Factors Influencing Stock Price Prediction: Demographics, Mental State, Company Origin, and Past Performance

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ABSTRACT

This study investigates the interplay between socio-demographic factors, mental state, and stock price prediction behavior among a sample of 150 individuals in Ulaanbaatar, Mongolia. Participants were tasked with completing incomplete graphs, varying in context in three survey groups, allowing for an exploration of how age, gender, and past value perceptions, and contextual things influence prediction patterns. The research aims to understand the cognitive biases underpinning investment decisions, particularly in a context of limited financial literacy. By analyzing completed graphs, the study identifies distinct decision-making tendencies across age and gender groups. Additionally, it examines whether the type of given context of the graph impacts prediction behavior in a certain way. While emotional bias was found to be less influential, the study reveals significant differences in predictions based on contextual differences, also the study revealed certain age and gender group tendencies bias proneness for certain biases. These findings contribute to a deeper understanding of investor psychology and provide insights for financial advisors seeking to tailor strategies based on client demographics.

Keywords: Stock Market; Prediction; Financial Market; Mental-State; Cognitive Bias; Emotional Bias

INTRODUCTION

Background of the study

The classic economic theory has performed surging domination in the 19th century, bringing new perceptions about the market and its participants' decision-making. John Stuart Mill, in a seminal work, *A System of Logic* (1843), described the concept of rational economic man in a broader way (Lama, 2022). Although the term "rational economic man" was not pioneered by Mill, he laid the groundwork for the concept, and subsequent visionaries like Milton Friedman further refined and popularized the notion. Friedman's contributions (1957) specially established the rationality assumptions governing economic agents, framing market participants as efficient driven by utility maximization, and became a fundamental assumption in economic theories that followed.

Both classical and neoclassical economics acknowledge the concept of rational behavior, but the main difference is neoclassical economics introduced models of decision-making, focusing on subjective preferences, marginal utility, and mathematical analysis. One of the most prominent hypotheses of neoclassical economic is Efficient Market Hypothesis (EMH), it was proposed by Eugene Fame (1970). EMH posits that, due to the assumption that all pertinent information is widely accessible and shared among market participants, current stock prices inherently encapsulate all available information, rendering attempts to outperform the market through stock picking or market timing highly improbable (Baldridge, 2022).

However, the concept of market efficiency was challenged by the occurrence of market falls and crashes, anomalies that defied the traditional economic theories. These unforeseen phenomena, referred to as market anomalies, questioned the Efficient Market Hypothesis (EMH). In the beginning of the 21th century, global financial falls including global crises of 2008, known for the irrationality in the market, became triggering event for the rise of behavioral economics. While the roots of behavioral economics can be tracked back to earlier notions of scholars, the field experienced a surge in attention and recognition following the crises. Within the framework of behavioral economics, individuals are viewed as susceptible beings to emotion and impulsivity, shaped by their surroundings and circumstances that are sometimes beyond their control (Witynski, UChicago News). Hence, repercussions of individuals engaging in irrational behavior within the market can, on a broader scale, result in unexpected events that opposes the traditional market theories.

During the dominance of traditional financial models, the ongoing evolution of behavioral economics existed. Some scholars even argue that certain aspects of Adam Smith's writings, especially *The Theory of Moral Sentiments* (1759), touch upon psychological and moral considerations that align with the foundational principles of behavioral economics. This suggests that although the formalization of behavioral economics as a distinct discipline occurred much later, certain concepts of the field may have been present as early as the 18th century.

The early influence on behavioral economics' emergence was rooted to the work of psychologists and economists in the late 19th and early 20th centuries. Ivan Pavlov, a Russian physiologist, conducted experiment on classical conditioning, and his work became known in United States after the publication of his lecture *The scientific investigation of the psychical faculties or process in the higher animals* (1906), studying how animals form associations between stimuli and responses. While not directly related to economics, Pavlov's work brought great insight for understanding conditioned responses and the role of stimuli in shaping behavior. (Clark, 2005).

Building on Pavlov's work, B.F. Skinner, an American psychologist, developed the principles of operant conditioning. His studies focused on how behavior is reinforced by rewards and punishments. While Skinner's work was primarily conducted within the field of psychology, his ideas have significant implications for understanding decision-making processes and incentives in economic contexts.

J.M. Keynes, in his work *The General Theory of Employment, Interest, and Money* (1936), emphasized the importance of psychological factors, uncertainty, and animal behaviors in shaping economic decisions. Consequently, not only psychologists, but some economists themselves started to support the concept of behavioral economics through their own notions. H.A. Simon, an American economist and Nobel laureate, in his book *Administrative Behavior: A Study of Decision-Making Processes* (1947), introduced concepts such as bounded rationality and satisficing. Simon argued that individuals do not always make fully rational decisions due to cognitive limitations.

The most well-known contribution made by scholars in behavioral economics is the groundbreaking research on cognitive and heuristic biases by psychologists D. Kahneman and A. Tversky. To compare with other previous studies, they putted more effort to reveal the systematic patterns of deviation from rationality in decision-making. Their co-produced works proposed theories and biases that are still being tested by today's scholars.

In 1974, Kahneman and Tversky (1974) introduced the concept of anchoring and adjustment in their work published in *Science*. This heuristic reveals the human tendency to make biased decisions by relying on an initial piece of information, with subsequent adjustments that may be insufficient (Kahneman & Tversky, 1974). Two years later, Kahneman and Tversky (1979) published their seminal work, "Prospect Theory: An Analysis of Decision under Risk," in *Econometrica*. This work expanded the influence of psychological factors in financial decisions by proposing concepts of framing effects, loss aversion, and reference points (Kahneman & Tversky, 1979).

Richard Thaler (2015) supported Prospect Theory through his descriptive approaches. He placed more emphasis on behavioral biases compared to Kahneman and Tversky, arguing that investors' suboptimal decisions can be caused by emotions such as egotism, uncertainty, fear, and optimism (Thaler, 2015). Furthermore, his earlier work with Werner De Bondt (1985) illuminated the field of behavioral economics. Their paper, "Does the Stock Market Overreact?" (published in The Journal of Finance), suggested that investors exhibit behavioral biases, such as overreacting to new information, leading to market bubbles and irrational public trends (Thaler & De Bondt, 1985).

Drawing on scholars' ideas regarding behavioral economics, numerous studies have been conducted, particularly those expanding our understanding of cognitive and emotional biases. Because of the unpredictable nature of emotional biases, varying across individuals based on their personalities, has posed a significant challenge for rectification. Despite this complexity, it's essential to note that both cognitive and emotional biases have undergone extensive research, although with a noticeable emphasis on the tangible manifestations of cognitive biases in people's studies. Recognizing this, the study took the approach of incorporating both emotional and cognitive biases in the questionnaire.

Definition of Terms

Term	Definition
Cognitive Biases	Cognitive biases, explored in the field of Behavioral Finance Microstructure (BFMI), deviate from rational decision-making models due to the complexity individuals face when processing information. These biases exemplify cognitive errors, such as belief perseverance and information-processing biases. In contrast to emotional biases, cognitive biases can be more readily reduced, especially with external assistance.
Emotional Biases	Emotional biases disrupt rational decision-making, as they arise from emotions rather than concrete evidence. These biases stem from psychological conditioning and intuitive responses, making correction challenging. The diverse reactions people have to certain situations further complicate the mitigation of emotional biases, as individual responses vary widely. This complexity underscores the difficulty of overcoming emotional biases and highlights the nuanced nature of these subjective influences on decision-making.
Representativeness Heuristic	Representativeness heuristic is cognitive bias that suggests individuals make intuitive judgements driven by mental shortcuts or stereotypes, often foregoing a thorough analysis of more detailed information. This manner of making quick conclusion is dependent on investor's past experience and his or her psychological condition. Thus, more experienced investors are prone to representativeness bias (Chen, 2004).
Home Bias	According to Del Gaudio et al. (2024), home bias describes an investor's tendency to favor companies or assets from their home country. This preference might be driven by a perceived advantage in terms of information, management, or control. Additionally, investors may feel more comfortable with familiar companies or experience a desire to support their local market.

Research Objectives

The study drew inspiration by the Robert Shiller's small experiment conducted in the dining hall of the Berkley College. Shiller passed paper with chart of S&P 500 from 1950 up to a few days prior to the experiment, asking participants to forecast the stock market's path between 2016-2050 by drawing the continuation. He concluded that people have tendency to think past itself is a representative of what will happen in the future. This experiment supported the idea of representativeness heuristic. (Shiller, 2012)

The research was designed to examine the influence of the representativeness heuristic in a richer context with diverse scenarios. This involved investigating its manifestation across different demographic groups, including age and gender. Furthermore, the study considered how company origin interacts with other factors, such as investor demographics and familiarity with the companies, to influence participants' predictions within the framework of the representativeness heuristic. To assess the influence of emotional biases, the research design also included a survey component that captured participants' current mental state. By analyzing this survey data, we can explore not only individual tendencies in behavioral economics but also broader psychological patterns across demographic groups. We will examine how these tendencies differ or remain similar, focusing on general psychological biases rather than just stock values. This will help us determine if non-expert investors exhibit distinct behavioral patterns in the stock market compared to other contexts.

Prior studies in behavioral economics, particularly within the field of stock market, have predominantly focused on the performances of retail and institutional investors. Thus, this research seeks to explore the behavioral tendencies of non-investors. The study findings have the potential to empower financial advisors to offer more effective and tailored services. By gaining insights into the interests of individuals and their customers through their socio-demographic data, financial advisors can become more aware of potential mistakes or biases their customers may be prone to. This awareness enables advisors to provide services that align closely with customer interests and proactively address potential pitfalls.

The following key research questions are underscored below:

i. Would individuals exhibit same representativeness heuristic behavior if presented with a chart of unknown item, as opposed to a stock chart?
ii. Which has a more significant impact on individual decision-making: emotional bias or cognitive bias?
iii. Among different gender and age groups, which is more prone to making decisions influenced by cognitive biases?
iv. Among different gender and age groups, which is more prone to making decisions influenced by emotional biases?

Research Hypothesis

H_1: Gender significantly influences stock price prediction patterns.

H_2: Age is associated with differences in stock price prediction patterns.

H_3: Specific mental states (e.g., low, very low, average) are associated with differences in stock price prediction patterns.

H_4: The representativeness heuristic significantly influences extrapolation patterns by leading individuals to rely on past performance to predict future trends.

H_5: The origin of the company significantly influences stock price prediction patterns through the activation of cognitive biases.

LITERATURE REVIEW

Previous Studies

Demographic Factors and Investment Performance

Gender: While early studies suggested that women might outperform men in investments, more recent research has challenged this notion. Subramaniam & Velnampy (2017) found that male investors in Sri Lanka achieved higher returns, potentially due to their higher risk tolerance. However, Feng and Seaholes (2008) found no significant gender difference in portfolio performance among Chinese investors. This suggests that factors beyond gender, such as risk tolerance and investment strategy, play a more critical role in determining investment success.

Age: Age can significantly influence investment behavior and performance. Subramaniam & Velnampy (2017) identified a clear age gap in investment performance, with investors aged 31-40 outperforming those over 60. This suggests that younger investors may adopt more aggressive strategies, while older investors may prioritize risk aversion and capital preservation.

Psychological Factors and Investment Behavior

Risk Tolerance: Numerous studies have explored the relationship between risk tolerance and investment performance. Pleiger et al. (2020) found that men tend to be more risk-tolerant than women, and individuals scoring high on "self-directedness" (independent and decisive) exhibit riskier financial behavior. Interestingly, the study found a positive correlation between risk-taking behavior and success in a stock market simulation.

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Overconfidence: Overconfidence can lead to excessive trading and both good and bad investment performance. Barber & Odeon (2016) found that men tend to be more overconfident than women, leading them to trade more frequently and underperform. However, the study also suggests that women may underestimate their abilities in certain situations, particularly when feedback is ambiguous.

Home Bias: The home bias, the tendency to favor domestic assets, has been a subject of extensive research. Karlsson & Nordén (2007) found that older, unmarried, less educated men with lower incomes are more likely to exhibit home bias. They attributed this to overconfidence and a lack of familiarity with foreign markets.

Research Gap

Prior research on investor performance regarding gender and age presents mixed findings. Some studies suggest men outperform women due to higher risk tolerance, while others report no significant difference or even the opposite. Age also appears to be a complex factor, with studies showing both outperformance by older investors and by certain age groups. These contrasting results underscore the necessity for further exploration into how demographic characteristics influence investment behavior.

As research on market performance across gender and age shows conflicting findings, it can be inferred that investment performance distinctions may be influenced by various factors. These factors could include regional differences in investment knowledge provision, levels of financial engagement among women and specific age groups, and common psychological characteristics related to gender and age in analyzing investments within different areas.

By examining the attitudes and commonality of investors across different gender and age groups, including those with varying levels of knowledge and experience, we can gain a more nuanced understanding of these dynamics. This approach should not only analyze investment performance through profit or loss but also consider the general tendencies and core psychological nature of people that might play a more significant role than investment knowledge.

METHODOLOGY

Research Design

As the primary objective is to examine how individuals formulate predictions at a single point in time and identify any recurring patterns across these initial predictions, this research employed a cross–sectional–design. This approach allowed for the collection of data from a broad sample at one point in time, facilitating the identification of prevalent trends in social-demographic groups (age and gender) regarding stock value prediction attitudes.

This research aimed to delve deeper than simply identifying group trends in stock market attitudes. We were particularly interested in exploring the possibility that individuals' attitudes towards the stock market can be entirely independent of their general psychological predispositions. To test this hypothesis, the survey materials incorporated elements of causal–research–design. This approach allowed us to examine how initial responses to data visualizations might be influenced by broader psychological factors, or conversely, how these initial responses might remain unaffected by such factors. Furthermore, the causal design enabled the study to investigate home bias from various points, the tendency to favor familiar investments. As the primary objective is to examine how individuals formulate predictions at a single point in time and identify any recurring patterns across these initial predictions, this research employed a cross–sectional–design. This approach allowed for the collection of data from a broad sample at one point in time, facilitating the identification of prevalent trends in social-demographic groups (age and gender) regarding stock value prediction attitudes.

Participants

The study involved data collected from a total of 150 participants aged between 13-60 years. To achieve a representative sample with balanced demographics, this study employed a partially purposive sampling approach. This involved stratifying the participant pool into five age categories: 13-17, 18-25, 26-35, 36-45, and 46-60. Within each age group, 10 individuals (5 male and 5 female) were purposely selected to participate in each of the three questionnaire groups, resulting in a total of 50 participants in each of the three-variation groups. Survey responses from 12 participants were deemed invalid — 7 due to incomplete submissions and 5 due to refusal to complete the survey in the midway. To maintain the integrity of the study and uphold proportional representation across the three variation groups, replacement participants were randomly selected. All participants identified as Mongolian (100%), with 28% reporting as high school students in the study population. The participant cohort exhibited gender parity, featuring an even distribution of 50% female and 50% male respondents.

Materials

Based on the study's objective to test multiple hypotheses, participants were divided into three experimental groups, utilizing structured questionnaire surveys. All three survey versions (Groups 1, 2, and 3) shared a common core structure, consisting of three parts:

- ***Socio-Demographic Measure***

The participants in this study were given a demographic data questionnaire requesting background information. This included self-report questions about gender and age.

- ***Subjective Mental State Assessment Scale***

To assess the potential influence of emotional biases on individual stock value prediction decisions, participants engaged in a brief self-reported evaluation of their current mental state. This subjective assessment utilized a 5-point ordinal scale (ranging from "Very Low" to "Very Good").

- ***Extrapolation Task***

To analyze participants' tendency to extrapolate future trends based on past data, they were presented with four separate graphs. Each graph displayed a time series with a discernible pattern (increasing, decreasing, or stable).

Participants were instructed to analyze each graph and extend the line representing the trend beyond the provided data points. This task aimed to evaluate their ability to infer potential future trends based on the available data, acknowledging the inherent uncertainty involved in such projections.

The key difference between the three survey versions resided in the final section, which presented participants with a line extrapolation task involving stock price charts. Here, survey paper will delve deeper into the variations within this task across the three groups:

Group 1: No Context

Participants in this group received no prior information or explanation about the nature of the line charts. The prompt simply instructed them to "predict the future trend for each of the four charts provided by drawing continuations of the lines." This group served as the baseline for comparison, allowing us to analyze participants' initial tendencies and potential biases in extrapolating future trends without any financial context.

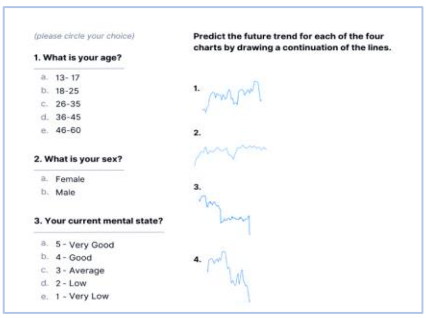

Figure 1. Survey Material for Group 1: Unknown Graph Extrapolation Task

Group 2: General Context

Participants in this group received a brief introduction informing them that the charts depicted stock market trends. However, no specific details about the companies or their financial performance were provided. The line continuation task remained the same, instructing participants to predict future trends for each chart by drawing continuations of the lines. This group allowed us to assess how general knowledge of stock market trends might influence responses compared to the baseline group with no context.

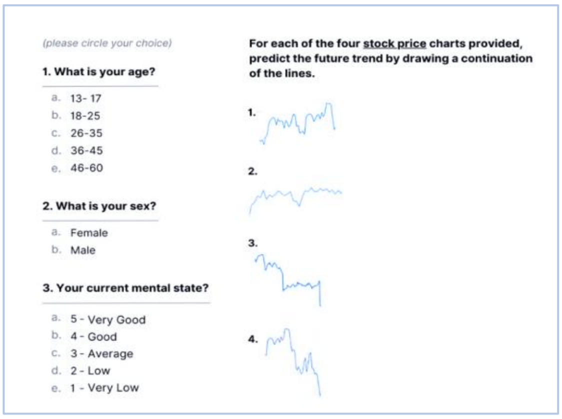

Figure 2. Survey Material for Group 2: Stock Price Graph Extrapolation Task with General Contex

Group 3: Full Context

Participants in this group received the most detail about the line charts. In addition to the general stock market context provided to Group 2, this group was also given information about the companies represented in each chart, including their names, general operation, and countries of origin. Similar to the other groups, they were instructed to predict future trends by continuing the lines on the charts. By introducing company information and potentially triggering home bias (preference for familiar investments), this group allowed us to investigate the potential influence of such biases on participants' responses.

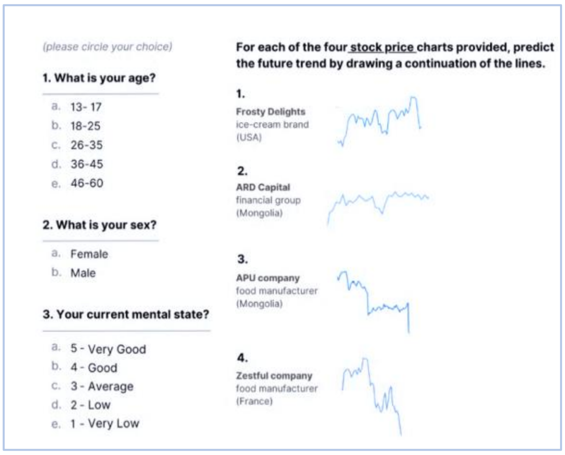

Figure 3. Survey Material for Group 3: Stock Price Graph Extrapolation Task with Full Context

RESULTS

The following section presents the results of the study on extrapolation tendencies across different groups. Analysis focuses on three distinct groups of participants: Group 1, who received no prior information about the line charts; Group 2, who were provided with general stock market context; and Group 3, who were given detailed company-specific information. By examining the patterns and biases in their extrapolations, study aimed to understand how varying levels of financial context influence participants' predictions. Additionally, the study compares these tendencies across different age groups and genders to identify any demographic variations in extrapolation behavior. The findings are structured to highlight both expected trends and any unexpected observations that emerged from the data.

Extrapolation Tendencies Across Groups

Group 1: No Context

Table 1. Group 1: Mental State Distribution of Participants by Gender

Gender	Very Low	Low	Average	Good	Very Good	TOTAL
Female, n	3	5	9	2	6	**25**
Male, n	2	7	5	6	5	25

Analyzing the drawn continuations can be challenging due to their subjective nature. To address this, the study categorized participants' extrapolations based on how they responded to the repeated patterns present in each graph. These patterns involved a sequence that was repeated at least twice within the line segments.

Extrapolation Table* Breakdown*:

1. **Age Groups:** The first column lists the participant age groups.
2. **Matched Patterns:** This section is further divided into:
   a. **Single Matched:** Participants continued **one repetition** of the pattern.
   b. **Multiple Matched:** Participants continued two or more repetition of the pattern.
3. **General Trend:** This category captures continuation in the same direction of the established trend in the graphs, but not showing matched pattern shape.
4. **Opposite Trend:** This category captures continuations in the **opposite direction** of the established trend.
5. **Ambiguous/Flat:** This category captures continuations that were unclear or showed no discernible trend.

To accurately capture the diverse extrapolation behaviors exhibited by participants, a graph-by-graph analysis was employed. Given that each participant responded to four distinct graphs, aggregating responses into a single data point would obscure the nuanced patterns emerging from individual graph continuations. For instance, a participant might have adopted a "Matched Patterns" strategy for one graph while opting for a "General Trend" approach for another. Consequently, each graph's extrapolation was treated as an independent data point, resulting in a dataset of 200 extrapolations for each of the three groups, despite a sample size of 50 participants per group.

Table 2. Group 1: Extrapolation Category Distribution by Age

Age Group	Matched Patterns (Single)	Matched Patterns (Multiple)	General Trend	Opposite Trend	Ambiguous/ Flat
13-17, n	-	20	8	8	4
18-25, n	12	20	-	8	-
26-35, n	4	28	-	8	-
36-45, n	8	20	4	-	8

46-60, n	4	32	4	-	-
Total, n (%)	28 (14%)	120 (60%)	16 (8%)	24 (12%)	12 (6%)

Analysis of participants' predictions revealed that 74% (n=148) consistently redrew the doubled pattern depicted within the graphs when extrapolating future trends. This behavior aligns with the representativeness heuristic, suggesting that individuals might tend to expect future outcomes to closely mirror past patterns, thereby reinforcing their expectations based on perceived similarities.

Interestingly, while overall gender differences in incorporating the doubled pattern were not statistically significant (76 female, 72 male), a closer look revealed a potential difference within the "Matched Patterns" groups. Participants who drew a single repetition of the doubled pattern were predominantly female (1:6 male-to-female ratio), while those who drew multiple repetitions were more likely to be male (3:2 male-to-female ratio).

To gain insights into the reasoning behind drawing single repetitions of the doubled pattern, the study interviewed two female participants from “Single Matched Pattern” group. Interestingly, their responses suggest a potential link between the lack of context and a cautious approach, which might be more prevalent among female participants in this specific instance. Further research with a larger and more balanced sample is needed to confirm this pattern.

The "Opposite Trend" category primarily consisted of male participants (5:1 male-to-female ratio) who reported feeling low or very low on the mental-state assessment. This suggests a potential correlation between negative emotional states and a tendency to predict outcomes contrary to established trends, particularly among men in this context. But except this category, no such mental-state correlation was observed.

Interestingly, all extrapolations in the "General Trend" category (8%, n=16) were performed by female participants. However, no clear link emerged between their self-reported mental state and extrapolation behavior. Similarly, the small sample size (n=12) in the "Ambiguous/Flat" category limits definitive conclusions about potential mental state associations. Nevertheless, within this category, a slight female predominance was observed (1:2 male-to-female ratio).

Group 2: General Context

Table 3. Group 2: Mental State Distribution of Participants by Gender

Gender	Very Low	Low	Average	Good	Very Good	TOTAL
Female, n	2	2	13	6	2	**25**
Male, n	1	2	16	2	4	25

Table 4. Group 2: Extrapolation Category Distribution by Age

Age Group	Matched Patterns (Single)	Matched Patterns (Multiple)	General Trend	Opposite Trend	Ambiguous/ Flat
13-17, n	4	24	8	-	4
18-25, n	16	16	4	-	4
26-35, n	8	32	-	-	-
36-45, n	8	24	-	8	-

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46-60, n	16	12	8	4	-
Total, n (%)	52 (26%)	108 (54%)	20 (10%)	12 (6%)	8 (4%)

Examining participant behavior in Group 2 reveals interesting behaviors in extrapolation tendencies. Overall, matched pattern groups combined had a slight male dominance (83 males, 77 females). While women were slightly more likely to select single pattern matches (6:7 male-to-female ratio), men dominated the multiple matched and opposite trend categories (59:49 male-to-female and 4:3 male-to-female ratios, respectively). The "General Trend" category was predominantly female (1:3 male-to-female ratio), with a concentration in the younger age group (18-25). The "Opposite Trend" category was dominated by older participants (36-45, 46-60). Notably, participants in the "Ambiguous/Flat" category had equal gender ratio and reported stable mental states, contrasting with the negative mental states of those in the "Opposite Trend" category in Group 1.

Except for the "Ambiguous/Flat" group's gender ratio, Group 2 closely replicated the category percentages and gender distributions observed in Group 1. This suggests that knowledge of the graph type (a stock price chart) did not significantly influence extrapolation patterns compared to when no graph type was specified. While providing context in Group 2 could potentially offer advantages, it did not substantially alter the overall extrapolation tendencies. This might be attributed to the limited specificity of the provided information, which primarily focused on the graph type rather than detailed market or company specifics. Consequently, participants may have relied on the representativeness heuristic, basing their predictions on past patterns without deeper analysis. However, no clear correlation between mental state and extrapolation behavior emerged in Group 2.

Group 3: Full Context

Overall Extrapolation Behavior: Group 3

Table 5. Group 3: Mental State Distribution of Participants by Gender

Gender	Very Low	Low	Average	Good	Very Good	TOTAL
Female, n	2	2	10	6	5	**25**
Male, n	7	4	3	4	7	25

The "flat" category, present in the other groups, was eliminated for Group 3 as no participants produced flat extrapolations.

Table 6. Group 3: Extrapolation Category Distribution by Age

Age Group	Matched Patterns (Single)	Matched Patterns (Multiple)	General Trend	Opposite Trend
13-17, n	13	14	5	8
18-25, n	5	20	3	12
26-35, n	8	23	-	9
36-45, n	10	14	4	12
46-60, n	9	14	6	11
Total, n (%)	45 (22.5%)	85 (42.5%)	18 (9%)	52 (26%)

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Examining the results from Group 3 reveals a notable inclination toward pattern matching, as demonstrated by the predominance of the "Matched Patterns" categories in Table 6. Although Group 3 provided a broad range of information about the graphs, the representative heuristic was strong, with multiple and single matched patterns accounting for 65% (n=130) of all extrapolations. Notably, Group 3 had a 42.5% rate in the Multiple Patterned categories, which was lower than Groups 1 and 2. It's important to consider that this data reflects extrapolations on a graph-by-graph basis rather than participant-by-participant.

A unique aspect of Group 3's data is the absence of "flat" extrapolations; all participants exhibited discernible upward or downward trends. This may suggest a high level of confidence or certainty among participants, even though some companies in the survey were fictional. It's possible that other contextual information provided helped participants feel more certain or prompted them to continue the established trend. This could indicate a perception that stock prices generally move sharply either up or down, rather than remaining stable. Alternatively, the presence of fictional companies might have introduced uncertainty, leading participants to default to continuing the given patterns in the graphs, thus reinforcing the representative heuristic in uncertain situations.

The "Opposite Trend" category also displayed a notable frequency across all age groups. Group 3 had a higher percentage (26%, n=52) in this category compared to Groups 1 and 2, which showed 12% and 6%, respectively. This indicates that while pattern matching was the predominant approach, some participants were open to considering alternative trends based on the context provided, regardless of the given patterns in the graph. This suggests that certain biases, such as home bias or other context-based considerations, may have influenced participants' decisions. Detailed tables for each stock graph (out of the four given graphs for each participant) are included below, offering more insight into the opposite trend and other behaviors observed.

Extrapolation Patterns by Each Graph: Group 3

The following tables present the extrapolation results for each of the four graphs presented to participants. The graphs, detailed in the Methodology section, represent a mix of real and fictional companies across various industries and countries. Each table displays the distribution of extrapolation categories (matched patterns, general trend, opposite trend) across age groups. This format allows for an in-depth analysis of how participants responded to different graph contexts.

Graph 1: *Frosty Delight*

a. Industry*:* Ice-cream producer brand

b. Country: USA

c. Key Features: The graph shows a clear upward trend with occasional minor fluctuations. It features a distinct double-pattern, marked by two cycles of rapid growth followed by phases of consolidation. The overall trend remains positive despite these fluctuations.

Table 7. Group 3: Graph 1: Extrapolation Category Distribution by Age

Age Group	General Trend (upward)	Opposite Trend (downward)	Matched Patterns (Single)	Matched Patterns (Multiple)
13-17, n	-	1	6	3
18-25, n	-	-	-	10
26-35, n	-	-	2	8
36-45, n	2	1	3	4

46-60, n	4	2	2	2
Total, n (%)	6 (12%)	4 (8%)	13 (26%)	27 (54%)

The provided data for Graph 1 indicates a strong preference for pattern matching among participants, as evidenced by the dominance of the "Matched Patterns" category, particularly in the "Multiple" subcategory, which accounts for 54% (n=27) of all responses. The high percentage of matched patterns (26% for single and 54% for multiple) reinforces this notion.

While the upward trajectory of the graph likely contributed to the overall optimism among participants, interviews revealed that the perception of ice cream as a seasonal product, particularly among the 18-25 and 26-35 age groups, significantly influenced their predictions. This contextual understanding, amplified by the survey conducted in June 2024 (summer), led to a higher proportion of upward-oriented extrapolations. Of the 27 participants whose drawings were categorized as 'Multiple Matched Patterns', 18 cited seasonal factors as their primary influence.

Considering, the "General Trend" category only accounts for 12% of responses, suggesting that while participants recognized the upward trajectory, they were more inclined to replicate the specific pattern rather than simply continuing the established general trend.

A gender disparity was observed in pattern continuation styles. While women were more likely to produce single, shorter matched patterns (10 women, 3 men), men tended to create multiple, longer matched patterns (16 men, 11 women). Additionally, a 1:3 female-to-male ratio emerged among those who drew continuations in the opposite direction. While the data did not reveal a consistent correlation between mental state and extrapolation, all three participants who drew opposite continuations reported a 'very low' mental state.

In Conclusion, While the upward trajectory of the graph contributed to optimism, seasonal factors played a particularly significant role in influencing predictions, especially among younger age groups. This suggests that participants were not solely relying on the representativeness heuristic but were also incorporating contextual knowledge into their extrapolations.

Graph 2: *Ard Capital*

a. Industry/Operation: Financial Group

b. Country: Mongolia

c. Key Features: The graph exhibits a cyclical pattern with alternating periods of growth and decline, oscillating around a relatively stable level. Although there are fluctuations, there isn't a clear overarching upward or downward trend. Despite the variations, there is a slight indication of an upward trend in the broader perspective.

Table 7. Group 3: Graph 2: Extrapolation Category Distribution by Age

Age Group	General Trend (upward)	Opposite Trend (downward)	Matched Patterns (Single)	Matched Patterns (Multiple)
13-17, n	2	2	4	2
18-25, n	2	1	1	6
26-35, n	-	-	2	8
36-45, n	2	-	1	7

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46-60, n	2	1	4	3
Total, n (%)	8 (16%)	4 (8%)	12 (24%)	26 (52%)

Interestingly, despite the given graph indicating a relatively flat trend with cyclical fluctuations, a high percentage (92%) of participants drew upward continuations. This could potentially be attributed to a combination of factors, including the familiarity of ARD Capital as a Mongolian company, which might have instilled a sense of optimism and confidence among participants.

An analysis of participant interviews suggests that age groups may have influenced extrapolation behavior for Graph 2. While the overall pattern of responses was consistent across age groups, the role of familiarity with ARD Capital, a well-known Mongolian financial company, became apparent. Younger participants (18-35) emphasized the company's popularity in shaping their upward projections, potentially reflecting a broader trend-following bias. Older participants (46-60) more frequently cited the company's Mongolian origin, suggesting a potential home bias influencing their optimistic outlook.

Men were significantly overrepresented in the "multiple" category (9:4 male-to-female ratio), while women were more likely to select the "single" pattern (1:2 male-to-female ratio). An equal gender distribution was observed in the "opposite" category, and a pronounced female dominance characterized the "general up" category (1:7 male-to-female ratio).

Overall, participants were optimistic about ARD Capital's future, likely influenced by their familiarity with the company as a well-known Mongolian brand. Age groups may have influenced extrapolation behavior, with younger participants emphasizing the company's popularity (possibly reflecting a halo effect) and older participants citing its Mongolian origin (indicating home bias). Additionally, gender disparities were observed, with men more likely to draw longer prediction lines and women favoring shorter continuations, potentially suggesting differences in risk tolerance or confidence levels.

Graph 3: *APU Company*

a. Industry/Operation*:* Food manufacturer

b. Country: Mongolia

c. Key Features: The graph exhibits a pronounced downward trend characterized by two consecutive patterns of minor fluctuations followed by sharp declines.

Table 7. Group 3: Graph 1: Extrapolation Category Distribution by Age

Age Group	General Trend (downward)	Opposite Trend (upward)	Matched Patterns (Single)	Matched Patterns (Multiple)
13-17, n	1	3	2	4
18-25, n	1	7	2	-
26-35, n	-	9	1	-
36-45, n	-	10	-	-
46-60, n	-	8	2	-
Total, n (%)	2 (4%)	37 (74%)	7 (14%)	4 (8%)

Group 3 strongly opted for the "Opposite Trend" (74%), predicting an upward trajectory despite the graph's

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given downward trend. This suggests a strong disregard for past performance in favor of a more optimistic outlook, possibly influenced by factors such as home bias related to APU Company's status as a well-known Mongolian brand.

Interestingly, while participants aged 26-60 demonstrated a strong preference for the "Opposite Trend" category, with minimal selection of other options, younger age groups (13-17 and 18-25) showed a relatively varied response.

Interview data revealed potential home bias among participants, particularly in the 46-60 age group who frequently cited support for domestic companies as influencing their downward projections. While this sentiment was also present among the 18-60 demographic, a tendency towards favoring familiar entities might explain the overall upward bias. Interestingly, while the 13-17 age group demonstrated familiarity with the company, their lack of upward projections, unlike older groups, suggests a potential reliance on representativeness heuristic rather than home bias, indicating a more complex relationship between familiarity and extrapolation in this demographic.

In contrast to the graph’s established trend, a total of 21 males and 16 females drew upward continuations. Women were more presented in the “single” pattern category (1:6 male-to-female ratio).

In general, participants demonstrated a strong disregard for past performance, predicting an upward trajectory despite the downward trend. Home bias among older participants and familiarity with APU Company influenced these projections. Gender disparities were observed in pattern continuation styles, with women more likely to draw shorter continuation similar in Graph 2 and men being more likely to draw opposite continuation then women.

Graph 4: *Zestful Company*

a. Industry/Operation: Food manufacturer

b. Country: France

c. Key Features: The graph depicts a downward trend marked by two distinct peaks resembling a mountain shape. These peaks represent temporary growth periods followed by sharp declines, resulting in a consistent negative trajectory.

Table 7. Group 3: Graph 1: Extrapolation Category Distribution by Age

Age Group	General Trend (downward)	Opposite Trend (upward)	Matched Patterns (Single)	Matched Patterns (Multiple)
13-17, n	2	2	1	5
18-25, n	-	4	2	4
26-35, n	-	-	3	7
36-45, n	-	1	6	3
46-60, n	-	-	1	9
Total, n (%)	2 (4%)	7 (14%)	13 (26%)	28 (56%)

The data reveals a strong preference for pattern matching, as evidenced by the dominance of the "Matched Patterns" category, particularly in the "Multiple" subcategory, which accounts for 56% of all responses. This suggests a significant reliance on the representativeness heuristic, with participants extrapolating future trends based on the observed cyclical pattern.

Graph 3 and Graph 4 shared similarities as both represented food manufacturers and exhibited double-patterned downward trends. However, while participants in Group 3 predominantly opted for the "opposite trend," those in Group 4 were more likely to replicate the given pattern into the given downward trend. This disparity might be attributed to the less steep decline in Graph 4 compared to the dramatic drop in Graph 3. Additionally, the fictional nature of Zestful Company versus the well-known Mongolian brand APU Company could have influenced participants' optimism in Graph 3 but not in Graph 4. Furthermore, as the primary difference between the two graphs was the country (Mongolian for APU and French for Zestful), the sequential presentation, with APU preceding Zestful, might have intensified a home bias among participants, leading to a more pronounced downward pattern replication in Graph 4.

While gender ratio in “multiple matched” category was (4:3 male-to-female), women were more likely to draw single pattern matched continuations (5:8 male-to-female ratio). Additionally, men dominated the "opposite" category (4:3 male-to-female ratio). The "General Trend" category primarily consisted of female participants from the same age group, who continued the downward trajectory established by the graph.

To conclude, participants exhibited a strong preference for pattern matching, replicating the downward trend in Graph 4. The less steep decline in Graph 4 compared to Graph 3, combined with the fictional nature of Zestful Company, might suggest that when faced with a less familiar or unfamiliar company, participants may rely more heavily on the representativeness heuristic. Gender disparities were observed, with men more likely to use multiple patterns and women favoring single patterns, similar to trends seen in Graphs 3 and 2.

Overall Extrapolation Behavior of All 4 Graphs: Group 3

The analysis of extrapolation patterns across the four graphs reveals distinct trends and influences on participant decision-making. While the representativeness heuristic was evident in all groups, its impact varied across graphs. Factors such as graph type, company familiarity (real vs. fictional), and age-related differences influenced participants' extrapolation behaviors.

The dominance of the "Matched Patterns" category in Graphs 1, 2, and 4 highlights the strong influence of the representativeness heuristic, with participants replicating observed patterns. Conversely, Graph 3 demonstrated a departure from this trend, with participants primarily opting for the "Opposite Trend," suggesting a potential interplay between optimism, home bias, and disregard for past performance.

Gender differences emerged in extrapolation patterns, with men more likely to select "Multiple Matched Patterns" and "Opposite Trend" categories, while women showed a preference for "Single Matched Patterns" and were likely to be presented more in the "General Trend" category for Graph 2 and 4. However, Group 3 exhibited a notably weaker correlation between mental state and extrapolation behavior.

The findings from this study highlight the complexity of human judgment in predicting future trends and emphasize the need for further research to understand the interplay of cognitive biases, demographic factors, and contextual influences on decision-making processes.

MAJOR FINDINGS

Representative Heuristic Influence: The study found a strong presence of the representativeness heuristic across all survey groups. Regardless of the level of contextual information provided, participants predominantly relied on past patterns to predict future trends.

Gender-Based Extrapolation Patterns: Consistent gender differences emerged in extrapolation behaviors across all groups, excluding the "ambiguous/flat" category. Women demonstrated a preference for shorter, single-pattern continuations and were more likely to follow general trends. In contrast, men tended towards longer, multiple-pattern continuations and were more inclined to predict opposite trends.

Minimal Mental-State Correlation: Contrary to expectations, participants' mental states showed negligible correlation with extrapolation tendencies. While a slight correlation emerged within the "opposite trend" category, it was not statistically significant overall. These findings suggest a limited role for emotional bias in extrapolation tasks.

Age and Home Bias: Older participants exhibited a stronger home bias, relying on the company's origin to inform their predictions. Younger participants were less influenced by home bias, demonstrating a greater focus on operational factors.

Hypothesis Testing

H_1: Gender significantly influences stock price prediction patterns. – Accepted

H_2: Age is associated with differences in stock price prediction patterns. – Accepted

H_3: Specific mental states (e.g., low, very low, average) are associated with differences in stock price prediction patterns. – Tentatively Rejected

H_4: The representativeness heuristic significantly influences extrapolation patterns by leading individuals to rely on past performance to predict future trends. – Accepted

H_5: The origin of the company significantly influences stock price prediction patterns through the activation of cognitive biases. – Accepted

DISCUSSION

The present study delves into the intricate interplay of cognitive biases, demographic factors, and contextual information in shaping individuals' stock price predictions. Our findings underscore the pervasive influence of the representativeness heuristic, as participants consistently relied on past patterns to inform future trends. This aligns with previous research emphasizing the impact of heuristics on investment behavior (Tversky & Kahneman, 1974).

Gender emerged as a significant factor influencing extrapolation patterns. Women exhibited a preference for single pattern matching and general trends, potentially reflecting a more cautious approach to investment decisions. Conversely, men demonstrated a higher propensity for multiple pattern matching and opposite trends, suggesting a potentially higher risk tolerance. These findings contribute to the ongoing discourse on gender disparities in financial decision-making (Barber & Odean, 2016).

While age influenced extrapolation behavior to some extent, its impact was less pronounced than gender. The observed tendency of younger participants to be less influenced by home bias warrants further investigation.

Contrary to expectations, mental state exhibited a minimal impact on prediction behavior, suggesting that cognitive factors might be more influential in shaping extrapolation patterns. However, the reliance on self-reported mental states limits the depth of this conclusion. Future research employing more objective measures of emotional state is warranted.

The provision of contextual information did not substantially alter the reliance on the representativeness heuristic. This suggests that the power of this cognitive bias may override the influence of additional information. However, further research is needed to explore the potential impact of different types of contextual information on prediction accuracy.

These findings have implications for financial education and investor behavior. By understanding the cognitive biases that underpin investment decisions, financial educators can develop targeted interventions to enhance financial literacy and promote more informed decision-making. Additionally, acknowledging gender and age-related differences in investment behavior can inform the development of tailored financial products and services.

Future research should focus on exploring the interplay between cognitive biases, demographic factors, and contextual information in greater depth. Longitudinal studies and the incorporation of diverse cultural contexts would provide valuable insights into the evolution of investment behavior and the effectiveness of interventions aimed at mitigating cognitive biases.

CONCLUSION

This study aimed to elucidate the impact of cognitive and emotional biases, demographic factors, and contextual information on non-expert investors' stock price predictions. By examining how individuals rely on heuristics and demographic tendencies in their investment decision-making, the study addressed a critical gap in understanding investment behavior.

Results demonstrated that participants were significantly influenced by the representativeness heuristic, relying heavily on past patterns to predict future trends. Gender and age also played a role, with distinct extrapolation patterns observed between men and women and across different age groups. While mental state showed limited influence, the study highlights the dominance of cognitive factors in shaping investment decisions.

These results underscore the need for further research to explore the interplay of these factors in greater detail and to develop strategies for counteracting the impact of biases on investment decision-making. Financial advisors can leverage these insights to offer more personalized advice, taking into account the specific biases and tendencies of their clients based on demographic characteristics.

Ultimately, this research contributes to a deeper comprehension of the psychological underpinnings of stock price predictions and emphasizes the critical role of certain factors in behavioral finance.

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