Myopic Loss Aversion and Portfolio Decisions: From the Lab to the Field [*]

Kazi Iqbal[†] Asad Islam[‡] John List[§] Vy Nguyen[¶] Sakif Rahman[||]

September 22, 2023

Abstract

Whether, and to what extent, behavioral anomalies uncovered in the lab can extend to natural environments by explaining decision making in the field remains of first order importance in economics and finance. We explore this in the context of myopic loss aversion (MLA). We use artefactual field experiments to elicit the extent of MLA exhibited by retail investors in constructed laboratory markets and link it to a proprietary, individual-level dataset of their private investment accounts. We find that MLA is associated with lower equity market investment levels and lower market beta of portfolios. The MLA effect is stronger for investors who are less experienced, who update themselves frequently about the market and who make changes to their portfolio frequently. Additional evidence shows that MLA investors react negatively to short term losses in their portfolio, and their investments also perform more poorly in the stock market.

JEL Classification: C93; D81; G11

Keywords: myopic loss aversion, stock market, portfolio decision, field experiments

[*]We are grateful to generous financial support from Monash University, to our partnered brokerages in Dhaka (Reliance, IIDFC, Lanka Motijheel, Lanka Uttara, PFI, Prime Bank, Mercantile, and Modern) and to Arif Islam, who provided us the confidential data for this study, as well as to the Bangladesh Institute of Development Studies for research support. We also thank Foez Mojumder for excellent research assistance and Chau Nguyen for involvement in the project at the initial stage. Finally, we appreciate the comments of Klaus Abbink, Peter Bossaerts, Chris Clapp, Silvio Contessi, Huu Duong, Glenn Harrison, Jean Paul Rabanal Sobrino, Jeffrey Lafrance, Thomas Langer, Matthew Leister, Birendra Rai, ChoonWang, and participants at the University of Chicago (Chicago, 2019, 2018), the Australia Conference of Economists (Melbourne, 2019), the Experimental Finance Conference (Copenhagen, 2019), the Advances with Field Experiments (Boston, 2018), the Academy of Behavior Finance (Chicago, 2018), the Behavioral and Experimental Economics and Finance Workshop (Sydney, 2017), and Monash University Seminars (Melbourne, 2017, 2018).

[†]Bangladesh Institute of Development Studies. Email: kiqbal@bids.org.bd

[‡]Monash Business School, Monash University; J-PAL. Email: asadul.islam@monash.edu

[§]Department of Economics, University of Chicago and NBER. Email: jlist@uchicago.edu (Corresponding author)

[¶]Blockchain Innovation Hub, RMIT University. Email: vy.nguyen2@rmit.edu.au

[||]Simon School of Business, University of Rochester. Email: Sakif.Rahman@simon.rochester.edu

1 Introduction

The behavior of economic agents can depart from the predictions of standard economic models. In order to explain various anomalies not rationalized by standard economic models, behavioral economists have relied on key insights from psychology resulting in the fields of economics and finance to experience the rising importance of behavioral economics in the last few decades.[1] Whether, and to what extent, behavioral anomalies uncovered in the laboratory environments can explain decision making in natural environments remains of first order importance in economics and finance. In this study, we explore this question in the context of myopic loss aversion in the behavior of stock market traders.

Arguably one of the most provocative puzzle which has attracted widespread attention across both economics and finance is the equity premium puzzle: the average annual real return on U.S. equities was roughly 7 percentage points higher than the real return on relatively riskless securities over the past century (Mehra & Prescott, 1985).[2] In an attempt to explain this puzzle, Benartzi and Thaler (1995) introduce myopic loss aversion (MLA) which is a behavioral trait that combines loss aversion and myopia in mental accounting. Subsequent literature complementing this theory have mostly utilized laboratory experiments to find evidence consistent with MLA (Gneezy et al., 2003; Gneezy & Potters, 1997; Haigh & List, 2005; Thaler et al., 1997). However, it remains to be seen if, and to what degree, such behavioral anomalies uncovered in controlled laboratory environments can explain behavior in the field. We provide evidence in this regard, by linking both laboratory and field settings to see how MLA uncovered in constructed laboratory markets is associated with actual, real life decisions of investors in financial markets.

Mehra and Prescott (1985) argue that the behavior of U.S. investors in the underlying data resemble a puzzle since it would require an implausibly high coefficient of relative risk aversion in their general equilibrium model with additively separable utility functions to explain the equity premium. In order to rationalize the equity premium and provide a satisfactory explanation for this puzzle, Benartzi and Thaler (1995) augment the standard model by incorporating two

[1] For recent literature reviews focusing on behavioral anomalies in individual investment and financial decision making, see Barber and Odean (2013), Hirshleifer (2015), and Barberis (2018).

[2] Over the period 1889-1978, the average yield on the S&P 500 Index was 7.9 percent, while the average yield on short-term debt was less than 1 percent (Mehra & Prescott, 1985).

general features of human cognition—myopia and loss aversion.[3] Myopia refers to the tendency for individuals to disproportionately focus on the short-term when making decisions involving a temporal component while loss aversion refers to the tendency to emphasize losses over gains of equal size (see e.g., Kahneman & Tversky, 1979). Investors subject to MLA pay too much attention to the short-term volatility of their portfolio and respond negatively to short-term downside changes. Thus, frequency of feedback on asset returns plays a key role in determining MLA investors' preferences over assets as they will be overly risk averse to assets with such volatility.[4] Building on this result, a set of creative studies (Gneezy & Potters, 1997; Thaler et al., 1997) demonstrate the effect of MLA using experimental laboratory settings in which participants were asked to make investment decisions involving risky assets under different levels of feedback frequencies. In accordance with MLA theory and observations about the equity premium puzzle, these studies find that participants in the low-frequency condition tended to invest more in risky assets. This finding has been extended to several modified experimental settings, such as using an asset market (Gneezy et al., 2003), a setting with flexibility in investment horizon (Fellner & Sutter, 2009), and settings with professional traders in a framed field experiment (Haigh & List, 2005).

While investment patterns observed in laboratory experimental settings are consistent with the predictions from MLA theory, it is not clear if the behavior of traders in experimental settings can extend to a financial market setting to explain actual, real life decisions of representative investors. This gap in the literature represents an important shortcoming in our understanding of whether the observed patterns in trading behavior and asset returns can be explained through MLA theory. This is because price is set by marginal traders in markets. So it is necessary that such behavioral tendencies are exhibited by marginal traders in their respective trading markets in order for MLA to explain the equity premium puzzle. To address this gap in the literature, we take advantage of data from two different sources: controlled data generated from a framed field experiment and naturally-occurring confidential data from private investment accounts.

In this study, we examine the prevalence of MLA in retail investors by eliciting such behavioral tendencies within experimental laboratory markets and study how it is associated with their

[3] After discussion of various frameworks and explanations, Kocherlakota (1996) and Mehra and Prescott (2003) are led to conclude that no single model that can explain the data patterns consistent with the equity premium. For a subclass of general equilibrium models in Mehra and Prescott (1985), the equity premium puzzle is even larger than recognized in the literature (Azeredo, 2014).

[4] As estimated by Barberis et al. (2001), models based on myopic loss aversion can generate substantial equity premia.

portfolio decisions in equity markets. We collaborate with eight brokerages in the Dhaka Stock Exchange (DSE) in Bangladesh and recruit a sample of traders across these brokerages to participate in a framed field experiment measuring their individual MLA. We then link their laboratory choices with proprietary data on their actual trading activities over a two-year period. In the generation of experimental data, we leverage the standard lab treatment (Gneezy & Potters, 1997), but use a within-subject design to estimate person-specific MLA from the framed field experiment. In Task 1, subjects were randomly assigned into either the high feedback frequency where they made the decision and learned about the outcome every individual round or the low feedback frequency in which decisions (and feedback) were made in blocks of three rounds. In Task 2, we switched treatment and repeated the experiment under the other feedback frequency. Our within-subject design not only permits us to examine data from a standard between-subjects approach, but also provides a unique MLA measure for each individual.

We report several findings. First, we confirm that the behavior of retail traders in the lab is largely consonant with MLA theory. We find a significant treatment effect under the standard between-subject design.Specifically, subjects invested 18.6% more when receiving a lower feedback frequency.We then analyze the within-subject distribution to obtain an individual-specific construct of MLA. We classify MLA traders as those who invest more under infrequent feedback and we find that 51.03% of our subjects exhibited MLA.

We then move to studying how retail investors' MLA affects their real life trading decisions in the stock market. First, we test the central prediction stemming from MLA theory and see whether myopic loss averse individuals exhibit lower risk taking in stock markets when compared to individuals who behave the opposite experimentally. We document that, on average, compared to reference category, MLA investors have lower levels of stock market investment as measured by the cost of the their equity portfolio. MLA investors' portfolio costs at least 1.1 experimental unit less on average for every unit of income. The observed effect is sizeable as MLA investors' level of stock market investment is 31% lower than the average stock market investment level of the reference group. We control for a variety of personal, demographic and trading information as well as include a rich set of fixed effects. We are thus able to not only compare between traders from similar cohorts with same general and brokerage firm specific trading experience but also compare between traders who hold similar portfolios, specializing mostly on stocks from the same industry on the same day.

We then conduct several robustness tests on the association between MLA and stock market investment levels. First, we find that the results are not affected when we control for other behvioral biases such as risk aversion, ambiguity aversion and time preference as well as individual beliefs about the future condition of the stock market or the economy in general. We then rule out selection bias as an explanation for our results by conducting our analysis on a balanced sample of traders matched on initial demographic and stock market trading information. Given our measurement of MLA at the individual level is based on a within subject design, we are aware that order effects may influence our measure and hence the documented relationship between MLA and stock market investment levels. Through regression residuals we extract the variation in differences in bets under two feedback frequency which is not due to the order of exposure to the feedback frequencies. We then redefine MLA based on this and find that the results are still robust. Next, we show that our results are also robust to various alternative measurements of MLA including continuous and decile based measures. Finally, we find that adjusting for investor duration in the sample, exluding outliers, controlling for business background, including alternate controls for age and income and measuring equity at close prices do not affect our results.

After establishing our main result, we perform several tests of cross sectional heterogeneity among individual investors. First, we look into differences across markets and trading characteristics. Measuring trading experience by the number of years in stock market trading, we find that investors with trading experience above the median of 8 years are less susceptible to myopic loss aversion suggesting that traders learn how to effectively overcome their bias as they gain relevant experience.[5] Then we show that the MLA effect in risk taking is smaller for traders who update themselves about the market less frequently. Finally, we show that MLA effect in risk taking is much stronger for the group of active investors who have higher than median portfolio changing frequency. Second, we look into differences across demographic characteristics and find that the MLA effect in risk taking is attenuated for older traders but is not statistically significantly attenuated with income and education level.

We also present additional evidence complementing our initial findings on MLA and risk tak-

[5]In the context of riskless decision making, market anomalies can be mitigated for real economic players with intense market experience (List, 2002, 2003, 2004). Some investors may become better at trading through experience while others may learn that they are the 'poor' types and stop trading (Seru et al., 2010).

ing in stock markets. Given that MLA individuals have lower stock market investment levels, we also investigate whether they exhibit lower risk taking within their portfolio as measured by portfolio market beta. We find that, indeed, this is the case. On average, MLA investors hold portfolios with a market beta which is around 0.03 to 0.08 lower than that of reference group representing an effect of about 2.8% to 7.1% of the portfolio beta of the reference group.

Theory suggests that myopic loss averse individuals pay too much attention to short-term volatility of their portfolio and negatively respond to short-term downside changes. We test whether such patterns in trading behavior are observed in the data. We document that, compared to the reference group, MLA investors are more likely to reduce the size of their equity investment when their portfolio opens at a lower price compared to the price on the previous day. This provides evidence that MLA individuals indeed react more aggressively and negatively to short-term adverse changes suggesting that they are paying too much attention to the short-term volatility of their portfolio which affects their stock market outcomes.

Prior studies demonstrating the effect of MLA in laboratory experiments also find that individuals under higher feedback frequency also have lower average earnings (Gneezy & Potters, 1997; Thaler et al., 1997).[6] We measure investor performance as the gross return on investment calculated by scaling the daily market value of the portfolio by the portfolio cost and test the relationship between MLA and stock market performance. Our results show that the performance of MLA individuals' equity investments is about 5% lower on average than that of the reference group. This supports previous findings in laboratory settings and confirm that the results also extend to the natural environment of traders. We go further and find evidence that the effect on MLA individuals' stock market performance is driven by their trading frequency. Measuring trading frequency based on trading volume in units of stock, trading amount in taka and trading turnover, we show that lower market performance of investments exists only for MLA investors who trade very frequently. Given MLA individuals are more likely to react to short-term downside changes, these results complement our earlier findings since it suggests that MLA individuals may trade more frequently in response to short-term downside changes but their equity investments end up performing more poorly.

[6]Our between-subject design also replicates prior experimental results and finds that lower feedback frequency leads to higher experimental earnings.

An important feature of the longitudinal aspect of our design is that it provides the distribution of individual MLAs. The lack of a within-subject design in the literature hinders our understanding of heterogeneity and the mechanisms of experimental treatment (Charness et al., 2012; Czibor et al., 2019). Our design allows us to examine whether, and the extent to which, MLA exists at the individual level among a group of traders. The evaluations of traders' behaviors under different feedback frequencies may benefit the targeted communication strategies of fund managers and also improve long-term investments in the stock market. For example, a risky trust fund could strategically issue financial statements less frequently to improve the sheer volume of investment and avoid market volatility.

Overall, our empirical insights lend support to MLA being a viable explanation for at least part of the equity premium puzzle that has been documented over the years. There are far-reaching implications of the equity premium puzzle, starting from the costs of recession induced macroeconomic variability, to estimates of the cost of capital, to investing in public services. In fact, our simple back of the envelope calculation suggests that the existence of MLA in only active stock market traders can lead to an aggregate demand for equity which is lower by about 13.4% of equity market capitalization of retail investors. Thus, understanding the origins of the equity premium puzzle represents an important challenge for the advancement of efficient public policies (Larson, List, & Metcalfe, 2016). It is also evident why equity premium is of fundamental importance in portfolio allocation, given it's wealth-building potential in the long-run.[7] Given our findings and that of the existing literature, less susceptibility to MLA can lead to significant gains in investment portfolios. This is especially important in our study, as we provide insights into the behavior of traders in an emerging market context, where differences in stock market participation could have serious implications for wealth inequality (Pástor & Veronesi, 2021).

Related Literature We view our results as speaking to several literature. First, we contribute to bridging the gap between experimental and natural trading behavior by examining the decisions made by the same group of non-professional traders in two quite distinct environments. Financial traders are a vital component of financial decision-making and price-setting processes. Thus,

[7] Back of the envelope calculation suggests that on average, MLA traders can make additional losses of about 14.33% of their annual income from their stock market investments.

observing their behavior under both experimental and natural domains serves several purposes. While our study not only provides evidence for the results of Gneezy and Potters (1997) via replication among non-professional traders as opposed to among professional traders (Haigh & List, 2005), but also link such laboratory behavior to their real life trading activities. In this way, we go beyond simply observing financial market traders only in controlled environments as in Alevy, Haigh, and List (2007) and we mitigate some of the concerns about extrapolating results from experimental studies to real life.[8] In addition, a more recent paper by Larson et al. (2016) extends the literature by using different timing in price realizations in a natural field experiment. While their setting was designed to mimic the complexity of trading platforms and market interactions, our paper uses the actual market environment for financial traders and confirms that behavioral patterns consistent with MLA also exists even in real life.

Our work also contributes to the growing literature in finance combining experimental data and observational data. A lot of studies have utilized surveys to study a wide array of economic and financial phenomena: trading motives and observed trading behavior (Dorn & Sengmueller, 2009; Liu et al., 2021), consistency between survey expectation and actual investments (Giglio et al., 2021a, 2021b), and subjective perceptions of consumption risk in portfolio choice decisions (Chinco et al., 2021). While similar to recent papers studying behavioral biases, beliefs and motives for trading (Giglio et al., 2021a; Liu et al., 2021), our paper is very different in contribution in at least two aspects. First, as opposed to a survey based design, our study utilizes laboratory experiments to measure MLA in studying portfolio decisions. Second, in contrast to both these papers which study multiple other behavioral biases, exceptions and beliefs as well as trading motives together and confirms some of their existence in trading data, we specifically focus on myopic loss aversion as an explanation for the equity premium puzzle by uncovering behavior consistent with myopic loss aversion in trading data.

Outline The remainder of the paper proceeds as follows. Section 2 describes the institutional details and the market environment of our traders. Section 3 presents the experimental design and results as well as describes the data on the traders' private investment accounts. Section 4

[8] Experimental studies are often based on relative small samples consisting student subjects which raises a general concern about extrapolating their results to real life (see e.g. Exadaktylos et al., 2013).

presents our empirical strategy. Section 5 presents the quantitative analysis on the effect of MLA on portfolio decisions. Section 6 looks at the aggregate implications of our empirical findings. Section 7 provides a discussion. Finally, section 8 concludes.

2 Institutional Details

The stock market in Bangladesh was first formed in 1954 as the East Pakistan Stock Exchange Association Ltd. and formal trading started in 1956. But it was in 1986 that the country's premier bourse took on the name of Dhaka Stock Exchange (DSE). In 1993, the Bangladesh Securities and Exchange Commission was established as the regulator of the country's capital markets. In 2013, in collaboration with S&P Dow Jones Indices, DSE introduced the DSE Broad Index (DSEX), DSE 30 Index (DS30), and the DSEX Shariah Index (DSES). The total market capitalization at DSE is about US $29 billion with 359 listed stocks and closed-end mutual funds.[9] DSE is open for trading Sunday through Thursday between 10:00 am – 2:30 pm Bangladesh Standard Time (BST), with the exception of holidays declared by the Exchange in advance.

As of June 2019, the total equity market capitalization in Bangladesh was US $40.67 billion and the ratio of market capitalization to GDP was 14%.[10] Trading of securities on the stock exchanges can only be done through brokers of the concerned exchanges with the execution of trades being through written orders submitted to the concerned broker. There are about 1.9 million beneficiary owner accounts and active trading occurs in 200,000 of these accounts.[11] These accounts are used to uniquely identify buyers and sellers of instruments. Therefore, it is mandatory to have an account before trading in the stock market. Retail investors hold 18.5% of the equity market capitalization.[12]

The bond market of Bangladesh is in infancy stages as there are only 5 issuers of bonds as of June 2019 and is dominated by government treasury bills and bonds. Issuance of debt instruments by quasi-government entities and corporations is in a developing stage. Reasons include a small investor base, relatively high issuance costs, and a lengthy issuance time compared with

[9] https://www.cfainstitute.org/-/media/documents/article/rf-brief/rfbr-apac-capital-markets-bangladesh.pdf

[10] The country's second stock exchange is the Chittagong Stock Exchange but DSE dominates turnover with more than 90% of all trading volume on any given day.

[11] https://www.cdbl.com.bd/BO_hst.php

[12] https://www.tbsnews.net/economy/stock/who-owns-how-much-stock-market-109156

bank loans. Corporate bonds are almost non-existent. As of June 2020, only 0.1% of all outstanding debt is listed as corporate bonds and the corporate bond market accounts for only 0.01% of GDP. The government bond market accounts for 7.9% of GDP. These bonds are primarily held by commercial banks and financial institutions to maintain statutory liquidity requirements or for safe investment purposes. As of June 2019, the investment from commercial banks, financial institutions and insurance companies in government securities totalled to US $19.5 billion or 82% of government securities. Individual investors generally do not participate in the bond market.

3 Experiment and Data

We describe the experimental design and results as well as the characteristics and trading information of our sample of traders in this section. In the spirit of Fehr and List (2004), we embedded our experiment within a financial training program for non-professional traders in the DSE. We recruited 341 traders from eight brokerage firms in Dhaka and offered them participation in a free intensive training program on trading techniques and risk diversification.[13] Before any of the professional training began, we conducted incentivized games to study the traders' behavioral biases.[14]

In brief, the MLA experiment proceeded as follows. First, subjects read and signed a consent form. Second, subjects were informed that (i) the experiment consisted of four segments that would last 2 hours each, (ii) their payments in each game depended on their performance, and (iii) all payments were blind and anonymous. At the beginning of each game, subjects received detailed written instructions; all instructions were also read aloud by the field staff. The subjects were given a few additional minutes to examine the instructions and (privately) ask questions, if any. The demographics as well as the market and trading information survey was conducted on the next day.

For each part of the experiment, the participants were informed of the payment procedure

[13]The training involved six sessions over a three-week period, and all the training and materials were free of charge. Each training session was conducted by senior professional traders in the brokerages—all the trainers were Chartered Financial Analysts at the time of training. The curriculum covered basic terminologies in the stock market, how to manage portfolio risk to maximize sound money-management principles and risk-analysis techniques, and how to utilize trading tools and market information available in the market. Traders who enrolled in this program consented to giving us their actual trading data via their brokerage.

[14]We study individual time preferences, risk aversion, ambiguity avoidance, and MLA, which is our focus in this paper.

ex ante. The experimental instructions for each task were generally not handed out until the previous task had been completed. Our research assistants were instructed to use neutral terms for all instructions. A translated sample of the instructions for all the games can be found in Appendix B (the version used in our experiment is written and announced in Bengali). The next section discusses the details of our experimental design.

3.1 Experimental design

3.1.1 Treatments

We adopted a similar treatment design to that of Gneezy et al. (2003) and Haigh and List (2005). Specifically, we randomly assigned participants to two treatment groups: frequent treatment, F, and infrequent treatment, I. Under Treatment F, the participants made a series of investment decisions over nine periods. In each period, the participants were given an endowment of 100 units (1 unit = 100 takas) that could be invested totally or partially (the possible investment amount [X] ranged from 0 to 100 units inclusive) in a lottery $L(1/3, 2.5X; 2/3, -X)$. Thus, the participants had a one-third chance of winning 2.5 times the amount invested and a two-thirds chance of losing the amount. Under this treatment, the participants placed an investment in every single round and learned about the outcome of each round directly after they recorded an investment and before they made their next investment.

The lottery and investment decisions under Treatment I were similar; however, the allocation decisions were made in blocks of three rounds. Specifically, in each decision round t in $1, 4, 7$, the participants placed their investments for rounds t, $t + 1$ and $t + 2$. The investment allocation had to be identical across the blocks of three rounds. At the ends of rounds 3, 6, and 9, the participants were informed of their combined earnings for the three blocks. In both treatments, the participants were informed that their final payments would equal the sum of all earnings of each round. Essentially, the two group decision tasks were identical in all aspects except in the frequency of feedback (see the upper part in Figure 1).

3.1.2 Experimental setting

Before the session, the enumerator randomly allocated the participants into two groups: approximately half the participants (182 participants) were allocated to Group F-I, and the remaining traders (159 participants) were allocated to Group I-F. As illustrated in the lower panel of Figure 1, the two groups were exposed to both frequent and infrequent feedback but in the opposite order. The following two-task procedure was adopted:

- In Task 1, each group invested under their initial randomly assigned treatment, that is, participants in Group F-I received frequent feedback and participants in Group I-F made decisions under infrequent feedback.
- In Task 2, we swapped the treatments between two groups. Participants in Group F-I were reassigned to the infrequent feedback treatment, while participants in Group I-F invested under frequent feedback.

We essentially have the full sample of 341 observations in a within-design experiment consisting of two between-subject comparisons. First, denote investment amount under frequent feedback as F1 (Task 1) and F2 in (Task 2); similarly, the infrequent feedback level of investments is referred to as I1 (Task 1) and I2 (Task 2). For simplicity, we refer to infrequent feedback as the "control" setting. The treatment effect of high-frequency feedback was obtained by comparing the means of the two groups.

In Task 1, the control group was Group I-F, so the average treatment effect of high feedback frequency would be $(F_1 - I_1)$. If the difference in the amount of money invested in F and I in Task 1 is significantly negative, then there is evidence of MLA. Notably, this analysis is identical to Gneezy et al. (2003).

The second set of between-subject comparisons is the reversal of the control-treatment group in Task 2. In this task, the control group is now group F-I, whose average investment amount is I_2. Hence, the treatment effect of frequent feedback is now $(F_2 - I_2)$.[15]

Combining Tasks 1 and 2, we analyze myopia and investment decisions under the scope of

[15]This holds under the assumption of independence between the two tasks. The variation between these two between-subject comparisons, if any, is likely due to learning or experimental carry-over effects.

a within-subject design - the within-difference is now $F_1 - I_2$ and $F_2 - I_1$.[16] This also attempts to capture real stock-market trading conditions, which involve non-professionals alternating between periods of high and low feedback frequency.

3.2 Experimental Results

3.2.1 Balance and participant characteristics

Between-subject designs rely on the success of the random assignment of the treatment. Table 1 provides the summary statistics and balance check for the randomization. The two groups were homogeneous across several demographic and trading characteristics. Most participants were male and held at least a bachelor's degree (64% held a master's degree). The average age of the participants was 37 years, and their average annual earnings was about 700,000 Taka which is equivalent to 9000 USD. These levels of education and income reflect the general distribution of the average non-professional traders in Dhaka. The participants started trading in the stock market with an initial endowment of about 450,000 Taka which is equivalent to 5780 USD and had approximately eight years of trading experience.

3.2.2 Between-subject results

Task 1 We first examine the prevalence of myopia in a standard setting (as in Gneezy et al. (2003) and Haigh and List (2005)) by comparing the difference in average endowment allocations made by the two groups in Task 1. We compare the unconditional mean difference between the investment levels under high-frequency feedback (F_1) and those under low-frequency information (I_1). Columns (1) to (3) of Table 2 shows the raw data of the mean differences and standard deviations of the investment allocations of the two treatment groups from Task 1.

First, we consider the average investments across all rounds. From columns (1) and (2), we observe that traders in control group I bet 69.92 units, while those in treatment F only bet 58.95. To attenuate data dependencies, we also divide the rounds into blocks of three and analyze the differences between the two treatments in each block, as shown in the last three rows of Table 2. In every block (blocks 1–2-3, 4–5-6 and 7–8-9), the average allocation into the risky lottery is higher

[16] We also allowed a difference in endowment by asking subjects to play an additional three rounds. They received no additional starting amount; they played the game with their own earnings up to that point equally divided into three.

in Treatment I. Using Mann-Whitney non-parametric tests, we find that the average investment across the blocks is statistically different (ρ-value=0.137 for block 1-3, 0.002 for block 4-6, 0 for block 7-9 and the block of all rounds). The results from Task 1 are consonant with the idea that MLA is prevalent amongst our traders.

Over the course of the decision rounds, participants repeated their allocation decisions under the same feedback conditions, so in each subsequent round, participants could reflect on their previous investment outcomes. In contrast to the findings of Gneezy et al. (2003), and similar to the results in Haigh and List (2005), we find that investment under frequent feedback decreased over the course of the experiment. We also find that investment under infrequent feedback increased over the course of the experiment.

Task 2 In Task 2, we seek to explore a different aspect of the trading experience by swapping the feedback frequencies between the two groups. Specifically, the 182 participants who had previously been assigned to Treatment F (i.e., the high-frequency investment condition) in Task 1 were now reassigned to Treatment I. Similarly, the 159 participants who were initially under Treatment I was assigned to Treatment F. The participants were informed of the new feedback frequency at the start of Task 2.

Columns (4) to (9) of Table 2 reports the results from Task 2 and compares the results from both between-subject designs. Columns (4) to (6) shows the raw data and the Mann-Whitney rank-sum tests for the investment amounts in Task 2. We compare the investment decisions in Tasks 1 and 2 in columns (7) to (9). As shown in column (6), in Task 2, the mean difference in investment amount across all rounds is only 3.86, as compared to the 10.97-unit between-treatment difference in Task 1 as shown in column (3). Thus, participants' degrees of MLA appear to be reduced by either learning, carry-over effects, or other psychological factors, as outlined in Charness et al. (2012). Similar to Task 1, we find that investment under frequent feedback decreased over the course of the experiment while investment under infrequent feedback increased over the course of the experiment. Overall, as documented in column (9), the difference between Task 1 and Task 2 are significantly different across all rounds.[17]

[17] We also attempt to account for the initial endowment difference using a separate new task: at the ends of Tasks 1 and 2, we asked each group to repeat the game under the same frequency treatment. However, this part differed in two respects: (1) The investment only lasted for three rounds and (2) we gave no initial endowment, so each subject had to

3.2.3 Within-subject distribution

While within-designs have certain weaknesses, a strength is that data generated from them can go beyond marginal distributions to produce the full joint distribution under certain assumptions (see Czibor et al. (2019)). This is because the combination of Tasks 1 and 2 generate data whereby all participants were exposed to both frequency environments. We can therefore tabulate the differences in investment allocation for each individual.

Figure 2 shows a histogram of the linear difference between the percentage of units allocated in high- and low-feedback treatments. A negative value indicates that the respondent made decisions consistent with MLA theory. While the average treatment effects show a large difference between the two treatments, this distribution shows that many subjects did not invest less under high-frequency feedback. Interestingly, the data reveal that the average MLA treatment effect is economically and statistically significant. Moreover, both the distributions of within subject treatment effects are similar between group F-I and group I-F.

We classify myopic loss averse traders as those who invest more under infrequent feedback. Table 3 provides the distribution of traders who invest less, the same, or more under frequent feedback. Overall, 51.03% of the participants exhibited MLA, investing an average of 25.45 experimental units (33.8%) less under high feedback frequency. Of the traders who did not exhibit MLA, 58 were myopic neutral and behaved exactly the same under both feedback frequencies, and those who were myopic loss seeking and invested more under frequent feedback account for 31.96% of the data.

A significant share of traders did not reduce their investment levels in response to high-frequency feedback in the market. However, a little more than half the traders did behave myopically. It maybe of interest to both regulatory bodies and stock brokerages to identify the relevant sub-groups that are MLA types. Of course, there are both observed and unobserved correlates for such behavior. As reported in Table B.3, the most important predictors of MLA are age, the initial level of capital endowment, and income. On average, traders who were older than the median age (35 years) and those with greater than median income (45,000 Taka monthly) were about 10–12%

play with their earnings earnings up to that point. As we can see from Appendix Table B.5, MLA still holds even with differences in the starting endowment of each trader but results are only significant for Task 1, when traders had no prior experience of the other treatment (the treatment to which they were not initially assigned).

less likely to exhibit MLA. However, being highly educated is not predictive of MLA. While those who were more educated as defined as having a masters degree were more likely to exhibit MLA, the correlation was not significant. Moreover, traders with initial stock market investment greater than the median level of 100,000 Taka were about 9% less likely to exhibit MLA.[18]

We further explore the heterogeneity in individual level MLA by decomposing the variance of within subject percentage differences in bets between the two feedback frequencies based on demographic and trading characteristics. Appendix Table B.4 reports the R-squares from the regression of percentage difference in bets on individual characteristics. Age and Income can only explain only 1.3% of the total variation. Adding other demographic characteristics such as dummies for gender, marital status and master's degree can explain only 2.2% of the total variation. Initial stock market investment and trading starting year can explain 7.7% of the total variation. Brokerage firm specific characteristics such as dummies for the brokerage firm and starting year as well as brokerage firm initial capital explains 13.2% of the total variations. Finally, including all demographic and trading characteristics can capture about 15.5% of the variations in percentage difference in bets. This suggests that while trading characteristics are better than demographic characteristics in capturing the variations in individual MLA, a lot of variations in MLA are still unexplained by observable investor characteristics.

3.3 Data

In this section, we describe the various data sources used in constructing our sample for the empirical analyses conducted in the paper. Our main data is confidential, individual level data on portfolio holdings and transactions of the traders who participated in the experiment and survey. We collected account-level data of all the participants consisting of official transaction statements recording all transactions from January 2015 through April 2017 from eight brokerages operating at the Dhaka Stock Exchange (DSE). We focus on their portfolio holdings and trading of common stocks and mutual funds from October 30, 2015 to August 31, 2016.[19] We also collected relevant

[18]The within-subject analysis allows us to categorize traders into three categories of myopia (Table 3). Given traders who are not myopic loss averse maybe either myopic neutral or myopic loss seeking, we re-examine the heterogeneity among the three levels of within-subject myopia, as shown in Figure B.2.

[19]Our participants also received trading training intervention as part of a RCT. The first session started from September 2, 2016, after this framed-field experiment was conducted. Therefore, we only focus on the period before the training intervention to ensure the trading behavior that we document is not subject to the effects of the training that

market information from the DSE. We therefore construct our final sample by merging: experimental and survey data, brokerage data and DSE market data.

3.3.1 Brokerage data on Portfolio and Transactions

The brokerage data consists of two separate datasets. The first dataset is the transaction ledger data which contains information on each transaction recorded daily for each trader at their respective brokerage firm. This dataset reflects the trading activity, including purchases, sales, IPO applications and allocations, and transaction and other administrative costs associated with the account and each activity of the traders. Some traders had more than one transaction on the same stock on the same day. To mitigate the effect of day trading and its noise, we netted all same-day trades of the same stock by the same investor and averaged their buying or selling prices. For example, if an investor buys 1,000 of stock A at 20 Taka, sells 700 of the same stock later that day at 22 Taka, and buys 100 more of stock A at the end of the day at 21 Taka, our data would record all three transactions as a net buy of 400 stocks at a price of 20.091.

The second dataset provided by the brokerages is the data on portfolio holdings of the traders holding an account at the brokerages from October 30, 2015 to July 31, 2016. Based on these data, we constructed and cross-verified the traders' daily portfolio holdings over this period excluding non-trading days (i.e., weekends and public holidays).[20] Moreover, combining the portfolio holdings data with the transaction ledger data results in a panel at the individual-stock-day level of 305,935 observations and which records over 31,000 net buy or sale transactions at the daily level for the participating traders over the sample period of this study. We construct various variables at the portfolio level from this data. Our final sample consists of 58,080 observations on individual portfolio information and characteristics at the daily level for the experiment and survey participants.

3.3.2 Market data

We supplement the brokerage data with a market dataset which comprises the day-end statistics of all the common stocks listed on the DSE from 1990 to 2017. We exclude stocks not actively traded

were received by some of the traders. The portfolio holdings data is available from Oct 30, 2015

[20]Our constructed portfolio holdings on 31 July 2016 are exact duplicates of the official version from the brokerages, confirming the reliability of the data.

at any given time from 2015 to 2017 or any companies lacking information on daily stock returns, trading turnover, market capitalization, or the fraction of shares held by institutional investors. We also restrict our sample by excluding those who were inactive during that period.

3.3.3 Summary Statistics of Brokerage Data

Table 4 summarizes all the data gathered for the daily transactions of the traders over the time period from October 30, 2015 through July 31, 2016.[21] Our data not only includes our experimental participants but also individuals chosen at random from the list of traders in these brokerage houses. The final sample comprised traders with a diverse range of individual characteristics, so most measurements varied considerably among the traders. Panels A reports statistics for variables at the individual portfolio level. The average daily cost of their portfolios was 1.53 million Taka (3 times their annual income) whereas the average daily market value was 1.33 million Taka suggesting that the traders were generally at a loss. Indeed, their performance was poor; that is while the monthly return of the composite DSE Index was about 0.02% from October 2015 through July 2016, the average and median monthly portfolio return in our sample is -1%.[22] This means that most people lost value and also under performed compared to the market. The median trader held 3 different stocks from 3 different DSE sectors and the average portfolio beta was 1.10 (compared to a beta of 1 for the DSE).[23] This indicates that traders generally did not have well diversified portfolios. Panel B reports statistics for variables at the individual transaction level. At the daily level, while the median trader did not engage in buying or selling stocks suggesting that most traders did not trade actively, the average trader bought and sold approximately 800 shares of stocks which translates to a value of roughly 30,000 Taka. Moreover, the average monthly turnover was 0.89 which is almost one.[24] This suggests that, on average, the traders fully reshuffle their portfolios almost once every month.

[21] All continuous variables except beta, number of stocks and sectors in the portfolio are winsorized at 2^{nd} and 98^{th} percentiles. Appendix Table B.2 gives the definition and sources for all variables.

[22] We calculate the net monthly return of portfolio by estimating the monthly return on each common stock investment using the beginning-of-month position statements for each individual.

[23] We measure stock beta by regressing stock-price variation on the market index variation of the day. We then form value weighted portfolio beta from individual stock beta. A beta larger than 1 implies that the portfolio is riskier compared to the systematic market risk.

[24] We follow Odean (1999) and estimate turnover as one-half the average equity monthly of all stock trades (purchases and sales) divided by the average monthly value of the portfolio.

4 Empirical Strategy

We are interested in studying the relation between myopic loss aversion uncovered in the lab and real life portfolio decisions. To do so, while controlling for differences in various demographic characteristics and relevant market participation information across traders, in our main specification we estimate regressions of the following form:

$$Y_{ibt} = \alpha + \beta MLA_{ib} + \mathbf{\Gamma}'\mathbf{X}_{ib} + \rho_{ib} + \psi_s + \theta_{by} + \tau_{kt} + \epsilon_{ibt} \tag{1}$$

where Y_{ibt} is the outcome variable of interest for individual, i, from brokerage firm, b, at day, t. MLA_{ib} is an indicator variable for each individual, i, from brokerage firm, b, which takes the value of 1 if average experimental investment under infrequent feedback exceeds that under frequent feedback and it takes a value of 0 if average experimental investment under frequent feedback exceeds that under infrequent feedback (thus our reference category is myopic loss seeking group).[25]

Our specification includes participation year (s) fixed effects, ψ_s and brokerage (b)-start year (y) fixed effects, θ_{by}. This ensures that we are comparing between individuals from similar cohorts with similar general stock market experience as well as from the same brokerage firm with similar brokerage specific experience which can influence trading behavior and portfolio outcomes.[26] We also control for dominant industry (k)-day (t) fixed effects, (τ_{kt}). This enables us to compare between traders who hold similar portfolios, comprising mostly of stocks from the same industry on the same day and allows us to remove time varying macroeconomic trends as well as industry specific dynamics which may result in heterogeneity in portfolio decisions.[27] We also include a vector of controls, $\mathbf{X}_{ib}$, which comprises of various demographic characteristics including the age, monthly income, education as measured by having a masters degree, gender and marital status of the trader as well as stock market participation characteristics including the initial stock market investment and initial level of capital at the brokerage firm. Since the traders were exposed to both

[25] A small group of traders were classified as myopic neutral. In robustness tests, we show that we get consistent results when we also include them in the reference category.

[26] Several studies document herding behavior in emerging stock markets: Indonesia (Bonser-Neal et al., 2002), Korea (Chang et al., 2000; Choe et al., 1999; Kim & Wei, 2002), Taiwan (Chang et al., 2000) which is driven by brokerage firm effects (Agarwal et al., 2011).

[27] We measure dominant industry in a portfolio based on broad sectoral classification of stocks at DSE. These major industries are insurance, textile, engineering, bank, pharamceuticals & chemicals, financial institutions, food & allied, fuel & power, bank, ceramic, pharmaceuticals & engineering and miscellaneous.

frequent and infrequent feedback frequency in the experimental design, ρ_{ib} captures the order of exposure to both feedback frequencies for each trader in order to control for potential order effects in our experimental construct of individual myopic loss aversion. Standard errors are clustered at the brokerage firm-month level. [28]

5 Results

5.1 Association between MLA & Risk Taking in Stock Market

Our main result comes from studying the association between myopic loss aversion and the extent of stock market participation. We test the main prediction from MLA theory and examine if elicited behavior in the lab consistent with MLA is associated with lower risk taking in real life portfolio decisions as defined by the level of equity market investment. The level of equity market investment is measured by the size of equity investment scaled by individual income.[29] Figure 3 presents graphical evidence of the association between MLA and risk taking in stock markets. For each group of investors, we plot the unconditional average daily level of equity market investment over our sample period where the the size of equity is measured using the weighted average cost price of each stock position in the portfolio using prices at the time of equity transaction times the number of stocks held. We can see that average investment levels of myopic loss averse investors is lower than that of myopic loss seeking investors. In order to formally test the relationship between MLA and equity market investment levels while controlling for individual and market factors, we estimate equation (1) with equity market investment as the dependent variable.

Table 5 reports the results from OLS estimates of equation (1). In Panel A, the size of equity is measured using the cost prices of the portfolio. All columns include a dummy for the sequence in which traders were exposed to both feedback frequencies. We add controls in stages. Across

[28] We also consider other clustering choices for robustness.

[29] We only consider equity market investment as the bond market is in very infant stage and bonds are generally not held by individual retail investors (see section 2 for details). In fact, none of the investors in our sample hold bonds. We scale the size of equity investment by income because information about individual wealth is rarely available in Bangladesh. While there is a wealth statement in personal income tax return form, only a small fraction of the population submit tax returns due to institutional weaknesses. In addition, within tax return, assets are reported at historical cost level – this is not reliable as asset values substantially change over time (ex. real estate values). So they do not reflect actual or current asset position. Hence, there is no official or administrative estimates of individual wealth.

all specifications, our measure of MLA generates negative and statistically significant coefficients ($p < 1\%$), indicating that myopic loss averse traders have lower level of equity market investment compared to myopic loss seeking traders. The coefficients are very stable across specifications, which is at least about -1.1. This means that compared to the reference group, MLA traders' portfolio costs about 1.1 Taka lower for every unit of income. The observed magnitude is substantial as it corresponds to 31% of the value for the average trader in the reference group .[30] Such an effect is similar to those generated in prior work studying the effect of MLA in a setting which mimics the complexity of trading platforms and market interactions (see Larson et al., 2016).

We note that passive appreciation or depreciation in prices can impact the size of equity for identical portfolios when measured at market price at which equity was bought. So, for testing the robustness of our results, we also calculate our portfolio measure of risk taking in the field for a hypothetical portfolio at constant prices which is insensitive to passive price changes. We start with the initial holdings at the start of our sample period, October 30, 2015 and assume there are no price changes afterwards. We keep track of all changes in individual portfolios measuring all stock level transaction at prices at the start of our sample period. In Panel B of Table 5, we repeat the results from Panel A using the hypothetical constant price portfolio for our measure of equity market investment level. We find that the results are qualitatively similar to those in Panel A meaning that the results are simply not mechanically driven by passive appreciation or depreciation of stock prices in investor portfolios.

5.2 Robustness

In this section, we perform a list of robustness checks on our main result in the previous section. We want to ensure that the lower risk taking in the field through lower stock market investment by myopic loss averse traders that we document is not explained by other factors not accounted for in the main analysis.

Other behavioral biases and beliefs. There may be concerns that the level of risk taking in stock markets documented in our main result may be driven by differences in individual traders' behav-

[30] The average cost of portfolio per unit of income for myopic loss seeking trader is 3.5. So, the magnitude corresponds to an effect of 31% (= 1.1/3.5).

ioral biases other than myopic loss aversion or their individuals beliefs about the future condition of the stock market or the economy in general. Therefore, we test for association between MLA and the extent of stock market participation while controlling for various behavioral biases and beliefs. We control for both risk aversion and ambiguity aversion. Prior works attribute differences in equity market participation to risk aversion, which serves as a mechanism through equity market participation is affected (Barnea et al., 2010; Dorn & Huberman, 2005; Malmendier & Nagel, 2011; Sias et al., 2020). Several studies show both theoretically and experimentally that ambiguity aversion can lead to non-participation and under participation in stock markets (Bossaerts et al., 2010; Cao et al., 2005; Dimmock et al., 2016; Dow & da Costa Werlang, 1992; Easley & O'Hara, 2009; Garlappi et al., 2007; Peijnenburg, 2018). We also control for time preferences as differences in time discounting can affect wealth inequality (Carroll et al., 2017; Epper et al., 2020; Krusell & Smith, 1998) and lower individual wealth through relatively high time discounting may in turn negatively impact stock market participation. Moreover, expectations about future stock market returns and beliefs about severe future market loss or gain can impact stock holdings (Giglio et al., 2021a; Liu et al., 2021; Sias et al., 2020). We experimentally elicit risk aversion, ambiguity aversion and time preferences through incentivized games.[31] We use survey based measures for individual beliefs about the future market and economic condition.

Table 6 reports the results. Column (1) is the baseline result and reports estimates from Column (5) of Panel A in Table 5. In each subsequent column, we study the association between MLA and the level of stock market investment while controlling for one particular behavioral bias or belief. We control for risk aversion, ambiguity aversion and time preference in columns (2), (3) and (4), respectively. The coefficient on risk aversion and ambiguity aversion is negative meaning that risk averse and ambiguity averse traders have lower levels of stock market investment. The coefficient on time preference is positive suggesting that traders who discount less and hence are more patient have higher level of stock market investment. While, these coefficients have expected signs, they are not sufficiently large enough to be statistically significant. In columns (5), (6) and (7) we control for survey based measures of beliefs from three separate questions. We ask each trader the following: 1) "Do you think the stock market in Bangladesh will fall in a large scale

[31] Section A.3 of the appendix gives the details of the experimental design for the measures of risk aversion, ambiguity aversion and time preference.

within next 6 months?"; 2) "Do you think the world stock market will fall in a large scale within next 6 months?"; 3) "Do you think that world economy will fall in crisis in next 6 months?". The answers were recorded in a scale of 1 (least likely) to 5 (most likely). Columns (5), (6) and (7) show that the coefficients on all three survey based measures are negative meaning that traders who were more pessimistic held smaller portfolios. Our measures of behavioral biases are elicited through incentivized games as opposed to surveys so that it is less likely that there is sufficient overlap between them and survey based measures of beliefs (for example high levels of survey based measures of risk aversion may be due to pessimistic beliefs about future). Nonetheless, in column (8), we regress the level of stock market investment on MLA while controlling for all behavioral biases and beliefs. We find that across all columns from (2) to (8), the coefficient on MLA is negative and highly significant. The coefficients remain very stable and are comparable to the coefficient in column (1).[32]

Differences based on Observables. MLA and the reference group could differ in a number of ways and hence may not be comparable. We can see in Table B.3 that MLA is correlated with characteristics such as income, age and initial level of endowment. Here, we consider investors with similar observable characteristics using matching. Specifically, we perform the nearest neighbor matching method without replacement to match one myopic loss averse trader to the nearest myopic loss seeking trader based on the log odds ratio of their propensity scores while excluding extreme observations (Imbens, 2015) .[33]

Panel A of Table 7 shows the comparison of means of observables between the myopic loss averse and myopic loss seeking traders for both the unmatched and matched sample of traders and performs the balance test based on differences between the two groups of traders. Panel A shows that the difference between MLA and the reference group across all observables is statistically insignificant at the 10% level in the matched sample. Panel B of Table 7 reports the estimates from the regressions of level of stock market investment on MLA using the matched sample of traders. Across all columns, the estimated coefficient on MLA is negative and statistically significant and are comparable to the baseline results in Table 5. These results indicate that there are

[32]Table B.6 presents results from repeating the analysis in Table 6 for the same daily equity portfolio at constant prices.

[33]We exclude traders from our matched sample with the largest 5% difference in propensity scores.

some unobervable (e.g., behavioural) differences which we do not control here and those differences are likely important in determining a person's MLA status.

Addressing concerns of experimental order effects. While a within-subject design is essential to get measures and distribution of MLA at the individual level as it is required to observe trader behavior under both feedback frequencies, within subject designs are susceptible to order effects (Charness et al., 2012). That is the observed experimental effects generally get milder when experiments are conducted with the subjects more than one time as they draw from their experience from their first exposure to the experiment. Our approach to uncovering individual MLA through within subject design is no exception. We can see from the between subject results in task 2 that the average differences in bets across the two feedback frequencies reduced compared to task 1. However, in our case such concern is minimized as we randomize the sequence in which traders are exposed to both feedback frequency so that there is no systematic relation between trader characteristics and their sequence of exposure and any order effects are equally likely to affect either myopic loss averse and the reference group. Moreover, we use within variations in experimental order in all our specifications. While controlling for experimental order partially addresses possible concerns of the impact of order effects in our eventual regression analysis, in this section, we introduce an additional test to further account for remaining concerns and minimize the impact of order effects in our measurement and analysis of MLA traders.

The idea is to minimize the impact of order effect in our measure of MLA by capturing the differences in bets across the two feedback frequencies which is not affected by the order of exposure to the two feedback frequency itself. That is we want to take the portion of variations in the difference in bets which is due to only being exposed to both feedback frequency and not related to the order of exposure. We do so by regressing the difference in bet between frequent and infrequent feedback for the same set of traders in our baseline sample on a dummy for the order of exposure and then using the regression residual as alternative measure of the difference in bets. We then reclassify our traders as either myopic loss averse or myopic loss seeking based on this residual difference in bets. Our regression takes the following form:

$$\Delta BET_i = \gamma_0 + \gamma_1 FFORDER_i + \epsilon_i \tag{2}$$

where $\Delta BET_i = I_i - F_i$ and $FFORDER_i$ captures whether individual i is group F-I or group I-F. We use the residual ϵ_i as the new difference in bet which is a cleaner version of the difference in bet in terms of possible contamination from order effects. We then reclassify our traders as myopic loss averse, $\overline{MLA}_i = 1$ if $\epsilon_i > 0$ or myopic loss seeking, $\overline{MLA}_i = 0$ if $\epsilon_i < 0$. We then replace MLA with $\overline{MLA}$ in our main regression specification:

$$Y_{ibt} = \alpha + \beta \overline{MLA}_{ib} + \mathbf{\Gamma}'\mathbf{X}_{ib} + \rho_{ib} + \psi_s + \theta_{by} + \tau_{kt} + \epsilon_{ibt} \tag{3}$$

Table 8 reports the estimates from equation 3 by regressing the level of stock market investment on the measure of MLA based on bet difference residuals. The coefficient on MLA is negative and statistically significant across all the columns. The magnitude of the coefficient on MLA stays about -1.5 when equity is measured at cost prices and about -1.1 when equity is measured at constant prices. This estimates are smaller than the coefficient estimates that we document in Table 5. We conclude that, while impact of experimental order effects influences the measurement of MLA in our within subject design and thus the documented relation between MLA and level of stock market investment, it does not fully explain the negative relation of MLA and risk taking in stock markets.

Alternate Measurements of MLA. In our main set of results in Table 5, we study the effect of MLA by classifying traders as either myopic loss averse or myopic loss seeking based on their average outcomes across all 9 rounds of experiment. In this section, we test whether our initial results are robust to alternative definitions for individual MLA. Table 9 reports the results.

Column (1) is the baseline result and reports estimates from Column (5) of Panel A in Table 5. In each subsequent column, we study the association between MLA and the level of stock market investment while varying our measurement of MLA. It may be that participants may take some time to understand the experiment before their actual behavior starts to kick in. So, in column (2) we measure MLA based only on the last one-third of the experiment, rounds 7 to 9. We try to minimize the impact outliers in experimental outcomes have on our measurement of MLA. We address this in column (3) by excluding the highest and lowest experimental bets across the 9 rounds and base our classification of MLA on this middle distribution of bets in 7 rounds. In column (4), we use only experimental outcomes from the supplemental 3 rounds of experiment based on varying experimental wealth. In column (5), we classify traders as MLA based on outcomes from all rounds (main and supplement) of experiment. We find the coefficient on MLA in columns (2) to (5) are all negative and statistically significant are comparable to the coefficient in column (1). Given a small set of participants were classified as myopic neutral, we also include them in the reference group in column (6). We see that relation between MLA and stock market investment levels is still negative and statistically significant. As expected, the coefficient estimate on MLA in column (6) has a smaller magnitude than the coefficient estimate on MLA in column (1). The first six columns report results from using dummy variable to classify investors as either types. We now test our main result using a continuous measure. In column (7), we regress stock market investment level on the percentage difference in bets across both experimental feedback frequency. In column (8), our variable of interest is individual rank based on deciles in the percentage differences in bets. The coefficients on both columns are negative and statistically significant. Overall, our results are robust to alternative definition and measurements of MLA.[34]

Other Robustness Checks. In Table 10 we perform additional robustness checks. Column (1) is the baseline result and reports estimates from Column (5) of Panel A in Table 5. Some investors may participate longer in the stock market than other investors. To ensure that participation and attrition from stock markets do not drive our results, in Column (2) we weight each observation by the inverse of the number of days the investor appears in our sample. We confirm that the results are not driven by traders with extreme behavioral biases in column (3) by excluding the top 2% of myopic loss averse and myopic loss seeking traders based on percentage difference in experimental bets. To allow stock market participation to be non linearly affected by income and age, we instead include dummies on income and age based on individual decile rank in column (4). Individual stock market behavior may be correlated with relevant background. To account for this, in column (5) we include dummies for whether the individual's primary major or secondary major in college was business as well as dummies for whether the primary occupation or the

[34]Table B.7 presents results from repeating the analysis in Table 9 for the same daily equity portfolio at constant prices.

secondary occupation is classified as being a businessman. In column (6), we measure the size of equity based on the daily closing price of each stock as opposed to the cost of portfolio based on the time of equity transaction. Across all columns the results are robust and the coefficients are comparable to the coefficient in column (1).[35]

5.3 Differences Across Individual Investors

In this section, we show which characteristics of traders are associated with the largest differentials in the level of stock market investment between myopic loss averse traders and the reference group. That is we conduct tests for cross section heterogeneity based on both market participation & trading characteristics and demographic characteristics.

Heterogeneity across Market & Trading characteristics. Prior studies have shown that inexperience can affect current and future stock market decisions and that gathering relevant experience can make investors better at trading through learning or through eliminating behavioral biases (Chiang et al., 2011; Feng & Seasholes, 2005; Greenwood & Nagel, 2009; Linnainmaa, 2006; Nicolosi et al., 2009; Seru et al., 2010). We test whether there is heterogeneity by trader experience in the observed MLA effects in field. Panel A of Table 11 shows the results of regressing stock market investment levels on MLA on sub samples based on years of trading experience. We split the samples based on the median trader experience in our sample of 8 years. The results show that the negative relation between MLA and the extent of stock market participation is only present in the sample of traders with lower than median level of trading experience. This means that the MLA effect in risk taking in the field is primarily driven by inexperienced traders and this effect is reduced when traders gain experience.

Experimental work on MLA attribute myopic loss averse behavior to greater frequency of feedback about investments (Gneezy et al., 2003; Gneezy & Potters, 1997; Haigh & List, 2005). While it is not possible to see exactly when the traders in our sample receive information about the market, we asked them whether they check prices and update themselves about the market frequently or infrequently. Panel B of Table 11 shows the results of regressing stock market investment levels on

[35] Table B.8 presents results from repeating the analysis in Table 10 for the same daily equity portfolio at constant prices.

MLA on sub samples split according to their answer of "Frequently" or "infrequently". We find that the MLA effect on stock market risk taking is much stronger in the sample of traders who frequently updated themselves about the market.

Experimental research in the context of myopic loss aversion also show that both longer investment horizons and longer commitment period lead to higher risk taking (Fellner & Sutter, 2009; Langer & Weber, 2008). Given traders who update themselves frequently show stronger MLA effects, we also test whether MLA effect is stronger for active investors compared to inactive investors.[36] We measure investor activeness in stock market by measuring the frequency of changes to their portfolio. Panel C of Table 11 shows the results of regressing stock market investment on MLA on sub samples split by the median level of portfolio changing frequency. The results show that the MLA effect on risk taking only exists for the sample of active traders.

Heterogeneity across Demographic characteristics. Prior literature study the relation between demographic characteristics and stock market participation. For example, Calvet, Campbell, and Sodini (2009) richer households rebalance to greater risk share in their portfolios while Goyal (2004) show the stock market outflows are negatively correlated for middle age individuals. Education has also been shown to positively affect financial market participation and equities ownership (Cole et al., 2014). We test whether the MLA effect that we document in the field is heterogenous in individual trader income, age and a dummy variable for whether the trader has a master's degree as a proxy for education level. Table B.9 reports the results. We find that the negative relation between MLA and stock market investment levels is attenuated for older traders but is not statistically significantly attenuated with income and education level.

5.4 Risk Taking within Portfolio

So far we have studied the relation between MLA and risk taking in the field at the extensive margin. In this section, we ask whether myopic loss aversion affects the intensive margin of risk taking. That is, not only whether MLA traders have lower levels of stock market investment, but also whether their portfolios are riskier. We measure risk taking within portfolio through the

[36] Investors who are less active in stock market can be indicative of as having both longer investment horizon and longer commitment period.

market beta of the portfolio. Individual stock beta is measured by regressing stock returns on the return on the market index variation of the day.[37] We calculate portfolio beta by weighting the market beta of individual stocks in the portfolio at their average cost price of each stock position.[38] Figure 4 presents graphical evidence of the association between MLA and portfolio beta. For each group of investors, we plot the unconditional average daily market beta of portfolio over our sample period. We can see that the portfolio beta of myopic loss averse investors mostly trends lower than that of myopic loss seeking investors.

Panel A of Table 12 reports the results of regressing individual portfolio beta on MLA. We find that the coefficient on MLA is negative and statistically significant across all columns. The magnitude of the estimated coefficients range from -0.03 to -0.08, that is on average, MLA traders have portfolio betas which are 0.03 to 0.08 lower than the reference group. This corresponds to an effect which is approximately 2.8% to 7.1% lower than the reference group.[39] Thus, MLA traders also show lower risk taking in the field at the intensive margin as they have lower extent of portfolio riskiness. In Panel B of Table 12, we repeat the results from Panel A by weighting stock beta at constant prices in order to ensure that price differentials at the time of transaction do not substantially effect individual portfolio beta. The coefficients in Panel B are all negative at the conventional level of significance and are similar to the coefficients in Panel A.

5.5 Reactions to Short Term Loss

Given myopic loss averse investors are less likely to take risk in the stock market, we ask the following question: Do myopic loss averse investors react more negatively to short term losses in their portfolio? According to theory, if investors are myopic loss averse, they will pay too much attention to short term portfolio volatility. So momentary downside changes to the value of their portfolio will affect them more thus result in them taking lower risk. To answer this, we first identify days in which individual portfolios experience downside changes, that is they open at a loss compared to the previous day. We then study how this affects their risk taking in terms of

[37]We do not use "excess" returns in calculation of beta since individual investors generally do not invest in government securities. Hence their actual risk free rate is 0.

[38]Such weighting by cost prices reflect the amount of money that was invested by the trader in each stock position.

[39]The beta of the portfolio for the average myopic loss seeking trader is 1.125. So, the effect corresponds to 2.7%(=0.03/1.125) to 7.1%(=0.08/1.125).

changes in their size of their equity investment based on portfolio cost.[40]

Table 13 reports the results of regressions of the likelihood of change in equity investment level on a dummy for capturing an event of loss in the value of portfolio. In Panel A, the dependent variable is a dummy to capture whether the investor decreased the size of their equity investment. Across all columns, the coefficient on *Portfolio Loss* is positive and statistically significant meaning that investors generally downsize their level of equity investment when there are negative changes to the portfolio value. More importantly, the interaction between MLA and *Portfolio Loss* is positive and statistically significant, suggesting that MLA investors react more to loss in portfolio value and are more likely to downsize their level of equity investment compared to the reference group. In column (5), which is our most strict specification in terms of controls and fixed effects, the coefficient on *Portfolio Loss* is 0.515 whereas the coefficient on the interaction term is 0.037. This suggests that MLA investors are 7.2% more likely to downsize their equity investment level in reaction to portfolio value losses compared to the reference group of traders.

In Panel B, we repeat the same exercise with the dependent variable now being a dummy to capture whether the investor increased the size of their equity investment. Across all columns, the coefficient on *Portfolio Loss* is negative and statistically significant suggesting that investors are also less likely to increase their equity investment in response to negative changes to the portfolio value. However, the interaction between MLA and *Portfolio Loss* is statistically insignificant across all columns. This suggests there is an asymmetry in the differential response of MLA investors to momentary portfolio losses. Overall, the results from Table 13 provide evidence that MLA investors are more aggressive in reducing their level of equity investment when experiencing short term losses in their portfolios thus contributing towards their lower level of risk taking in stock market.

5.6 Stock Market Performance

So far, we have provided evidence that myopic loss averse individuals have lower levels of risk taking in the stock market. It is important to ask whether this lower risk taking translates to lower

[40] We measure the size of equity investment using the cost of portfolio as they reflect the amount of money invested by the trader in the stock market.

performance in the stock market.[41] We look at the performance of individual investor portfolio or their potential profits on their investments when benchmarked against the cost of the portfolio. We test whether the gross stock market return on investment or performance as measured by the daily market value of the portfolio scaled by the cost of the portfolio is lower for MLA individuals. Figure 5 presents graphical evidence of the association between MLA and the performance of stock market investment. For each group of investors, we plot the unconditional average daily gross return on equity investment over our sample period. Returns of myopic loss averse investors appears to be lower than that of myopic loss seeking investors especially at the beginning of the sample period. Nonetheless, we leverage on our regression specification to study the relationship between stock market performance and MLA while controlling for various factors.

Table 14 reports the results. We find that the coefficient on MLA is negative and statistically significant across all columns. The magnitude of the estimated coefficients range from -0.043 to -0.057. That is, on average, MLA traders have a gross return on their overall stock market investment which is about 4.3% to 5.7% lower than the reference group. This corresponds to an effect which is approximately 4.4% to 5.9% lower than the reference group.[42] Thus, MLA traders lower risk taking in the field also results in lower stock market performance or potential profits on their investments.

Given the MLA effect is stronger for investors who actively change their portfolio as shown in section 5.3, and that prior research such as Barber and Odean (2000) and Barber and Odean (2001) show the investors who trade more perform poorly, we study the role of trading frequency in the relation between MLA and stock market performance. Table B.10 repeats the exercise from Table 14 but on sub samples split on measures of trading frequency. In particular, we consider three measures of trading frequency which are the trading volume in units of stocks, the trading amount in Taka and trading turnover. We then form sub samples based for high and low trading frequency based on the median trading frequency. The results from all three measures in Table B.10 show that while the coefficient on MLA is small but positive in sub samples with low trading frequency, the coefficient on MLA is highly negative and statistically significant for sub samples

[41] Prior work which study Myopic loss aversion in the lab show that MLA individuals earn lower profits (Gneezy et al., 2003; Gneezy & Potters, 1997; Haigh & List, 2005; Thaler et al., 1997)

[42] The daily gross return of the portfolio for the average myopic loss seeking trader is 97.3%. So, the effect corresponds to 4.4%(=4.3/97.3) to 5.9%(=5.7/97.3). Therefore, both the average myopic loss averse and myopic loss seeking traders' investments under perform compared to the cost of their portfolio.

with high trading frequency. This suggests that the negative relation between MLA and market performance of investments is driven by those traders who trade more in the market.

6 Aggregate Implications

We have shown that myopic loss averse investors have lower risk taking in the field in terms of lower levels of stock market investment. What does this imply for the aggregate demand for equity by stock market investors in Bangladesh? We will be able to only give a very rough answer under specific assumptions. We begin by defining myopic loss seeking individuals as our baseline, in concordance to our empirical results, relative to which we measure the effect of myopic loss aversion on the aggregate demand for equity. We require the strong assumption that the distribution of myopic loss aversion among our sample of investors is representative of the distribution of myopic loss aversion among stock market investors in Bangladesh. Under these assumptions, the effect on aggregate demand for equity is our estimated regression coefficient from the regression of stock market investment on MLA times the average investor annual income times fraction of MLA investors times the number of investors in the stock market. Our most conservative coefficient estimate is -1.1 while 51.03% of our investors are myopic loss averse. The average investor income is 0.7 million Taka and there are about 200,000 beneficiary owner accounts with active trading.[43] Therefore, focusing on the sample of active beneficiary account owners, myopic loss aversion leads to about ($1.1 \times 700{,}000 \times 0.5103 \times 200{,}000$) = 78.5 billion Taka lower aggregate demand for equity which is about US $1.01 billion. This is a sizeable effect as the equity market capitalization for retail investors is US $7.52 billion and thus corresponds to about of 13.4% of the equity market capitalization.[44]

We also document that myopic loss averse individuals perform poorly in the stock market. Our most conservative estimate of the coefficient on MLA when regressing stock market performance on MLA is -0.0433. Given the average cost of the portfolio in our estimation sample is 3.31 times the annual income of traders, this represents an additional loss of ($0.0433 \times 3.31 \times 100$) = 14.33% of annual income for the average MLA investor. but what is the aggregate implication for potential

[43]We gauge the number of investors by beneficiary owner accounts since they are used to uniquely identify buyers and sellers of instruments.

[44]The equity market capitalization is US $40.67 billion and retail investors holdings account for 18.5%.

stock market earnings or profits for MLA investors? We rely on the assumptions made above to again give a very rough answer. On aggregate, the group of MLA investors suffer additional losses of about ($0.0433 \times 3.31 \times 700{,}000 \times 0.5103 \times 200{,}000$) = 10.2 billion Taka or US $131 million.

7 Discussion

We first discuss about the generalizability of our experimental and empirical results. To do so, we follow four transparency SANS conditions outlined by List (2020). The four SANS conditions are Selection, Attrition, Naturalness, and Scalability. First, our selection of traders is based on responses to the random invitation to all clients of our partnered stock brokerages. These traders did not have a financial advisor at the time of the study. In other words, they made investment decisions based on their own strategy. Our sample reflects the non-professional or retail traders in the market. Second, we have a zero attrition rate in the experiment, and more than 90 percent of the traders consent to give access to their trading data. Third, our subjects are placed under both ends of the spectrum of the naturalness of the choice task and investment environment. The experimental session happens in a laboratory setting, in which investment decisions are potentially on the artificial margin and the experiment uses a certain type of risk portfolio that is standard in the literature. We then observe the same traders' naturally-occurring data from the stock market by analyzing their portfolio and trading decisions.

There is a trade off between designs which are fully based on laboratory experiments versus those studies fully based on the field. While laboratory experiments give full control to the experimenter to vary experimental conditions, the experimental subjects are generally not the same ones from the real setting whose behavior we are actually interested in. On the other hand, while natural field experiments are done on the population whose behavior is of interest, the experimental design generally will not allow studying subject behavior in their actual natural environment and only allow for studying behavior in a simpler setting which may mimic their actual environment. This is especially true in the case of myopic loss aversion, as it is impossible to randomize the frequency of price feedback by traders and observe their behavior in stock markets. So, it is nearly impossible to study the causal effect of feedback frequency on traders' portfolio decisions. Therefore, we study myopic loss aversion through artefactual field experiments conducted on the population whose behavior is of interest. First, it allows us to leverage on standard experimental designs utilized in past experiments and see whether they replicate for the population whose behavior is of interest. Second, through a within subject design, it also allows us to link experimental measures at the individual level to individual portfolio and transaction data to study whether they predict trader behavior in the field - that is their real life trading environment. This is especially important for us, since the main goal of our research is to understand whether behavioral anomalies uncovered in the laboratory manifest themselves in the field.

8 Conclusion

Whether, and to what extent, behavioral anomalies uncovered in laboratory environments can reflect decision making in the field is of major importance in both economics and finance. In this study, we attempt to answer this in the context of myopic loss aversion (MLA), which has been advanced as a theoretical explanation for the equity premium puzzle (Benartzi & Thaler, 1995). Several key laboratory experiments find that subjects in the lab behave according to the theory (Gneezy et al., 2003; Gneezy & Potters, 1997; Haigh & List, 2005; Thaler et al., 1997). We leverage on the standard experimental techniques used in the literature but modify it to a within subject design to uncover an individual specific measure of MLA for stock market traders. We then link the experimental data to confidential information on private investment accounts of these traders to study how MLA effects their real life portfolio decisions. First, we confirm MLA results in lower risk taking in stock markets in terms of both reduced investment levels and lower portfolio betas. Moreover, the MLA effect on reduced stock market investment levels is stronger for traders who are less experienced, traders who update themselves about the market frequently and traders who change their portfolio frequently. We find additional evidence that MLA investors are more likely to decrease their investment size but are not less likely to increase their investment size in response to short term losses on their portfolio. Finally, we show that MLA traders' investments also have poorer stock market performance. Beyond testing the theory in the natural trading environment of traders by showing that the real life trading behavior conforms to theoretical explanations, these results have implications for both the stock market in aggregate as well as for economic policies.

References

Agarwal, S., Chiu, I.-M., Liu, C., & Rhee, S. G. (2011). The brokerage firm effect in herding: Evidence from indonesia. *Journal of Financial Research*, *34*(3), 461–479.

Alevy, J. E., Haigh, M. S., & List, J. A. (2007). Information cascades: Evidence from a field experiment with financial market professionals. *The Journal of Finance*, *62*(1), 151–180.

Azeredo, F. (2014). The equity premium: a deeper puzzle. *Annals of Finance*, *10*(3), 347–373.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance*, *55*(2), 773–806.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics*, *116*(1), 261–292.

Barber, B. M., & Odean, T. (2013). The behavior of individual investors. In *Handbook of the economics of finance* (Vol. 2, pp. 1533–1570). Elsevier.

Barberis, N. (2018). Psychology-based models of asset prices and trading volume. In *Handbook of behavioral economics: applications and foundations 1* (Vol. 1, pp. 79–175). Elsevier.

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. *The quarterly journal of economics*, *116*(1), 1–53.

Barnea, A., Cronqvist, H., & Siegel, S. (2010). Nature or nurture: What determines investor behavior? *Journal of Financial Economics*, *98*(3), 583–604.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral science*, *9*(3), 226–232.

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *Quarterly Journal of Economics*, *110*(1), 73–92.

Bonser-Neal, C., Jones, S. L., Linnan, D., & Neal, R. (2002). Herding, feedback trading and foreign investors. *Indiana University*.

Bossaerts, P., Ghirardato, P., Guarnaschelli, S., & Zame, W. R. (2010). Ambiguity in asset markets: Theory and experiment. *The Review of Financial Studies*, *23*(4), 1325–1359.

Calvet, L. E., Campbell, J. Y., & Sodini, P. (2009). Fight or flight? portfolio rebalancing by individual investors. *The Quarterly journal of economics*, *124*(1), 301–348.

Cao, H. H., Wang, T., & Zhang, H. H. (2005). Model uncertainty, limited market participation, and asset prices. *The Review of Financial Studies*, *18*(4), 1219–1251.

Carroll, C., Slacalek, J., Tokuoka, K., & White, M. N. (2017). The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, *8*(3), 977–1020.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), 1651–1679.

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *Journal of economic behavior & organization*, *81*(1), 1–8.

Chiang, Y.-M., Hirshleifer, D., Qian, Y., & Sherman, A. E. (2011). Do investors learn from experience? evidence from frequent ipo investors. *The Review of Financial Studies*, *24*(5), 1560–1589.

Chinco, A., Hartzmark, S. M., & Sussman, A. B. (2021). A new test of risk factor relevance. *Journal of Finance, forthcoming*.

Choe, H., Kho, B.-C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? the korean experience in 1997. *Journal of Financial economics*, *54*(2), 227–264.

Cole, S., Paulson, A., & Shastry, G. K. (2014). Smart money? the effect of education on financial outcomes. *The Review of Financial Studies*, *27*(7), 2022–2051.

Czibor, E., Jimenez-Gomez, D., & List, J. A. (2019). The dozen things experimental economists should do (more of). *Southern Economic Journal*, *86*(2), 371–432.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2016). Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, *119*(3), 559–577.

Dorn, D., & Huberman, G. (2005). Talk and action: What individual investors say and what they do. *Review of Finance*, *9*(4), 437–481.

Dorn, D., & Sengmueller, P. (2009). Trading as entertainment? *Management Science*, *55*(4), 591–603.

Dow, J., & da Costa Werlang, S. R. (1992). Uncertainty aversion, risk aversion, and the optimal choice of portfolio. *Econometrica: Journal of the Econometric Society*, 197–204.

Easley, D., & O'Hara, M. (2009). Ambiguity and nonparticipation: The role of regulation. *The Review of Financial Studies*, *22*(5), 1817–1843.

Epper, T., Fehr, E., Fehr-Duda, H., Kreiner, C. T., Lassen, D. D., Leth-Petersen, S., & Rasmussen, G. N. (2020). Time discounting and wealth inequality. *American Economic Review*, *110*(4), 1177–1205.

Exadaktylos, F., Espín, A. M., & Branas-Garza, P. (2013). Experimental subjects are not different. *Scientific reports*, *3*(1), 1–6.

Fehr, E., & List, J. A. (2004). The hidden costs and returns of incentives—trust and trustworthiness among ceos. *Journal of the European Economic Association*, *2*(5), 743–771.

Fellner, G., & Sutter, M. (2009). Causes, consequences, and cures of myopic loss aversion–an experimental investigation. *The Economic Journal*, *119*(537), 900–916.

Feng, L., & Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of finance*, *9*(3), 305–351.

Garlappi, L., Uppal, R., & Wang, T. (2007). Portfolio selection with parameter and model uncertainty: A multi-prior approach. *The Review of Financial Studies*, *20*(1), 41–81.

Giglio, S., Maggiori, M., Stroebel, J., & Utkus, S. (2021a). Five facts about beliefs and portfolios. *American Economic Review*, *111*(5), 1481–1522.

Giglio, S., Maggiori, M., Stroebel, J., & Utkus, S. (2021b). The joint dynamics of investor beliefs and trading during the covid-19 crash. *Proceedings of the National Academy of Sciences*, *118*(4).

Gneezy, U., Kapteyn, A., & Potters, J. (2003). Evaluation periods and asset prices in a market experiment. *The Journal of Finance*, *58*(2), 821–837.

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The quarterly journal of economics*, *112*(2), 631–645.

Goyal, A. (2004). Demographics, stock market flows, and stock returns. *Journal of Financial and Quantitative Analysis*, *39*(1), 115–142.

Greenwood, R., & Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics*, *93*(2), 239–258.

Haigh, M. S., & List, J. A. (2005). Do professional traders exhibit myopic loss aversion? an experimental analysis. *The Journal of Finance*, *60*(1), 523–534.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*, 133–159.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, *92*(5), 1644–1655.

Imbens, G. W. (2015). Matching methods in practice: Three examples. *Journal of Human Resources*, *50*(2), 373–419.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econo-*

metrica, *47*(2), 263–291.

Kim, W., & Wei, S.-J. (2002). Foreign portfolio investors before and during a crisis. *Journal of international economics*, *56*(1), 77–96.

Kocherlakota, N. R. (1996). The equity premium: It's still a puzzle. *Journal of Economic literature*, *34*(1), 42–71.

Krusell, P., & Smith, A. A., Jr. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy*, *106*(5), 867–896.

Langer, T., & Weber, M. (2008). Does commitment or feedback influence myopic loss aversion?: An experimental analysis. *Journal of Economic Behavior & Organization*, *67*(3-4), 810–819.

Larson, F., List, J. A., & Metcalfe, R. D. (2016). *Can myopic loss aversion explain the equity premium puzzle? evidence from a natural field experiment with professional traders* (Tech. Rep.). National Bureau of Economic Research.

Lauriola, M., & Levin, I. P. (2001). Personality traits and risky decision-making in a controlled experimental task: An exploratory study. *Personality and individual differences*, *31*(2), 215–226.

Linnainmaa, J. (2006). Learning from experience. *Available at SSRN 891580*.

List, J. A. (2002). Preference reversals of a different kind: The" more is less" phenomenon. *American Economic Review*, *92*(5), 1636–1643.

List, J. A. (2003). Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, *118*(1), 41–71.

List, J. A. (2004). Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, *72*(2), 615–625.

List, J. A. (2020). *Non est disputandum de generalizability? a glimpse into the external validity trial* (Tech. Rep.). National Bureau of Economic Research.

Liu, H., Peng, C., Xiong, W. A., & Xiong, W. (2021). Taming the bias zoo. *Journal of Financial Economics*.

Malmendier, U., & Nagel, S. (2011). Depression babies: do macroeconomic experiences affect risk taking? *The quarterly journal of economics*, *126*(1), 373–416.

Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of Monetary Economics*, *15*(2), 145–161.

Mehra, R., & Prescott, E. C. (2003). The equity premium in retrospect. *Handbook of the Economics of Finance*, *1*, 889–938.

Nicolosi, G., Peng, L., & Zhu, N. (2009). Do individual investors learn from their trading experience? *Journal of Financial Markets*, *12*(2), 317–336.

Odean, T. (1999). Do investors trade too much? *American economic review*, *89*(5), 1279–1298.

Pástor, L., & Veronesi, P. (2021). Inequality aversion, populism, and the backlash against globalization. *The Journal of Finance*, *76*(6), 2857–2906.

Peijnenburg, K. (2018). Life-cycle asset allocation with ambiguity aversion and learning. *Journal of Financial and Quantitative Analysis*, *53*(5), 1963–1994.

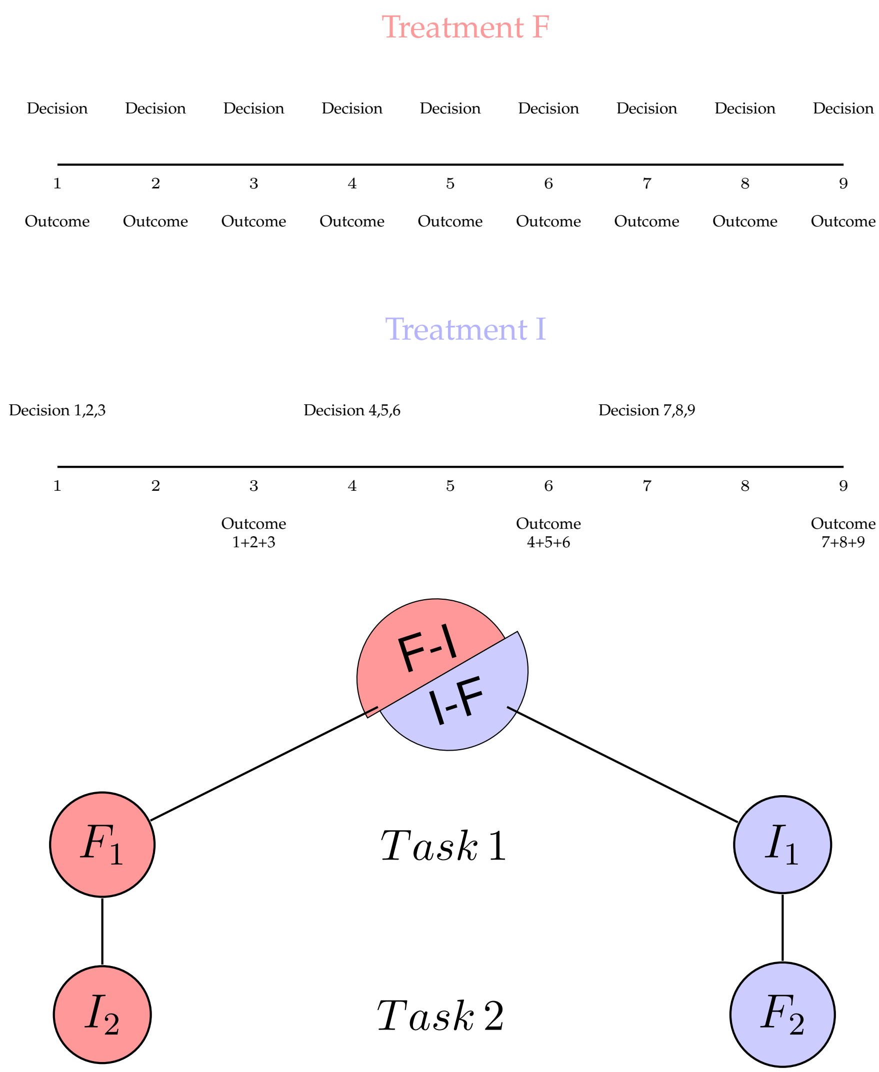
Seru, A., Shumway, T., & Stoffman, N. (2010). Learning by trading. *The Review of Financial Studies*, *23*(2), 705–739.

Sias, R., Starks, L., & Turtle, H. J. (2020). *Molecular genetics, risk aversion, return perceptions, and stock market participation* (Tech. Rep.). National Bureau of Economic Research.

Thaler, R. H., Tversky, A., Kahneman, D., & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. *The quarterly journal of economics*, *112*(2), 647–661.

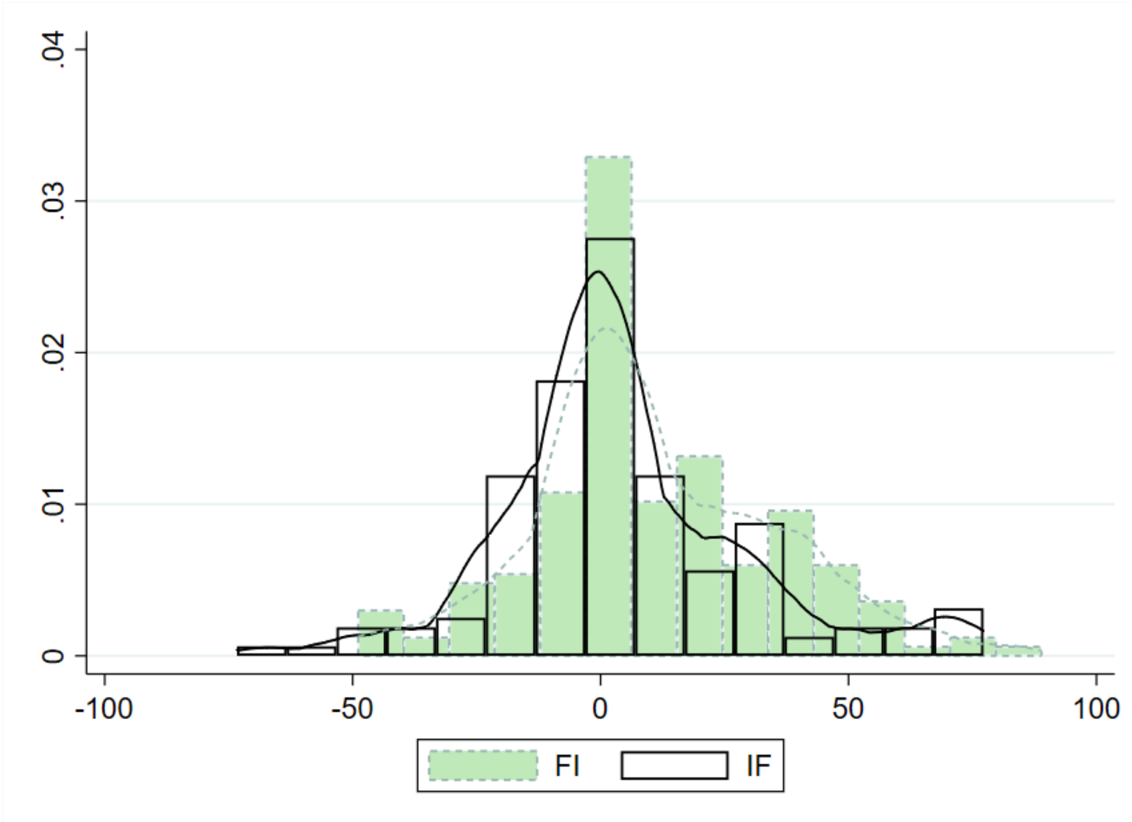
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, *5*(4), 297–323.

Figure 1: Illustration of treatment and task design



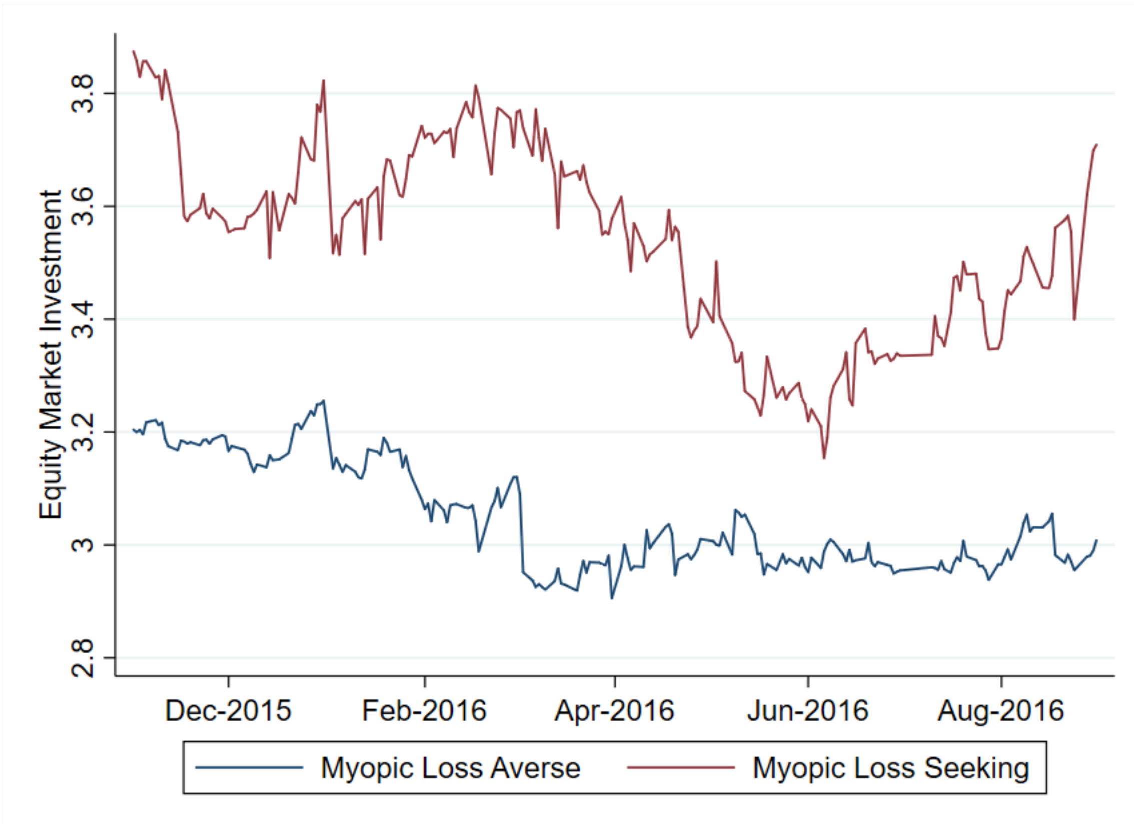
Note: In Treatment F, participants record their decision at the beginning of each round, then receive the feedback at the end of the same round. In Treatment I, partipants make the decision in block of three round, and receive the cumulative feedback at the end of every third round. Group FI was exposed to Treatment F in Task 1, then invests under Treatment I in Task 2. Group I-F follows the opposite direction of treatment allocations.

Figure 2: Distributions of Within-subject treatment effect



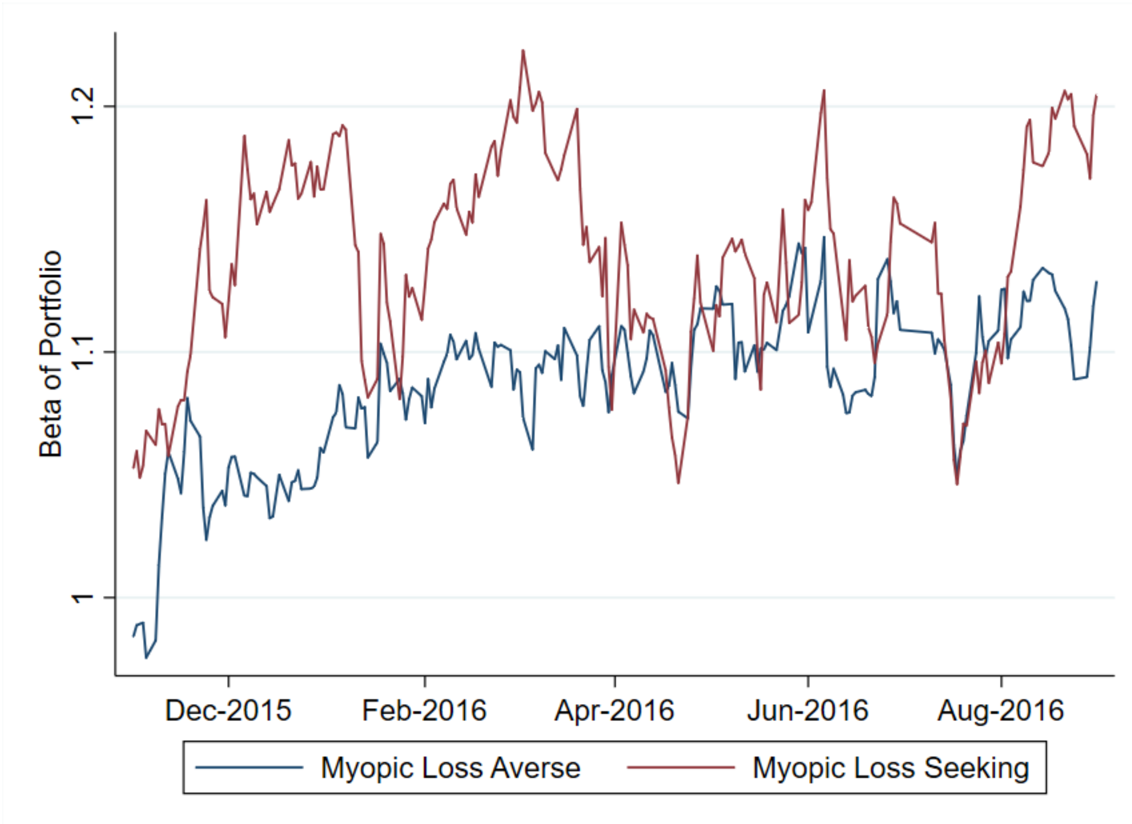
Note: This figure shows the distribution of the within-subject treatment effect by the order in which subjects were introduced to both feedback frequency in the experiments. FI denotes subjects who received the frequent feedback or Treatment F in Task 1. IF denotes subjects who received infrequent feedback or Treatment I in Task 1.

Figure 3: Equity Market Investment Levels by Investor Type



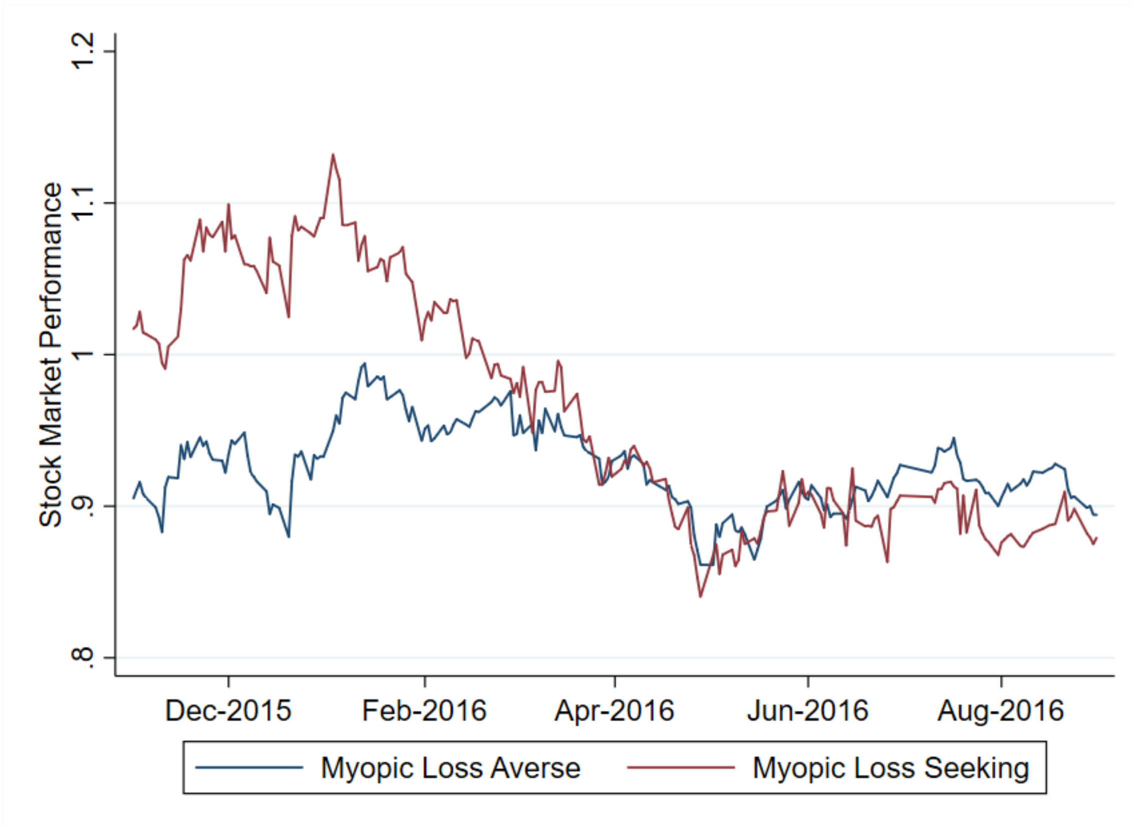
Note: This figure plots the average equity market investment at the daily level for two groups of investors: Myopic loss averse and myopic loss seeking. Equity market investment is measured as the cost of the equity portfolio scaled by income. The sample period is from Oct 30, 2015 to July 31, 2016.

Figure 4: Beta of Portfolio by Investor Type



Note: This figure plots the average beta of equity portfolio at the daily level for two groups of investors: Myopic loss averse and myopic loss seeking. Portfolio beta is calculated by weighting the market beta of individual stock in the portfolio at their average cost prices. The sample period is from Oct 30, 2015 to July 31, 2016.

Figure 5: Stock Market Performance by Investor Type



Note: This figure plots the average market performance on equity investment at the daily level for two groups of investors: Myopic loss averse and myopic loss seeking. Stock market performance is defined as gross return on equity investment measured by scaling daily market value of portfolio by the cost of portfolio. The sample period is from Oct 30, 2015 to July 31, 2016.

Table 1: Summary Statistics & Balance Across Two Treatment Groups

	All		Group F-I		Group I-F		
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Difference
Income (Million)	0.70	0.76	0.68	0.75	0.72	0.77	-0.05
Age (years)	37.46	9.16	37.46	9.30	37.46	9.02	-0.00
Male	0.95	0.21	0.95	0.21	0.96	0.21	-0.00
Having a Masters Degree	0.64	0.48	0.62	0.49	0.66	0.48	-0.04
Married	0.73	0.44	0.72	0.45	0.74	0.44	-0.02
Brokerage Initial Capital (Million)	0.74	1.67	0.78	1.85	0.70	1.44	0.07
Initial Investment (Million)	0.45	1.11	0.46	1.18	0.44	1.04	0.02
Trading Starting Year	2007.08	5.30	2007.09	5.17	2007.07	5.47	0.02
Brokerage Starting Year	2011.26	3.51	2011.16	3.43	2011.38	3.60	-0.22

Note: This table reports summary statistics and balance tests for the intial characteristics of the traders. The definition of variables are given in Appendix Table B.1. The final column reports the difference and performs t-tests for significance of difference. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Mann-Whitney Test for Treatment Effect - Task 1 & Task 2

	Average Investment under Task 1			Average Investment under Task 2			Task 1 versus Task 2		
	(1) Frequent($\bar{F}_1$)	(2) Infrequent($\bar{I}_1$)	(3) Difference	(4) Frequent($\bar{F}_2$)	(5) Infrequent($\bar{I}_2$)	(6) Difference	(7) ($\bar{F}_2 - \bar{F}_1$)	(8) ($\bar{I}_2 - \bar{I}_1$)	(9) (Task 2-Task 1)
All Rounds	58.95	69.92	10.97***	65.84	69.70	3.86	6.89**	-0.22	-7.11***
	(25.56)	(25.71)		(29.04)	(26.05)				
Rounds 1-3	63.00	67.62	4.62*	68.69	66.40	-2.29	5.68*	-1.23	-6.91***
	(27.70)	(28.50)		(29.33)	(29.33)				
Rounds 4-6	59.00	69.12	10.12***	64.58	68.67	4.09	5.58	-0.45	-6.03***
	(31.38)	(30.28)		(33.42)	(31.83)				
Rounds 7-9	54.84	73.02	18.18***	64.25	74.03	9.79***	9.41**	1.01	-8.39***
	(33.83)	(29.70)		(33.04)	(33.24)				
Observations	182	159	341	159	182	341		341	

Note: This table reports findings from the experiments of myopic loss aversion. Columns (1)-(3) report results from Task 1. Columns (4)-(6) report results from Task 2. Columns (7)-(9) compares between the results of Task1 and Task 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Within-subject distribution

	Panel A - Pooled Data		Panel B - Only F-I		Panel C - Only I-F	
	(1) Distribution	(2) Difference	(3) Distribution	(4) Difference	(5) Distribution	(6) Difference
Myopic Loss Averse	174 (51.03%)	-25.45 (-33.89%)	106 (58.24%)	-25.78 (-33.91%)	68 (42.77%)	-24.93 (-33.87%)
Myopic Neutral	58 (17.01%)	0	27 (14.84%)	0	31 (19.50%)	0
Myopic Loss Seeking	109 (31.96%)	16.71 (31.86%)	49 (26.92%)	15.83 (32.41%)	60 (37.74%)	17.43 (31.46%)
Observations	341		182		159	

Note: This table reports number of traders classified as either myopic loss averse, myopic neutral or myopic loss seeking. Panel A reports individual level distribution. Panel B reports distribution for the traders who received frequent feedback first. Panel C reports distribution for the traders who received infrequent feedback first.

Table 4: Summary Statistics of Portfolio and Transaction Data

	Obs.	Mean	Std Dev	p10	p50	p90
Panel A - Portfolio						
Cost (Million) - Daily	63441	1.53	3.07	0.01	0.34	4.01
Market Value (Million) - Daily	63441	1.33	2.58	0.02	0.32	3.88
Cost/Income - Daily	56750	3.06	10.11	0.04	0.66	6.47
Market Value/Income - Daily	56750	2.60	8.33	0.04	0.60	5.12
Beta - Daily	63301	1.10	0.46	0.49	1.14	1.65
Total number of stocks - Daily	63440	5.21	5.61	1.00	3.00	11.00
Total number of sectors - Daily	63440	3.51	2.50	1.00	3.00	7.00
Return - Monthly	3045	-0.01	0.07	-0.10	-0.01	0.08
Panel B - Transaction						
Number of shares bought ('000) - Daily	63441	0.80	2.74	0.00	0.00	1.75
Number of shares sold ('000) - Daily	63441	0.77	2.70	0.00	0.00	1.50
Total value of buys (Million) - Daily	63441	0.03	0.10	0.00	0.00	0.08
Total value of sales (Million) - Daily	63441	0.03	0.10	0.00	0.00	0.07
Turnover - Monthly	3063	0.89	1.51	0.00	0.15	2.87

Note: This table reports summary statistics for variables based on brokerage data. Definition of variables are given in Appendix Table B.2. Panel A reports statistics for variables based on portfolio holdings data. Panel B reports statistics for variables based on transactions data.

Table 5: MLA & Risk Taking in Stock Market

	Equity Market Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Equity measured at cost prices					
MLA	-1.307**	-1.106**	-1.278***	-1.702***	-1.996***	-1.913***
	(0.547)	(0.446)	(0.445)	(0.485)	(0.553)	(0.550)
Demographics						
Income	-0.701***	-0.680***	-0.669***	-1.129***	-2.026***	-2.064***
	(0.203)	(0.174)	(0.185)	(0.180)	(0.337)	(0.354)
Age	-0.003	-0.049**	-0.084***	-0.068**	-0.098***	-0.096***
	(0.020)	(0.024)	(0.028)	(0.026)	(0.034)	(0.035)
Male	-18.227***	-19.878***	-19.986***	-19.620***	-13.505***	-13.399***
	(2.847)	(2.821)	(2.818)	(2.769)	(2.403)	(2.376)
Master Degree	-3.794***	-3.649***	-3.278***	-3.151***	-3.647***	-3.696***
	(0.451)	(0.435)	(0.408)	(0.394)	(0.430)	(0.461)
Married	-1.011*	-0.461	0.214	0.264	0.237	0.145
	(0.566)	(0.657)	(0.729)	(0.734)	(0.799)	(0.833)
Market Participation						
Initial Investment		0.386***	0.427***	0.239**	0.250	0.195
		(0.122)	(0.113)	(0.094)	(0.164)	(0.162)
Broker Initial Capital			0.732***	0.910***	1.511***	1.518***
			(0.079)	(0.081)	(0.207)	(0.209)
Observations	47049	47049	47049	47049	47049	47048
Adj. R-squared	0.164	0.225	0.253	0.283	0.438	0.419
	Panel B: Equity measured at constant prices					
MLA	-0.962**	-0.849**	-0.971**	-1.383***	-1.627***	-1.554***
	(0.482)	(0.387)	(0.390)	(0.423)	(0.492)	(0.491)
Demographics						
Income	-0.643***	-0.683***	-0.607***	-1.024***	-1.768***	-1.798***
	(0.180)	(0.156)	(0.143)	(0.140)	(0.275)	(0.291)
Age	0.001	-0.036*	-0.067***	-0.052**	-0.073**	-0.071**
	(0.016)	(0.021)	(0.025)	(0.022)	(0.029)	(0.030)
Male	-15.477***	-16.884***	-16.952***	-16.632***	-11.439***	-11.347***
	(2.431)	(2.392)	(2.405)	(2.359)	(2.057)	(2.038)
Master Degree	-3.084***	-2.923***	-2.596***	-2.498***	-2.761***	-2.795***
	(0.382)	(0.378)	(0.353)	(0.340)	(0.379)	(0.405)
Married	-0.814*	-0.360	0.292	0.282	0.155	0.058
	(0.466)	(0.543)	(0.613)	(0.615)	(0.688)	(0.713)

	(1)	(2)	(3)	(4)	(5)	(6)
Market Participation						
Initial Investment		0.343***	0.287***	0.154*	0.109	0.064
		(0.102)	(0.105)	(0.090)	(0.151)	(0.150)
Broker Initial Capital			0.728***	0.880***	1.438***	1.445***
			(0.071)	(0.071)	(0.182)	(0.184)
Observations	47049	47049	47049	47049	47049	47048
Adj. R-squared	0.158	0.220	0.248	0.280	0.441	0.423
FF Sequence	Y	Y	Y	Y	Y	Y
Participation Year FE		Y	Y	Y	Y	Y
Broker FE			Y	Y		
Start Year FE			Y	Y		
Dominant Ind. FE				Y	Y	
Day FE				Y	Y	
Broker $\times$ Start Year FE					Y	Y
Dominant Ind. $\times$ Day FE						Y

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion and a set of control variables. Equity market investment is measured as the size of equity portfolio scaled by income. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. In Panel A, the size of equity is measured at cost prices. In Panel B, the size of equity is measured at constant prices based on prices at the start of our sample period, Oct 30, 2015. Column (1) includes only demographic controls. Column (2) also includes general market participation controls and fixed effects. Column (3) also includes brokerage firm specific controls and fixed effects. Columns (4)-(6) also include fixed effects based on the day and the dominant industry of the investors' portfolio. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Robustness - Other Behavioral Biases & Beliefs

	Equity Market Investment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MLA	-1.913***	-1.946***	-1.914***	-2.075***	-1.899***	-1.835***	-1.703***	-2.002***
	(0.550)	(0.535)	(0.597)	(0.576)	(0.551)	(0.493)	(0.489)	(0.582)
Risk Aversion		-0.052						-0.019
		(0.082)						(0.118)
Ambiguity Aversion			-0.107					-0.168
			(0.100)					(0.106)
Time Preference				1.972				1.354
				(1.248)				(1.355)
Domestic Stock Crash					-0.166**			0.005
					(0.079)			(0.111)
Global Stock Crash						-0.949**		-1.116*
						(0.393)		(0.571)
Global Econ. Crisis							-0.578***	-0.178
							(0.211)	(0.340)
FF Sequence	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Dominant Ind. $\times$ Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	47048	47048	45024	46419	47048	47048	47048	44395
Adj. R-squared	0.419	0.419	0.425	0.421	0.419	0.424	0.421	0.435

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion while controlling for other behavioral biases and investor beliefs. Equity market investment is measured as the cost of equity portfolio scaled by income. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. Column (1) is the baseline result. In columns (2)-(4) we separately control for each of risk aversion, ambiguity aversion and time preference measured through experimental games described in detail in section C.2. In columns (5)-(7) we separately control for each investor belief based on their answers to the following: 1) ”Do you think the stock market in Bangladesh will fall in a large scale within next 6 months?”; 2) ”Do you think the world stock market will fall in a large scale within next 6 months?”; 3) ”Do you think that world economy will fall in crisis in next 6 months?”. The answers were recorded in a scale of 1 (least likely) to 5 (most likely). In column (8), we control for all behavioral biases and investor beliefs. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Robustness - Matching

Panel A - Balance Test for Matching

	Unmatched			Matched		
	MLA=1	MLA=0	Difference	MLA=1	MLA=0	Difference
Income	0.724	0.587	-0.137*	0.659	0.564	-0.095
	(0.600)	(0.519)		(0.511)	(0.501)	
Age	38.851	35.241	-3.610***	35.929	34.500	-1.429
	(9.762)	(7.250)		(7.528)	(6.842)	
Initial Investment	0.487	0.282	-0.205*	0.336	0.300	-0.036
	(0.985)	(0.644)		(0.706)	(0.712)	
Broker Initial Capital	0.762	0.415	-0.347***	0.436	0.394	-0.041
	(1.115)	(0.802)		(0.603)	(0.736)	
Master Degree	0.661	0.657	-0.003	0.667	0.631	-0.036
	(0.475)	(0.477)		(0.474)	(0.485)	
Married	0.786	0.676	-0.110**	0.762	0.690	-0.071
	(0.412)	(0.470)		(0.428)	(0.465)	
Male	0.929	0.972	0.044	0.964	0.964	0.000
	(0.258)	(0.165)		(0.187)	(0.187)	
FF Sequence	0.399	0.546	0.147**	0.464	0.464	0.000
	(0.491)	(0.500)		(0.502)	(0.502)	
Participation Year	2006.946	2007.444	0.498	2008.357	2008.298	-0.060
	(5.392)	(5.322)		(4.202)	(4.610)	
Start Year	2011.101	2011.398	0.297	2011.643	2011.893	0.250
	(3.552)	(3.645)		(2.568)	(2.625)	
Observations	168	108	276	84	84	168

Panel B - MLA & Risk Taking in Stock Market for matched sample

Equity measured by:	Cost Price			Constant Price		
Dep. Var.: Equity Market Investment	(1)	(2)	(3)	(4)	(5)	(6)
MLA	-1.887***	-1.763***	-1.645***	-1.464***	-1.395***	-1.285***
	(0.560)	(0.498)	(0.483)	(0.503)	(0.448)	(0.436)
FF Sequence	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y	Y	Y
Dominant Ind. FE		Y			Y	
Dominant Ind. $\times$ Day FE			Y			Y
Observations	29060	29060	29016	29060	29060	29016
Adj. R-squared	0.390	0.423	0.388	0.387	0.425	0.391

Note: This table presents the results pf the MLA effect on equity market investment for a sample of traders matched on initial characteristics using the method of Imbens (2015). Panel A presents the balance test for matching. Panel B presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion for the matched sample of traders. Equity market investment is measured as the size of equity portfolio scaled by income. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. In columns (1)-(3) of Panel B, the size of equity is measured at cost prices. In columns (4)-(6) of Panel B, the size of equity is measured at constant prices based on prices at the start of our sample period. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Robustness - Addressing Experimental Order Effects

Equity measured by:	Cost Price			Constant Price		
Dep. Var.: Equity Market Investment	(1)	(2)	(3)	(4)	(5)	(6)
MLA	-1.500***	-1.574***	-1.506***	-1.149***	-1.217***	-1.155***
	(0.382)	(0.376)	(0.375)	(0.335)	(0.335)	(0.336)
FF Sequence	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y	Y	Y
Dominant Ind. FE		Y			Y	
Dominant Ind. $\times$ Day FE			Y			Y
Observations	47049	47049	47048	47049	47049	47048
Adj. R-squared	0.413	0.439	0.418	0.415	0.442	0.422

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion while addressing experimental order effects. Equity market investment is measured as the size of equity portfolio scaled by income. We correct for order effects in our measure MLA in the following way. First, we estimate the following regression: $\Delta BET_i = \gamma_0 + \gamma_1 FFORDER_i + \epsilon_i$. Here, $\Delta BET_i = I_i - F_i$, the difference in average bet between frequent and infrequent feedback in lab experiment and $FFORDER_i$ captures whether individual i is group F-I or group I-F. MLA equals 1 if $\epsilon_i > 0$ and MLA equals 0 if $\epsilon_i < 0$. The sample period is from Oct 30, 2015 to July 31, 2016. In columns (1)-(3), the size of equity is measured at cost prices. In columns (4)-(6), the size of equity is measured at constant prices based on prices at the start of our sample period. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Robustness - Alternative Measures of MLA

	Equity Market Investment							
	(1) Rounds 1-9	(2) Rounds 7-9	(3) Middle Distribution	(4) Supplement	(5) All Rounds	(6) Including Myopic Neutral	(7) Continuous	(8) Decile
MLA	-1.913***	-2.193***	-2.272***	-2.411***	-2.232***	-1.769***	-0.647***	-0.310***
	(0.550)	(0.538)	(0.547)	(0.312)	(0.394)	(0.330)	(0.096)	(0.051)
FF Sequence	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Broker × Start Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Dominant Ind. × Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	47048	40336	46420	55419	56040	56750	56131	56131
Adj. R-squared	0.419	0.537	0.420	0.414	0.410	0.411	0.410	0.411

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on different measures of myopic loss aversion. Equity market investment is measured as the cost of equity portfolio scaled by income. Column (1) is the baseline result . Column (2) measures MLA using only the last 3 rounds of experimental data. Column (3) measures MLA by excluding the highest and lowest bet in Task 1 and 2. Column (4) measures MLA using data from supplemental 3 rounds varying experimental wealth. Column (5) measures MLA using experimental data from all rounds (main and supplement). Column (6) measures MLA in the same way as column (1) but includes myopic neutral traders in the base category. Column (7) measures MLA using a continuous variable based on the percentage difference in bets across both experimental feedback frequency. Column (8) measures MLA through individual rank based on deciles in the percentage differences in bet. The sample period is from Oct 30, 2015 to July 31, 2016. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Other Robustness Checks

	Equity Market Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Number of days Weighted	Excluding Outliers	Alternate Controls: Income & Age dummies	Business background: Major & Job dummies	Equity measured at close prices
MLA	-1.913***	-2.045***	-2.128***	-1.560**	-2.429***	-1.671***
	(0.550)	(0.526)	(0.589)	(0.604)	(0.683)	(0.488)
FF Sequence	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y	Y	Y
Dominant Ind. $\times$ Day FE	Y	Y	Y	Y	Y	Y
Observations	47048	47048	44217	47048	47048	47048
Adj. R-squared	0.419	0.401	0.427	0.446	0.494	0.422

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion under various robustness tests. Equity market investment is measured as the cost of equity portfolio scaled by income. Column (1) is the baseline result. Column (2) weights each observation by the inverse of the number of days the investor appeared on the sample. Column (3) excludes the top 2% of myopic loss averse and myopic loss seeking traders based on percentage difference in experimental bets. Column (4) includes dummies on income and age based on individual decile rank as opposed to continuous variables. Column (5) includes dummies for whether the individual's primary major or secondary major in college was business as well as dummies for whether the primary occupation or the secondary occupation is classified as being a businessman. Column (6) measures the size of equity based on the daily closing price of each stock as opposed to the cost of portfolio. The sample period is from Oct 30, 2015 to July 31, 2016. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Heterogeneity: Market Participation & Trading Characteristics

Equity measured by:	Cost Price		Constant Price	
Dep. Var.: Equity Market Investment	(1)	(2)	(3)	(4)
Panel A - Years of Experience:	< 8	≥ 8	< 8	≥ 8
MLA	-3.362***	0.425	-3.055***	0.861***
	(0.798)	(0.384)	(0.692)	(0.288)
P-value (MLA[< 8] = MLA[≥ 8])	0.000		0.000	
Observations	23798	23041	23798	23041
Adj. R-squared	0.430	0.658	0.433	0.722
Panel B - Updating Frequency:	Infrequent	Frequent	Infrequent	Frequent
MLA	-1.010*	-7.503***	-1.067**	-6.294***
	(0.512)	(1.706)	(0.501)	(1.458)
P-value (MLA[Infrequent] = MLA[Frequent])	0.000		0.001	
Observations	20421	26435	20421	26435
Adj. R-squared	0.719	0.677	0.710	0.679
Panel C - Investor Activeness:	Low	High	Low	High
MLA	-0.114	-6.847***	0.258*	-5.796***
	(0.198)	(1.656)	(0.135)	(1.482)
P-value (MLA[Low] = MLA[High])	0.000		0.000	
Observations	24244	22691	24244	22691
Adj. R-squared	0.806	0.715	0.781	0.708
FF Sequence	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y
Dominant Ind. $\times$ Day FE	Y	Y	Y	Y

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion on sub samples based on trading characteristics. Equity market investment is measured as the size of equity portfolio scaled by income. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. In columns (1) and (2), the size of equity is measured at cost prices. In columns (3) and (4), the size of equity is measured at constant prices based on prices at the start of our sample period, Oct 30, 2015. In Panel A, the regressions are based on samples formed on the median trading experience of 8 years. In Panel B, the regressions are based on samples formed on whether the trader updates about the market frequently or infrequently. In Panel C, the regressions are based on samples formed on the median level of investor activeness as measured by how frequently they change their portfolio allocation. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: MLA & Extent of Portfolio Riskiness

	Beta of Portfolio				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Beta weighted by cost prices				
MLA	-0.0304**	-0.0341***	-0.0788***	-0.0825***	-0.0736***
	(0.0116)	(0.0125)	(0.0228)	(0.0256)	(0.0251)
Observations	46359	46359	46359	46359	46358
Adj. R-squared	0.049	0.070	0.184	0.203	0.221
	Panel B: Beta weighted by constant prices				
MLA	-0.0209*	-0.0266**	-0.0589**	-0.0641**	-0.0564**
	(0.0113)	(0.0124)	(0.0239)	(0.0260)	(0.0260)
Observations	46886	46886	46886	46886	46885
Adj. R-squared	0.057	0.072	0.195	0.212	0.228
FF Sequence	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y
Broker FE		Y			
Broker × Start Year FE			Y	Y	Y
Dominant Ind. FE				Y	
Dominant Ind. × Day FE					Y

Note: This table presents coefficient estimates of the OLS regressions of beta of investors' portfolios on myopic loss aversion. We measure individual stock beta by regressing stock returns on the return on the market index of the day. We then form value weighted beta of portfolio from individual stock beta. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. In Panel A, the individual stock beta is weighted at their cost prices to form market beta of the portfolio. In Panel B, the individual stock beta is weighted at constant prices based on prices at the start of our sample period, Oct 30, 2015 to form market beta of portfolio. Column (1) includes only controls and fixed effect for the year the investor starts trading. Column (2) and (3) also includes brokerage firm specific fixed effects. Columns (4) and (5) also include fixed effects based on the day and the dominant industry of the investors' portfolio. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: MLA & Reaction to Short term Portfolio Loss

	Equity Investment Level: Increase/Decrease				
	(1)	(2)	(3)	(4)	(5)
	Panel A: 𝟙 Equity Investment Decrease				
𝟙 Portfolio Loss	0.490***	0.493***	0.503***	0.503***	0.515***
	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)
𝟙 Portfolio Loss × MLA	0.057***	0.054***	0.038***	0.038***	0.037***
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
Observations	46377	46377	46377	46377	46376
Adj. R-squared	0.297	0.301	0.326	0.330	0.333
	Panel B: 𝟙 Equity Investment Increase				
𝟙 Portfolio Loss	-0.504***	-0.499***	-0.479***	-0.474***	-0.482***
	(0.008)	(0.009)	(0.011)	(0.011)	(0.011)
𝟙 Portfolio Loss × MLA	0.010	0.006	-0.004	-0.008	-0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Observations	46377	46377	46377	46377	46376
Adj. R-squared	0.281	0.288	0.315	0.320	0.321
FF Sequence	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y
Broker FE		Y			
Broker × Start Year FE			Y	Y	Y
Dominant Ind. FE				Y	
Dominant Ind. × Day FE					Y

Note: This table presents coefficient estimates of the OLS regressions of investors' decision to change their level of equity investment on portfolio loss and its interaction with myopic loss aversion. Portfolio loss is defined as the event when the market value of investor's portfolio opens at a lower value compared to the value on the previous day. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. The increase or decrease in equity investment is identified based on changes in cost of portfolio. In Panel A, the dependent variable is a dummy for when the investor decreased their equity investment size. In Panel B, the dependent variable is a dummy for when the investor increased their equity investment size. Column (1) includes only controls and fixed effect for the year the investor starts trading. Column (2) and (3) also includes brokerage firm specific fixed effects. Columns (4) and (5) also include fixed effects based on the day and the dominant industry of the investors' portfolio. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: MLA & Stock Market Performance

	Stock Market Performance				
	(1)	(2)	(3)	(4)	(5)
MLA	-0.0528***	-0.0433**	-0.0540***	-0.0570***	-0.0573***
	(0.0188)	(0.0180)	(0.0173)	(0.0166)	(0.0158)
FF Sequence	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y
Broker FE		Y			
Broker $\times$ Start Year FE			Y	Y	Y
Dominant Ind. FE				Y	
Dominant Ind. $\times$ Day FE					Y
Observations	47049	47049	47049	47049	47048
Adj. R-squared	0.055	0.072	0.340	0.374	0.382

Note: This table presents coefficient estimates of the OLS regressions of the performance of investors' stock market investment on myopic loss aversion. Stock market performance is defined as the daily gross return on the investment measured as the market value of the portfolio scaled by the cost of the portfolio. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. Column (1) includes only controls and fixed effect for the year the investor starts trading. Column (2) and (3) also includes brokerage firm specific fixed effects. Columns (4) and (5) also include fixed effects based on the day and the dominant industry of the investors' portfolio. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A A Simple Conceptual Framework

We rely on the setting in Benartzi and Thaler (1995) to provide a simple exposition of myopic loss aversion in a static setting. Consider an individual who has the following value function:

$$\begin{cases} u(z) = -\lambda z^{\alpha} & \text{for } z < 0 \\ u(z) = z^{\beta} & \text{for } z \geq 0 \end{cases} \tag{4}$$

in which the parameter λ reflects his loss aversion ($\lambda > 1$ for risk-averse agent) and z represents the change in wealth. Tversky and Kahneman (1992) referred to α and β ($0 < \alpha, \beta < 1$) as the diminishing sensitivity. When α is small, the agent is more risk-averse in the gain domain and risk-seeking in the loss domain and the opposite relationship applies for β. For the linear case $\alpha = \beta = 1$, the benchmark case of 'pure loss aversion' is included into the analysis.

Let S_n denote the value of the aggregate distribution of n independent draws of the gamble $L(-x, 2/3; 2.5x, 1/3)$, with a linear case $\alpha = \beta = 1$ an individual who faces gamble S_1 and S_3 will obtain:

$$S_1 = -\frac{2}{3}\lambda x + \frac{2.5x}{3} \tag{5}$$

$$S_3 = \frac{1}{27}7.5x + \frac{6}{27}4x + \frac{12}{27}0.5x - \frac{8}{27}\lambda 3x \tag{6}$$

While S_1 is negative for any $\lambda \geq 1.25$, S_3 remains positive as long as $\lambda \leq 1.5625$. In other words, a loss averse individual perceives three gambles more positively if they evaluate such gambles in a form of a single unit bundle. The average traders who fail to properly evaluate a sequence of investment should always find lotteries with frequent feedback less attractive (see Figure B.1).

Appendix B Additional Tables and Figures

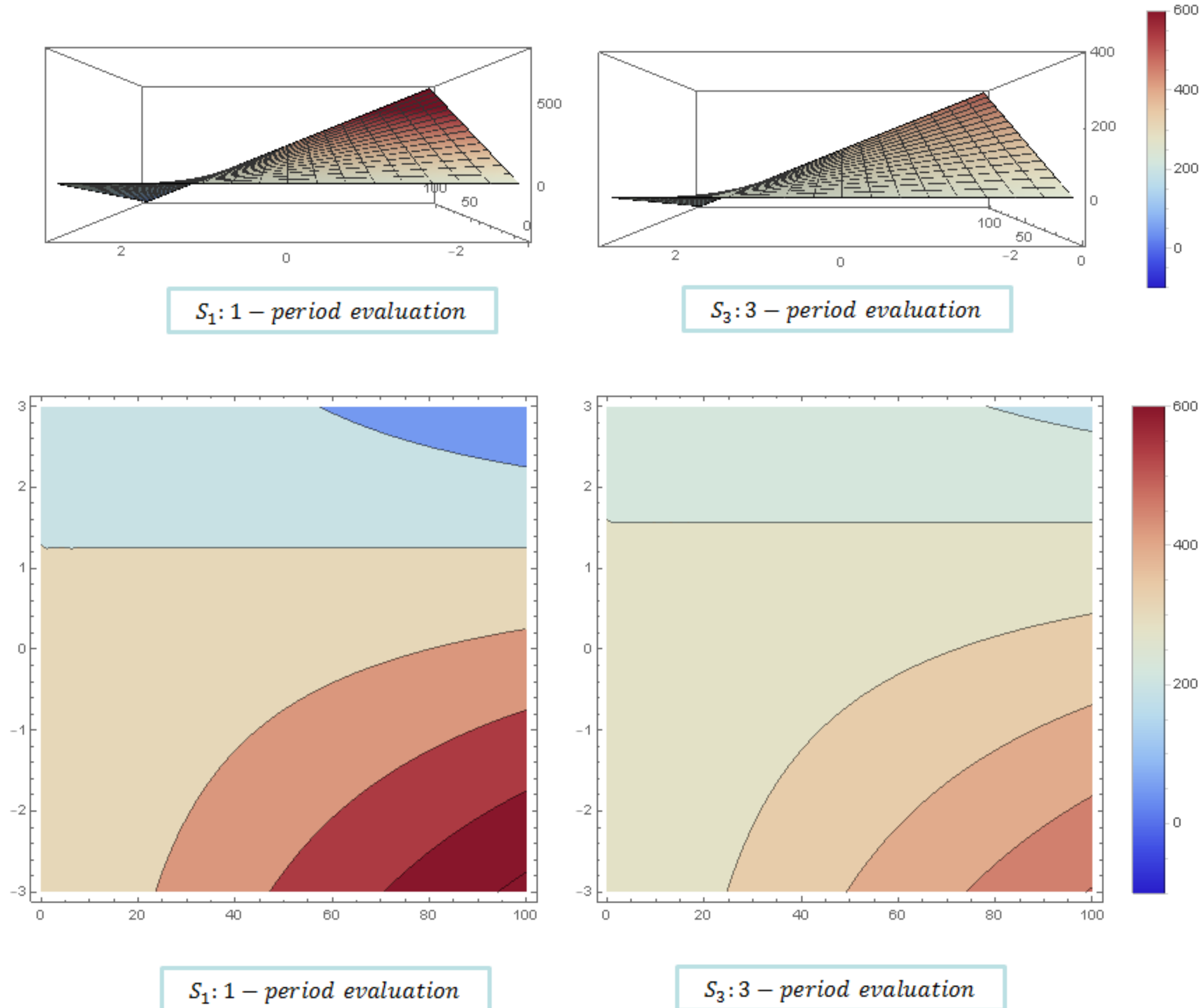
Table B.1: Definition of experiment and survey based variables

Variable	Origin	Definition
MLA	Experiment	Equals 1 if investment under frequent feedback is less than investment under infrequent feedback and equals 0 if opposite
Income	Survey	Annual income in millions of Taka
Age	Survey	Age in years
Male	Survey	Equals 1 if male and equals 0 otherwise
Having a Masters Degree	Survey	Equals 1 if having a masters degree and equals 0 otherwise
Married	Survey	Equals 1 if married and equals 0 otherwise
Initial Investment	Survey	Investment amount when starting to trade in stock market in millions of Taka
Brokerage Initial Capital	Survey	The starting capital at the current brokerage firm in millions of Taka
Trading starting year	Survey	The year the individual joined the stock market
Brokerage starting year	Survey	The year the individual started trading at the current brokerage firm
Risk aversion	Experiment	Index computed by the crossover level risk-sensitivity approach (section C.2.3)
Ambiguity avoidance	Experiment	Index computed by the crossover level ambiguity-sensitivity approach (section C.2.2)
Time preference	Experiment	Measure of discounting or patience (section C.2.1)
BD Stock Crash	Survey	Answer to ”Do you think the stock market in Bangladesh will fall in a large scale within next 6 months?”: 1 (least likely) to 5 (most likely)
Global Stock Crash	Survey	Answer to ”Do you think the world stock market will fall in a large scale within next 6 months?”: 1 (least likely) to 5 (most likely)
Global Econ. Crisis	Survey	Answer to ”Do you think that world economy will fall in crisis in next 6 months?”: 1 (least likely) to 5 (most likely)
Trading Experience	Survey	Number of years in stock market trading
Updating Frequency	Survey	Equals 1 if individual updates about the market frequently and equals 0 if infrequently

Table B.2: Definition of variables based on portfolio, transactions and market data

Variables	Data sources	Definition	Frequency
Number of shares bought	Transactions	Total units of stock purchases in thousands	Daily
Number of shares sold	Transactions	Total units of stock sales in thousands	Daily
Total value of buys	Transactions	Total value of stock purchases in millions of Taka	Daily
Total value of sales	Transactions	Total value of stock sales in millions of Taka	Daily
Turnover	Transactions	One-half the average equity monthly of all stock trades (purchases and sales) divided by the average monthly value of the portfolio	Monthly
Cost	Transactions, Portfolio	Weighted average cost price of each stock position in the portfolio using transaction prices times the number of stocks held in millions of Taka	Daily
Market Value	Portfolio, Market	The market value of the portfolio in millions of Taka	Daily
Beta	Portfolio, Market	The market beta of the portfolio by weighting market beta of individual stocks	Daily
Total number of stocks	Portfolio	total quantity or units stocks in portfolio	Daily
Total number of sectors	Portfolio	Number of different DSE sectors represented by stocks in the portfolio	Daily
Return	Portfolio, Market	Net monthly return of each individual's portfolio calculated from estimating the monthly return on each common stock investment using the beginning-of-month position statements	Monthly
Equity Market Investment	Portfolio, Transactions	Size of equity scaled by income	Daily
Portfolio Loss	Portfolio, Market	Equals 1 if portfolio opens at a lower price than previous day equals 0 otherwise	Daily
Equity Investment Increase	Transactions, Portfolio	Equals 1 if cost of portfolio increases and equals 0 otherwise	Daily
Equity Investment Decrease	Transactions, Portfolio	Equals 1 if cost of portfolio decreases and equals 0 otherwise	Daily
Stock Market Performance	Portfolio, Market	The gross return on investment defined as market value of portfolio scaled by portfolio cost	Daily
Investor Activeness	Portfolio, Transactions	Equals 1 if the individuals has higher than median level of portfolio changing frequency and equals 0 otherwise	
Trading Frequency	Transactions	Equals 1 for greater than median volume of trades in units of stock/amount of trades in millions of Taka/turnover of trades and equals 0 otherwise	

Figure B.1: Plots for Equations (5) and (6)



Notes: This figure compare and contrast the value function of loss-averse agents on repeated evaluation of single lottery versus joint evaluation of multiple lotteries.

Table B.3: Sub-group analysis: Correlation between MLA & individual characteristics

	MLA			
	(1)	(2)	(3)	(4)
High Income	-0.120**			
	(0.050)			
High Age		-0.096*		
		(0.050)		
High Education			0.024	
			(0.053)	
High Initial Investment				-0.088*
				(0.050)
FF Sequence	Yes	Yes	Yes	Yes
Observations	341	341	333	341

Standard errors in parentheses

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

Figure B.2: Within-subject myopia and trader characteristics

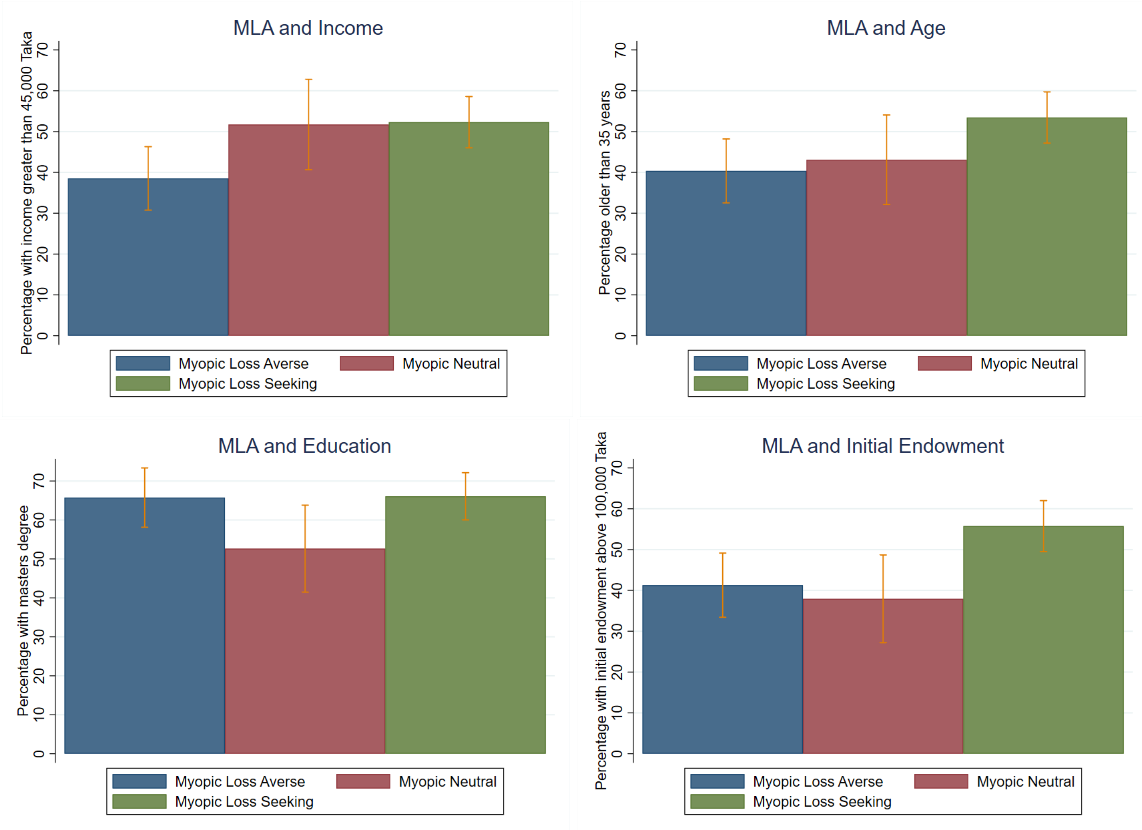


Table B.4: Decomposing Variance in Myopic Loss Aversion by individual characteristics

R^2 (%) of regressing % bet diff. on characteristics					
	1.3	2.2	7.7	13.2	15.5
Age, Income	Y	Y			Y
Gender, Married, Master's degree		Y			Y
Initial Investment, Trading Start Year			Y	Y	Y
Brokerage firm, Brokerage Start Year, Brokerage Initial Capital				Y	Y

Note: This table reports R^2 in percentage of regressions of percentage difference in average bet between two feedback frequencies in experiments of myopic loss aversion on individual demographic and trading characteristics.

Table B.5: The differences between two treatments in Supplementary Games

	Supplementary Game Task 1			Supplementary Game Task 2		
	(1) Treatment F	(2) Treatment I	(3) Difference	(4) Treatment F	(5) Treatment I	(6) Difference
Rounds 1-3	152.95	171.98	19.04*	171.04	181.82	10.79
	(119.83)	(122.21)		(127.13)	(146.94)	
Observations	182	159	341	159	182	341

Note: This table reports findings from the supplemental rounds of experiments of myopic loss aversion which varies experimental wealth. Columns (1)-(3) report results from Task 1. Columns (4)-(6) report results from Task 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Robustness - Other Behavioral Biases & Beliefs

	Equity Market Investment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MLA	-1.554***	-1.557***	-1.483***	-1.676***	-1.548***	-1.494***	-1.388***	-1.505***
	(0.491)	(0.479)	(0.527)	(0.510)	(0.491)	(0.447)	(0.445)	(0.525)
Risk Aversion		-0.005						0.038
		(0.076)						(0.104)
Ambiguity Aversion			-0.065					-0.108
			(0.093)					(0.097)
Time Preference				2.005*				1.398
				(1.074)				(1.166)
Domestic Stock Crash					-0.068			0.072
					(0.075)			(0.103)
Global Stock Crash						-0.735**		-0.855*
						(0.333)		(0.485)
Global Econ. Crisis							-0.457**	-0.160
							(0.179)	(0.291)
FF Sequence	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Broker $\times$ Start Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Dominant Ind. $\times$ Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	47048	47048	45024	46419	47048	47048	47048	44395
Adj. R-squared	0.423	0.423	0.429	0.425	0.423	0.427	0.424	0.437

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion while controlling for other behavioral biases and investor beliefs. Equity market investment is measured as the portfolio size in constant prices scaled by income where we use prices at the beginning of our sample period. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. Column (1) is the baseline result. In columns (2)-(4) we separately control for each of risk aversion, ambiguity aversion and time preference measured through experimental games described in detail in section C.2. In columns (5)-(7) we separately control for each investor belief based on their answers to the following: 1) "Do you think the stock market in Bangladesh will fall in a large scale within next 6 months?"; 2) "Do you think the world stock market will fall in a large scale within next 6 months?"; 3) "Do you think that world economy will fall in crisis in next 6 months?". The answers were recorded in a scale of 1 (least likely) to 5 (most likely). In column (8), we control for all behavioral biases and investor beliefs. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Robustness - Alternative Measures of MLA

	Equity Market Investment							
	(1) Rounds 1-9	(2) Rounds 7-9	(3) Middle Distribution	(4) Supplement	(5) All Rounds	(6) Including Myopic Neutral	(7) Continuous	(8) Decile
MLA	-1.554***	-1.709***	-1.789***	-1.987***	-1.791***	-1.409***	-0.504***	-0.239***
	(0.491)	(0.477)	(0.487)	(0.281)	(0.355)	(0.299)	(0.086)	(0.045)
FF Sequence	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Broker × Start Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Dominant Ind. × Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	47048	40336	46420	55419	56040	56750	56131	56131
Adj. R-squared	0.423	0.540	0.423	0.419	0.414	0.417	0.415	0.416

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on different measures of myopic loss aversion. Equity market investment is measured as the portfolio size in constant prices scaled by income where we use prices at the beginning of our sample period. Column (1) is the baseline result . Column (2) measures MLA using only the last 3 rounds of experimental data. Column (3) measures MLA by excluding the highest and lowest bet in Task 1 and 2. Column (4) measures MLA using data from supplemental 3 rounds varying experimental wealth. Column (5) measures MLA using experimental data from all rounds (main and supplement). Column (6) measures MLA in the same way as column (1) but includes myopic neutral traders in the base category. Column (7) measures MLA using a continuous variable based on the percentage difference in bets across both experimental feedback frequency. Column (8) measures MLA through individual rank based on deciles in the percentage differences in bet. The sample period is from Oct 30, 2015 to July 31, 2016. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Other Robustness Checks

	Equity Market Investment				
	(1)	(2)	(3)	(4)	(5)
	Baseline	Number of days Weighted	Excluding Outliers	Alternate Controls: Income & Age dummies	Business background: Major & Job dummies
MLA	-1.554***	-1.742***	-1.740***	-1.221**	-1.987***
	(0.491)	(0.468)	(0.526)	(0.530)	(0.603)
FF Sequence	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y
Broker × Start Year FE	Y	Y	Y	Y	Y
Dominant Ind. × Day FE	Y	Y	Y	Y	Y
Observations	47048	47048	44217	47048	47048
Adj. R-squared	0.423	0.404	0.431	0.453	0.496

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion under various robustness tests. Equity market investment is measured as the portfolio size in constant prices scaled by income where we use prices at the beginning of our sample period. Column (1) is the baseline result. Column (2) weights each observation by the inverse of the number of days the investor appeared on the sample. Column (3) excludes the top 2% of myopic loss averse and myopic loss seeking traders based on percentage difference in experimental bets. Column (4) includes dummies on income and age based on individual decile rank as opposed to continuous variables. Column (5) includes dummies for whether the individual's primary major or secondary major in college was business as well as dummies for whether the primary occupation or the secondary occupation is classified as being a businessman. The sample period is from Oct 30, 2015 to July 31, 2016. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Heterogeneity: Demographic Characteristics

Equity measured by:	Cost Price			Close Price		
Dep. Var.: Equity Market Investment	(1)	(2)	(3)	(4)	(5)	(6)
MLA	-2.433**	-23.929***	-3.085*	-1.833*	-21.435***	-2.298
	(1.065)	(5.168)	(1.673)	(0.946)	(4.465)	(1.447)
MLA × Income	0.904			0.485		
	(0.962)			(0.849)		
MLA × Age		0.631***			0.570***	
		(0.135)			(0.117)	
MLA × Master's Degree			1.758			1.116
			(1.769)			(1.511)
FF Sequence	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y
Broker × Start Year FE	Y	Y	Y	Y	Y	Y
Dominant Ind. × Day FE	Y	Y	Y	Y	Y	Y
Observations	47048	47048	47048	47048	47048	47048
Adj. R-squared	0.419	0.438	0.420	0.423	0.444	0.423

Note: This table presents coefficient estimates of the OLS regressions of level of equity market investment on myopic loss aversion as well interactions with demographic characteristics. Equity market investment is measured as the size of equity portfolio scaled by income. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. In columns (1)-(3), the size of equity is measured at cost prices. In columns (4)-(6), the size of equity is measured at constant prices based on prices at the start of our sample period, Oct 30, 2015. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: MLA & the Role of Trading Frequency in Stock Market Performance

Trading Frequency measured by:	Trading Volume		Trading Amount		Trading Turnover	
Dep. Var.: Stock Market Performance	(1)	(2)	(3)	(4)	(5)	(6)
Trading Frequency:	Low	High	Low	High	Low	High
MLA	0.0481**	-0.126***	0.0323*	-0.121***	0.0223	-0.130***
	(0.0191)	(0.0351)	(0.0188)	(0.0339)	(0.0233)	(0.0337)
FF Sequence	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Participation Year FE	Y	Y	Y	Y	Y	Y
Broker × Start Year FE	Y	Y	Y	Y	Y	Y
Dominant Ind. × Day FE	Y	Y	Y	Y	Y	Y
Observations	23644	23344	23856	23086	24174	22734
Adj. R-squared	0.645	0.329	0.644	0.343	0.684	0.363

Note: This table presents coefficient estimates of the OLS regressions of the performance of investors' stock market investment on myopic loss aversion on sub samples based on median trading frequency. Stock market performance is defined as the daily gross return on the investment measured as the market value of the portfolio scaled by the cost of the portfolio. MLA is defined as those traders who bet lower on average under frequent feedback compared to infrequent feedback in lab experiment and the base category is myopic loss seeking traders. The sample period is from Oct 30, 2015 to July 31, 2016. Columns (1) and (2) measure trading frequency by the trading volume in units of stocks. Columns (3) and (4) measure trading frequency by the trading amount in Taka. Columns (5) and (6) measure trading frequency by turnover of trades. Standard errors are clustered at the brokerage firm-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C Experimental Design & Instructions

C.1 Experimental Instructions for Myopic Loss Aversion

General instructions for subjects - English version

Welcome to our experimental study of decision-making. The experiment will last about 2 hours. The instructions for the experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. All the money you earn is yours to keep, and will be paid to you, privately and in cash, immediately after the experiment or on an agreed date later. The experiment will consist of 4 tasks. After each task has been finished, the instructions for the next task will be distributed to you. When everyone is seated, we will go through the instructions of task 1 of the experiment. After that, you will have the opportunity to study the instructions on your own, and to ask questions. If you have a question, please raise your hand, and I will come to your table. Please do not talk or communicate with the other participants during the experiment. These apply to all tasks. Are there any questions about what has been said until now?

C.1.1 Task 4 (Myopic loss aversion)

General instruction for both treatments The experiment will consist of two parts. The instructions for the second part will be distributed to you after the first part has been finished. Before we start the experiment, however, you will be asked to pick one envelope from this pile. In the envelope you will find your Response Sheet. This form will be used to register your decisions and earnings.

C.1.2 Task 4: Myopic loss aversion Instructions for Treatment F

Part 1 Part 1 consists of 9 successive rounds. In each round you will start with an amount of 100 units (1 unit=10 taka). You must decide which part of this amount (between 0 units and 100 units) you wish to bet in the following lottery: "You have a two-thirds chance (67%) to lose the amount you bet and a one-third (33%) to win two-and-a-half times the amount you bet." You are requested to record your choice on your response sheet. Suppose you decide to bet an amount of X units ($0 <= 100 <= 100$) in the lottery. Then, you must fill in the amount X in the column headed Amount in lottery, in the row with the number of the present round. Whether you win or lose in the lottery depends on your personal win colour. This colour is indicated on top of your response sheet. Your win colour can be red, blue, or white, and is the same for all 9 rounds. In any round, you win in the lottery if your win colour matches the round colour that will be drawn by an enumerator, and you lose if your win colour does not match the round colour.

The round colour is determined as follows. After you have recorded your bet in the lottery for the round, the enumerator, in a random manner, pick one colour from a cup containing three colours: red, blue, and white. The colour drawn is the round colour for that round. If the round colour matches your win colour you win in the lottery; otherwise, you lose. Since there are three colours one of which matches your win colour the chance of winning in the lottery is one-third (33%) and the chance of losing is two-thirds (67%).

Hence your earnings in the lottery are determined as follows. If you have decided to put an amount of X units in the lottery, then your earnings in the lottery for the round are equal to –X if the round colour does not match your win colour (you lose the amount bet) and equal to +2.5X if the round colour matches your win colour (you win two-and-a-half times the amount bet).

The round colour will be shown to you by the enumerator. You are requested to record this colour in the column Round colours, under win or lose, depending on whether the round colour does or does not match your win colour. Also you are requested to record your earnings in the lottery in the column Earnings in lottery. Your total earnings for the round are equal to 100 units (your starting amount) plus your earnings in the lottery. These earnings are recorded in the column Total earnings, in the row of the corresponding round. Each time we will come by to check your response sheet for errors in calculation.

After that, you are requested to record your choice for the next round. Again you start with an amount of 100 units, a part of which you can bet in the lottery. The same procedure as described above determines your earnings for this round. It is noted that your private win colour remains the same, but that for each round, a new round colour is drawn by the enumerator. All subsequent rounds will also proceed in the same manner. After the last round has been completed, your earnings in all rounds will be summed. This amount determines your total earnings for part 1 of the task. Then, the instructions for part 2 will be announced.

Part 2 Part 2 is almost identical to part 1, but differs in two respect. First, part 2 consists of three rounds (instead of 9 rounds). Second, in part 2 you do not get any additional starting amount from us. You play with the money you have earned in part 1. To that purpose, we first decide your earnings in part 1 by three. The resulting amount is your starting amount S for each of the three rounds. Again you are asked which part of this amount (between 0 and S) you wish to bet in the lottery. "You have a two-thirds chance (67%) to lose the amount you bet and a one-third (33%) to win two-and-a-half times the amount you bet."

You are asked to record your choice on the response sheet. If you decide to bet an amount of X units ($0 <= X <= S$), then you must fill in the amount X under Amount in lottery.

Your private win colour is the same as in part 1 and can be found on top of your response sheet. After you have recorded your bet for the present round, the enumerator will again, in a random manner, pick one colour from a cup containing three colours: red, blue, and white. The colour drawn is the round colour. If this round colour matches your win colour, you win in the lottery, otherwise you lose.

If you have decided to bet an amount X in the lottery, then your earnings in the lottery are equal to –X if the round colour does not match your win colour (you lose the amount bet for the round) and equal to +2.5X if the round colour does match your win colour (you win two-and-a-half times the amount bet for the round).

You are again requested to record the round colour and your earnings in the lottery on the response sheet. Your total earnings for the round are equal to your starting amount S plus your earnings in the lottery. You are asked to record these on your response sheet. We will come by to check your form for errors.

After that you are requested to make your choice for the next round. Again you can choose to bet part of your staring amount in the lottery. The same procedure as described above determines your earnings. Round 3 will proceed in the same manner. After that, your earnings in the three rounds will be added. This amount determines your total earnings in parts 1 and 2 of the task.

C.1.3 Task 4: Myopic loss aversion Instructions for Treatment I

Part 1 Part 1 consists of 9 successive rounds. In each round you will start with an amount of 100 units (1 unit=10 taka). You must decide which part of this amount (between 0 units and 100 units) you wish to bet in the following lottery: "You have a two-thirds chance (67%) to lose the amount you bet and a one-third (33%) to win two-and-a-half times the amount you bet."

You are requested to record your choice on your response sheet. Suppose you decide to bet an amount of X units $(0 <= 100 <= 100)$ in the lottery. Then, you must fill in the amount X in the column headed Amount in lottery, in the row with the number of the present round. Please note that you fix your choice for the next three rounds. Thus, if you decide to bet an amount X in the lottery for round 1, then you also bet an amount X in the lottery for rounds 2 and 3.

Whether you win or lose in the lottery depends on your personal win colour. This colour is indicated on top of your response sheet. Your win colour can be red, blue, or white, and is the same for all 9 rounds. In any round, you win in the lottery if your win colour matches the round colour that will be drawn by an enumerator, and you lose if your win colour does not match the round colour.

The round colour is determined as follows. After you have recorded your bet in the lottery for the round, the enumerator, in a random manner, pick one colour from a cup containing three colours: red, blue, and white. The colour drawn is the round colour for that round. If the round colour matches your win colour you win in the lottery; otherwise, you lose. Since there are three colours one of which matches your win colour the chance of winning in the lottery is one-third (33%) and the chance of losing is two-thirds (67%).

Hence your earnings in the lottery for the three rounds are determined as follows. If you have decided to put an amount of X units in the lottery, then your earnings in the lottery for the three rounds are equal to $-X$ for each round colour that does not match your win colour (you lose the amount bet) and equal to $+2.5X$ for each round colour that matches your win colour (you win two-and-a-half times the amount bet). The three round colours will be shown to you by the enumerator. You are requested to record these colours in the column Round colours, under win or lose, depending on whether the round colour does or does not match your win colour. Also you are requested to record your earnings in the lottery in the column Earnings in lottery. Your total earnings for the three rounds are equal to 300 units (three times your starting amount) plus your earnings in the lottery. These earnings are recorded in the column Total earnings, in the row of the corresponding rounds. Each time we will come by to check your response sheet for errors in calculation.

After that, you are requested to record your choice for the next three rounds. For each of the three rounds you again start with an amount of 100 units, a part of which you can bet in the lottery. The same procedure as described above determines your earnings for these three rounds. It is noted that your private win colour remains the same, but that for each round, a new round colour is drawn by the enumerator. The subsequent three rounds (7-9) will also proceed in the same manner. After the last round has been completed, your earnings in all rounds will be summed. This amount determines your total earnings for part 1 of the task. Then, the instructions for part 2 will be announced.

Part 2 Part 2 is almost identical to part 1, but differs in two respect. First, part 2 consists of three rounds (instead of 9 rounds). Second, in part 2 you do not get any additional starting amount from us. You play with the money you have earned in part 1. To that purpose, we first decide your earnings in part 1 by three. The resulting amount is your starting amount S for each of the three rounds. Again you are asked which part of this amount (between 0 and S) you wish to bet in the lottery. "You have a two-thirds chance (67%) to lose the amount you bet and a one-third (33%) to win two-and-a-half times the amount you bet."

You are asked to record your choice on the response sheet. If you decide to bet an amount of X units ($0 <= X <= S$), then you must fill in the amount X under Amount in lottery. Again you fix your choice for the next three rounds. Thus, if you decide to bet an amount X in the lottery for round 1, then you also bet an amount X in the lottery for rounds 2 and 3. Your private win colour is the same as in part 1 and can be found on top of your response sheet. After you have recorded your bet for the present round, the enumerator will again, in a random manner, pick one colour from a cup containing three colours: red, blue, and white. The colour drawn is the round colour. If this round colour matches your win colour, you win in the lottery, otherwise you lose.

If you have decided to bet an amount X in the lottery, then your earnings in the lottery are equal to –X for each round colour that does not match your win colour (you lose the amount bet for the round) and equal to +2.5X for each round colour that matches your win colour (you win two-and-a-half times the amount bet for the round).

You are again requested to record the round colours and your earnings in the lottery on the response sheet. Your total earnings for the three rounds are equal to three times your starting amount S, plus your earnings in the lottery. You are asked to record these on your response sheet. We will come by to check your form for errors.

After that you are requested to make your choice for the next round. Again you can choose to bet part of your staring amount in the lottery. The same procedure as described above determines your earnings. Round 3 will proceed in the same manner. After that, your earnings in the three rounds will be added. This amount determines your total earnings in parts 1 and 2 of the task.

C.2 Experimental Design for Games of Risk, Ambiguity, and Time Preference

C.2.1 Time Preference

The instructions introduced the time-preference questions and informed the traders that the game had been designed to encourage truthful report. Specially, we present the traders with a menu of choice containing 30 questions under the form: ”What amount of money p taka, if paid to you tomorrow would make you indifferent to m taka paid to you in t days? ”. The set of time t includes six values 3 days, 1 week, 2 weeks, 1month, 2 months, 3 months and the five values of money m are 100 taka, 200 taka, 300 taka, 500 taka, 1000 taka . The questions were presented in a random order so that there was no apparent pattern in the values of m or t. At the end of the game, we chose one random question to determine the subject's payment. To encourage traders to answer true to their preference, we employ the Becker Degroot-Marschak (BDM) mechanism as the payment method (Becker, DeGroot, & Marschak, 1964). For a given payment question (M,T), we used a spinner to choose a number between 0 and M randomly. If the chosen random number Z is less than the subject answer P, then the subject would be paid M taka T days from now. If Z is greater than P, then the subject would be paid Z on the day after the experiment.[45] Since each number between 0 and M has equal probability of being chosen, this procedure ensure that the only way for traders to maximize their welfare is to answer truthfully.

[45]1For example, if in the chosen question the subject answered that 300 taka tomorrow would make him indifferent to 400 taka in two months, we would use the spinner to choose a number between 0 and 400. If the chosen number is less than 300, the subject would get 400 taka after 2 months. If the chosen number is greater than 300, say 350, the subject would get 350 taka tomorrow.

It is expected that given a fixed amount of money (for example, 100 taka now, 100 taka in 3 days and 100 taka in 3 months), people will discount heavier when the time is further into the future - this means an average agent always prefer present than the future and will be willing to pay for a higher discount to avoid having to wait. Given the same time frame, time preference for different amount of money (for example, 100 taka in 3 months, 500 taka in 3 months, and 1000 taka in 3 months) is slightly trickier to predict. On the one hand, agents may be more patient if the expected earning amount is large enough since more substantial discount for a considerable amount of money will means they will receive much less. For example, given the three months time frame, subjects may be willing to receive only 80 taka now instead of 100 taka in 3 months (forfeiting 20% or 20 taka), but the same agent will not accept 800 taka now in exchange for 1000 taka in 3 months. On the other hand, subjects may avoid delayed payment for a large amount of money for trust reason. However, this reason can be ruled out due to the BDM method of payment.

For simplicity, we assume a linear relationship and calculate the discount factor for each combination of money value m and time t as:

$$D_t(p, m) = \frac{p}{m} \tag{7}$$

in which p stands for the necessary amount of money received today to make one indifferent to m amount receives in the future. In unreported results, we find that holding m constant, the discount factor trends downward across all the time variables (strong monotonicity). Thus traders heavily discount payment in further future than nearer time. We calculate our measure of discount factor for the individual trader by averaging the discount factors across t and m:

$$D = \sum_m \frac{\sum_t \frac{D_t(p,m)}{6}}{5} \tag{8}$$

C.2.2 Ambiguity Aversion

To evaluate the traders' attitude towards ambiguity, we follow the Ambiguity - Probability tradeoff by Lauriola and Levin (2001) - an approach that modifies the two urn Ellsberg setting into multiple trials game.[46] The game featured a probability-ambiguity trade off instead of gambling task to separate ambiguity preference with risk-taking behaviour. Prior studies show that the degree of ambiguity seeking is negatively correlated to the winning likelihood of the unambiguous-distribution lottery. Thus, the weighting function for ambiguity is an inverse S-shaped, over-weighting small likelihoods and under-weighting higher likelihood.

The game was played for 11 trials. In each trial, there were two boxes that contained 10 balls of two different colours. For one box, the distribution of the balls is displayed on the label while the other box does not offer any information on the colour composition. Across all eleven trials, we first announced the winning colour then traders were asked to choose between those two boxes. After recording their answers, subjects continued to play the subsequent trial without knowing the outcome of the previous selection. After the final round, we used a spinner to select one payment round randomly. We then drew a ball out of the subject's box of choice for the selected round, and the subject would receive 1000 taka if the ball was winning colour and zero otherwise.

The proportion of winning balls was manipulated so that the winning probability p of the known-distribution box range from 0 to 100 percent, with 10 percent interval. Out of 11 rounds, two rounds represented the boundary probability - zero or a hundred percent chance of winning. An ambiguity-neutral agent should switch at the "50% box". To prevent the spillover effects of the within-subject design and avoid order effects which can easily confound inferences about ambiguity preference, we employed a few randomizations in the design. First, each round used different pairs of colour (for e.g. Red and Green in Round 1, Pink and Orange in Round 2, etc.). Secondly, the position of two boxes was randomly assigned to Left or Right in each round. Thirdly, the order of winning colour on the box label within each round was also randomly allocated. Moreover, the trials were also randomized so that there was no pattern in the sequence of winning probability.

It can be argued that a rational trader would continue to avoid the ambiguous-probability box (box A) as long as the winning probability p of the other box does not fall below his subjective preference p^*. We use the term matching probability to refer to the known probability of winning for Box A that makes the respondent indifferent between Box A and Box B. The ambiguity crossover point is defined as the value of p^* at which ambiguity aversion turns into ambiguity seeking. The

[46]In Ellsberg experiment, participants faced with two urns that contain a mixture of red and black balls. They were informed about the winning colour and asked to select one out of two urns: an urn with 50% red and 50% black balls or an urn with an unknown proportion of each color. The unknown distribution was decided based on a random draw.

higher the cross level, the higher the level of ambiguity aversion the individual trader exhibits. For example, if cross level equals 4, it would mean the trader switched to the ambiguous-box (box A) when the probability of winning is less than 40 %. Hence, the ambiguity-neutral trader is expected to switch at cross level 6 when the chance of winning fall below 50 %.

C.2.3 Risk Aversion

We follow Holt and Laury (2002) for this setting. Consider an individual who is confronted with a sequence of eleven paired lotteries; each pair has the same winning probability but differs in payoff and expected value. To be specific, in each round our subjects were asked to choose between two boxes labeled ”A” and ”B”, each box contains 10 balls with the same distribution of two different colors. At the beginning of the session, subjects were informed about the winning color and the payoff of each box. Box A offers 385 taka if the winning colour was drawn and 10 taka otherwise while the payment for box B 200 taka and 160 taka respectively.

Similar to the ambiguity avoidance game setting, the 11 trials winning probability ranges from 0 to 100 percent, with 10 percent intervals. The order of the trial was randomized to prevent any pattern that may influence the subjects' decision. So, subjects choose between a safe box with high variances and low returns and a risky box (high variances, high returns) for each of the ten paired lottery choices. Similar to the sensitivity approach using multiple trials with different probability in the ambiguity games, the traders would switch to the risky option as soon as the winning probability is high enough to compensate for the risk. Given the payoff (200,160) for box A and (385,10) for box B, the risk-neutral trader should switch to box B if $p > 54.8\%$.[47] Therefore, risk neutral trader should have a crossover point equal to 6 - equivalent to the winning probability of 50% winning while risk-averse agents would opt to switch at points higher than 6.

[47]That is the payoff from B exceeds the payoff from A: $385(1-p)+10p > 200(1-p)+160p$