*Rank*High Vol*			-0.004			-0.078
			(0.012)			(0.144)
*Rank*Signal*			0.000			-0.040
			(0.015)			(0.157)
High Mu	0.381**	0.214	0.412**	3.279*	2.486	3.969*
	(0.157)	(0.136)	(0.199)	(1.708)	(1.805)	(2.146)
High Vol	0.213	0.175	0.233	1.881	2.316	2.264
	(0.134)	(0.110)	(0.161)	(1.349)	(1.485)	(1.510)
Signal	0.086	0.182	0.085	-0.221	0.026	-0.023
	(0.146)	(0.125)	(0.189)	(1.414)	(1.678)	(1.640)
Constant	-0.269***	-0.243***	-0.282**	24.899***	24.896***	24.602***
	(0.097)	(0.089)	(0.116)	(1.012)	(1.152)	(1.072)
N	72454	72454	72454	72454	72454	72454
R^2(Pseudo R^2)	0.112	0.112	0.112	0.045	0.045	0.045

Standard errors in parentheses

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

Table 5
Decision Quality and Attention Distribution

The table reports the results of a prediction-level regression of the prediction quality on the characteristics of information set and attention distribution:

$$Error_{s,r} = \alpha_s + \sum_c \beta_c Char_{c,s,r} + \delta X_{s,r} + \epsilon_{s,r}$$

where s indexes subjects, r indexes rounds, c indexes each characteristic of attention distribution, and X are the control variables. The dependent variables are the precision of submitted prediction measured by equation (15), equation (16), and equation (17). Characteristics of the attention distribution include the following variables: *# Gaze Path* is the*# Gaze Path* is the average number of gaze path used by subjects to acquire information before prediction each round; *# Ret* is the average number of returns seen by subjects each round; *# Prc* is the average number of prices seen by subjects each round; $m^r(recent)$ is the attention allocated to three most recent returns available; $m^r(tail)$ is the attention allocated to the highest and lowest ranked returns in a price chart; $m^l(tail)$ is the attention allocated to the highest and lowest ranked prices in a price chart. *Round Dur* is the average duration of each gaze path in seconds. $\hat{\mu}$ is the average slope of a price chart each round. $\hat{\sigma}$ is the standard deviation of returns each round. Standard errors are clustered at the subject level in all specifications.

	(1)	(2)	(3)	(4)	(5)
Dep. Var	$Error(\hat{\mu})$	$Error(\hat{\mu})$	$Error(\hat{\mu})$	$Error(\mu)$	$Error(RS)$
# Gaze Path	-0.335***		-0.335***	-0.454***	-0.649***
	(0.093)		(0.093)	(0.092)	(0.154)
# Ret	-0.584**		-0.618**	-0.422	0.271
	(0.229)		(0.311)	(0.279)	(0.464)
# Prc	1.442***		1.438***	1.990***	2.025**
	(0.448)		(0.452)	(0.395)	(0.784)
$m^r(recent)$		0.073*	-0.013	-0.011	0.053
		(0.038)	(0.050)	(0.044)	(0.079)
$m^r(tail)$		0.167***	0.162***	0.128***	0.039
		(0.041)	(0.041)	(0.037)	(0.060)
$m^p(tail)$		-0.001	-0.001	0.016	0.006
		(0.019)	(0.019)	(0.017)	(0.031)
Round Dur	0.601**	-0.107	0.590**	0.749***	1.146**
	(0.291)	(0.118)	(0.291)	(0.283)	(0.480)
$\hat{\mu}$	-2.826***	-2.754***	-2.805***	-2.947***	-1.355*
	(0.428)	(0.428)	(0.426)	(0.355)	(0.715)
$\hat{\sigma}$	4.193***	4.098***	4.148***	3.662***	3.487***
	(0.559)	(0.557)	(0.561)	(0.517)	(0.879)
Subject FEs	✓	✓	✓	✓	✓
N	4284	4284	4284	4284	4284
R^2	0.113	0.112	0.116	0.131	0.048

Standard errors in parentheses

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

Table 6
Demographics and Attention Distribution

The table reports the results of OLS regression of the characteristics of attention distribution on the demographical variables collected from the post-experimental survey:

$$Dist_{s,r} = \sum_d \beta_d Demo_{d,s} + \delta X_{s,r} + \zeta_s + \psi_m + \epsilon_{s,r}$$

where s indexes subjects, r indexes rounds, and d indexes each demographical variable. ζ_s and ψ_m are subject and treatment fixed effects. The dependent variables are the characteristics of the attention distribution including the following variables: *# Gaze Path* is the*# Gaze Path* is the average number of gaze path used by subjects to acquire information before prediction each round; *# Ret* is the average number of returns seen by subjects each round; *# Prc* is the average number of prices seen by subjects each round; $m^r(recent)$ is the attention allocated to three most recent returns available; $m^r(tail)$ is the attention allocated to the highest and lowest ranked returns in a price chart; $m^p(tail)$ is the attention allocated to the highest and lowest ranked prices in a price chart. *Male* is a dummy that equals one if a subject is a male. *GPA(3)* is a categorical variable of three groups sorted on the GPA. STEM is a dummy that equals one if a subject has a science, technology, engineering, or mathematics major. *# Stat(3)* is a categorical variable of three groups sorted on the number of statistics courses taken. *# Fin(3)* is a categorical variable of three groups sorted on the number of finance courses taken. *# EXP(3)* is a categorical variable of three groups sorted on the survey results on the investment experience. *# CRT(3)* is a categorical variable of three groups sorted on the survey results on the Critical Reasoning Test from Frederick (2005).

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	*#Path*	*#Ret*	*#Prc*	$m^r(recent)$	$m^r(tail)$	$m^p(tail)$
Male	-1.524	-0.293	-0.148	2.750	0.591**	2.140**
	(3.205)	(0.611)	(0.343)	(3.230)	(0.274)	(1.038)
STEM	5.015**	1.017*	0.401	-6.131*	-0.513	-2.048**
	(2.358)	(0.587)	(0.281)	(3.134)	(0.343)	(0.853)
GPA(3)	-0.551	-0.312	-0.130	1.353	0.207	-0.175
	(1.737)	(0.373)	(0.201)	(1.993)	(0.259)	(0.532)
# Stat(3)	-2.444	0.076	-0.110	-0.497	-0.174	0.271
	(2.544)	(0.475)	(0.296)	(2.332)	(0.301)	(0.648)
# Fin(3)	-0.644	0.127	-0.041	-1.323	-0.149	-0.780
	(1.821)	(0.401)	(0.233)	(2.117)	(0.246)	(0.575)
EXP(3)	-2.268	0.173	-0.193	-1.057	-0.195	-0.727
	(2.138)	(0.416)	(0.226)	(2.123)	(0.228)	(0.623)
CRT(3)	2.412	0.423	0.375*	-3.586*	-0.192	-1.220*
	(1.751)	(0.380)	(0.196)	(1.913)	(0.268)	(0.672)
Subject FEs	✓	✓	✓	✓	✓	✓
Treatment FEs	✓	✓	✓	✓	✓	✓
N	4291	4291	4291	4291	4291	4291
R^2	0.076	0.045	0.053	0.051	0.010	0.016

Standard errors in parentheses

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

Appendix A. Additional Figures and Tables

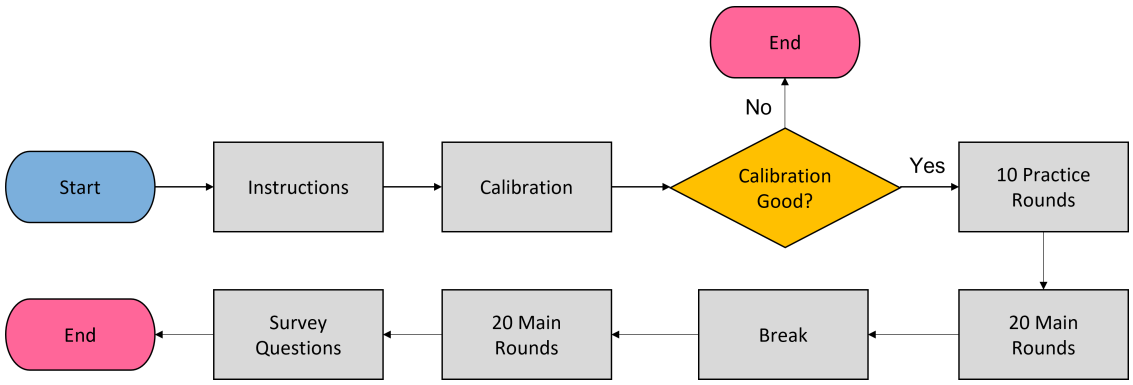
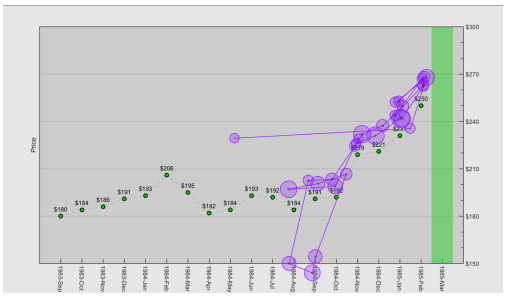
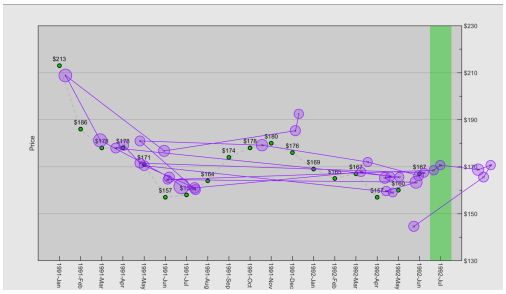


Figure A.1
Experiment Flow

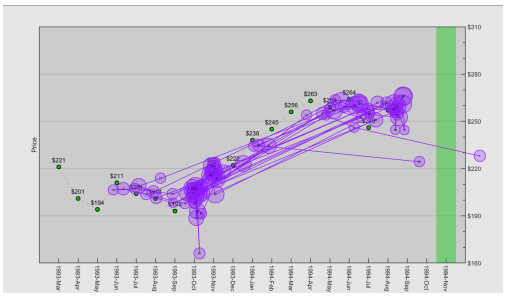
The figure illustrates the flow of experiments. Subjects receive printed instructions, which the experimenter reads aloud. Subjects take a post-instruction quiz and continue only when all of their answers are correct. Next, the eye-tracking device is calibrated. Subjects could not continue the experiment if the calibration is poor, and receive a show-up fee. After the calibration stage, subjects take ten practice rounds to learn about the task. Subjects make 40 rounds of predictions with a break after the first 20 rounds. The experiment ends with post-experimental survey and payment realizations.



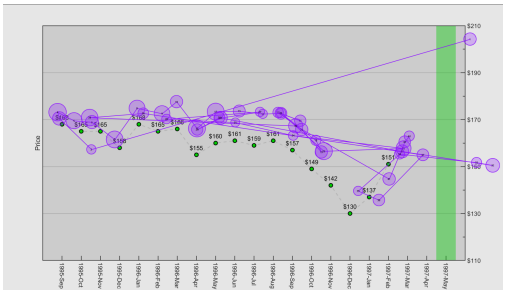
(A) Subject id = 1, Round = 3



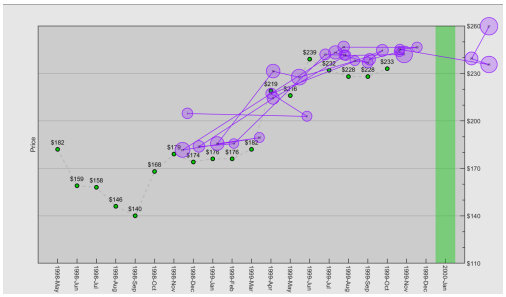
(B) Subject id = 23, Round = 33



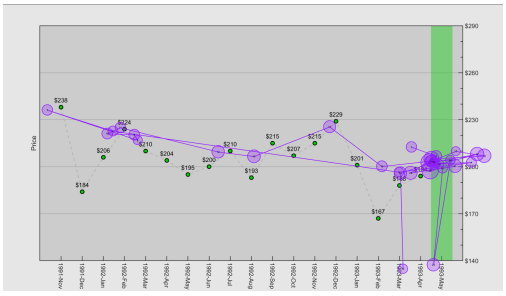
(C) Subject id = 49, Round = 18



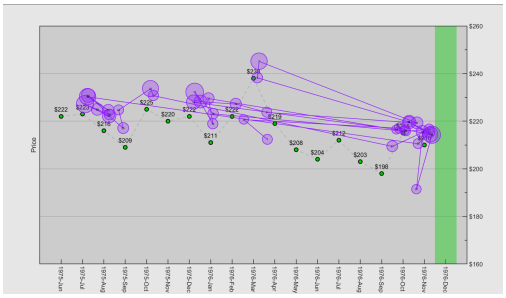
(D) Subject id = 76, Round = 32



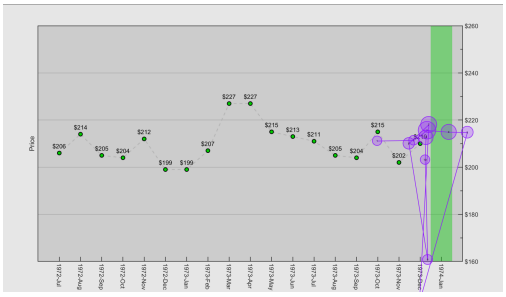
(E) Subject id = 97, Round = 36



(F) Subject id = 102, Round = 4



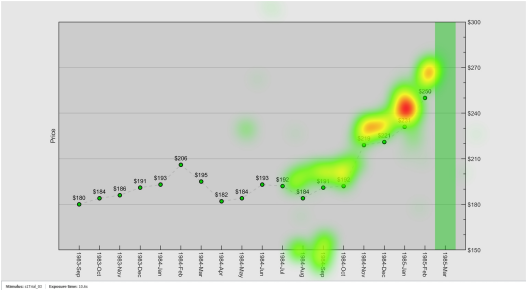
(G) Subject id = 136, Round = 6



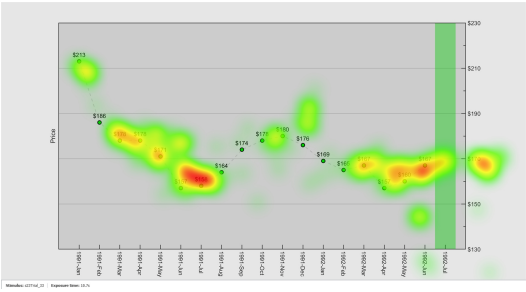
(H) Subject id = 157, Round = 23

Figure A.2
Additional Gaze Paths

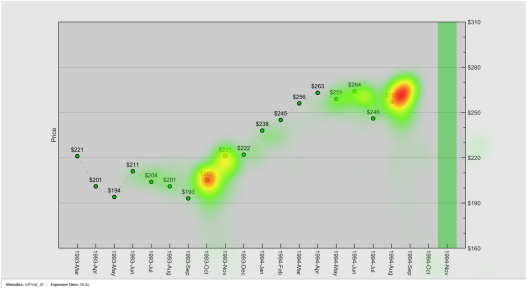
The figure presents the gaze paths collected from the actual experiment. Yellow circles represent the fixation points, and lines represent how fixation has shifted from one to another. Numbers in circle represent the order of fixations.



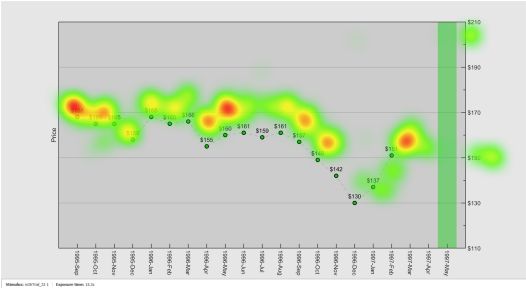
(A) Subject id = 1, Round = 3



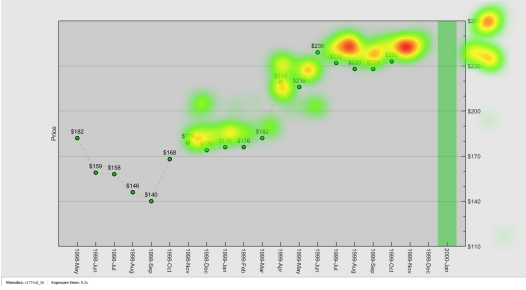
(B) Subject id = 23, Round = 33



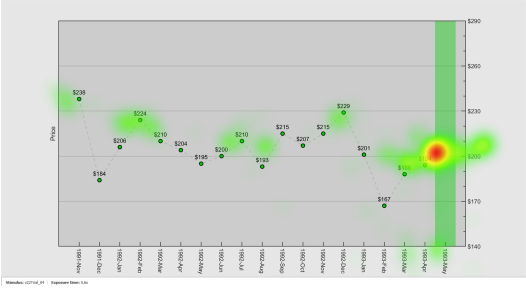
(C) Subject id = 49, Round = 18



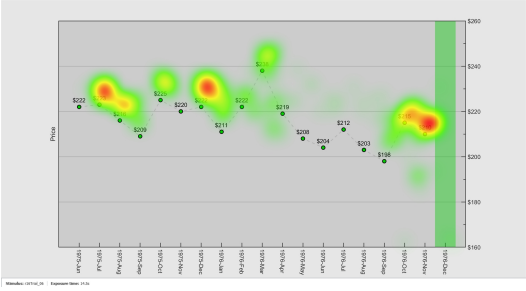
(D) Subject id = 76, Round = 32



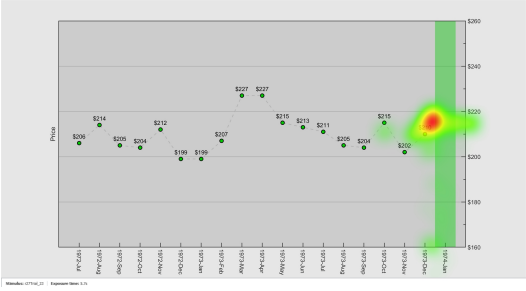
(E) Subject id = 97, Round = 36



(F) Subject id = 102, Round = 4



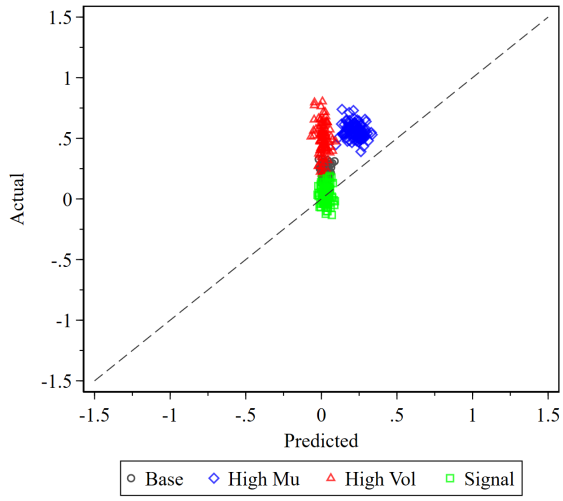
(G) Subject id = 136, Round = 6



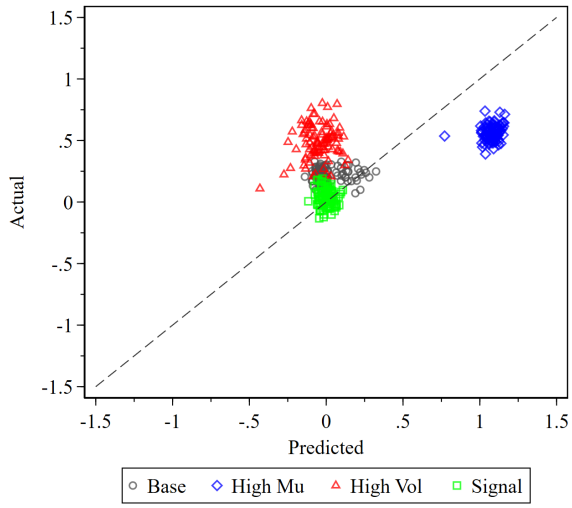
(H) Subject id = 157, Round = 23

Figure A.3
Additional Saliency Maps

The figure shows examples of saliency map from the actual experiment. The "hotter" the colors, the more and longer fixations are in one area.



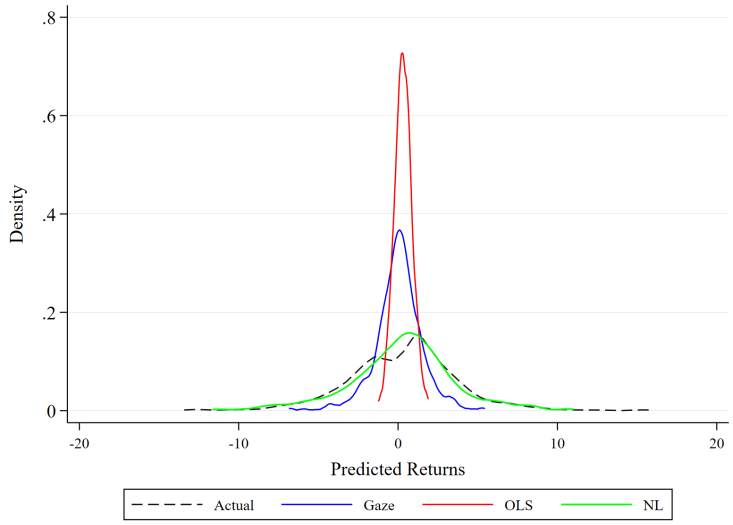
(A) Predicted Response from OLS model



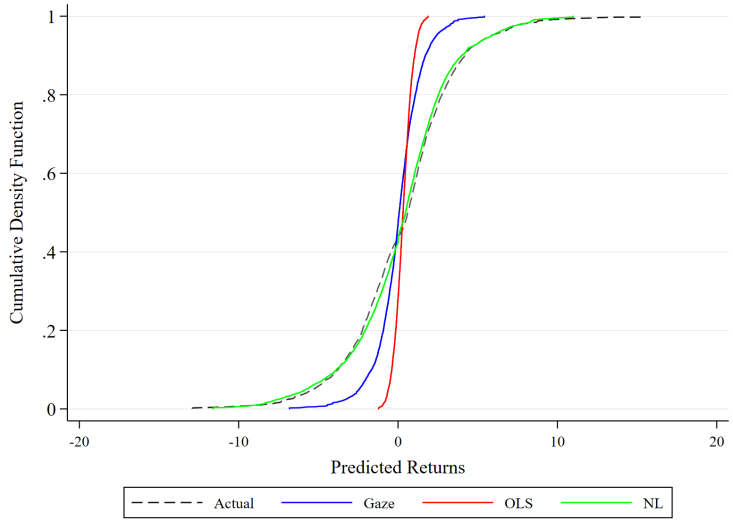
(B) Predicted Response from NL model

Figure A.4
Quantitative Fits of the OLS and NL Model

The figure depicts the quantitative fit of OLS and Non-linear regression using past returns from non-parametric bootstrap. First, we create a bootstrapped sample by randomly sampling with replacement for each treatment. Next, the coefficients of models are estimated at the treatment level from equation (1) and (2). Then, the fitted prediction is computed from the coefficients at the round level without adding intercepts. We repeatedly perform the sampling procedure for one hundred times. Grey colored circles represent the average of samples from the *Base* treatment. Blue colored diamonds represent the average of samples from the *High Mu* treatment. Red colored triangles represent the average of samples from the *High Vol* treatment. Green colored squares represent the average of samples from *Signal* treatment. The Y-axis represents the average of actual response, while the X-axis represents the average of predicted response. Panel A is the result using the OLS model. Panel B is the result using the Non-linear regression model



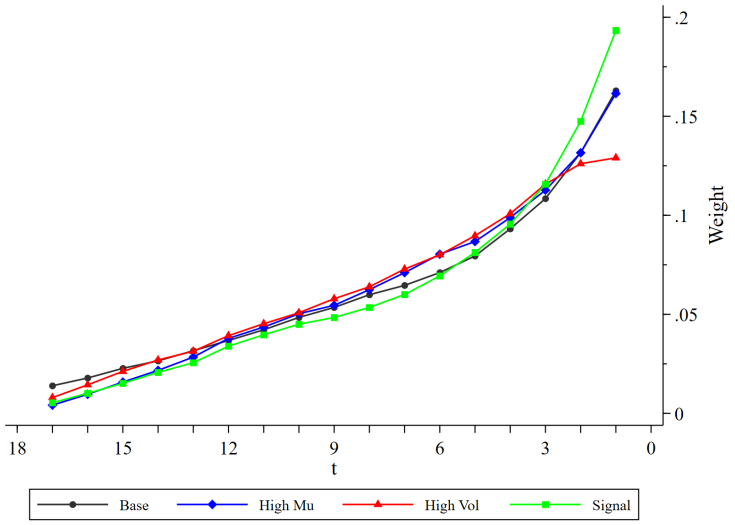
(A) Kernel Density Function



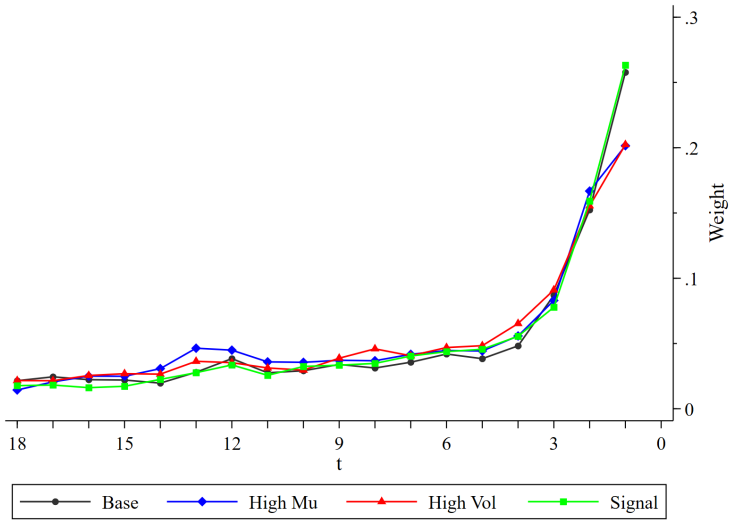
(B) Cumulative Distribution Function

Figure A.5
Distribution of Return Response and Extrapolative Models

The figure illustrates the kernel density and the cumulative distribution function of the actual return response, attention based measure of prediction, OLS based measure of prediction, and nonlinear regression based measure of prediction.



(A) Return



(B) Price

Figure A.6
Attention to Past Price Path: Time

The figure compares the attention allocation with regard to the time k from r_{t-k} across treatments. Panel (a) depicts the average attention allocated for each return group. Panel (b) depicts the average attention allocated for each price group.

Table A.1
Survey on Prediction Strategy

The table is the summary of a subjects' description of their own strategy for return prediction. The key words are extracted from the machine-learning textual analysis, and then categorized into several strategy groups.

Category	Example of Key Phrases	Count	%
A. Trend			
Trend	General line, Trend analysis, Extrapolation to predict the future price	124	83.78
Recent Trend	Trend over the past few months, Recent time data informed the way stock was moving, Local trends	55	37.16
General Trend	Follow general trends in data over the past 18 months , General direction the price was moving in, General curve of the whole dataset	35	23.65
B. Pattern			
Pattern	Pattern between how many data points up and then how many down, Patterns repeating multiple times/symmetrical, Pattern that had happened in the time around the last 4 months	45	30.41
Seasonality	Looked at the previous years trend to see if there was any visible seasonality, If there were any seasonal/monthly trends, If there was a similar trend in the same period in the previous years (seasonality), Comparing it to the same sections of months that I was trying to predict	13	8.78
Repeated Pattern	Past patterns that kind of looked like the one I had to predict, Previous trends that were similar in the graph, Finding a similar trend in the earlier months	10	6.76
Contrarian	What goes up must come down and vice versa, Make a prediction based on regression to the mean, Downfall afterwards if there was a large peak	7	4.73
C. Prices			
Peak and Trough	Lines from peaks and troughs to form a triangle, If the price was at a peak it was unlikely that it would keep growing, Make sure to look at the lowest and highest prices	14	9.46
Latest Price	Choose a fairly similar price as the latest one, Small guess that does not deviate too much from the current stock price, Select the current price as the predicted price	12	8.11
Average Price	Look for support from the previous price levels, Average out the recent months, Averaged old prices and guessed a little lower.	10	6.76
D. Others			
Gut Feeling	Mainly guessed and put what I felt was close, Used an intuitive approach for some of the selections, Just had a gut feeling about a certain number and picked it	12	8.11
Heuristic Limit	Most stocks don't swing 10% in a month, Within 5 10 of the original price, Within the boundaries of previous high or low	7	4.73
Volatility	Observed the volatility of the price to see if it could increase or decrease rapidly, See if the stock was volatile or not, Based on how volatile the stock is	6	4.05
Miscellaneous	Recent Pattern (4), Recent Average (4), Trend from peak and trough (4), Regression (4), Aggressive prediction under volatility (2), Optimism (2), Discontinuity after peak and trough (2), Technical analysis (2), Conservative prediction under volatility (2), Personal Experience (1), Random walk (1), Sentiment (1)	29	19.59

Table A.2
Learning and Determinant of Attention: Return

The table reports the results of a return-level linear regression of the attention parameter on the return characteristics and categorical variables for treatments:

$$m_{s,r,k} = \alpha_s + \beta Time_{s,r,k} + \delta Abs(Z)_{s,r,k} + \xi Time_{s,r,k} * Second_{s,r} + \phi Abs(Z)_{s,r,k} * Second_{s,r} + \psi Second_{s,r} + \epsilon_{s,r,k}$$

where s indexes subjects, r indexes rounds, and k indexes for time k for r_{t-k}. From column (1) to (3), the dependent variable is the dummy that equals one if the attention parameter m_k is positive. From column (4) to column (6) the dependent variable is the attention parameter m_k. *Time* is a variable that represents the distance to the current time, k, from r_{t-k}. *Abs(Z)* is computed as the absolute value of a standardized return using the true parameters of the data generating process. *Second* is a dummy that equals one if the data is from the latter half of total rounds. Standard errors are clustered at the subject level in all specifications.

	(1) Logit	(2) Logit	(3) Logit	(4) OLS	(5) OLS	(6) OLS
Time	-0.236***	-0.239***	-0.236***	-0.837***	-0.836***	-0.837***
	(0.003)	(0.006)	(0.003)	(0.007)	(0.010)	(0.007)
Abs(Z)	0.041**	0.041**	-0.014	0.095**	0.095**	0.145**
	(0.017)	(0.017)	(0.043)	(0.045)	(0.045)	(0.057)
*Time*Second*		0.000			-0.000	
		(0.000)			(0.000)	
*Abs(Z)*Second*			0.003			-0.002
			(0.002)			(0.003)
Second	-0.130***	-0.168**	-0.170***	0.009	0.014	0.046
	(0.043)	(0.074)	(0.054)	(0.007)	(0.058)	(0.044)
Constant	3.238***	3.258***	3.259***	13.727***	13.724***	13.708***
	(0.056)	(0.064)	(0.061)	(0.078)	(0.078)	(0.072)
N	72454	72454	72454	72454	72454	72454
R^2 (Pseudo R^2)	0.182	0.184	0.182	0.275	0.277	0.275

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3
Learning and Determinant of Attention: Price

The table reports the results of a price-level linear regression of the attention parameter on the return characteristics and categorical variables for treatments:

$$m_{s,r,k} = \alpha_s + \beta Time_{s,r,k} + \delta Rank_{s,r,k} + \xi Time_{s,r,k} * Second_{s,r} + \phi Rank_{s,r,k} * Second_{s,r} + \psi Second_{s,r} + \epsilon_{s,r,k}$$

where s indexes subjects, r indexes rounds, and k indexes for Prc_{t-k}. From column (1) to (3), the dependent variable is the dummy that equals one if the attention parameter m_k is positive. From column (4) to column (6) the dependent variable is the attention parameter m_k. *Time* is a variable that represents the distance to the current time, k, from Prc_{t-k}. *Rank* is the relative ranking of Prc_{t-k} in a price chart each round. *Second* is a dummy that equals one if the data is from the latter half of total rounds. Standard errors are clustered at the subject level in all specifications.

	(1) Logit	(2) Logit	(3) Logit	(4) OLS	(5) OLS	(6) OLS
Time	-0.235***	-0.232***	-0.235***	-0.836***	-0.823***	-0.836***
	(0.003)	(0.004)	(0.003)	(0.007)	(0.009)	(0.007)
Rank(Prc)	0.007**	0.007**	0.009*	0.017**	0.017**	0.012
	(0.003)	(0.003)	(0.005)	(0.008)	(0.008)	(0.013)
*Time*Second*		-0.007			-0.026*	
		(0.007)			(0.014)	
*Rank(Prc)*Second*			-0.003			0.010
			(0.006)			(0.016)
Second	-0.130***	-0.059	-0.100	0.008	0.241*	-0.090
	(0.043)	(0.097)	(0.063)	(0.007)	(0.122)	(0.148)
Constant	3.203***	3.166***	3.188***	13.637***	13.518***	13.687***
	(0.058)	(0.064)	(0.059)	(0.109)	(0.124)	(0.151)
N	72454	72454	72454	72454	72454	72454
R^2 (Pseudo R^2)	0.182	0.184	0.182	0.275	0.277	0.275

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B. Instructions

Thank you very much for volunteering to participate in this study. The experiment will take 30 minutes to 1 hour to complete. The procedure of the experiment is as follows: 1) instructions and consent forms, 2) calibration of the eye-tracking machine, 3) 10 practice rounds, 4) the first 20 rounds of tests, 5) break time, 6) the last 20 rounds of tests, and 7) a survey.

Experimental Details

In each of the 40 rounds, you will make predictions of the simulated stock prices presented on the computer screen. For each round, you will read the stock price graph and submit your response. For half of the rounds, you will make predictions of the **stock price 1 month later**. For the other half of the rounds, you will make predictions of the **stock price 3 months later**. When you are ready to submit, use the numerical keys on your keyboard to enter your prediction and press [enter]. There is no time limit for each round.

Figure 1 (page 3) is a screenshot of the actual experiment. The y-axis is the price of a stock denoted in USD, and the x-axis is the date. Therefore, each dot represents the stock price at the end of that month. Figure 1a is an example of the 1 month prediction task. In this example, you are asked to predict the price as of August 1995 after seeing the prices of **past 18 months**, from February 1994 ($240) to July 1995 ($265). On the other hand, figure 1b is the 3 month prediction task. In this example, you are asked to predict the price as of April 1981 after seeing the prices of past 18 months, from August 1979 ($211) to January 1981 ($246).

During the experiment, an eye-tracking device will record the movement of your eyes (pupils). To ensure proper operation of the device, it is important to stay focused during the calibration, as the quality of data is affected by the calibration result. Please keep the optimal distance between the monitor and your eye, **24.8 in (63cm)**. For best results, please remain seated in the same position until the end of the main test. The observer may ask you to correct your posture during the experiment if needed. Natural head movements are allowed, but the movements shouldn't be beyond a **5.9 × 3.9 in (15 × 10cm)** range.

Payments

Total payments are the sum of 1) the base payment, 2) the bonus payment from the main experiment, and 3) the bonus payment from the last 6 questions of survey. The base payment is **$5**. You will receive the base payment even if you decide to leave during the experiment.

The bonus payment from the main experiment is based on your answers during the experiment. The payment will depend on the accuracy of your prediction. You will have the opportunity to learn about your accuracy after each round, as illustrated in **figure 2 (page 4)**. Your price denotes the prediction you submitted in the current round. The actual price is the price that is actually realized for the predicted period. Difference(%) is the difference between your price and the actual price in percentage return and computed as follows:

$$\textit{Difference(\%)} = \left| \frac{\textit{Actual price} - \textit{Predicted price}}{\textit{Latest available price}} \right| \times 100.$$

Finally, the round score (RS) is computed using the following formula:

$$RS = \begin{cases} max\left[0, 1 - \dfrac{\textit{Difference(\%)}}{10}\right] \times 100, & \text{if 1 month prediction} \\ max\left[0, 1 - \dfrac{\textit{Difference(\%)}}{17.3}\right] \times 100, & \text{if 3 months prediction} \end{cases}$$

Table 1 (page 5) details the relation between rounds score and payment. Consider a case where the latest available stock price is $200 and the actual stock price is $220. If your prediction is exactly $220 (*Difference(%)* = 0), you will receive a score of 100. For 1 month prediction **(table 1a)**, if your prediction is between $200 and $240 (*Difference(%)* $\leq$ 10) you will receive a score between 0 and 100. If your prediction is lower than $200 or higher than $240 (*Difference(%)* $>$ 10), you will receive a score of 0. For 3 months prediction **(table 1b)**, if your prediction is between $186 and $256 (*Difference(%)* $\leq$ 17.3) you will receive a score between 0 and 100. If your prediction is lower than $186 or higher than $256 (*Difference(%)* $>$ 17.3), you will receive a score of 0.

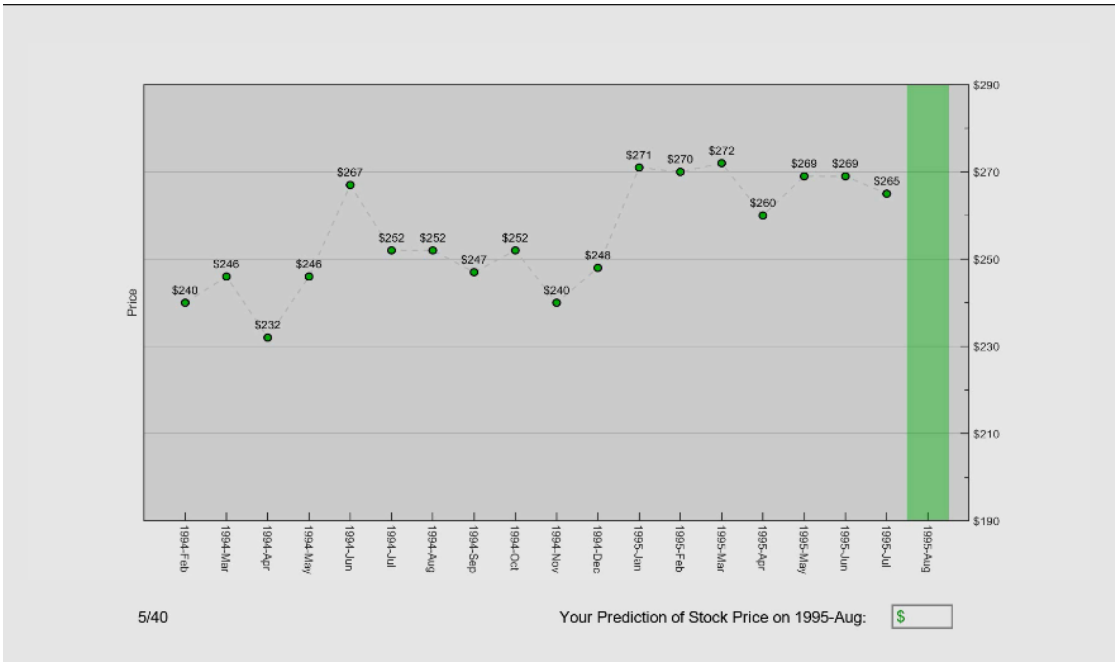
After 40 rounds, your bonus payment from the main experiment will be computed from your total score, the sum of your scores for all rounds. Specifically, bonus payment in US dollars is equal to your total score divided by 125. If your total score is 1,500, then your bonus payment will be $12. Participants typically earn between **$10 and $20** from the main

experiment.

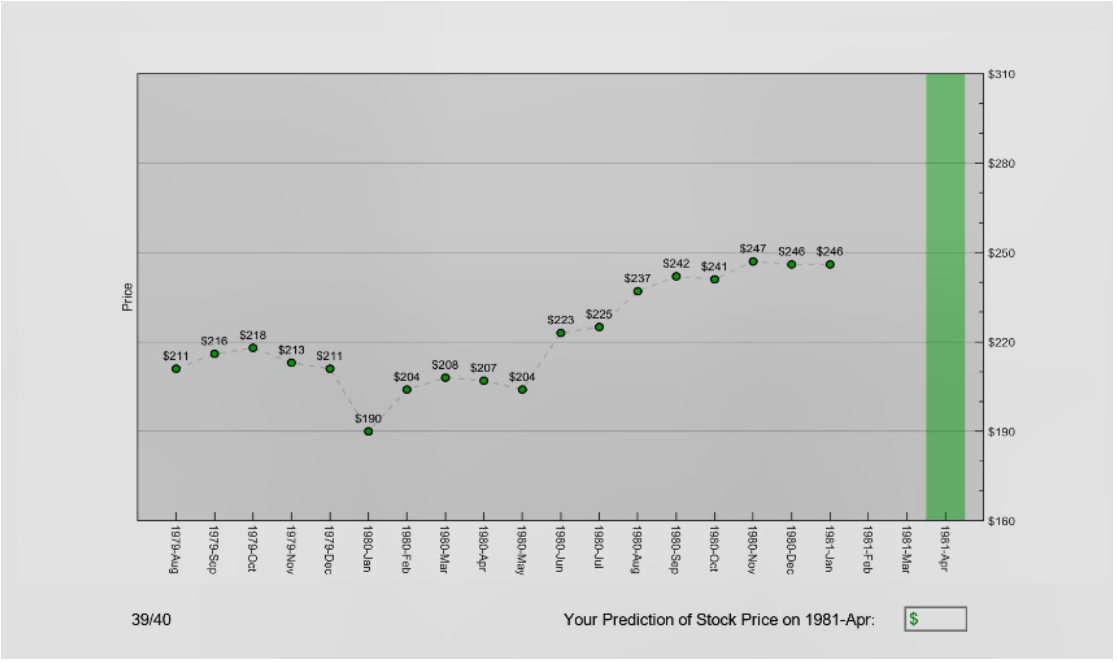
Finally, you will also receive the bonus payment for each correct answer from Q11 to Q16 of the post-experimental survey. These last 6 questions will test your knowledge of mathematics and statistics. You would be rewarded with **$1.50** if you submit correct answers for all 6 questions ($0.25 for each).

Quiz: True or False

- There are 50 main rounds in total. (T/F)
- You will predict the price of a stock that actually exists. (T/F)
- There are two forecasting horizons: 1 month and 6 months. (T/F)
- You will be provided with the past 18 months of stock prices each round. (T/F)
- Your bonus payment will not be dependent on the accuracy of your prediction. (T/F)
- You will earn a bonus payment of $0.40 for a round score of 50. (T/F)
- You will earn $12 as a total payment from the experiment for a score of 1500. (T/F)



(A) 1-month forecast



(B) 3-month forecast

Figure B.1
Main Stage

Figure B.2
Round and Total Score

Table B.1
Payment and Prediction Accuracy

(A) 1 month prediction

Difference (%)	Round Score	Round Payment ($)
0.0	100	0.80
1.0	90	0.72
2.0	80	0.64
3.0	70	0.56
4.0	60	0.48
5.0	50	0.40
6.0	40	0.32
7.0	30	0.24
8.0	20	0.16
9.0	10	0.08
10.0	0	0.00

(B) 3 months prediction

Difference (%)	Round Score	Round Payment ($)
0.0	100	0.80
1.0	94	0.75
2.0	88	0.70
3.0	83	0.66
4.0	77	0.62
5.0	71	0.57
6.0	65	0.52
7.0	60	0.48
8.0	54	0.43
9.0	48	0.38
10.0	42	0.34
11.0	36	0.29
12.0	31	0.25
13.0	25	0.20
14.0	19	0.15
15.0	13	0.10
16.0	8	0.06
17.0	2	0.02
18.0	0	0.00

Appendix C. Survey Questions

- What is your gender?
  - Male
  - Female
  - Prefer not to say
- What is your cumulative college GPA?
  - 3.7-4.0
  - 3.3-3.7
  - 3.0-3.3
  - 2.7-3.0
  - Below 2.7
- How many statistics courses have you taken in college?
  - 0
  - 1 or 2
  - 3 or more
- How many finance courses have you taken in college?
  - 0
  - 1 or 2
  - 3 or more
- What is your college major?
- Please describe the strategy you used to make price prediction in detail.
- Do you have any experience investing in financial assets (e.g. stocks, bonds, mutual funds, pension funds, etc.)?
  - Extensive experience
  - Some experience
  - Limited experience

  - No experience at all

- What is your investment attitude?
  - Very conservative
  - Conservative
  - Moderate
  - Aggressive
  - Very Aggressive

- You are offered a chance to buy a lottery, where the possibility to win $1,000 is 10%. How much would you pay at most to buy a lottery?

- Protecting my portfolio is more important to me than higher returns.
  - Strongly disagree
  - Disagree
  - Neutral
  - Agree
  - Strongly agree

- A bat and a ball cost $1.10 in total. The bast costs $1.00 more than the ball. How much does the ball cost?

- If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

- In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

- What is the median of the following numbers? 10, 30, 60, 70, 90, 150, 220, 760?

- A fair coin is tossed 6 times. What do you think about the likelihood of seeing Pattern A: H-T-H-T-T-H vs. Pattern B: H-H-H-T-T-T?
  - Pattern A is more likely than Pattern B
  - Pattern B is more likely than Pattern A
  - They are equally likely

  - None of the above

- A town has two hospitals. The larger hospital has on average 50 babies born every day. The smaller hospital has on average 10 babies born every day. We know that about 50 percent of babies are boys. For a period of 6 months, the hospitals recorded the number of days when more than 70 percent of the babies born are boys, and called them "baby boy days". Which of the following do you think is most likely?

  - The larger hospital recorded more "baby boy days" than the smaller hospital.
  - The smaller hospital recorded more "baby boy days" than the larger hospital.
  - The two hospitals recorded the same number of "baby boy days".