# A Tale of Two Zoos:

# Machine Learning Insights on Retail Investors

Pulak Ghosh[*], Huahao Lu[†], Hong Zhang[‡], Jian Zhang[§]

## Abstract

This paper employs various machine learning models to analyze how stock characteristics (the "factor zoo") and behavioral biases (the "bias zoo") affect the returns of millions of retail investors in India. We observe that Neural Networks outperform other machine learning and OLS models in uniquely predicting both good and bad out-of-sample performance. Moreover, behavioral biases exert a more significant influence than holding-weighted firm characteristics. Among all predictors, (under)diversification, portfolio turnover, and momentum are the leading factors to influence overall retail returns. Additionally, turnover, the disposition effect, and diversification emerge as the three most important factors in predicting the returns for newly initiated trading.

**Keywords: Machine Learning, behavioral biases, Retail Investors**
**JEL Codes: D90, G40,**

[*] Department of Decision Sciences and Centre of Public Policy, Indian Institute of Management Bangalore, Email: pulak.ghosh@iimb.ac.in
[†] PBC School of Finance, Tsinghua University, Email: luhh.21@pbcsf.tsinghua.edu.cn
[‡] Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, Singapore 178899; E-mail: hongzhang@smu.edu.sg.
[§] The University of Hong Kong, Faculty of Business and Economics, Email: zhangj1@hku.hk

## I. Introduction

Over the last few decades, the academic community has demonstrated that trading strategies based on a multitude of firm characteristics can yield striking returns (i.e., the "factor zoo"; see, e.g., McLean and Pontiff 2016; Harvey, Liu, and Zhu 2016; Hou, Xue, and Zhang 2020; Kelly and Pedersen 2022 for recent evidence). One important implication from this literature is that investing in stocks with the proper firm characteristics, purposefully or not, may allow retail investors to achieve better returns. A distinct yet interrelated literature investigates the various psychological heuristics and biases to which retail investors are susceptible (i.e., the "bias zoo"; see Barber and Odean 2013; Hirshleifer 2015; and Barberis 2018 for literature reviews). Important questions arise when we combine insights from the two streams of studies. Between behavioral heuristics and firm characteristics, which contribute more to the investment returns of retail investors? Moreover, within the realm of behavioral heuristics and firm characteristics, which factors exert more influence? These questions carry crucial normative implications. Retail investors globally utilize stock markets to build wealth, save for retirement, and achieve various financial objectives. However, vulnerability to biases and exposure to (wrong) characteristics may impede these goals and impact price efficiency. Hence, scrutiny of these questions is vital, not only for the investors themselves but also for academic researchers, policymakers, and financial institutions dedicated to promoting financial well-being and stability.

Our paper aims to shed initial light on these questions by employing various machine learning models to understand how behavioral heuristics and stock characteristics affect retail investors' investment returns. To achieve this goal, we utilize a unique and proprietary account-level dataset containing the daily trading activities of retail investors on the National Stock Exchange of India (NSE). As the most populous country in the world, India provides an ideal testing ground to understand retail investors, with the NSE being its largest stock exchange hosting over 19 million investors. We accordingly examine 5% of randomly selected retail investor accounts on the NSE, resulting in a final sample of over 10 million investor-month return observations. Using this dataset, we construct 23 holding-weighted stock characteristics and 13 proxies of behavioral heuristics and characteristics, referred to as *behavioral biases* when there is no confusion.

We employ the *Feedforward Neural Network* (*FNN*) and an enhanced *Residual Neural Network* (*ResNN*) as our main machine-learning models, while also examining traditional OLS and machine-learning models (e.g., LASSO, Ridge, and Random Forest). The benefit of Neural Network models is that they can reliably estimate a complex functional relationship among a large set of predictors. Of the two Neural Network models, FNN is more traditional, while ResNN reflects the more recent development in convolution deep learning. Its key feature, "residual connections", is widely adopted in recent architectures such as BERT and ChatGPT. Later sections will delve into further details, demonstrating ResNN's superior capability for our purposes.

Our primary objective is to predict retail investors' overall investment returns using machine learning models based on ranks of behavioral biases and stock characteristics.[5] For each model, we categorize retail investors into five quintiles according to predicted returns. The *High* and *Low* groups comprise the top and bottom 20% of predicted winners and losers among investors, respectively. We then calculate the value-weighted out-of-sample returns of the high and low groups, along with their return difference. We also use the locally estimated three-factor and four-factor models to adjust these returns. Importantly, in line with the literature (e.g., Kaniel et al., 2023), we train a model on one subset of the data and use it to predict returns on another subset, ensuring that all our predictions are out-of-sample.

We observe that the two Neural Network models outperform other models in predicting total returns for retail investors. Both FNN and ResNN identify investors who can generate significantly positive out-of-sample returns. Despite being retail investors, the top 20% of predicted winners can generate a monthly return of 1.5% and 1.2%. The economic magnitude remains approximately the same when risk-adjusted (e.g., 1.7% and 1.4% adjusted by four factors). In contrast, all other models fail to predict winners. Given how difficult it is to predict four-factor adjusted superior mutual fund performance in the US (e.g., Carhart 1997), the superior performance of retail investors strongly suggests that Neural Networks capture crucial characteristics of retail investors.

On the loser side, the *ResNN*-predicted *Low* group delivers a significantly negative monthly return of $-3.1\%$, allowing the *High* group to outperform the *Low* group by 4.4% per month. Next,

[5] We use ranks to normalize the distribution of all imputs so their importance can be more easily inferred. This method is widely used for machine learning models (e.g., Kelly, Pruitt, and Su, 2019; Freyberger, Neuhierl, and Weber, 2020). To calculate an investor's total investment returns, we calculate the daily return generated by her existing portfolios at the beginning of a given date and then compound her daily returns into monthly returns. This approach allows us to further decompose the investor's monthly total returns into two sources, the part generated by the holding at the beginning of the month (i.e., holding-based returns) and the part generated by the newly initiated trading during the month (i.e., new trading-based returns). As we will see shortly, behavioral biases and firm characteristics play different roles in affecting the two sources of returns.

we observe that the *Low* group selected by FNN, OLS, and Ridge can only deliver a marginally negative return, though the *High* group still significantly outperforms the *Low* group by 4.0%, 2.5%, and 2.5%, respectively. Lastly, Lasso and Random Forest do not exhibit significant predicting power on the *Low* group or the high-minus-low spread. Overall, *FNN* and, particularly, *ResNN* outperform other models in identifying true winners and losers among retail investors.

As Neural Network models exhibit superior predictive capabilities for investor returns, our next step is to utilize them to explore the relative importance of behavioral biases and firm characteristics. While our previous analysis utilized both sets of predictors, we now examine each set independently to shed light on their relative importance. To be consistent with the literature (e.g., Kaniel, Lin, Pelger, and Van Nieuwerburgh 2023), we use the traditional FNN model to investigate and demonstrate this standalone predicting power.

When firm characteristics are used alone, FNN-predicted *High* and *Low* groups fail to deliver significantly positive or negative out-of-sample returns. Nor can FNN predict a significant *High*-minus-*Low* return spread. In contrast, using behavioral biases alone can predict a significant *High*-minus-*Low* return spread, primarily driven by the negative returns on the loser side. This comparison highlights the relative importance of behavioral biases in affecting returns.

Moreover, we can conduct variable gradient analysis to demonstrate the relative importance of each variable when behavioral biases and stock characteristics are both used. In this case, the FNN identifies diversification, portfolio turnover, and momentum as the top three leading factors to influence overall retail returns. The first two variables could be related to the behavioral biases of under-diversification and overconfidence. Under-diversification is among the most common features of retail investors (e.g., Barber and Odean 2000; Benartzi and Thaler 2001) as many investors may not fully understand the benefits of diversification (Lusardi and Mitchell 2011). Overconfidence often causes investors to trade too aggressively, allowing their high portfolio turnover to reduce their welfare (Odean 1998; Barber and Odean 2000). The third denotes perhaps the most famous anomalies in the literature. It is interesting to observe that behavioral biases occupy two out of the top three factors affecting investment returns.[6]

[6] Part of momentum effect may be related to investors' biases. For instance, the disposition effect may induce investors to load on loser's momentum. Since our goal is to identify the direct impact of predictors, we attribute such return to momentum. Additionally, observed portfolio diversification and turnover may also be related to alternative sources of

Next, we notice that investors' total returns can stem from two distinct sources: holding an existing portfolio for a specified period, such as a month (i.e., holding returns), and initiating new trades during the month (i.e., trading returns). Behavioral theories propose that the motivations for initiating trades may differ from those for continuation. For instance, the disposition effect (e.g., Shefrin and Statman, 1985) suggests that unrealized capital gains motivate investors to trade (i.e., sell), whereas loss aversion incentivizes investors to retain losing assets, thus influencing holding returns. Another example is the salience theory (Bordalo, Gennaioli, and Shleifer 2012; 2013; 2020), which suggests that salient information, such as extreme stock prices, may also attract investors' attention to initiate new trades. Hence, the next question we explore is how behavioral biases and firm characteristics affect the two sources of returns

To address this issue, we adjust our objective to predict trading or holding returns using Neural Networks. We first validate the predicting power by observing the predicted *High* (*Low*) group to generate significantly positive (negative) total returns. This predicting power also gives rise to a significantly positive *High*-minus-*Low* total return spread.[7] We then employ the variable gradient analysis to assess the relative importance of each variable in predicting each source of returns.

Our main finding is that behavioral biases play an even more important role in predicting trading returns. This observation is intuitive, as characteristics-related returns likely contribute more to less rebalanced portfolios, whereas new trading is often initiated by behavioral reasons. Consistent with this notion, we observed that portfolio turnover, the disposition effect, and the degree of portfolio diversification emerge as the three most important factors in predicting new trading returns. Noticably, the disposition effect also emerges as a leading predictor for trading, confirming the importance of disposition-related preferences in initiating trading (e.g., realization utility or the utility predicted by prospect theory).[8] Turnover and diversification remain leading predictors for both total and trading returns.

---

biases, such as local bias, local information, and financial literacy. Since our purpose is to compare behavioral biases and stock characteristics, we do not further nail down the economic sources of behavioral bias.

[7] In other words, we observe that the predicted winners (losers) in one source of return can deliver positive (negative) total returns. Unreported results confirm that the predicted winners (losers) in one source of return can also deliver positive (negative) total returns in the respective source. We report the predictability of total returns because it is more difficult to achieve.

[8] Since Shefrin and Statman (1985), the development of this literature has been extensive, though the causes and consequences of the disposition effect are still under debate (see, among others, Grinblatt and Han, 2005; Barberis and Xiong, 2009, 2012; Calvet, Campbell, and Sodini, 2009; Ivkovic and Weisbenner, 2009; Kaustia, 2010; Ben-David and Hirshleifer, 2012; Henderson, 2012;

The relative importance of behavioral biases and firm characteristics can also be quantified by the joint explanatory power of all predictors falling into each category. We observe that the joint explanatory power of behavioral biases slightly exceeds that of firm characteristics in predicting total returns. However, the former dominates the latter in predicting trades, with behavioral bias predictors jointly occupying almost 95% of the total predicting power. These observations confirm the importance of behavioral biases particularly for explaining the trading of retail investors.

We finally conduct a battery of robustness checks. In the main analysis, we exclude 30% of small stocks because these stocks are difficult to trade in emerging markets (Liu et al. 2019) and may overstate the predicting power of machine learning models (Avramov, Cheng, and Metzker 2019 and Cong et al., 2020). We show that our main conclusions are robust to different thresholds of removal (e.g., 20% or 40%). Interestingly, when fewer small stocks are excluded, the *Low* group identified by alternative models (e.g., Linear, Lasso, Ridge) exhibits more significant out-of-sample returns. However, only Neural Network models (FNN and ResNN) can generate significantly positive returns. These patterns suggest that the prediction power of alternative models may originate from the impact of small stocks invested by losers.

Our results are related to several strands of literature. A growing literature demonstrates that machine-learning models can help predict asset prices in different sectors of the markets, ranging from the equity premium to option pricing in the US and global markets.[9] Karolyi and Van Nieuwerburgh (2020) and Kelly and Xiu (2023) provide recent reviews. Our analysis is closely related to recent studies applying machine-learning models to predict the performance of institutional investors, such as mutual funds (e.g., Li and Rossi, 2020; DeMiguel, Gil-Bazo, Nogales, and Santos, 2023; Kaniel, Lin, Pelger, and Van Nieuwerburgh 2023) and hedge funds (Wu, Chen, Yang, and Tindall, 2021). We contribute by using a battery of machine-learning tools to scrutinize the performance of a large sample of retail investors. This extension is important, as

Li and Yang, 2013; Frydman et al., 2014; An, 2016; Chang, Solomon, and Westerfield, 2016; Fischbacher, Hoffmann, and Schudy, 2017; Frydman and Wang, 2020). DellaVigna (2009; 2018), Hirshleifer (2015), and Barberis (2018) provide recent surveys.

[9] See, among others, Freyberger, Neuhierl, and Weber (2020), Gu, Kelly, and Xiu (2020), and Chen, Pelger, and Zhu (2023) for stock returns and characteristics, Leippold, Wang, and Zhou (2022) for the Chinese equity market, Bianchi, Büchner, and Tamoni (2021) for bond risk premium, Easley, López de Prado, O'Hara, and Zhang (2021) for market microstructure, Filippou et al. (2022) for currencies, Bali, Beckmeyer, Mörke, and Weigert (2023) for option pricing. Avramov, Cheng, and Metzker (2021) notice that the predicted returns could drop substantially in magnitude when small firms are excluded.

the economic rationale guiding retail investors' investments can differ from that of institutional investors. It allows us to establish a more comprehensive understanding of investor decisions.

In doing so, we contribute to the literature on behavior finance. One important goal of this literature is to use psychological insights to explain many anomalies in individuals' financial decision-making. This effort leads to profound insight into how individual investors make decisions (see, e.g., Barber and Odean 2013, Hirshleifer 2015, Barberis 2018 for literature reviews). The multitude of proposed behavioral biases, however, also gives rise to a "lack of discipline" concern (Fama, 1998). Indeed, if the excessive return predictability of characteristics-based anomalies already imposes a "multidimensional challenge" (Cochrane 2011), the concern becomes even more prominent when examining retail investors, as both psychology-based and characteristics-based anomalies may influence their returns. To consolidate the multitude of behavioral biases, a few recent papers use survey-based methods to nail down their relative importance (e.g., Choi and Robertson, 2020; Liu, Peng, Xiong, and Xiong, 2022). Our novelty is to use machine learning tools to reduce the dimension of both types of anomalies, which can shed light on a more parsimonious conceptual framework of asset pricing and investor behavior.

In a closely related paper, Balasubramaniam and Campbell (2023) also use a large sample of Indian retail accounts to shed light on investor attributes that can give rise to investor clientele effects for stock characteristics.[10] Our paper differs in that we first validate machine learning models based on their predicting power on investor returns and then use the most reliable tools (i.e., neural networks) to examine the importance of investor bias and stock characteristics. In other words, investor returns play a pivotal role in our analysis, which differs from their focus on investor holdings. A unique feature of our approach is to identify investor bias and stock characteristics that can directly impact the returns and thus welfare of retail investors.

Lastly, we also make methodological contributions by introducing Residual Neural Networks (*ResNN*) into financial analysis. Despite the popularity of Neural Networks in finance, a widely acknowledged challenge in deep learning is that deeper neural networks are more difficult to train (i.e., the vanishing gradient problem). *ResNN* addresses this difficulty by reformulating the output

[10] In the literature, researchers have also used Scandinavian account-level household data to examine the attributes that affect investors' investment decisions. A common finding is that the decisions of households are strongly influenced by behavioral biases (see, among others, Massa and Simonov 2006; Døskeland and Hvide 2011; Grinblatt et al. 2016). We instead systematically explore a list of attributes to determine their relative importance.

of a particular layer as a learning residual function plus the layer's input (He et al., 2015).[11] The key feature of *ResNN*—"residual connections", or the addition of the original input to the output of a deeper layer within a neural network—is also widely used in Transformer models such as BERT and ChatGPT. This feature allows *ResNN* to be trained deeper and more easily optimized. Our results confirm that *ResNN* serves as a suitable tool for comprehensive financial tasks, such as analyzing retail investors.

The remaining article is organized as follows. Section II describes the data and machine learning models. Section III provides baseline tests for predicting retail investors' returns. Section IV examines the importance of behavioral heuristics and firm characteristics. Section V provides additional tests and robustness checks, followed by a short conclusion with policy implications.

## II. Data, Main Variables, and Machine Learning Models

This section describes the data and explains how we construct our main variables. We then briefly describe the machine learning models used in our later analysis.

### A. Data

We collected data from multiple sources. To characterize the impact on investors' trading behavior, we obtain a comprehensive database of all trading records on the NSE of India for the period 2004-2020. The NSE is the leading exchange in India and the world's 9th-largest stock exchange as of May 2021.[12] For each transaction, we can observe the anonymized permanent account number (PAN) of the individual[13], the transaction date, the ticker of the security, the number of shares purchased or sold, and the execution price. We require all transactions to be associated with stocks included in the Prowess Database (similar to CRSP in the US) maintained by the Centre for Monitoring Indian Economy (CMIE). Additionally, we retain only securities that are common shares of domestic stocks and exclude trading activities related to ETFs and foreign stocks.

[11] Residual Neural Networks were originally developed to improve image recognition and won the *ImageNet* 2015 competition. As of now, the seminar work of He et al., 2015 has garnered more than 189,026 Google citations.
[12] https://www.world-exchanges.org/our-work/statistics
[13] The PAN is a unique identifier issued to all taxpayers by the Income Tax Department of India. The trading data are at the individual level so that it is not a concern if a given individual investor may hold multiple accounts.

The initial sample consists of more than 19 million unique accounts. We focus on a stratified random sample representing 5% of the full sample. For each retail investor, we further obtain sociodemographic data including gender, age, and, most importantly, geographic identifier (i.e., India PIN code), which allows us to identify the district of residence for each investor. We exclude accounts that have a negative balance, as such accounts could incur missing information or short selling. Our final sample includes 203, 941 valid individual accounts and more than 10 million investor-month portfolio-return observations.

**B. Main Variables**

Our objective is to use machine-learning tools to predict investors' total returns. To construct the time series for an investor's total investment returns, we calculate the daily return generated by her existing portfolios at the beginning of a given date and then compound her daily returns into monthly returns. This approach allows us to further decompose the investor's monthly total returns into two sources, the part generated by the holding at the beginning of the month (i.e., holding-based returns) and the part generated by the newly initiated trading during the month (i.e., new trading-based returns). As we will see shortly, behavioral biases and firm characteristics play different roles in affecting the two sources of returns.

In constructing portfolio returns, we exclude 30% of small stocks because these stocks are difficult to trade in emerging markets (Liu et al. 2019) and may overstate the predicting power of machine learning models (Avramov, Cheng, and Metzker 2019 and Cong et al., 2020). Due to the presence of some extreme values in the distribution of investors' monthly returns, we applied a winsorizing procedure at the 1st and 99th percentiles to mitigate the impact of outliers. Later sections will show that our results are robust to these data screening process.

We resort to the recent behavioral and asset pricing literature to construct the list of predators. This data enables us to construct 13 investor characteristics, most of which are proxies for behavioral biases. Below we describe how we construct these variables.

**The Disposition Effect:** Many studies have demonstrated the behavioral bias of investors to sell stocks that have gained profits while choosing to continue holding stocks that have incurred losses (Shefrin and Statman, 1985; Odean, 1998).

Following Sui and Wang (2023), we estimate the disposition effect through the following model:

$$Sell_{i,j,t} = \alpha + \beta_i Gain_{i,j,t-1} + \epsilon_{i,j,t}$$

where i, j, and t represent investor i, stock j, and time t, respectively. $Sell_{i,j,t}$is a dummy variable that equals 1 if investor i sells stock j at time t and 0 otherwise. $Gain_{i,j,t-1}$is also a dummy variable that equals 1 if investor i gains a profit on stock j at time t-1 and 0 otherwise. To avoid look-ahead bias, we estimate this model using a rolling window approach, where $\beta_i$ represents the disposition effect of the investor.

**Diversification:** We measure the degree of diversification for each investor based on the number of stocks held in their portfolio. Specifically, we calculate the daily count of stocks in the investor's investment portfolio and subsequently take the monthly average.

**Turnover:** We employ investor turnover as a proxy for their trading activity. Prior research has consistently shown that increased trading frequency is often associated with inferior performance (Odean 1998; Barber and Odean 2000). We calculate the daily turnover as the ratio of the trading amount to the total value of the investor's portfolio, followed by monthly averaging.

**Local Bias:** Many studies indicate that investors often exhibit a preference for companies located in close geographic proximity (Ivkovic and Weisbenner, 2005; Massa and Simonov, 2006). We utilized geographical location data for company headquarters and matched it with investors' registered addresses based on postal codes. Employing the Google Maps API, we obtained latitude and longitude coordinates for both the headquarters of each company and the registered addresses of investors. Subsequently, using the Haversine formula, designed for computing surface distances between any two points on a sphere, we calculated the km distances from each investor to every company. We then performed a weighted summation of distances for companies held in each investor's portfolio, considering the weights associated with each holding.

**Extrapolation:** Extrapolation refers to the tendency of investors to preferentially purchase stocks that have exhibited superior performance in the recent past. Consequently, we initially computed the excess returns of each stock over the market return in the preceding three months. Subsequently, we aggregated these excess returns, considering the investor's portfolio weights for the respective stocks.

**Lottery Preference:** We employed three variables to represent the lottery-like characteristics of stocks: the relative size of prices, idiosyncratic volatility, and idiosyncratic skewness, following the definition outlined in Kumar (2009). The estimation of idiosyncratic volatility and idiosyncratic skewness is based on the CAPM Model. Similar to our summation of extrapolation, we aggregated these proxy variables for the three lottery preference at the investor level using a value-weighted approach.

**Past Performance:** We employed the investor's portfolio returns over the preceding three months as a proxy variable for their investment capability.

**Total Asset:** To capture the potential wealth effect, we also calculate the total market value of the stocks held by investors in the previous month as an investor characteristic.

To ensure equal power of these proxies, each proxy is ranked in the cross-section (between 0 and 1). We then use the ranks as preditors presentating investors' behavior biases.

In addition to these investor behavioral proxies, we computed the 23 most important stock characteristics based on their holdings. Since these stock characteristics are common in the literature, we do not explain them in details. All stock characteristics underwent rank normalization across the cross-section. Subsequently, we weighted these ranked characteristics based on the investor's holdings of each stock.

Table 1 tabulates these variables as well as their detailed definitions. The Online Appendix (Table IN1) presents the summary statistics of our main variables. We can see all portfolio-level variables have a reasonable distribution. Based on these summary statistics, it is reasonable to examine further how behavioral biases and firm characteristics affect retail investors' investment returns. We will undertake this task in the next section.

### C. Machine-Learning Models

In order to examine further how behavioral biases and firm characteristics affect retail investors' investment returns, we employ a list of machine learning models, including Lasso, Ridge, Random Forests, and Neural Networks.

#### C.1 Lasso and Ridge

When the number of predictors in a model is substantial, simple linear models may struggle to effectively fit the data, potentially leading to overfitting issues. Lasso and Ridge are both models grounded in the linear assumption, yet, in comparison to simple linear models, the distinction lies in the incorporation of regularization into the model's objective function. The objective of estimating model parameters is no longer solely minimizing the error between fitted values and observed values; rather, it involves introducing penalties for the magnitude of linear model parameters. Lasso penalizes the first moment of model parameters, denoted as "l1" parameter penalization, whereas Ridge penalizes the second moment, known as "l2" parameter penalization. Specifically, a model with regularization can be expressed in the following form:

$$\min_{\beta \in R^p} \{ \frac{1}{N} ||y - X\beta||_2^2 + \lambda ||\beta||_1 + \gamma ||\beta||_2^2 \}$$

Where $\beta$ is the model parameters, $\lambda$ and $\gamma$ are regularization coefficients, and in the context of the Lasso model, $\gamma$=0, while for the Ridge model $\lambda$=0.

### C.2 Random Forests

Random Forest is an ensemble learning method that operates by constructing a multitude of decision trees during the training phase. Decision trees are commonplace in machine learning, offering a non-linear modeling approach in contrast to linear models. Notably, decision trees are non-parametric models. A tree is constructed by iteratively splitting the dataset into subsets, forming successive child nodes. The splits are based on predictor variables that most effectively discriminate among potential outcomes.

Random Forests employ an ensemble strategy by averaging multiple deep decision trees, each trained on different segments of the same training set. This approach aims to mitigate variance, offering a robust modeling technique.

### C.3 Neural Network

Neural networks are currently highly popular models in various application domains, having achieved tremendous success in fields such as natural language processing and computer vision. According to the universal approximation theorem (Kurt et al. 1989), neural networks can approximate any function between input x and output y. In this context, we employed a multi-layer perceptron (MLP) network, also known as a feed-forward network (FNN), which is a standard and widely applicable neural network model.

A multi-layer perceptron network consists of an input layer, an output layer, and one or more hidden layers. In each layer of the multi-layer perceptron, the input undergoes a linear transformation followed by an element-wise non-linear transformation (activation function). For the l-th layer of the MLP, its computational process can be expressed as follows:

$$X^l = g(W^{(l)T}X^{(l-1)} + b^{(l)})$$

Where $X^{(l-1)} \in R^{D^{l-1}}$ is the input to the $l$-th layer of the network, $W^{(l)} \in R^{D^{l-1} \times D^l}$ and $b^{(l)} \in R^{D^l}$ are the learnable parameters for the $l$-th layer, and $g(*)$ is the non-linear activation function. It is noteworthy that the output layer does not utilize a non-linear activation function. Instead, it directly aggregates the output from the previous layer through a linear mapping to form predictions for future returns, i.e.,

$$X^{output} = W^{(output)T}X^{(-1)} + b^{(output)}$$

For the choice of the activation function, we employ the most common rectified linear unit function (ReLU) in this context.

$$g(z) = ReLU(z) = \max(z, 0)$$

### C.4 Residual Learning

A Residual Neural Network (ResNN) is a deep learning model in which the weight layers learn residual functions concerning the layer inputs. It is characterized by skip connections, termed "residual connections," which perform identity mappings and are combined with the layer outputs through addition. This architecture facilitates the training of deep learning models with tens or hundreds of layers, leading to improved accuracy as the depth of the network increases. Notably, the concept of identity skip connections, or residual connections, extends beyond Residual Networks and finds application in various other models such as Transformer models (e.g., BERT, GPT models like ChatGPT).

Under the paradigm of residual connections, the computation for each layer can be expressed in the following form:

$$X^l = g\left(W^{(l)T}X^{(l-1)} + b^{(l)}\right) + X^{(l-1)}$$

The benefit of *ResNN* is that it can be trained deeper and be more easily optimized (see He et al., 2015 for more details).

### D. Data sampling and Optimization

We employed the cross-validation method to train and assess the performance of our model. Following the approach outlined by Kaniel et al. (2023), we uniformly divided the entire dataset into three parts. In each iteration, we trained the model on two of the folds and tested its performance on the remaining fold. This approach offers the advantage of testing the model on every sample in the dataset, enhancing the robustness of model comparisons by mitigating the influence of specific periods. Additionally, within the training data, we randomly set aside 30% of the samples for validation purposes.

After partitioning the data, we employed a gradient-based approach to train the neural network model. There are various training strategies for neural networks, and a common solution is to utilize the Adam optimizer. To enhance the optimization speed and performance of the model, the Adam optimizer randomly selects a subset of samples (batch) from the training data for gradient updates in each iteration.

A key parameter of the Adam optimizer is the learning rate, which dictates the step size for updates along the gradient direction. A well-chosen learning rate involves a trade-off between convergence speed and avoiding overshooting. Thus, it is essential to dynamically adjust the learning rate based on the training process's state. Therefore, we implemented a learning rate scheduler during training. A learning rate scheduler is a predefined framework that modifies the learning rate between epochs or iterations as the training advances. In this context, we employed a learning rate decay strategy, gradually reducing the learning rate as the training progresses.

Neural networks often exhibit strong expressive power and the ability to fit any arbitrary function, but they are also susceptible to the issue of overfitting. Overfitting occurs when a neural network performs well on the training data but poorly on unseen test data. Previous research generally attributes overfitting to the model memorizing the noise and details of the training data excessively while neglecting the overall distribution of the data, resulting in a decrease in the model's generalization ability.

To mitigate overfitting, we employed EarlyStopping and Dropout. EarlyStopping is a regularization technique in model training. If the model's performance on the validation dataset does not improve consistently, training is halted to prevent the model from excessively fitting the training data. Dropout involves ignoring the output of certain hidden layer nodes during training, setting these nodes' output values to zero. This approach reduces interactions between hidden layer nodes, thereby minimizing overfitting in neural networks (Hinton et al., 2012).

## III. Predicting Total Returns for Retail Investors

We now use all the models to predict retail investors' total investment returns.

### A. The Portfolio Analysis Approach

Our baseline tests involve a machine-learning-based portfolio analysis. We first use all the models to predict retail investors' total investment returns. We then sort retail investors into five quintiles according to predicted returns, with the *High* and *Low* groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. we also use the locally estimated three-factor and four-factor models to adjust these returns.

### B. The Performance of Model Selected Investors

Table 2 tabulates the predicted returns of investor quintiles. Columns 1-3 present average monthly returns and alpha adjusted through local FF-3 and Carhart-4 models. Columns 4-6 depict results for the high group, while columns 7-9 detail outcomes for the high minus low return.

We observe that the two Neural Network models outperform other models in predicting retail investors' total returns. In particular, both FNN and ResNN identify investors who can generate significantly positive out-of-sample returns. Indeed, the top 20% of retail investors can generate a monthly return of 1.5% and 1.2%, which remains highly significant with a similar economic magnitude when risk-adjusted (e.g., 1.7% and 1.4% adjusted by four factors). In contrast, all other models fail to predict winners. Given how difficult it is to predict four-factor adjusted superior mutual fund performance in the US (e.g., Carhart 1997), the superior retail performance strongly suggests that Neural Network models capture important properties of retail investors.

On the loser side, the ResNN-predicted *Low* group delivers a significantly negative monthly return of −3.1%, allowing the *High* group to outperform the *Low* group by 4.4% per month. Moreover, NN, OLS, and Ridge can select retail investors that deliver marginal negative returns, whereas Lasso and Random Forest do not exhibit significant predicting power. The *High* group also significantly outperforms the *Low* group by 4.0%, 2.5%, and 2.5% using NN, OLS, and Ridge.

## IV. The Importance of Predictors

Since Neural Network models exhibit superior power in predicting investor returns, we next employ them to investigate the relative importance of behavioral biases and firm characteristics in affecting retail investors' investment returns.

### A. The Stand-alone Power of Behavioral Biases and Firm Characteristics

Our previous analysis uses both behavioral biases and firm characteristics as predictors (i.e., the NN model). However, we can use each set of predictors alone, which can shed light on the relative importance of these predictors in predicting retail investors' investment returns. We report the results in Table 3.

The first line of the table reports the results when firm characteristics are used alone. Neural Network fails to select the *High* and *Low* groups that can deliver significantly positive or negative out-of-sample returns. Nor can firm characteristics alone predict a significant *High*-minus-*Low* return spread.

The second line of the table reports the results when behavioral biases are used alone. Different from the first line, using behavioral biases alone can predict a significant *High*-minus-*Low* return spread, with its power mostly arising from the negative return (loser) side. This comparison reveals the relative importance of behavioral biases in affecting returns.

The third line reports outcomes from simultaneously incorporating behavioral biases and firm characteristics. Similar to the preceding two lines, we employ the FNN model. The simultaneous utilization of these two features enables us to predict a significant High-minus-Low return spread, primarily driven by the positive return (winner) side.

However, despite the ability to generate the highest winner-minus-loser spread by incorporating all predictors, it fails to significantly predict the loser group return.

Counterintuitively, the addition of more features results in the diminishment of the model's original capabilities. This counterintuitive discovery suggests that the increased complexity of the model, induced by the incorporation of additional inputs, renders it challenging to optimize and train effectively, leading to a partial loss of predictive capacity (He et al., 2015).

Hence, we introduce a residual learning framework to facilitate the training of networks. Specifically, after passing through hidden layers, we merge the portion of investor behavioral bias from the previous layer's input with the output of the hidden layer. These merged inputs collectively pass through the output layer to obtain the final predictions.

The last line demonstrates that our designed Residual Neural Network can effectively predict future returns for both loser and winner groups. For the loser group, it yields a substantial -3.1% excess return and a -2.6% alpha after adjusting with the Carhart4 model. Conversely, for the winner group, it generates a notable 1.2% excess return and a 1.4% alpha under Carhart4 model adjustments. These outcomes exhibit statistical significance at the 1% confidence level. Additionally, the produced winner-minus-loser excess return of 4.4% surpasses that of the standard neural network.

Intuitively, results of the first line suggest that the model struggles to predict effectively when solely utilizing interactions within stock features. However, incorporating interactions among investor behavioral biases enables the prediction of loser returns (the second line). Furthermore, only after considering interactions between investor behavioral biases and holding-based characteristics, winner returns become predictable (the third line). This underscores the importance of emphasizing the role of internal interactions among investor behavioral biases in the model. Therefore, if we directly incorporate them onto the output of the hidden layer, we are actually making the final predictions to more comprehensively consider the influence of these interaction terms. Consequently, the residual network achieves the simultaneous prediction of both winner and loser returns.

### B. Variable Gradient Analysis

In accordance with the methodologies proposed by Sadhwani et al. (2020) and Horel and Giesecke (2020), we can conduct variable gradient analysis to demonstrate the relative importance of each variable when behavioral biases and stock characteristics are both used.

$$Importance(x) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\partial R_{i,t+1}^{pred}}{\partial x_{i,t}}\right)^2$$

Where T represents the number of periods in the data, and $N_t$ denotes the total number of investors in the t-th period. We computed the *Importance(x)* for each out-of-sample test sample and then averaged the results. The partial derivative measures the gradient of the model's predicted output with respect to each variable. It is noteworthy that the gradient can be positive or negative, so squaring is performed to gauge importance. In a more intuitive sense, for linear models, the partial derivative simplifies to the variable coefficient in linear regression. Intuitively, a larger partial derivative implies a greater influence of a variable on the model's output, indicating greater importance in predicting future returns.

The results are plotted in Figure 2. The NN identifies diversification, portfolio turnover, and momentum as the top three leading factors to influence overall retail returns. The first two variables could be related to the behavioral biases of under-diversification and overconfidence. Under-diversification is among the most common features of retail investors (e.g., Barber and Odean 2000; Benartzi and Thaler 2001) as many investors may not fully understand the benefits of diversification (Lusardi and Mitchell 2011). Overconfidence often causes investors to trade too aggressively, allowing their high portfolio turnover to reduce their welfare (Odean 1998; Barber and Odean 2000). The third denotes perhaps the most famous anomalies in the literature. It is interesting to observe that behavioral biases occupy two out of the top three factors affecting investment returns.[14]

### C. Predicting Trading Returns As an Alternative Objective

Next, we recognize that investors' total returns may originate from two different sources: from holding an existing portfolio for a given period of, for instance, a month (i.e., holding returns) and from newly initiated trading during the month (i.e., trading returns). Behavioral theories suggest that the motivations to initiate trading may differ from those of continuation. For instance, the well-documented disposition effect (e.g., Shefrin and Statman, 1985) suggests that unrealized capital gains motivate investors to trade (i.e., sell), whereas unrealized capital losses incentivize

[14] Note that observed portfolio diversification and turnover may also be related to alternative sources of biases, such as local bias, local information, and financial literacy. Since our purpose is to compare behavioral biases and stock characteristics, we do not further nail down the economic sources of behavioral bias.

investors to hold onto losing assets and thus affect holding returns. For another example, salient information, such as extreme stock prices, may also attract investors' attention to initiate new trades according to the salience theory (Bordalo, Gennaioli, and Shleifer 2012; 2013; 2020), even though traditional financial theory suggests investors should pay more attention to returns rather than the level of prices. Hence, the next question we ask is how behavioral biases and firm characteristics affect the two sources of returns.

To address this issue, we shift the predicting goal, using behavioral biases and firm characteristics to predict holding returns or trading returns in the Neural Network. Table 4 tabulates the results. Panel A delineates the average monthly returns for Low group, High group, and High-minus-Low group generated by utilizing different subsets of predictors and models when the training objectives are total return, trading return, and holding return.

Notably, relying solely on firm characteristics results in a significantly discernible High-minus-Low return spread only when the training objective is holding return, and this spread is exclusively driven by positive returns in the High group. Conversely, when exclusively employing behavioral biases, a noteworthy High-minus-Low return spread is observed, irrespective of the training objective being total, trading, or holding return. The simultaneous use of both subsets of predictors amplifies the return spread. Furthermore, it is evident that when the training objective is trading return, the predictive power primarily emanates from forecasts related to the Loser group. Conversely, when the training objective is holding return, the predictive power predominantly arises from forecasts related to the Winner group.

Panels B and C respectively present results adjusted with the FF-3 and Carhart-4 models, mirroring the outcomes observed in Panel A. Our results validate the predicting power by observing the *High* (*Low*) group to generate significantly positive (negative) total returns and the *High*-minus-*Low* to deliver a significantly positive total return spread.[15]

### D. Variable Gradient Analysis for Trading Returns

[15] In other words, we observe that the predicted winners (losers) in one source of return can deliver positive (negative) total returns. Unreported results confirm that the predicted winners (losers) in one source of return can also deliver positive (negative) total returns in the respective source. We report the predictability of total returns because it is more difficult to achieve.

We then use the variable gradient analysis to assess the relative importance of each variable in predicting each source of returns. The results are plotted in Figure 2.

Our main finding is that behavioral biases play a relatively more important role in predicting trading returns than holding returns. This observation is intuitive: given the return predicting power of firm characteristics, characteristics-related returns contribute more to less rebalanced portfolios. On the other hand, new trading could be initiated by behavioral reasons. Consistent with this notion, we observed that portfolio turnover, the disposition effect, and the degree of portfolio diversification emerge as the three most important factors in predicting new trading returns, followed by the opening and closing price of stocks. The disposition effect emerges as a leading predictor for trading, in addition to turnover and diversification, which are leading predictors in predicting both total and trading returns.

## V. Additional Analyses

This section provides additional analysis to shed light on the economic interpretation and robustness of our existing results.

### A. The Joint Power of Behavioral Biases and Firm Characteristics

The relative importance of behavioral biases vis-à-vis firm characteristics can also be expressed as the joint explanatory power of all predictors falling into each category. Figure 3 illustrates the Relative Importance of Behavioral Bias vs. Firm Characteristics.

Based on our earlier delineation, where predictors are categorized into Investor Behavioral Bias and Firm Characteristics, we define the variable importance measure of a group by computing the average of the importance measures within that group. Without loss of generality, we normalize the variable importance to sum up to 1.

Generally, the relative importance of Stock features gradually decreases as the prediction target shifts from Holding Return to Trading Return. Specifically, for Holding Return, the relative importance of Stock features and Investor features is 46.0% and 54.0%, respectively. In predicting total returns, we observe that the joint explanatory power of behavioral biases slightly exceeds that of firm characteristics, where the relative importance is 39.2% for Stock features and 60.8% for Investor features. However, when it comes to predicting tradeing return, behavioral bias predictors take the lead, accounting for nearly 95% of the total predictive power. These observations confirm the importance of behavioral biases particularly for the trading and its related return of retail investors.

### B. Robustness Checks

We finally conduct a battery of robustness checks. In the main analysis, we exclude 30% of small stocks because these stocks are difficult to trade in emerging markets (Liu et al. 2019) and may overstate the predicting power of machine learning models (Avramov, Cheng, and Metzker 2019 and Cong et al., 2020).

Table 5 examines whether our main conclusions are robust to different thresholds of removal (e.g., 20% or 40%). Columns 1-3 present the results for the *Low* group, columns 4-6 report the outcomes for the *High* group, and columns 7-9 detail the *High*-minus-*Low* return spread. Interestingly, when fewer small stocks are excluded, the *Low* group identified by alternative models (e.g., Linear, Lasso, Ridge) exhibits more significant out-of-sample returns. However, only Neural Network models (FNN and ResNN) can generate significantly positive returns. These patterns suggest that the prediction power of alternative models may originate from the impact of small stocks invested by losers.

## Conclusions

This paper employs various machine learning models to analyze the returns for millions of retail investors in India. We observe that Neural Network outperforms other models, including traditional linear OLS models, in predicting investor returns. In particular, the more recently developed Residual Neural Network (*ResNN*) exhibits superior power in identifying both good and bad out-of-sample performance. Such a predicting power suggests that Neural Network models comprehend important information about investors that contributes to their returns.

We further conduct variable gradient analysis, which indicates that behavioral biases in general play a more important role than holding-weighted stock characteristics. This analysis enables us to identify the most important behavioral biases and stock characteristics that affect retail investors' investment returns. Indeed, we identify diversification, portfolio turnover, and momentum as the leading factors to influence overall retail returns. Additionally, turnover, the disposition effect, and diversification emerge as the three most important factors in predicting new trading-generated returns.

Our results call for further research, potentially utilizing state-of-the-art machine learning tools, to comprehensively understand the relative importance of behavioral biases and firm characteristics to retail investors.

## References


Acharya, V.V., Steffen, S., 2020. The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *The Review of Corporate Finance Studies*, 9(3), pp.430-471.

An, L., 2016. Asset pricing when traders sell extreme winners and losers. *Review of Financial Studies* 29, pp.823-861.

An, L., Engelberg, J., Henriksson, M., Wang, B. and Williams, J., 2019. The portfolio-driven disposition effect. *PBCSF-NIFR Research Paper.*

Avramov, D., Cheng, S., and Metzker, L. (2023). Machine learning vs. economic restrictions: Evidence from stock return predictability. Management Science, 69(5):2587–2619.

Avramov, D., Cheng, S., Metzker, L., and Voigt, S. (2023). Integrating factor models. The Journal of Finance, 78(3):1593–1646.

Balasubramaniam, V., and Campbell, J.Y. (2023). Who Owns What? A Factor Model for Direct Stock Holding, working paper.

Bali, T. G., Beckmeyer, H., Morke, M., and Weigert, F. (2023). Option Return Predictability with Machine Learning and Big Data. The Review of Financial Studies, 36(9):3548–3602.

Barber, B. M. and 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. and Odean, T. (2013). Chapter 22 - the behavior of individual investors. volume 2 of Handbook of the Economics of Finance, 1533–1570. Elsevier.

Barberis, N. (2018). Chapter 2 - psychology-based models of asset prices and trading volume., Handbook of Behavioral Economics - Foundations and Applications 1, 79–175. North-Holland.

Benartzi, S. and Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. The American Economic Review, 91(1):79–98.

Bianchi, D., Buchner, M., and Tamoni, A. (2020). Bond risk premia with machine learning. Econometric Modeling: Capital Markets - Risk eJournal.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and asset prices. American Economic Review, 103(3):623–28.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2020). Memory, attention, and choice. Quarterly Journal of Economics, 135(3):1399–1442.

Carhart, M. M. (1997). On persistence in mutual fund performance. The Journal of Finance, 52(1):57–82.

Cochrane, J. H. (2011). Presidential address: Discount rates. The Journal of Finance, 66(4):1047–1108.

DeMiguel, V., Gil-Bazo, J., Nogales, F. J., and Santos, A. A. (2023). Machine learning and fund characteristics help to select mutual funds with positive alpha. Journal of Financial Economics, 150(3):103737.

Døskeland, T., and Hvide, H.K., 2011, Do individual investors have asymmetric information based on work experience?, Journal of Finance 66, 1011-1041.

Easley, D., Lopez de Prado, M., O'Hara, M., and Zhang, Z. (2020). Microstructure in the Machine Age. The Review of Financial Studies, 34(7):3316–3363.

Fama, E. F. and French, K. R. (1998). Value versus growth: The international evidence. The Journal of Finance, 53(6):1975–1999.

Grinblatt, M., Ikäheimo, S., Keloharju, M., Knüpfer, S., (2016) IQ and Mutual Fund Choice. Management Science 62(4):924-944.

Gu, S., Kelly, B., and Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. The Review of Financial Studies, 33(5):2223–2273.

Harvey, C. R., Liu, Y., and Zhu, H. (2015). . . . and the Cross-Section of Expected Returns. The Review of Financial Studies, 29(1):5–68.

He, K., Zhang, X., Ren, S., and Sun, J. (2015). Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778.

Hinton, G. E., Srivastava, N., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R. (2012). Improving neural networks by preventing co-adaptation of feature detectors. ArXiv, abs/1207.0580.

Hirshleifer, D. (2015). Behavioral finance. Annual Review of Financial Economics, 7(1):133–159.

Horel, E. and Giesecke, K. (2020). Significance tests for neural networks. J. Mach. Learn. Res., 21(1).

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks, 2(5):359–366.

Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. Review of Financial Studies, 33(5):2019–2133.

Ivoovic, Z. and Weisbenner, S. (2005). Local does as local is: Information content of the geography of individual investors' common stock investments. The Journal of Finance, 60(1):267–306.

Jensen, T. I., Kelly, B., and Pedersen, L. H. (2023). Is there a replication crisis in finance? The Journal of Finance, 78(5):2465–2518.

Kaniel, R., Lin, Z., Pelger, M., and Van Nieuwerburgh, S. (2023). Machine-learning the skill of mutual fund managers. Journal of Financial Economics, 150(1):94–138.

Kumar, A. (2009). Who gambles in the stock market? The Journal of Finance, 64(4):1889–1933.

Leippold, M., Wang, Q., and Zhou, W. (2022). Machine learning in the chinese stock market. Journal of Financial Economics, 145(2):64–82.

Liu, H., Peng, C., Xiong, W. A., and Xiong, W. (2022). Taming the bias zoo. Journal of Financial Economics, 143(2):716–741.

Liu, J., Stambaugh, R. F., and Yuan, Y. (2019). Size and value in china. Journal of Financial Economics, 134(1):48–69.

Lusardi, A. and Mitchell, O. S. (2011). Financial literacy around the world: an overview. Journal of Pension Economics & Finance, 10(4):497–508.

Massa, M. and Simonov, A. (2006). Hedging, familiarity and portfolio choice. Review of Financial Studies, 19(2):633–685.

Mclean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? The Journal of Finance, 71(1):5–32.

Odean, T. (1998). Are investors reluctant to realize their losses? The Journal of Finance, 53(5):1775–1798.

Sadhwani, A., Giesecke, K., and Sirignano, J. (2020). Deep Learning for Mortgage Risk*. Journal of Financial Econometrics, 19(2):313–368.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of Finance, 40(3):777–790.

Sui, Pengfei and Wang, Baolian, Stakes and Investor Behaviors (August 27, 2023). Available at SSRN: https://ssrn.com/abstract=4219861 or http://dx.doi.org/10.2139/ssrn.4219861

## Table 1: Variable Names and Explanations

This table tabulates the list of firm characteristics and behavioral biases that we use in our analysis. The first six categories represent firm characteristics and the last consists of behavioral biases. Panel B summarizes the literature on behavioral biases.

| Name | Explanation | Name | Explanation |
|---|---|---|---|
| ***Profitability*** | | ***Investor Behavioral Bias*** | |
| ROA | Return on assets | Distance | Local Bias |
| NSOLA | Net Sales Over Lagged Assets | Tot_Asset | Investor Total Asset |
| COGS | Cost of Goods Sold over lagged assets | Extrapolation | Extrapolation |
| SaleGrow | Sales Growth | Disp | Disposition Effect |
| ***Past Returns*** | | Month_Diver | Diversification |
| R1_0 | Last month return | Investor_Tvr | Investor Turnover |
| R2_1 | Return from t-2 to t-1 | Past_Perform | Investor Past Performance |
| R12_7 | Intermediate momentum | IVOL | Idiosyncratic Volatility (Proxy for Lottery Preference) |
| R12_2 | Momentum | Low_Price | Low Price Rank (Proxy for Lottery Preference) |
| ***Investments*** | | High_Price | High Price Rank (Proxy for Lottery Preference) |
| DPI2A | Change in property, plants, and equipment | Open_Price | Open Price Rank (Proxy for Lottery Preference) |
| NI | Net Share Issues | Close Price | Close Price Rank (Proxy for Lottery Preference) |
| ***Intangibles*** | | Skew | Idiosyncratic Skewness (Proxy for Lottery Preference) |
| NIA | Net Intangible Asset | | |
| ***Value*** | | | |
| TobinQ | Tobin's Q | | |
| Div_Yield | Dividend Yield | | |
| EPS | Earnings Per Share | | |
| BVPS | Book Value Per Share | | |
| PE | Price to Earnings | | |
| PB | Price to Book Value | | |
| ***Trading Frictions*** | | | |
| TA | Total Asset | | |
| Size | Market Equity | | |
| Turnover | Monthly Turnover | | |
| TradVol | Monthly Trading Volume | | |
| Leverage | Financial leverage | | |
| NOE | Number of Employees Growth | | |

Panel B: Summary of theories on investor behavioral bias.

| Bias | Proxy | Papers |
|---|---|---|
| The disposition effect | Regression coefficient | Shefrin and Statman (1985), Odean (1998), Ben-David and Hirshleifer (2012) |
| Lottery preference | Ivol<br>Iskew<br>Stock price | Kumar (2009), Harvey and Siddique (2000), Bordalo, Gennaioli, and Shleifer (2012; 2013; 2020) |
| Extrapolation | Excess return of holding stocks | Barber and Odean (2013) |
| Underdiversification | Number of stocks in an investor's portfolio | Barber and Odean (2000), Benartzi and Thaler (2001), Lusardi and Mitchell (2011) |
| Local bias | Average distance between an investor's location and the headquarters of the stocks the investor bought | Ivkovic and Weisbenner (2005), Massa and Simonov (2006) |
| Turnover | The frequency of trading for the investors | Odean (1998), Barber and Odean (2000) |

**Table 2. Model Comparison: Predict Total Return**

This table reports the comparison of performance of different model, including Linear, Lasso, Ridge, Random Forest, Standard Multi-Layer Perceptions (FNN) and Residual Neural Network. We filter out bottom 30% small stocks. We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. we also use the locally estimated three-factor and four-factor models to adjust these returns. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Low Group | | | High Group | | | High Minus Low | | |
| | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 |
| Linear | -0.018* | -0.017 | -0.014 | 0.007 | 0.007 | 0.008 | 0.025*** | 0.024*** | 0.022*** |
| | (-1.77) | (-1.63) | (-1.40) | (1.37) | (1.33) | (1.52) | (3.34) | (3.14) | (2.95) |
| Lasso | -0.008 | -0.006 | -0.004 | 0.008 | 0.008 | 0.010* | 0.016** | 0.014* | 0.013* |
| | (-0.75) | (-0.53) | (-0.34) | (1.56) | (1.61) | (1.90) | (2.06) | (1.80) | (1.68) |
| Ridge | -0.018* | -0.017 | -0.014 | 0.007 | 0.007 | 0.008 | 0.025*** | 0.024*** | 0.022*** |
| | (-1.76) | (-1.61) | (-1.38) | (1.36) | (1.32) | (1.52) | (3.32) | (3.10) | (2.91) |
| Random Forest | -0.015 | -0.014 | -0.012 | -0.011 | -0.009 | -0.007 | 0.004 | 0.005 | 0.005 |
| | (-1.24) | (-1.17) | (-1.03) | (-1.08) | (-0.90) | (-0.70) | (0.47) | (0.59) | (0.63) |
| FNN | -0.025* | -0.024 | -0.021 | 0.015*** | 0.015*** | 0.017*** | 0.040*** | 0.039*** | 0.038*** |
| | (-1.74) | (-1.62) | (-1.43) | (2.66) | (2.70) | (3.08) | (3.38) | (3.24) | (3.11) |
| Residual Neural Network | -0.031** | -0.029** | -0.026** | 0.012** | 0.013** | 0.014** | 0.044*** | 0.042*** | 0.041*** |
| | (-2.38) | (-2.17) | (-2.00) | (2.00) | (2.08) | (2.33) | (4.57) | (4.38) | (4.26) |

## Table 3. Information Set Comparison: Holding-Based Characteristics vs. Investor Behavioral Biases

This table reports the comparison of performance of different subset of predictors, including utilizing firm characteristics or investor behavioral biases alone, as well as using both in a standard Feedforward Neural Network (FNN) and a Residual Neural Network (ResNN). We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. we also use the locally estimated three-factor and four-factor models to adjust these returns. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Low Group | | | High Group | | | High Minus Low | | |
| | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 |
| Stock Characteristics | -0.003 | -0.001 | 0.001 | 0.006 | 0.006 | 0.008 | 0.009 | 0.007 | 0.007 |
| | (-0.23) | (-0.08) | (0.09) | (1.01) | (1.02) | (1.32) | (0.99) | (0.79) | (0.72) |
| Behavioral Biases | -0.025** | -0.024** | -0.022** | 0.008 | 0.009 | 0.010* | 0.033*** | 0.033*** | 0.032*** |
| | (-2.62) | (-2.43) | (-2.25) | (1.46) | (1.55) | (1.80) | (5.63) | (5.41) | (5.29) |
| Stock Chars + Behavioral | -0.025* | -0.024 | -0.021 | 0.015*** | 0.015*** | 0.017*** | 0.040*** | 0.039*** | 0.038*** |
| | (-1.74) | (-1.62) | (-1.43) | (2.66) | (2.70) | (3.08) | (3.38) | (3.24) | (3.11) |
| Residual Neural Network | -0.031** | -0.029** | -0.026** | 0.012** | 0.013** | 0.014** | 0.044*** | 0.042*** | 0.041*** |
| | (-2.38) | (-2.17) | (-2.00) | (2.00) | (2.08) | (2.33) | (4.57) | (4.38) | (4.26) |

## Table 4. Predictor Comparison when Predicting Holding and Trading-based Returns

Panel A: Excess Return

This table reports the comparison of performance of different subset of predictors, including utilizing firm characteristics or investor behavioral biases alone, as well as using both in a standard Feedforward Neural Network (FNN) and a Residual Neural Network (ResNN). We shift the predicting goal to predict holding returns or trading returns. We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Total Return | | | Trading Return | | | Holding Return | | |
| | Low | High | High Minus Low | Low | High | High Minus Low | Low | High | High Minus Low |
| Stock Characteristics | -0.003 | 0.006 | 0.009 | -0.000 | -0.006 | -0.006 | -0.005 | 0.012** | 0.017* |
| | (-0.23) | (1.01) | (0.99) | (-0.05) | (-0.71) | (-1.11) | (-0.38) | (1.99) | (1.96) |
| Behavioral Biases | -0.025** | 0.008 | 0.033*** | -0.031*** | 0.003 | 0.034*** | -0.022** | 0.010* | 0.031*** |
| | (-2.62) | (1.46) | (5.63) | (-4.01) | (0.42) | (17.75) | (-2.00) | (1.69) | (4.32) |
| Stock Chars + Behavioral | -0.025* | 0.015*** | 0.040*** | -0.034*** | 0.003 | 0.037*** | -0.019 | 0.012** | 0.031** |
| | (-1.74) | (2.66) | (3.38) | (-4.10) | (0.43) | (13.81) | (-1.16) | (2.18) | (2.35) |
| Residual Neural Network | -0.031** | 0.012** | 0.044*** | -0.028*** | 0.003 | 0.031*** | -0.023 | 0.012** | 0.035*** |
| | (-2.38) | (2.00) | (4.57) | (-3.67) | (0.39) | (14.69) | (-1.61) | (2.25) | (3.04) |

Table 4 (Panel B): FF-3 Alpha

This table reports the comparison of performance of different subset of predictors, including utilizing firm characteristics or investor behavioral biases alone, as well as using both in a standard Feedforward Neural Network (FNN) and a Residual Neural Network (ResNN). We shift the predicting goal to predict holding returns or trading returns. We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. We use the locally estimated three-factor models to adjust these returns. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Total Return | | | Trading Return | | | Holding Return | | |
| | Low | High | High Minus Low | Low | High | High Minus Low | Low | High | High Minus Low |
| Stock Characteristics | -0.001 | 0.006 | 0.007 | 0.001 | -0.005 | -0.006 | -0.003 | 0.013** | 0.016* |
| | (-0.08) | (1.02) | (0.79) | (0.09) | (-0.60) | (-1.13) | (-0.26) | (2.12) | (1.85) |
| Behavioral Biases | -0.024** | 0.009 | 0.033*** | -0.029*** | 0.004 | 0.034*** | -0.020* | 0.010* | 0.031*** |
| | (-2.43) | (1.55) | (5.41) | (-3.73) | (0.58) | (17.00) | (-1.82) | (1.79) | (4.13) |
| Stock Chars + Behavioral | -0.024 | 0.015*** | 0.039*** | -0.032*** | 0.004 | 0.036*** | -0.019 | 0.013** | 0.032** |
| | (-1.62) | (2.70) | (3.24) | (-3.82) | (0.59) | (13.23) | (-1.12) | (2.27) | (2.34) |
| Residual Neural Network | -0.029** | 0.013** | 0.042*** | -0.027*** | 0.004 | 0.031*** | -0.021 | 0.013** | 0.034*** |
| | (-2.17) | (2.08) | (4.38) | (-3.40) | (0.56) | (14.20) | (-1.48) | (2.33) | (2.90) |

Table 4 (Panel C): Carhart-4 Alpha

This table reports the comparison of performance of different subset of predictors, including utilizing firm characteristics or investor behavioral biases alone, as well as using both in a standard Feedforward Neural Network (FNN) and a Residual Neural Network (ResNN). We shift the predicting goal to predict holding returns or trading returns. We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. We use the locally estimated four-factor models to adjust these returns. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | Total Return | | | Trading Return | | | Holding Return | |
| | Low | High | High Minus Low | Low | High | High Minus Low | Low | High | High Minus Low |
| Stock Characteristics | 0.001 | 0.008 | 0.007 | 0.003 | -0.004 | -0.006 | 0.000 | 0.015** | 0.015* |
| | (0.09) | (1.32) | (0.72) | (0.35) | (-0.41) | (-1.17) | (0.03) | (2.57) | (1.68) |
| Behavioral Biases | -0.022** | 0.010* | 0.032*** | -0.028*** | 0.006 | 0.033*** | -0.018 | 0.012** | 0.030*** |
| | (-2.25) | (1.80) | (5.29) | (-3.55) | (0.84) | (16.79) | (-1.65) | (2.09) | (4.04) |
| Stock Chars + Behavioral | -0.021 | 0.017*** | 0.038*** | -0.031*** | 0.006 | 0.036*** | -0.015 | 0.014** | 0.029** |
| | (-1.43) | (3.08) | (3.11) | (-3.65) | (0.84) | (13.12) | (-0.90) | (2.62) | (2.17) |
| Residual Neural Network | -0.026** | 0.014** | 0.041*** | -0.025*** | 0.006 | 0.031*** | -0.020 | 0.014*** | 0.034*** |
| | (-2.00) | (2.33) | (4.26) | (-3.22) | (0.82) | (14.07) | (-1.35) | (2.74) | (2.87) |

## Table 5. Robustness Checks on Model Comparison

This table reports the comparison of performance of different model, including Linear, Lasso, Ridge, Random Forest, Standard Multi-Layer Perceptions (FNN) and Residual Neural Network. We filter out bottom 40% small stocks. We then sort retail investors into five quintiles according to predicted returns, with the High and Low groups consisting of 20% of predicted winners and losers among investors, respectively. Finally, we report the value-weighted out-of-sample returns of the high and low groups as well as their return difference. we also use the locally estimated three-factor and four-factor models to adjust these returns. The OLS standard error is used to construct t-stats. The t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: (Filter out 40% small stocks)

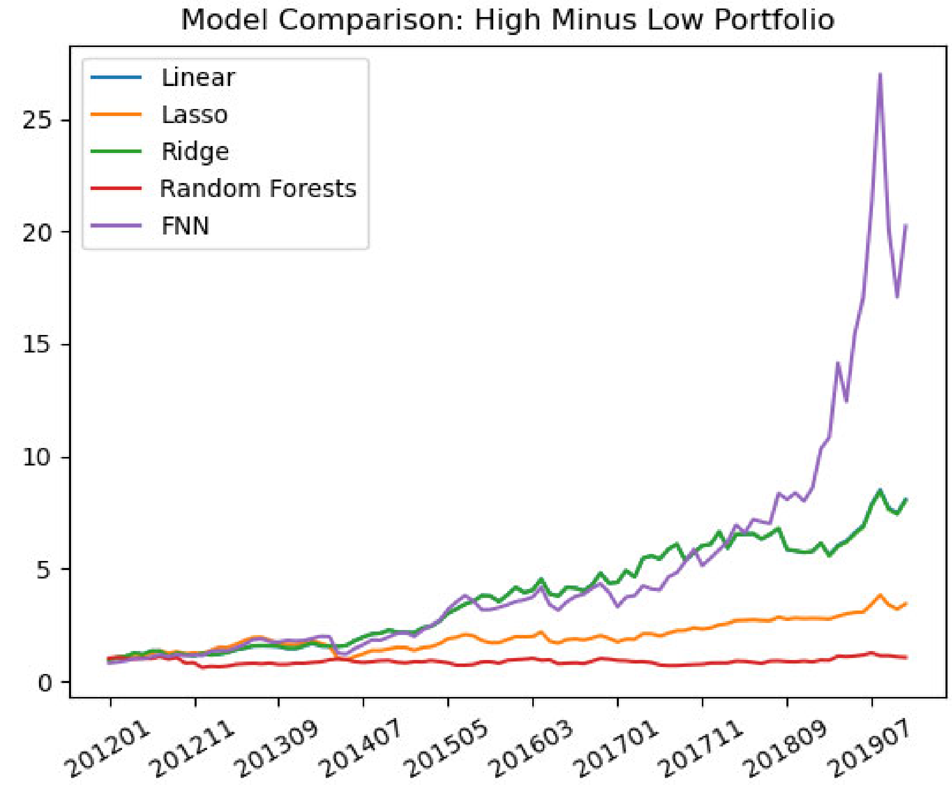
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | Low Group | | | High Group | | | High Minus Low | |
| | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 |
| Linear | -0.015 | -0.014 | -0.011 | 0.007 | 0.007 | 0.008 | 0.022** | 0.021** | 0.020** |
| | (-1.36) | (-1.25) | (-1.04) | (1.36) | (1.33) | (1.51) | (2.61) | (2.44) | (2.27) |
| Lasso | -0.016 | -0.016 | -0.006 | 0.006 | 0.006 | 0.011 | 0.022* | 0.021* | 0.017 |
| | (-1.15) | (-1.09) | (-0.41) | (0.99) | (0.92) | (1.66) | (2.00) | (1.88) | (1.40) |
| Ridge | -0.014 | -0.013 | -0.011 | 0.007 | 0.007 | 0.008 | 0.021** | 0.021** | 0.019** |
| | (-1.30) | (-1.19) | (-0.98) | (1.37) | (1.34) | (1.52) | (2.55) | (2.37) | (2.21) |
| Random Forest | -0.011 | -0.010 | -0.008 | 0.000 | 0.002 | 0.003 | 0.011 | 0.012 | 0.012 |
| | (-0.96) | (-0.87) | (-0.73) | (0.02) | (0.15) | (0.24) | (1.22) | (1.28) | (1.23) |
| FNN | -0.020 | -0.017 | -0.015 | 0.013** | 0.014** | 0.016** | 0.033*** | 0.031*** | 0.030*** |
| | (-1.62) | (-1.42) | (-1.22) | (2.60) | (2.61) | (3.01) | (3.47) | (3.25) | (3.14) |
| Residual Neural Network | -0.027** | -0.026** | -0.024** | 0.012** | 0.013** | 0.015** | 0.034*** | 0.033*** | 0.032*** |
| | (-2.55) | (-2.34) | (-2.19) | (2.03) | (2.12) | (2.39) | (4.80) | (4.55) | (4.48) |

Panel B: (Filter out 20% small stocks)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | Low Group | | | High Group | | | High Minus Low | |
| | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 | Mean | FF-3 | Carhart-4 |
| Linear | -0.022** | -0.021** | -0.018* | 0.008 | 0.008 | 0.009* | 0.030*** | 0.029*** | 0.028*** |
| | (-2.30) | (-2.12) | (-1.91) | (1.55) | (1.56) | (1.76) | (4.35) | (4.12) | (3.95) |
| Lasso | -0.022* | -0.022* | -0.013 | 0.006 | 0.006 | 0.011* | 0.028*** | 0.028*** | 0.025*** |
| | (-1.87) | (-1.80) | (-1.04) | (1.04) | (0.98) | (1.73) | (3.19) | (3.05) | (2.48) |
| Ridge | -0.022** | -0.021** | -0.018* | 0.008 | 0.009 | 0.010* | 0.030*** | 0.029*** | 0.028*** |
| | (-2.30) | (-2.12) | (-1.91) | (1.57) | (1.58) | (1.78) | (4.37) | (4.13) | (3.96) |
| Random Forest | -0.018* | -0.018* | -0.015 | 0.005 | 0.007 | 0.010 | 0.024*** | 0.025*** | 0.025*** |
| | (-1.72) | (-1.67) | (-1.44) | (0.44) | (0.53) | (0.80) | (3.08) | (3.08) | (3.09) |
| FNN | -0.024** | -0.021* | -0.018 | 0.013** | 0.013** | 0.015*** | 0.036*** | 0.034*** | 0.033*** |
| | (-2.04) | (-1.77) | (-1.58) | (2.45) | (2.47) | (2.86) | (3.99) | (3.69) | (3.57) |
| Residual Neural Network | -0.027** | -0.026** | -0.024** | 0.016*** | 0.017*** | 0.019*** | 0.037*** | 0.037*** | 0.037*** |
| | (-2.13) | (-2.03) | (-1.87) | (2.84) | (2.93) | (3.33) | (3.94) | (3.85) | (3.76) |

**Figure 1: The Cumulative Returns of High-minus-Low Return Spread from Various Models**

Figure 1 shows the value-weighted out-of-sample return difference between high and low groups. We first use all the models to predict retail investors' total investment returns. We then sort retail investors into five quintiles according to predicted returns, with the *High* and *Low* groups consisting of 20% of predicted winners and losers among investors, respectively.



## Figure 2: Top Variable Importance of Behavioral Bias vs. Stock Characteristics

We can conduct variable gradient analysis to demonstrate the relative importance of each variable when behavioral biases and stock characteristics are both used. $Importance(x) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\partial R_{i,t+1}^{pred}}{\partial x_{i,t}}\right)^2$, where T represents the number of periods in the data, and $N_t$ denotes the total number of investors in the t-th period. We computed the *Importance(x)* for each out-of-sample test sample and then averaged the results. The partial derivative measures the gradient of the model's predicted output with respect to each variable. Intuitively, a larger partial derivative implies a greater influence of a variable on the model's output, indicating greater importance in predicting future returns.

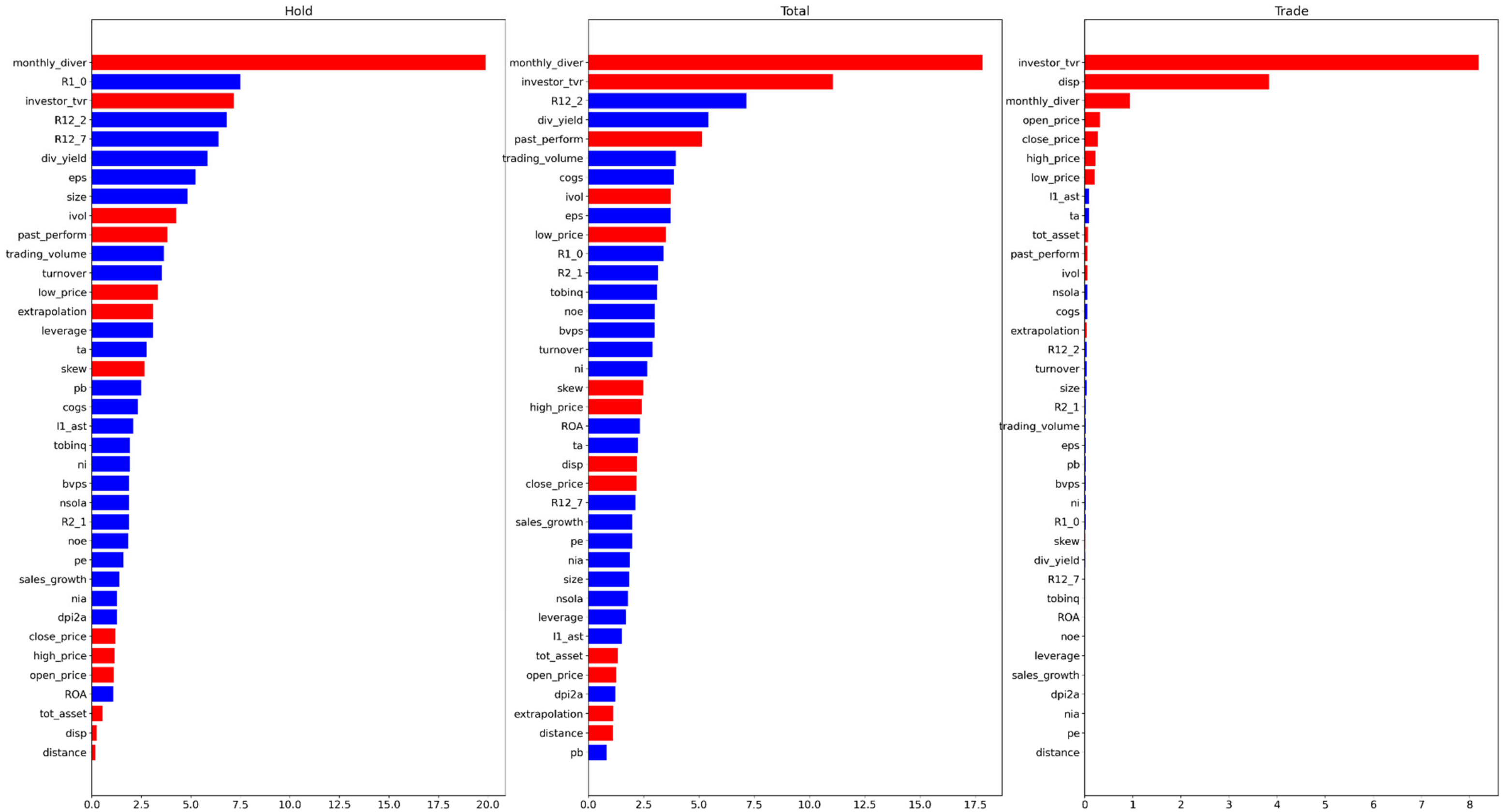
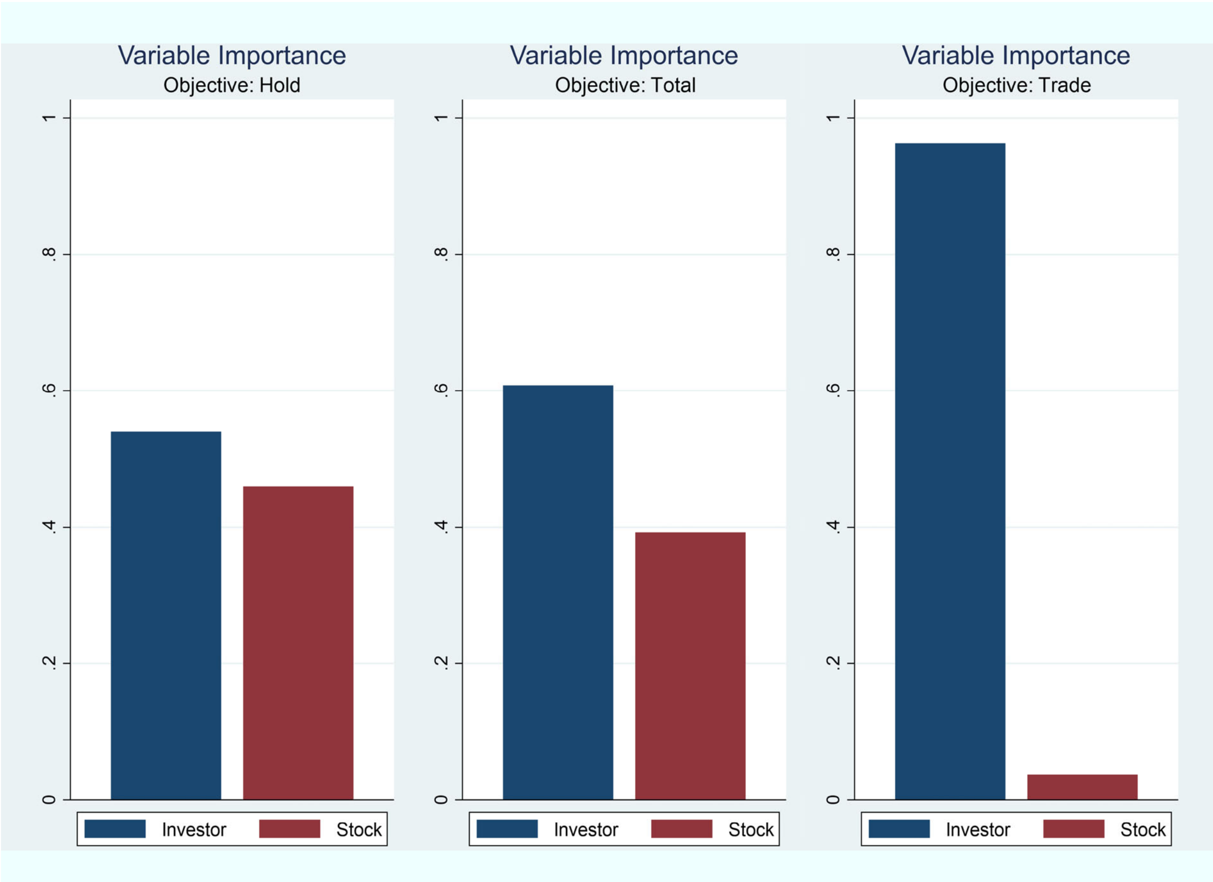


**Figure 3: The Relative Importance of Behavioral Bias vs. Firm Characteristics**

This figure shows the relative importance of behavioral biases vis-à-vis firm characteristics. Based on our earlier delineation, where predictors are categorized into Investor Behavioral Bias and Firm Characteristics, we define the variable importance measure of a group by computing the average of the importance measures within that group, which can also be expressed as the joint explanatory power of all predictors falling into each category. Without loss of generality, we normalize the variable importance to sum up to 1.



# Online Appendix

## Appendix **Table 1: Summary Statistics of Main Variables.**

Panel A: Holding based firm characteristics

| Variable | N | Mean | SD | p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|---|---|
| Dpi2a | 1.011e+07 | -0.324 | 0.750 | -1.342 | -0.893 | -0.339 | 0.185 | 0.684 |
| R1_0 | 1.011e+07 | 0.0630 | 0.719 | -0.930 | -0.417 | 0.0980 | 0.566 | 0.994 |
| R2_1 | 1.011e+07 | 0.0460 | 0.722 | -0.949 | -0.441 | 0.0780 | 0.553 | 0.984 |
| R12_7 | 1.011e+07 | 0.0330 | 0.738 | -0.987 | -0.473 | 0.0560 | 0.568 | 0.994 |
| R12_2 | 1.011e+07 | 0.0230 | 0.747 | -1.019 | -0.496 | 0.0450 | 0.575 | 0.999 |
| Net Issue | 1.011e+07 | 1.192 | 0.533 | 0.467 | 0.974 | 1.365 | 1.582 | 1.671 |
| Nsola | 1.011e+07 | -0.371 | 0.742 | -1.376 | -0.952 | -0.394 | 0.134 | 0.615 |
| Cogs | 1.011e+07 | -0.404 | 0.738 | -1.428 | -0.966 | -0.423 | 0.0710 | 0.580 |
| ROA | 1.011e+07 | 0.0530 | 0.702 | -0.839 | -0.441 | 0.0500 | 0.526 | 0.995 |
| Sales Growth | 1.011e+07 | 0.124 | 0.711 | -0.870 | -0.301 | 0.159 | 0.578 | 1.050 |
| Nia | 1.011e+07 | 0.725 | 0.744 | -0.336 | 0.321 | 0.861 | 1.318 | 1.559 |
| PB | 1.011e+07 | 0.171 | 0.733 | -0.856 | -0.330 | 0.241 | 0.709 | 1.079 |
| PE | 1.011e+07 | 0.120 | 0.663 | -0.760 | -0.294 | 0.132 | 0.536 | 0.989 |
| BVPS | 1.011e+07 | 0.323 | 0.739 | -0.746 | -0.158 | 0.419 | 0.882 | 1.213 |
| EPS | 1.011e+07 | 0.253 | 0.802 | -0.960 | -0.295 | 0.367 | 0.867 | 1.239 |
| Leverage | 1.011e+07 | 0.0250 | 0.719 | -0.917 | -0.456 | 0.00400 | 0.533 | 1.030 |
| TobinQ | 1.011e+07 | 0.163 | 0.725 | -0.840 | -0.354 | 0.198 | 0.695 | 1.090 |
| Div Yield | 1.011e+07 | 0.497 | 0.771 | -0.651 | 0.0500 | 0.640 | 1.085 | 1.404 |
| TA | 1.011e+07 | 1.190 | 0.516 | 0.471 | 0.985 | 1.363 | 1.557 | 1.650 |
| Size | 1.011e+07 | 1.141 | 0.514 | 0.411 | 0.898 | 1.283 | 1.529 | 1.657 |
| Turnover | 1.011e+07 | 1.192 | 0.506 | 0.498 | 0.973 | 1.349 | 1.563 | 1.669 |
| Trading Vol | 1.011e+07 | 1.227 | 0.499 | 0.560 | 1.025 | 1.389 | 1.585 | 1.677 |
| NOE | 1.011e+07 | 0.839 | 0.734 | -0.198 | 0.442 | 1.012 | 1.418 | 1.625 |

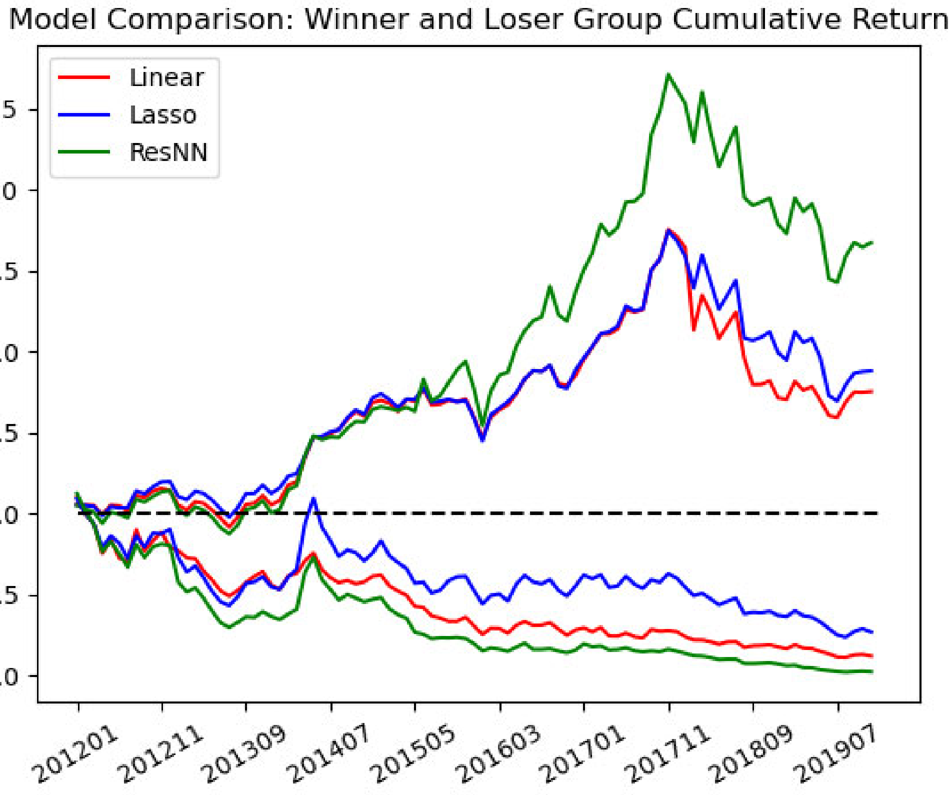
Appendix Table 1: Summary Statistics of Main Variables.

Panel B: Investor behavioral biases

| Variable | N | Mean | SD | p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|---|---|
| Tot Asset | 1.011e+07 | 1.187 | 0.521 | 0.462 | 0.979 | 1.363 | 1.560 | 1.651 |
| Diver | 1.011e+07 | 9.669 | 17.013 | 1.000 | 2.000 | 5.000 | 11.000 | 22.000 |
| Disp | 1.011e+07 | 0.001 | 0.008 | -0.004 | -0.001 | 0.002 | 0.003 | 0.004 |
| ivol | 1.011e+07 | -0.0570 | 1.018 | -1.416 | -0.944 | -0.157 | 0.877 | 1.360 |
| iskew | 1.011e+07 | -0.0150 | 1.031 | -1.408 | -0.924 | -0.126 | 0.915 | 1.399 |
| Distance | 1.011e+07 | 877.144 | 498.822 | 258.547 | 528.240 | 858.926 | 1185.493 | 1484.389 |
| Investor Tvr | 1.011e+07 | -0.128 | 0.909 | -0.662 | -0.627 | -0.589 | -0.534 | 1.498 |
| Open Price | 1.011e+07 | 0.317 | 0.773 | -0.852 | -0.181 | 0.426 | 0.910 | 1.258 |
| High Price | 1.011e+07 | 0.315 | 0.773 | -0.854 | -0.184 | 0.424 | 0.907 | 1.257 |
| Low Price | 1.011e+07 | 0.318 | 0.773 | -0.849 | -0.180 | 0.428 | 0.911 | 1.259 |
| Close Price | 1.011e+07 | 0.317 | 0.773 | -0.851 | -0.181 | 0.427 | 0.910 | 1.258 |
| Extrapolat~n | 1.011e+07 | 0.0380 | 0.174 | -0.155 | -0.0510 | 0.0430 | 0.135 | 0.228 |
| Past Perform | 1.011e+07 | 1.009 | 0.124 | 0.897 | 0.947 | 1.004 | 1.063 | 1.130 |

## Online Appendix Figure IN1: High vs. Low Group Returns from Selected Models.

Figure 1 shows the value-weighted out-of-sample returns of the high and low groups. We first use all the models to predict retail investors' total investment returns. We then sort retail investors into five quintiles according to predicted returns, with the *High* and *Low* groups consisting of 20% of predicted winners and losers among investors, respectively.



# Online Appendix Figure IN2: Top Variable Importance of Behavioral Bias vs. Stock Characteristics

In Figure 2, we delve deeper into the analysis of the direction of influence each variable has on the prediction outcomes. Specifically, we define the directional impact of a variable as:

$$Direction(x) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\partial R_{i,t+1}^{pred}}{\partial x_{i,t}}$$