Predicting Mutual Fund Performance in China: A Machine Learning Approach

Zezhou Xu, Hong Yan, Chao Zi *

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Abstract

Through machine learning (ML), a comprehensive set of fund characteristics can consistently predict mutual fund performance in China. The difference between high- and low-performing funds is large and persists for over a year. While characteristics of the stocks that funds hold are not predictive, fund activeness and their past performance are important predictors. We also find that the past returns of sibling funds (funds managed by the same manager) and family funds have important predictive power. The interaction effects between these predictors and macroeconomic conditions largely account for ML's superior prediction relative to linear methods.

*Shanghai Advanced Institute of Finance (SAIF), Shanghai Jiao Tong University. Email: zzxu.20@saif.sjtu.edu.cn (Z. Xu), hyan@saif.sjtu.edu.cn (H. Yan), czi@saif.sjtu.edu.cn (C. Zi)

1 Introduction

China's mutual fund industry is growing rapidly. At the end of 2021, Chinese mutual funds had $3.53 trillion in assets under management, ranked first in Asia and fourth in the world, with more than 700 million fund investors. Although the literature has extensively studied mutual funds in the US and consistently shown that active equity funds lack performance persistence (e.g., Blake et al. (1993), Malkiel (1995), Carhart (1997)), so far, little is known regarding mutual fund performance predictability and persistence in China.

China's mutual fund market has two key features that distinguish it from the U.S. market. First, Chinese equity mutual funds have a much larger turnover ratio than U.S equity mutual funds. The average turnover ratio of Chinese equity mutual funds is 300%, contrasting to the 66% of U.S equity mutual funds. This mirrors the high turnover ratio in the Chinese stock market, as the market is dominated by retail investors. This also leads to the evaluation of equity mutual fund performance that is heavily dependent on short-term returns. Therefore, fund managers have incentives to raise portfolio performance through active trading. Second, Chinese and U.S. fund investors have different financial objectives. According to the research report of the Investment Company Institute (ICI) [1], in the U.S., employer-sponsored retirement plans are often the gateway to mutual fund ownership, and the majority of mutual fund investors are focused on retirement saving with long term objectives. In China, however, as shown by Asset Management Association of China (AMAC) [2], mutual fund investors tend to invest on their own and seek quick wealth growth. Therefore, as mutual fund investors and fund managers in China pay more attention to short-term fund returns, factors predicting future fund performance could have unique Chinese characteristics.

Identifying and testing the factors capable of predicting mutual fund performance is a challenging task. Recent research in the U.S. has used machine learning techniques to identify mutual-fund characteristics that help differentiate the high-performing funds from low-performing funds (e.g., Li and Rossi (2020), DeMiguel et al. (2021), Kaniel et al. (2022)). In this paper, we extend this methodology to investigate the mutual fund characteristics, some unique to the Chinese market, that can help separate the corn from the chaff and identify mutual funds with persistent superior

[1] See https://www.ici.org/system/files/2021-10/per27-12.pdf.

[2] See https://www.amac.org.cn/researchstatistics/report/tzzbg/202201/P020220107702402352747.pdf

performance.

We construct a large set of fund characteristics for empirical fund performance predictability research in China. In the first step, we collect 33 signals that have been shown to possess forecasting power for fund returns in the U.S.. In the second step, we extend a given set of a fund's characteristics by averaging its sibling funds' and family funds' characteristics [3]. The intuition is that the characteristics of its related funds can be informative about a particular fund (Pástor and Stambaugh (2002)). Specifically, for a given fund and a characteristic, we average the characteristic values of other funds managed by the same manager, weighted by their respective amount of total net assets. Thus, we construct additional 33 fund-level characteristics, which we name as *manager* information set. Similarly, we generate another bunch of fund-level characteristics by value-weighted averaging the values of the characteristics of the equity mutual funds belonging to the same family of a given fund and name the bunch as *family* information set. In the third step, we further enlarge the set of fund characteristics by looking into the stocks that fund holds. We select 33 predictive stock factors in the Chinese stock market and merge them with mutual fund holdings to construct characteristic exposures at the fund level. In total, our fund information set consists of 132 (33$\times$4) fund characteristics. In the fourth step, we add two macro variables.

Given the large information set and the fact that China has experienced a series of structure breaks such as various financial reforms and expanding market openness, more flexible methods are necessary. The potential nonlinear associations between fund characteristics and performance as well as interaction effects of predictors are usually missed by simple linear regression models, but machine learning is well suited for such challenging problems. Therefore, we employ machine learning techniques, which are playing more and more important roles in finance and economic research. Machine learning methods can accommodate irrelevant or highly correlated predictors and lower the risk of overfitting than simple linear models. In this paper , we adopt LASSO and PLS to conduct variable selection and dimension reduction, and employ several tools known as Boosting Regression Trees (BRT) and Neural Networks with 1 through 3 hidden layers (NN1$\sim$NN3). In addition to using OLS as our benchmark model, we also include two naive references: equal-weighted and value-weighted long portfolios of all actively-managed equity funds.

[3]We refer to funds managed by the same manager as sibling funds and funds managed by the same fund management company as family funds

Our monthly dataset of actively-managed equity funds in the Chinese market spans from January 2003 to January 2022. We split the full sample period chronologically into three sub-periods with the same length of observations, of which two of the periods are used to train and tune the models and the third one is for out-of-sample evaluation. To tune the hyper-parameters of machine-learning models, we use time-series cross-validation which reserves a section of the training sample for evaluation. After training, we can predict fund performance at the end of each month in the testing period using the trained models and new values of predictors in that month. We then form a *long-only* portfolio that long the funds in the top model-predicted performance group and hold for one month [4]. Finally, we evaluate the portfolio performance (monthly return, sharp ratio, and alpha with respect to Carhart (1997)'s four-factor model) over the entire out-of-sample period.

We show that our information set can consistently help differentiate the high-performing from low-performing funds and identify funds with superior and persistent skills. The portfolio of top-decile funds selected by models (including simple linear models) exploiting our information set earns on average more than 2 percent monthly return and more than 1.5 annualized Sharpe ratio in the testing period, which is economically and statistically higher than the naive strategy of long all active equity mutual funds on a value-weighted basis. The latter earns on average 1.5 percent monthly return and 1.12 Sharpe ratio in the same period. We further show that machine-learning models can more intelligently digest the information set and help identify funds with superior performance. For example, the top-decile fund portfolio identified by LASSO achieves an average 2.6-percent monthly return and 1.7 Sharpe ratio. Our results are robust and even stronger when we divide funds into more groups. For example, the portfolio of top-0.5% funds selected by LASSO can earn on average astonishingly 3.2-percent monthly return and 1.83 Sharpe ratio.

We also test whether our information set enables models to identify funds with persistent superior performance. Our results show that top-decile funds can persistently outperform the bottom-decile funds in the 12 months after their formation. Such results are pervasive for all models that we employ, including the simple linear model. Another test we conduct is calculating the transition matrix between monthly performance deciles, which enables us to identify funds

[4]Note that, mutual funds cannot be short, a long-short portfolio is helpful for gauging the efficacy of model forecasts, though is not practical as an investment strategy.

with superior and persistent skills.

We further perform a battery of robustness tests of machine-learning portfolio performance to various implementation choices. First, our results continue to hold if we apply a dynamic approach by expanding the training sample forward and reestimating the models whenever the portfolio is rebalanced. A dynamic approach allows for changes over time in the relation between fund characteristics and performance. Second, our results are robust to longer holding periods. Third, the long-only portfolios are still profitable after allowing for transaction costs.

We next try to understand the sources of the outperformance of our information set combined with machine learning. First, we show that information on sibling funds and family funds matter for the performance prediction. The omission of these two information sets largely lowers the model performance. However, we do not find the characteristics of a fund's stock holdings have predictive power for the fund's future performance, consistent with the finding in the U.S. (Kaniel et al., 2022). Second, consistent with the study in the U.S. market (Kaniel et al., 2022), we show that macro information matters for performance prediction in the Chinese market. As shown in our study, discarding macro variables from the information set lowers model performance. Third, we show that a fund's prior month excess return and its tracking error are the most important predictors in China, contrasting to the findings in the U.S. market that fund return momentum and fund flow are the most important predictors. Interestingly, a fund's prior month's excess return negatively predicts its performance, while such a relation is positive in the U.S. market. It thus implies a short-term reversal phenomenon in the Chinese mutual fund market, which is not recorded in America. Further, we show that the average prior month excess returns of sibling funds and family funds, respectively, are also important predictors, which positively predict the fund performance. Finally, we show that our models consistently pick out high-performing funds which are smaller, younger, of higher expense ratio, and more active.

We next try to understand the outperformance of machine-learning techniques by looking into model mechanisms. In particular, we are trying to unpack the black box of nonlinear machine-learning models (BRT and Neural network). We firstly show that nonlinear models do capture the nonlinear associations between fund characteristics and expected return, the interaction effects among fund characteristics, and the interaction effects between fund characteristics and macro variables. Next, we provide evidence that a large part of the outperformance of nonlinear machine-learning models over the simple linear model stems from the former's ability to identify the interaction effects between fund characteristics and fund size as well as macro variables. Specifically, we show that adding interaction terms of fund characteristics and fund size or interaction terms of fund characteristics and macro variables into the simple linear model significantly improves the model performance.

Finally, we study the behavior of mutual fund flows in China and investigate the drivers of fund flows. We show that investors in China do not react to our models' performance predictions. That is, investors pay no attention to our information set. Instead, they are significantly reacting to fund ratings. The finding is consistent with Ben-David et al. (2022)'s study on U.S. mutual fund investors. Employing Berk and Van Binsbergen (2016)'s methodology, we further show that Chinese mutual fund investors mainly rely on the fund rating.

Related literature. Our paper relates to four different strands of mutual fund literature. First, it contributes to the literature that documents associations between fund characteristics and performance. In Berk and Green (2004)'s model, investors supply the capital with infinite elasticity to funds they expect to outperform, based on historical performance, which further indicates that the fund performance (e.g., net alpha) is unpredictable given that there are diseconomies of scale in portfolio management. Nevertheless, much literature devotes to exploring mutual fund performance predictability by identifying high-performing funds using fund characteristics, such as fund size (Chen et al., 2004), fund fees and costs (Elton et al., 1993; Pástor et al., 2017, Bergstresser et al., 2008), fund flows (Gruber, 2011, Zheng, 1999; Lou, 2012). Extant literature has also established predictors using past returns of the focal funds, such as past one-year return (Hendricks et al., 1993), past alphas (Carhart, 1997, Mamaysky et al., 2007, Kacperczyk et al., 2014, Busse and Irvine, 2006) and R-squared (Amihud and Goyenko, 2013), and also past returns of other related funds (Cohen et al., 2005, Busse and Irvine, 2006, Hunter et al., 2014). Fund holdings have also been exploited to construct a variety of fund-level characteristics that have been shown to be able to predict fund performance, such as tracking error and active share documented in Cremers and Petajisto (2009), active weights (Doshi et al., 2015), risk shifting (Huang et al., 2011), return gap (Kacperczyk et al., 2008), industry concentration (Kacperczyk et al., 2005), cash holding (Simutin, 2014), among others. Other papers have successfully used the characteristics of underlying stocks including momentum (Grinblatt et al., 1995), size and book-to-market ratio (Chan et al., 2002), accruals (Ali et al., 2008), accruals quality (Nallareddy and Ogneva, 2017), alpha (Elton et al., 2011), tangibility (Gupta-Mukherjee, 2014), analysts recommendations (Kacperczyk and Seru, 2007), abnormal returns after earnings announcements (Jiang and Zheng, 2018), and mispricing factors (Avramov et al., 2020).

The staggering list of predictors that have been argued to possess forecasting power for fund returns implicates that there are facts that betray the conditions of Berk and Green (2004)'s model. For example, the empirical evidence regarding diseconomies of scale in portfolio management is mixed (Chen et al., 2004; Reuter and Zitzewitz, 2010; Pástor et al., 2015; Zhu, 2018). Also, frictions may prevent investors from driving fund performance towards zero (Dumitrescu and Gil-Bazo, 2018; Roussanov et al., 2021). Jones and Mo (2021) construct a comprehensive sample of 27 mutual fund predictors published in literature, though they find that the ability of fund characteristics to predict performance has declined over time due to increased arbitrage activities and mutual-fund competition. Our paper aims to predict fund performance by exploiting a large set of characteristics simultaneously. Compared to the extant literature, the main distinction of our characteristic set is the emphasis on the informativeness of related funds (sibling funds and family funds) which is missed in the existing studies.

Second, our paper is related to the growing literature that employs machine learning tools in empirical studies in the finance literature (see Karolyi and Van Nieuwerburgh (2020) and Masini et al. (2021) for a summary), such as predicting asset returns (Freyberger et al. (2020) and Gu et al. (2020) studying equity, Bianchi et al. (2021), Bianchi et al. (2021) bonds, Filippou et al. (2021) currencies and Wu et al. (2021) hedge funds), constructing robust stochastic discount factor with many characteristics (Kozak et al., 2020; Chen et al., 2019; Bryzgalova et al., 2020; He et al., 2021), estimating and evaluating risk factors (Lettau and Pelger, 2020; Kelly et al., 2019; Feng et al., 2020), among others. In the context of mutual funds, Pattarin et al. (2004), Moreno et al. (2006) and Mehta et al. (2020) employs machine learning to classify mutual funds by investment category. Chiang et al. (1996) and Indro et al. (1999) use neural networks to predict mutual-fund net asset value and return, respectively. More closely related to this paper, Li and Rossi (2020), DeMiguel et al. (2021) and Kaniel et al. (2022) study mutual fund performance with machine-learning techniques. Focusing on the Chinese mutual fund market, we find some interesting contrasting results compared with these studies concentrating on the US market. For example, fund return momentum is shown as the most important predictor in the U.S., while we find that short-term reversal in fund returns is the most important predictor in China. On the other hand, we record the consistent results with the U.S. market that characteristics of stocks that the fund holds have no predictive power and that macro information matters for performance prediction.

Third, our paper contributes to machine learning literature in emerging markets. Emerging markets have a relatively short history and some key features that distinguish them from the U.S. market. Though most empirical studies concentrate on the U.S. market, it is still worth conducting comparative research in emerging markets given their distinct market features. In this strand of literature, one representative is Leippold et al. (2022) who build and analyze a comprehensive set of return prediction factors using various machine learning algorithms in the Chinese stock market and documented distinguishing results from those in the U.S. market. We are the first to contribute to the research on mutual fund performance predictability in China by building a comprehensive set of fund characteristics.

Fourth, our paper fits into the large literature on mutual fund flows. Early work establishes that fund flows respond to fund returns (Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998); fund risk (Clifford et al., 2013, Huang et al., 2012), benchmark and name adoption (Sensoy, 2009). An important question is about the drivers of mutual fund flows. Barber et al. (2016) and Berk and Van Binsbergen (2016) answer the question by looking at which factor investors attend to when picking actively-managed equity mutual funds. They reach a similar conclusion that CAPM dominates any other factor models. More recently, however, Ben-David et al. (2022) show that fund flow data is most consistent with investors relying on fund ratings rather than any factor model. Following the statistical test in Berk and Van Binsbergen (2016), we conduct the horse race among fund rating, factor model alphas, and our model predictions. We show that investors in China mainly rely on the fund ratings rather than any other model.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 contains our main results. Section 4 concludes. A large amount of additional material on our data construction, estimation precedences, and additional robustness checks are placed in an online Appendix.

2 Data

Our sample contains actively-managed equity mutual funds spanning from January 2003 to January 2022. Following DeMiguel et al. (2021), we perform the analysis at the share-class level to keep the analysis as close as possible to the actual selection problem faced by investors. Put differently, we do not aggregate the different share classes of a fund and treat them as individual funds [5]. We do not filter our sample to avoid our results being prone to sample selection or data snooping (cautioned by e.g., Lo and MacKinlay (1990)) and also assuage the overfitting problem by increasing the ratio of observation count to parameter count. In total, our sample contains 3153 unique share classes with share-month observations amounting to 131846. All related data is downloaded from WIND and CSMAR, both of which are reliable Chinese financial research databases.

2.1 Fund Characteristics

We construct a large set of fund-level characteristics in three steps.

Step 1 - Share Information Set. We search for the literature and collect 33 fund characteristics that possess predictive power of fund performance in the U.S. mutual fund market. Table 1 provides abbreviations and descriptions for all signals. Online Appendix A contains details on the constructions of each predictor. In the following sections, we dub the 33 signals as *Share Information Set (SIS)*.

Step 2 - Family and Manager Information Set. We next extend a fund's information set by incorporating the information of its sibling and family funds. The idea aligns with the intuition in Pástor and Stambaugh (2002) that characteristics of related funds to a given fund can be informative about the skill of that fund.

Specifically, for a given fund and a signal, we average the signal values of the fund's sibling equity mutual funds (managed by the same manager), using the fund's total net asset as weights. Therefore, we construct additional 33 fund-level characteristics, which we name as *Man-*

[5] The return discrepancy of diverse share classes of a fund comes from the different charging methods. The short name of a mutual fund tells the fund's charging method through the capital letter at the end of the name. In general, class-A share charges front-end fees for purchase while class-B share charges back-end fees or redemption. In recent years, the class-C share is growing rapidly. Different from class A and B which charge at once, C charges a sale-service fee on a daily basis and charges no purchase and redemption anymore.

ager Information Set (MIS). Similarly, we generate another bunch of fund-level characteristics by value-weighted averaging the signal values of a given fund's family equity mutual funds signal-by-signal and name as *Family Information Set (FIS)*.

In the Online Appendix A, we report the percentage of fund-month observations in which the fund is under the management of a family (manager) who simultaneously runs a bunch of funds. In our sample, we have over half (53.3%) of the observations in which the fund has sibling funds and nearly all (97.5%) of observations in which the fund has family funds.

Step 3 - Holding Information Set. We further enlarge a fund's information set by looking into the stocks that the fund holds. Literature (Green et al., 2017; Hou et al., 2020) recorded a staggering list of equity characteristics to predict equity performance. Therefore, it is appropriate to incorporate the stock-level information based on the fund holdings.

Since the set of stock characteristics is far larger than that of fund characteristics, we do not employ all of them and instead artificially choose a subset. Specifically, we sort individual stocks into quintiles by univariate stock characteristics and compute sharpe ratio of the long-short portfolio. Then, we pick out the 33 stock characteristics with the highest sharpe ratios, as listed in Panel (B) of Table 1.

For each stock characteristic, to construct the fund's exposure, we take the value-weighted average of the characteristic values of stocks that the fund holds, using the relative weight of the fund's stock portfolio as weights. We dub these 33 fund exposures as *Holding Information Set (HIS)*. [6].

In total, our fund information set consists of 132 (33×4) fund-level characteristics. In the Online Appendix A, we report the summary statistics of all fund characteristics. Note that, the average monthly Carhart (1997) alpha of Chinese actively-managed equity mutual funds is 43 basis points, which is economically and statistically significant. As a comparison, the average of monthly Carhart (1997) alpha of the U.S. active equity mutual funds, as recorded in Kaniel et al. (2022), is nearly zero (-3 bps). Another striking observation is that the average annual turnover

[6] Most of the stock characteristics are released to the public with a delay. To avoid the forward-looking bias, we follow Gu et al. (2020)'s convention that, when computing results for the month $t+1$, we use monthly characteristics measured as of month t, quarterly characteristics measured by the end of the month $t-4$, and annual characteristics measured by the end of the month $t-6$. Regarding missing characteristics, we replace them with the cross-sectional median at each month for each stock, respectively. Finally, we conduct industry neutralization for each stock characteristic by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation within each industry.

ratio of Chinese active equity funds is up to 300%, compared to 82.6% of the U.S. active equity mutual funds (Kaniel et al. (2022)). It implies that Chinese active equity fund managers on average rebalance the whole portfolio every four months

2.2 Macroeconomic Variables

Our choice of macroeconomic variables is similar to Kaniel et al. (2022), including investor sentiment (Baker and Wurgler, 2006) and Composite Index of Leading Economic Indicators (CILEI), a series which captures the state of the macroeconomy [7]. We plot the time series of the two macroeconomic variables in Figure 1 and notice that they are not highly correlated (correlation coefficient $\rho = 0.05$).

2.3 Predicting Target

Our predicting target is the normalized ranking of monthly fund return in excess of one-month risk-free rate [8]. Specifically, we rank cross-sectional fund excess return period-by-period and map these ranks into [-1,1] and set missing values to the cross-sectional median of zero. Different from DeMiguel et al. (2021) and Kaniel et al. (2022) who set fund alpha as the predicting target, we use fund excess return as the target due that it is more straightforward while using fund alpha as the target could be biased to the choice of benchmark factor models and introduce the potential estimation error. In unreported results, we show that our results are qualitatively and quantitatively similar when we use monthly fund excess return as predicting target.

The predictors are the Share, Family, Manager, and Holding Information Set combined with two macroeconomic variables. All fund-level characteristics (i.e., the four information sets) are firstly converted to monthly frequency by using the most recent available data for each month. Then, following Kelly et al. (2019) and Freyberger et al. (2020), we cross-sectionally rank all characteristics period-by-period and map these ranks into [-1,1] and set missing characteristic values

[7] CILEI is a composite of 12 economic indicators including personal income, personal composition expenditure, national association of purchasing manager, durable orders, industrial production, capacity utilization, retail sales, consumer credit, housing start and building permits, construction spending, consumer price index and producer price index.

[8] Our risk-free rate data is downloaded from the website https://www.factorwar.com/data/factor-models/. Specifically, the risk-free rate is set as the interest rate of three-month fixed bank deposits before July 2002, the coupon rate on three-month central bank bills from August 2002 to September 2006, and Shanghai Three-month Interbank Offered rate since October 2006

to the cross-sectional median of zero.

3 Results

3.1 Univariate Sorting

As an initial step, we test how each fund characteristic relates to mutual fund performance. For one thing, we aim to check the robustness of the predictability of each predictor recorded in the U.S. mutual fund market. For another, it offers us the initial sense of which information sets (SIS, MIS, FIS, and HIS) is most useful by simply counting the number of statistically significant predictors within each information set.

For each characteristic, we sort funds into quintiles based on the value of the characteristic at the end of the month t. Then, we form a long-short portfolio that long the top quintile portfolio and short bottom quintile TNA-weightedly and hold it in month $t+1$. Through the monthly rolling procedure, we obtain time series of the long-short portfolio returns. We report the sign and absolute value of monthly return, monthly sharpe ratio and Carhart (1997) four-factor alpha of univariate sorted portfolios in Table 2, ranked by sharpe ratio. The stars report the significance of a test that the mean of the long-short portfolio return is different from zero. Another thing to remind is that we use the notation 'f', 'F' and 'M' to help differentiate the fund characteristics sorted into share, family, and manager information sets, respectively. To save space, we only present some of the results. A complete table is in the Online Appendix B.

We want to highlight two findings. First, though the signs are mostly consistent with the documents in the U.S., the statistical significance only exists in a small part of the characteristics. It could be due to the institutional environment distinctions between the Chinese and U.S. mutual fund market. Also, the increased arbitrage activity and mutual-fund competition could also partially explain the worse out-of-sample performance of fund predictors which are recorded in the earlier U.S. market in the Chinese mutual fund market. Second, as shown in Figure 2, the numbers of statistically significant predictors in share, family, and manager information sets are evenly matched. However, few of fund characteristics in the holding information set are statistically significant. This foreshadows the results in our main analysis that either of share, family, and manager information sets play an independent role in predicting the fund performance while holding information set cannot help predict the fund performance.

Interaction Effects with Macro Variables As Kaniel et al. (2022), we also find interaction effects between fund characteristics and macroeconomic variables. Table 2 report the performance of univariate sortied long-short portfolios, conditional on the level of CILEI [9]. Specifically, we split the sample into two parts based on the value of CILEI in the prior month, in which high (low) CILEI consists of the sample with CILEI higher (lower) than the median level. It is shown that the associations between the fund return and some characteristics such as family excess return, family realized alpha and manager prior-month return are stronger in above-median CILEI periods, while some characteristics, like manager TNA, have significant associations with fund returns only in below-median CILEI periods.

3.2 Machine Learning Algorithm

Sample Partitioning In the Online Appendix A, we plot the time series of the number of actively-managed equity mutual funds and fund-month observations in our sample (Figure A.1). It shows that the observations have experienced exponential growth in recent years. Therefore, it is more appropriate to partition the sample based on the observation length rather than the time length. We split the full sample into three subperiods with the same length of observations, of which two of the periods are used to train and tune the models and the third one is for out-of-sample evaluation.

In-Sample Estimation Essentially, our training procedure is estimating the parameter vector $\vec{\theta}$ of the following model:

$$r_{i,t+1} = F(\mathbf{X}_{i,t}; \vec{\theta}) + \epsilon_{i,t+1}$$

where $r_{i,t+1}$ is the predicting target and $\mathbf{X}_{i,t}$ is one-month-lagged fund information set. F is a model which takes the linear or nonlinear functional form of input variables. As a tradition, we consider the simple linear model which is the inner product of input variables and estimating parameters. Faced with high-dimensional information set and also potential nonlinear associations and interaction effects, we adopt machine-learning techniques including two advanced linear model

[9]See Table B.1 in the Online Appendix B for the interaction effects between investor sentiment and fund predictors.

(LASSO and PLS) and four nonlinear models (Boosting Regression Trees and Neutral Networks with 1 3 hidden layers). In the Online Appendix C, we provide the details of model descriptions.

Cross-Validation To tune the hyper-parameters of machine-learning models, we use time-series cross-validation which reserves the last quarter of the training sample for validation. Table C.1 in the Online Appendix C makes a summary of the decision of hyper-parameters for each machine-learning model.

Out-of-sample Prediction Having estimated the model, we form the model's prediction of fund performance at the end of each month in the testing period using the estimated model and new information in that month. We sort funds into deciles based on the predicted fund performance. We then long and hold the top-decile funds in the next month.

3.3 Optimal Prediction

Weighting Schemes To form the fund portfolio, we take several weighting schemes: equal-weighted, value-weighted using fund's total net asset as weights, and value-weighted using the model prediction as weights [10]. In particular, as argued by Kaniel et al. (2022), the prediction weights exploits the heterogeneity in the prediction and assigns a higher relative weight to predictions that deviate form the center of the decile.

Figure 3 shows the out-of-sample performance of top-decile portfolios by different weighting schemes for each estimated model. Consistent with DeMiguel et al. (2021), we find that the TNA-weighted portfolio underperforms the equal-weighted portfolio, which implies that the average dollar invested in active funds earns lower (risk-adjusted) returns than the average fund. Further, consistent with Kaniel et al. (2022), we find that a prediction-weighted approach raises higher portfolio performance. We use model predictions to form portfolio weights for the rest of the paper.

Performance Spread Our first essential question is can our information set help differentiate high-performing from low-performing funds.

[10] We follow Kaniel et al. (2022) to define the relative weights by shifting and scaling weights: $\tilde{\mu}_{i,t} = \hat{\mu}_{i,t} - \min_{i \in \text{Top}} \left(\hat{\mu}_{i,t}\right)$, where μ are the predictions of models. For top-performing funds, we subtract the smallest model prediction within the group to ensure that the top portfolio is a long-only portfolio. Then, we scale the values to sum up to 1, i.e., $w_{i,t}^{\text{pred}} = \frac{\tilde{\mu}_{i,t}}{\sum_{i=1}^{N} \tilde{\mu}_{i,t}}$.

At the end of each month in the testing period, we sort mutual funds according to model predictions into deciles, then long the top group of funds and short the bottom group of funds value-weighted, using the normalized prediction values as weights. Table 3 reports the monthly out-of-sample performance of long-short fund portfolios. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). We find that, for each model, the predicted portfolio D10 significantly outperforms the portfolio D1. In particular, machining-learning models perform much better than the simple linear model in differentiating the high from low-performing funds.

We plot the out-of-sample cumulative return of top-decile, mid-decile and bottom-decile fund portfolios predicted by models in Figure 4. We observe the apparent performance spreads between different decile portfolios for each model. It implies that our information set indeed helps differentiate high-performing from low-performing funds.

Abnormal Performance Can our information set help identify funds with superior skills over the average fund market? If yes, such outperformance reflect compensation for risk or a true abnormal performance?

To begin, we define the fund market as the equal-weighted or TNA-weighted average of all actively-managed equity mutual funds. Therefore, the fund market portfolio is defined as a portfolio that long all active equity funds. We then construct a long-short portfolio that long the model-predicted top-decile fund portfolio and short the fund market portfolio. Table 3 reports the out-of-sample performance of the long-short portfolios as well as their exposures to Carhart (1997)'s four risk factors.

The average raw return of long-short portfolio for each model is positive and economically and statistically significant. Even for the simple linear model, we show that its predicted top-decile fund portfolio outperforms the fund market portfolio by 44 bps on a monthly average. Among all models, LASSO makes the best prediction noticing that its predicted top-decile fund portfolio outperforms the fund market portfolio the most, amounting to an average of 100 bps per month.

All long-short portfolios earn economically and statistically significant abnormal returns relative to Carhart (1997)'s four-factor model. Moreover, a large fraction of long-short portfolio performance cannot be explained by the four risk factors since the regression R-squares are below 50%.

To sum, the results indicate that our fund information set helps identify funds with superior skills over the average fund market and such outperformances are not just compensation for exposure to standard risk factors.

Performance Persistence Literature consistently shows that active equity funds lack performance persistence (e.g., Blake et al. (1993), Malkiel (1995), Carhart (1997)). Can our information set help identify funds with superior and persistent skills?

To test the performance persistence of model-predicted fund portfolios, we track their performances in the following year after their formation. In detail, at the end of each month t in the testing period, we sort all funds into deciles based on the model predictions and track the portfolio performance for one year ($t+1$ to $t+12$). Following Wermers (1999), we then average performance for $t+N$ (N=1,2,..., 12) across all formation period t. In Table D.7, D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). Within the year after formation, the funds in the top group perform better than the bottom group most of the time (months). For example, the monthly excess return difference between the top group (D10) and bottom group (D1) predicted by LASSO is positive 11 out of 12 months, with a monthly average value of 42 basic points.

As an alternative test, we draw a transition matrix demonstrating the probability a fund transfer from one decile to another decile. Specifically, at the end of each month t in the testing period, we sort mutual funds according to model predictions into deciles. We then calculate how many percentages of funds in decile i of the month t fall into decile j of the month $t+1$. Finally, we obtain the value of cell (i, j) by averaging the corresponding values across all months. In Figure 5, a flush slopes down to the right indicating that the winners selected by our models will most likely continue to be winners in the following months. In the Online Appendix D, we further show the results with longer horizons, that is, how many percentages of the fund in decile i of the month t fall into decile j of the month $t+N$ (N=3, 6, 12). Though the flush pattern turns weaker, we still observe that winners tend to be players that perform above average.

To sum, our information set can identify funds with superior and persistent skills.

Machine Learning v.s. Simple Linear Model So far, we have shown that our large information set can consistently help differentiate high-performing from low-performing funds and identify funds with superior and persistent skills. Based on our information set, even the simple linear model which is not fit into high-dimensional problem and ignores potential nonlinear relationship and interaction effects outperforms the fund market. Can machine-learning techniques more efficiently use the information set than the simple linear model? Table 5 reports the out-of-sample monthly return difference between machine-learning predicted top-decile fund portfolio and simple-linear-model predicted top-decile fund portfolio. LASSO, PLS, BRT and Neural Network with 2 hidden layers economically and statistically significantly outperform the simple linear model. Again, LASSO performs the best which outperforms the simple linear model by 56 bps per month.

Robustness Our results are robust to the number of groups that we divide into, portfolio holding horizons, different measures of fund performance and considering the transaction costs. In the Online Appendix E, we provides more details of our robustness results.

3.4 Variable Importance

Our metric of variable importance is based on the average squared gradient of the model prediction. Following Kaniel et al. (2022), the metric for variable j is defined as:

$$SSD_j = \sum_{i,t \in \mathcal{T}_1} \left(\frac{\partial g(z;\theta)}{\partial z_j} \Big|_{z=z_{i,t}} \right)^2$$

where z_j denotes the j^{th} element of input variables, and g is the fitted model with parameter vector θ. We measure SSD within the training sample, $\mathcal{T}$. The higher the SSD for a variable, the larger effect the variable has on the model prediction. We compute the SSD for each variable and for each model. The final importance measure of a variable is the average of its SSD values over all models.

In Figure 6, we demonstrate the variables of top importance. A complete list is in the Online Appendix F. In shows that investor sentiment is the most important variable, followed by family prior-month excess return, fund tracking error, fund prior-month excess return, and manager prior-month excess return. Among all listed top important variables, variables in the manager information set accounts for the most.

Which Information Set Is Most Useful? Following Kaniel et al. (2022), we estimate models using each information subset (Share, Family, Manager and Holding Information Set). We also estimate models using four information subsets without macro information. We quantity the economic benefit of each information subset by averaging the out-of-sample performance of long-short decile portfolios over all estimated models (Table 7).

Intuitively, the models estimated using all information (four information subsets and macro information) achieve the best out-of-sample performance, with an average annual return of the long-short portfolios of 6.7 percent and sharpe ratio of 1.43. Discarding the macro information makes the performance decline by a lot. In particular, the average sharpe ratio of the long-short portfolios drops from 1.43 to 0.89.

Manager Information Set is most useful among four information subsets. The average sharpe ratio of long-short portfolios predicted by models estimated using manager information set is 0.57, higher than that using share information set (0.49) and family information set (0.37). However, we do not find holding information set contributes positive economical benefit. Instead, we show that the average sharpe ratio of long-short portfolios predicted by models estimated using holding information set is negative (-0.41).

Characteristics of Superior Funds How superior funds predicted by our models look like? In particular, we focus on some fund attributes such as age, size, expense ratio and several fund trading activeness measures such as active share (Cremers and Petajisto (2009)), active weight (Doshi et al. (2015)) and return gap (Kacperczyk et al. (2008)).

We sort funds into quintiles according to model predictions each month. Then, we calculate the mean values of fund characteristics of each quintile portfolio and average across all months. In Table D.9, Q1 (Q5) represents the quintile portfolio containing funds that are expected to perform the worst (best). All models identify similar patterns, that is, funds that are expected to perform the best (Q5) are younger, smaller, more active, and of higher expense ratio than funds expected to perform the worst (Q1). Our findings are consistent with Kacperczyk et al. (2014), who also show that superior funds tend to be younger, smaller, more active, and of higher expense ratio.

Some Comparisons with the U.S. Literature We make some meaningful comparisons between our results in the Chinese mutual fund market and results in the U.S. market.

First, we find that fund tracking error and prior month excess return are the most important predictors in China. Kaniel et al. (2022) show that, in the U.S. market, fund momentum and fund flow are the most important predictors (Panel B of Figure 6). Moreover, as shown in Figure 6, fund prior-month excess return is an important predictor in both Chinese and U.S. market. Interestingly, it negatively predicts the fund performance in China (Table 2), while such relation is positive in the U.S. market (Kaniel et al. (2022)). It thus implies a short-term reversal phenomenon in the Chinese mutual fund market, which is not recorded in America. To sum, the environment differences between these two markets may induce such distinctions. More formal researches are worthy doing in the future.

Second, we find that macro information matters for fund performance predictions in the China, consistent with Kaniel et al. (2022)'s results in the U.S. market. Kaniel et al. (2022) also recorded that the average characteristics of a fund's stock holdings have little predictive power for the fund's future performance in U.S. market, which is also documented by us in the Chinese market. Interestingly, Li and Rossi (2020) show that, in the U.S. market, it is feasible to select funds using their holding information on the prominent stock anomalies.

Third, we find that the superior funds predicted by our models are younger, smaller, more active, and of higher expense ratio. Our findings are consistent with Kacperczyk et al. (2014) who also show that superior funds tend to be younger, smaller, more active, and of higher expense ratio.

3.5 Model Mechanisms

In this section, we aim to partially disentangle the economic mechanism of nonlinear machining models. We first show that the nonlinear associations and interaction effects are successfully captured by nonlinear models such as boosting regression trees (BRT) and neural networks (NNs).

We further show that interaction effects are the main enablers of the outperformance of nonlinear models over the simple linear model.

Nonlinear Associations Figure 7 traces out the model-implied marginal impact of fund characteristics on expected fund excess return. Following Gu et al. (2020), the data transformation normalizes characteristics to the [-1,1] interval, and holds all other variables fixed at their median value of zero. The vertical axis is the normalized ranking of model-predicted fund performance. To simplify our work, we choose the most important characteristic in each information subset, including fund tracking error, manager prior-month excess return, family prior-month excess return, and fund exposure to stock's depreciation and amortization per share (*d&a_pr*).

Not surprisingly, the simple linear model detects linear association while BRT and NN3 detect nonlinear predictive associations. In particular, neural networks detect a convex association and BRT portrays an irregular stair-stepping-like association.

Interaction Effects The exploration of the interaction effects is vexed by vast possibilities for identity and functional forms for interacting variables. Focuing on black-box-like NN3 model, we document a handful of interaction effects of fund total net asset and fund age with our four selected characteristics.

In Figure 8, we depict how expected fund returns vary as we simultaneously vary values of a pair of characteristics over their support interval [-1,1] while holding all other variables fixed at their median value of zero. We show the interactions of fund total net asset with our four selected fund characteristics in the first four subgraphs and the interaction of fund age with these four characteristics in the last four subgraphs. The association between tracking error and fund performance is more pronounced within large funds. Among small funds, the relation is slightly convex. Likewise, the interaction effect is also documented in the association between *d&a_pr* and fund performance. For funds with larger TNA, the sensitivity of their expected return to this variable tends to be smaller. We do not find the interaction effect of fund TNA with family or manager prior-month excess return, observing that all curves can be vertically shifted from each other. However, we do document their interactions with fund age. For older funds, the sensitivity of expected return to the manager prior-month excess return (family prior-month excess return) is smaller (larger). Instead, we find no interaction with fund age for tracking error and *d&a_pr*.

Figure 9 illustrates interactions between fund characteristics and macro variables. Among our two macro variables (investor sentiment and CILEI), we find remarkable interaction effects between fund characteristics and CILEI. For example, when CILEI is high, the relationship between tracking error and fund performance is negative, which is positive during low CILEI. *d&a_pr* positively (negatively) relates to the fund performance during the period with high (low) CILEI.

Augmented Linear Model Though we have confirmed the ability of nonlinear models to capture nonlinearity and interactions, we still cannot draw a conclusion that they contribute to the outperformance of nonlinear models over the simple linear model. Further evidences are required.

We design several augmented linear models which add additional terms to the simple linear model. The trials of adding new terms are uncountable. We only consider several trials. For example, we add quadratic terms for each fund characteristic due to the convex associations that we record. We also consider adding iteration terms between fund characteristics and fund TNA (age) and iteration terms between fund characteristics and macro variables.

Table 9 reports the out-of-sample top-decile fund portfolio performance predicted by augmented linear models. We find that when adding interaction terms between fund characteristics and fund TNA, the sharpe ratio of the long-top portfolio increases. For example, the portfolio that goes long top-decile funds predicted by the augmented linear model earns an out-of-sample monthly return of 217 bps with a sharpe ratio of 1.59, compared to 208 bps and 1.57 for the simple linear model. The improvement is more prominent when we divide funds into more groups. The sharpe ratios of long top-2%, top-1%, and top-0.5% funds predicted by the augmented linear model are 1.56, 1.61, and 1.70, respectively, either of which is higher than those of fund portfolio predicted by the simple linear model (1.48, 1.45 and 1.38 for top-2%, 1%, and 0.5%). Similar improvement occurs when we augment the simple linear model by adding interactions between fund characteristics and macro variable CILEI. Lastly, we do not record any enhancement for linear models augmented with quadratic terms of fund characteristics.

To sum up, we show that the detection of interaction effects by nonlinear models indeed heightens the model performance.

3.6 Investors Reaction

Given the results that our information set can help identify the funds with superior skills. One interesting question is do investors react to the model predictions?

We calculate monthly net fund flow as the difference between total net asset growth rate and net value growth:

$$\text{Flow}_{\,i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + r_{i,t}) \tag{1}$$

where $TNA_{i,t}$ is the total net asset of fund i at the end of month t, and $r_{i,t}$ is i's return in month t.

In addition to the model predictions in this paper, we also include the fund ratings and several classic factor model alphas as indicators for the fund flow. We run the following panel regression of fund flow on one-month-lagged indicators:

$$\text{Flow}_{\,i,t} = intercept + Indicator_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where $Indicator_{i,t-1}$ contain fund ratings, CAPM alpha, Fama and French (1993) alpha, Carhart (1997) alpha, and our model predictions. Our regressions consider the time and entity fixed effects. The calculation of standard errors considers the cluster of time and entity.

In Table 10, we report the univariate regression results in Column 1 to 11. We find that investors significantly and positively react to fund ratings and the factor-model alphas. However, none of our model predictors help predict the fund flow. That is, investors do not react to any of our model predictions. It implies that our information set has not been reacted by the investors yet.

Considering that the indicators could be highly related, we run the multivariate regression in which all indicators are on the right side (columns 12). After controlling for other indicators, only fund rating exhibits positive and significant predictive power for fund flow. Put differently, investors only react to fund ratings. Neither factor model alphas nor our model predictions help predict the fund flow. Our findings are consistent with Ben-David et al. (2022) who studied the U.S. investors and showed that they rely on the Morningstar ratings heavier than any other factor models. We show that Chinese mutual fund investors mainly rely on fund ratings.

Institutional Flow v.s Retail Flow We further differentiate the institutional investors and retail investors on how they react to different indicators. To formally determine which indicators investors are mainly depending on, we conduct the horse race test proposed by Berk and Van Binsbergen (2016).

To explain the methodology, let $Flow_{i,t}$ denote fund flow of fund i during month t and $\mathcal{I}_{i,t-1}$ denote the indicator of fund i at the end of mouth $t-1$, then run the following panel regression:

$$\phi\left(F_{low_{i,t}}\right) = \beta_0^{\mathcal{I}} + \beta_1^{\mathcal{I}} \phi\left(\mathcal{I}_{i,t-1}\right) + \epsilon_{i,t} \tag{3}$$

where $\phi(flow_{i,t})$ and $\phi(\mathcal{I}_{i,t-1})$ is the sign which takes on values of {-1,1}. Then a linear transformation of the regression slope, intuitively, is directly related to the frequency in which the indicator and flow sign match each other:

$$\frac{\beta_1^{\mathcal{I}}+1}{2} = \frac{\mathcal{P}\left(\phi\left(\text{ Flow }_{i,t}\right)=1 \mid \phi\left(\mathcal{I}_{i,t-1}\right)=1\right)+\mathcal{P}\left(\phi\left(\text{ Flow }_{i,t}\right)=-1 \mid \phi\left(\mathcal{I}_{i,t-1}\right)=-1\right)}{2} \tag{4}$$

To test the significance of outperformance, we further conduct pairwise indicator horse races. For any two indicators $\mathcal{I}_1$ and $\mathcal{I}_2$, run regression:

$$\phi(Flow_{i,t}) = \gamma_0 + \gamma_1\left(\frac{\phi(\mathcal{I}_{i,t-1}^1)}{\hat{var}(\phi(\mathcal{I}_{i,t-1}^1))} - \frac{\mathcal{I}_{i,t-1}^2}{\hat{var}(\phi(\mathcal{I}_{i,t-1}^2))}\right) + \xi_{i,t} \tag{5}$$

where $\hat{var}$ is sample variance. Then $\mathcal{I}_1$ is considered a better indicator of fund flow than $\mathcal{I}_2$ if $\gamma_1 > 0$ with statistical significance.

Our indicators include fund ratings, CAPM alpha, Fama and French (1993) 3-factor model alpha, Carhart (1997) 4-factor model alpha, and our model predictions.

To make the fund rating indicator have a sensible sign (-1 or 1), we consider investors will increase allocation to funds with ratings $\geq i$ and decrease allocation to those with ratings $< i$, then the variable $rate \geq i$ has value of 1 for funds with ratings $\geq i$ and -1 for funds with ratings $< i$. Here, I choose $i = 4$. Our fund rating data is from Jian Fintech Corporation.

We estimate regression (3) for individual and institutional fund flow respectively. Following Berk and Van Binsbergen (2016), we double cluster standard error by fund and time. The estimates of $\frac{\beta_1+1}{2}$ are shown in the first column of Table 11. Consistent with Ben-David et al. (2022), we show that fund rating is the best measure of predicting the direction of individual fund flow in China. This measure has individual investors reallocating money into over four-star funds, gets the sign of flows right 62% of the time. Interestingly, we document distinct findings for institutional investors. Among all indicators, the complex nonlinear neural networks win the horse race, which gets the sign of institutional fund flow right 55% of the time and outperforms the fund rating and any other models. The statistical evidence is also shown in Table 11. For individual investors, fund rating significantly outperforms any other models. In stark contrast, neural networks dominate in predicting the institutional fund flow.

4 Conclusion

We add to the research on mutual fund performance predictability in China by building a comprehensive set of fund characteristics. Combined with machine learning, our information set can consistently differentiate high from low-performing mutual funds, and identify funds with persistent superior performance.

Our results are consistent with the studies in the U.S. market in several aspects. Firstly, we all show that the characteristics of stocks that fund holds are not predictive of the fund performance. Secondly, we agree that macro information matters for performance prediction.

However, we also document some contrasting results. For example, Kaniel et al. (2022) records that the most important predictors in the U.S. market are fund momentum and fund flow, while we record that the most important predictors in China are fund short-term reversal and fund tracking error. Such difference could be attributed to the feature differences between the Chinese and the U.S. mutual fund market.

Moreover, as DeMiguel et al. (2021) shows that mutual-fund characteristics alone are enough to predict positive alpha in the U.S., we suggest that the addition of information about sibling and family funds can largely improve the model performance in China. It is worth applying the idea in the U.S. market and testing its contribution on the fund performance predictability.

From the practitioners' perspective, our study also inspires that the incorporation of machine-learning techniques as new tools can help investors benefit from active management. With the booming of China's mutual fund industry, more data is available for the AI algorithms applied to the Robo-advisor for fund investment.

This paper focuses on actively-managed equity mutual funds. It is worthy of further study on bond mutual funds, AI-driven fund allocation, etc.

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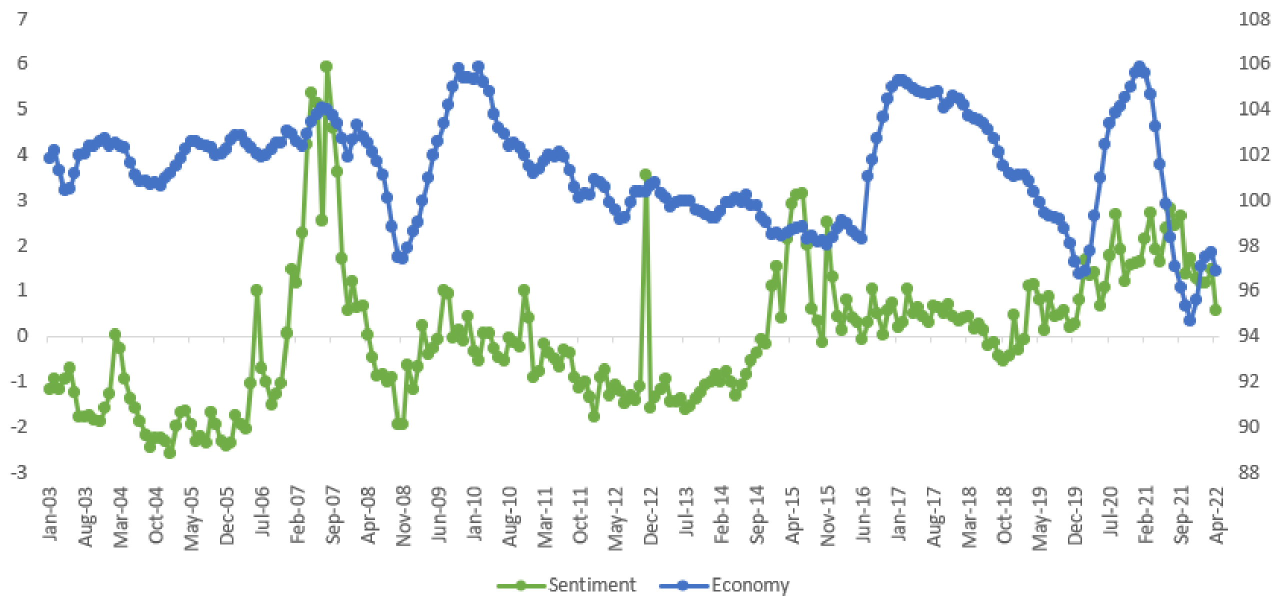


Figure 1: Macroeconomic time series plots

This figure shows the macroeconomic time series plots. The primary y-axis plots Baker and Wurgler (2006) investor sentiment and the secondary y-axis plots Composite Index of Leading Economic Indicators (LICEI).

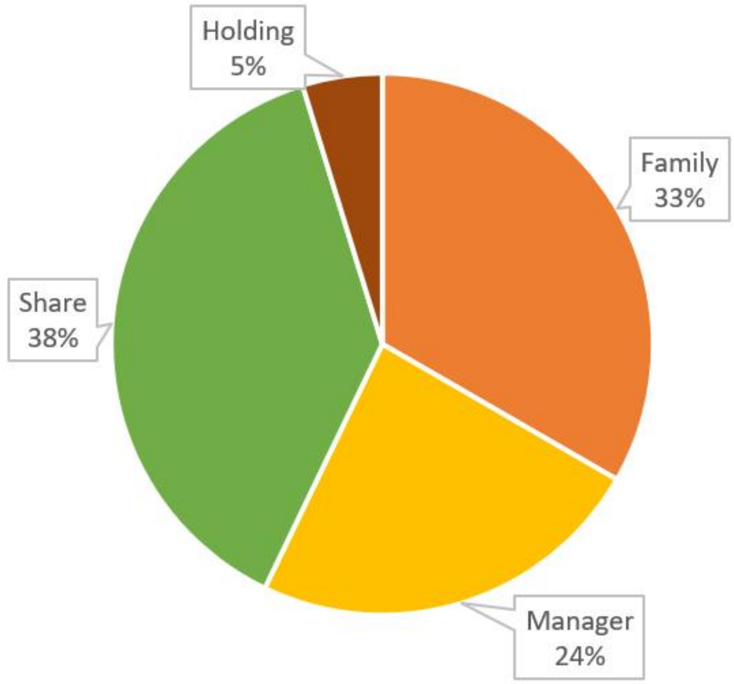
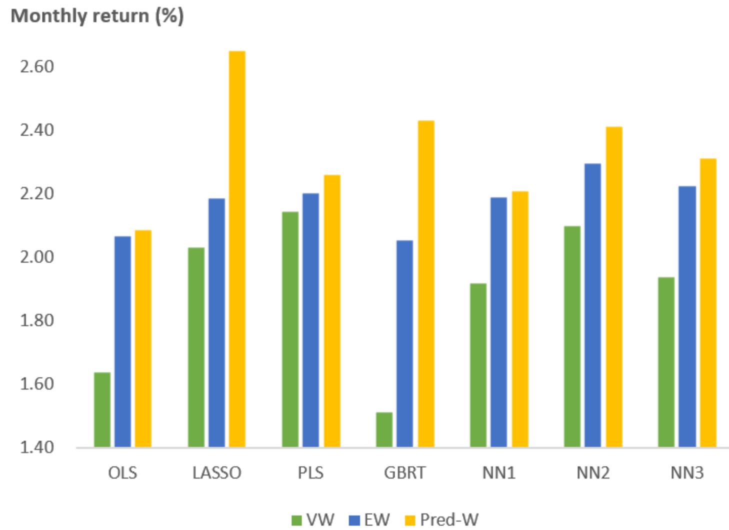
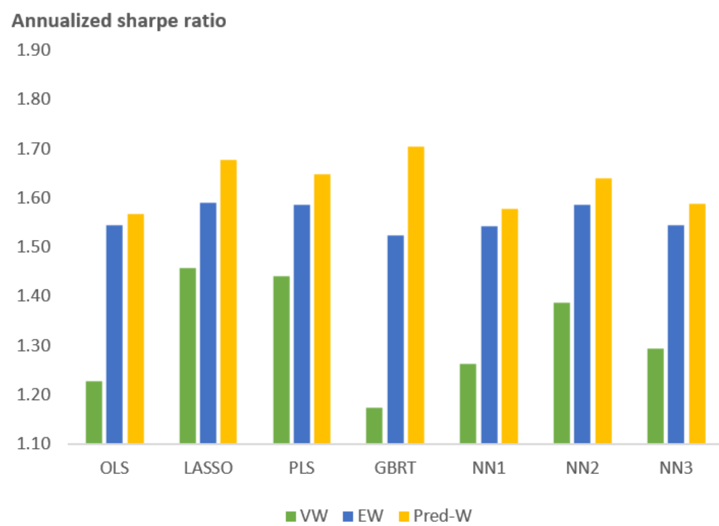


Figure 2: Variable significance in different fund information subsets

This figure shows the proportion of number of fund characteristics that have significant predictive power for fund performance in share, family, manager and holding information set to total number of significant fund characteristics.



(a) Monthly return



(b) Annualized sharpe ratio

Figure 3: Out-of-sample performance of top-decile portfolios by different weighting schemes This figure shows the out-of-sample performance (monthly return in panel (a) and annualized sharpe ratio in panel (b)) of long-top fund portfolios predicted by simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.). For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into quintiles, then long the top quintile of funds. We consider multiple weighting schemes including equal-weighted, and value-weighted using the normalized fund total asset value as weights and value-weighted using the normalized prediction values as weights. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

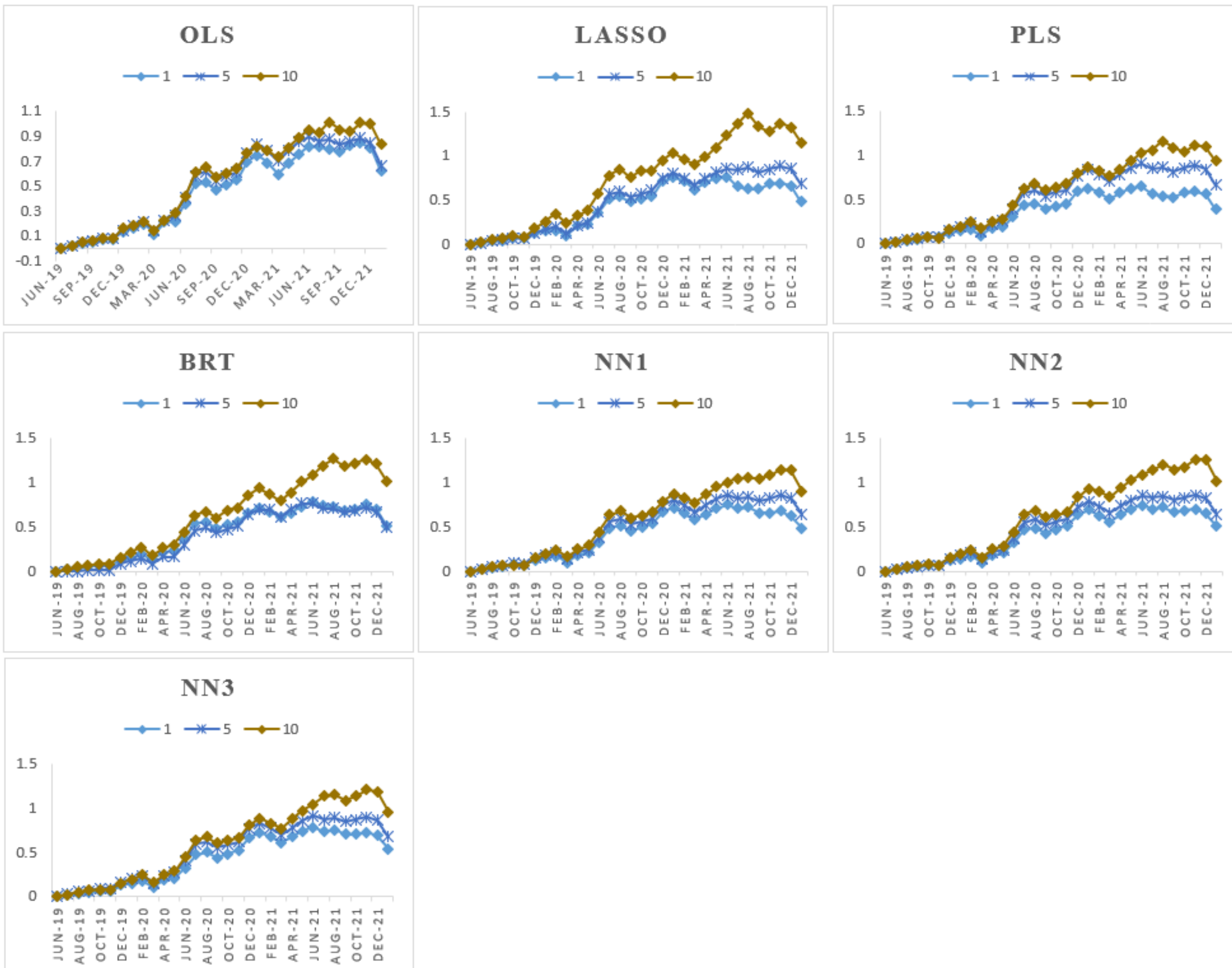


Figure 4: Performance spread predicted by models

This figure shows the cumulative returns of top-decile, mid-decile and bottom-decile fund portfolios predicted by models.

OLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.55	0.21	0.10	0.05	0.03	0.02	0.02	0.01	0.01	0.00
2	0.21	0.26	0.20	0.11	0.08	0.06	0.04	0.03	0.02	0.02
3	0.10	0.18	0.19	0.17	0.12	0.09	0.06	0.04	0.03	0.02
4	0.06	0.13	0.17	0.18	0.16	0.12	0.08	0.06	0.04	0.02
5	0.04	0.09	0.12	0.15	0.17	0.15	0.12	0.08	0.05	0.03
6	0.03	0.06	0.09	0.12	0.15	0.16	0.15	0.11	0.08	0.04
7	0.02	0.04	0.06	0.08	0.12	0.16	0.16	0.17	0.12	0.07
8	0.01	0.03	0.04	0.06	0.08	0.12	0.16	0.21	0.18	0.11
9	0.01	0.02	0.03	0.04	0.06	0.08	0.12	0.19	0.26	0.21
Winner	0.01	0.01	0.02	0.03	0.03	0.04	0.06	0.10	0.21	0.51

LASSO

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.20	0.15	0.11	0.06	0.05	0.05	0.06	0.09	0.10	0.12
2	0.13	0.15	0.14	0.10	0.06	0.06	0.07	0.09	0.10	0.10
3	0.10	0.12	0.17	0.16	0.06	0.06	0.08	0.09	0.09	0.07
4	0.06	0.09	0.11	0.25	0.14	0.07	0.08	0.08	0.06	0.06
5	0.05	0.07	0.08	0.10	0.35	0.09	0.07	0.07	0.06	0.04
6	0.04	0.06	0.07	0.07	0.10	0.39	0.09	0.07	0.07	0.04
7	0.06	0.07	0.08	0.08	0.07	0.12	0.26	0.10	0.09	0.07
8	0.08	0.09	0.08	0.07	0.06	0.07	0.14	0.20	0.12	0.10
9	0.12	0.11	0.08	0.07	0.05	0.05	0.10	0.12	0.16	0.15
Winner	0.14	0.09	0.07	0.06	0.05	0.04	0.06	0.10	0.14	0.26

PLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.52	0.22	0.10	0.05	0.04	0.02	0.02	0.01	0.01	0.01
2	0.21	0.26	0.20	0.12	0.07	0.05	0.04	0.03	0.02	0.02
3	0.11	0.19	0.20	0.17	0.12	0.08	0.05	0.04	0.03	0.02
4	0.06	0.11	0.17	0.18	0.16	0.12	0.09	0.06	0.04	0.03
5	0.05	0.08	0.12	0.15	0.17	0.16	0.12	0.08	0.05	0.04
6	0.03	0.06	0.09	0.11	0.15	0.16	0.16	0.12	0.08	0.05
7	0.03	0.04	0.06	0.09	0.11	0.15	0.18	0.16	0.12	0.07
8	0.02	0.03	0.04	0.07	0.09	0.12	0.16	0.21	0.18	0.11
9	0.01	0.03	0.04	0.05	0.06	0.08	0.11	0.17	0.26	0.21
Winner	0.01	0.02	0.02	0.03	0.04	0.05	0.07	0.12	0.20	0.48

BRT

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.18	0.10	0.05	0.03	0.02	0.01	0.01	0.01	0.02	0.01
2	0.09	0.10	0.08	0.05	0.03	0.02	0.02	0.02	0.02	0.02
3	0.05	0.06	0.07	0.06	0.04	0.03	0.03	0.03	0.03	0.03
4	0.03	0.04	0.04	0.04	0.05	0.04	0.05	0.03	0.04	0.04
5	0.02	0.03	0.03	0.05	0.04	0.06	0.03	0.03	0.04	0.04
6	0.02	0.02	0.03	0.03	0.04	0.03	0.07	0.08	0.03	0.03
7	0.02	0.02	0.02	0.03	0.04	0.06	0.03	0.05	0.09	0.04
8	0.02	0.03	0.03	0.04	0.05	0.06	0.08	0.07	0.11	0.04
9	0.02	0.03	0.04	0.04	0.03	0.06	0.03	0.10	0.08	0.12
Winner	0.02	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.12	0.16

NN1

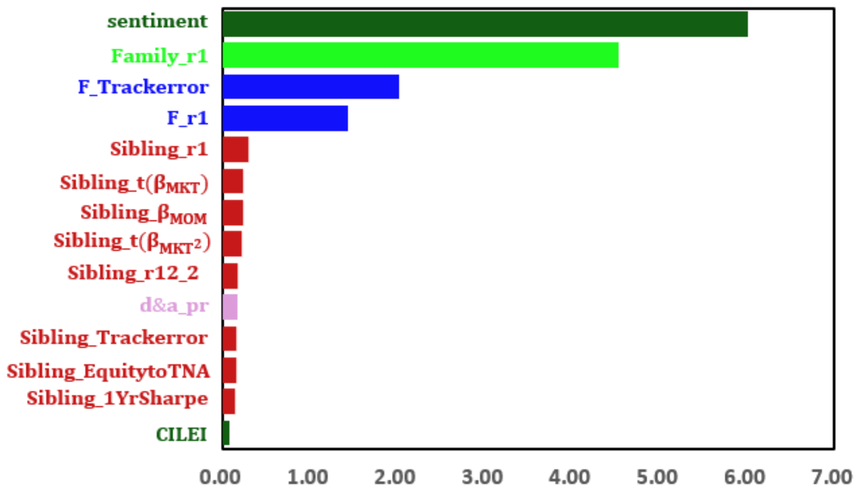
	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.38	0.19	0.12	0.08	0.06	0.05	0.04	0.03	0.03	0.02
2	0.18	0.19	0.15	0.13	0.10	0.07	0.06	0.05	0.05	0.04
3	0.12	0.15	0.14	0.14	0.11	0.10	0.08	0.07	0.05	0.04
4	0.09	0.12	0.14	0.13	0.13	0.11	0.10	0.09	0.07	0.05
5	0.07	0.10	0.11	0.13	0.13	0.12	0.11	0.10	0.08	0.06
6	0.06	0.08	0.10	0.10	0.12	0.13	0.13	0.11	0.10	0.07
7	0.05	0.07	0.08	0.10	0.11	0.13	0.14	0.13	0.13	0.08
8	0.04	0.05	0.07	0.08	0.10	0.11	0.13	0.15	0.15	0.12
9	0.03	0.04	0.05	0.08	0.08	0.10	0.12	0.15	0.18	0.18
Winner	0.02	0.03	0.04	0.04	0.06	0.07	0.08	0.12	0.17	0.39

NN2

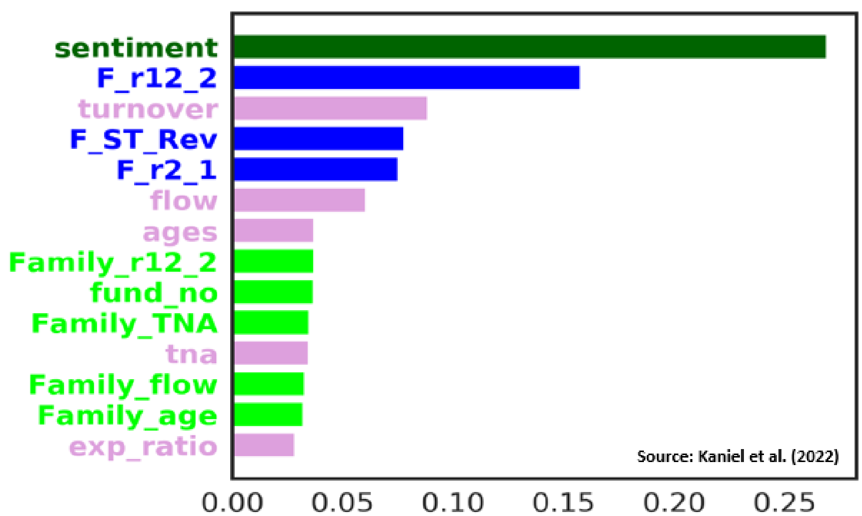
	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.43	0.20	0.11	0.08	0.05	0.05	0.03	0.02	0.02	0.01
2	0.19	0.20	0.18	0.12	0.09	0.07	0.06	0.05	0.03	0.03
3	0.12	0.16	0.17	0.15	0.12	0.09	0.08	0.06	0.04	0.03
4	0.08	0.12	0.14	0.15	0.13	0.11	0.09	0.08	0.07	0.04
5	0.06	0.10	0.11	0.13	0.13	0.13	0.12	0.10	0.09	0.05
6	0.04	0.08	0.09	0.12	0.13	0.14	0.13	0.12	0.10	0.06
7	0.04	0.06	0.09	0.09	0.11	0.14	0.15	0.14	0.12	0.08
8	0.03	0.05	0.06	0.08	0.10	0.12	0.14	0.16	0.16	0.12
9	0.02	0.04	0.05	0.06	0.08	0.10	0.12	0.16	0.20	0.19
Winner	0.02	0.02	0.03	0.04	0.05	0.06	0.08	0.12	0.19	0.40

Figure 5: Out-of-sample performance persistence of decile portfolios predicted by models

This figure shows the out-of-sample performance persistence of decile portfolios predicted by models. For each model, we draw a transition matrix in which the cell (i, j) represents the probability a fund in decile i in month t transfers to decile j in month $t+1$. Specifically, at the end of each month t in the testing period, we sort mutual funds according to model predictions into deciles. We then calculate how many percentages of funds in decile i of the month t fall into decile j of the month $t+1$. Finally, we obtain the value of cell (i, j) by averaging the corresponding values across all months. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.



(a) Top important variables in China



(b) Top important variables in U.S.

Figure 6: Variable importance

This figure shows the variable importance in predicting fund returns. importance measurement is based on the average squared gradient of the model prediction. Following Kaniel et al. (2022), the importance of characteristic j is defined as $SSD_j = \sum_{i,t \in \mathcal{T}_1} \left(\left. \frac{\partial g(z;\theta)}{\partial z_j} \right|_{z=z_{i,t}} \right)^2$, where z_j denotes the j^{th} element of input variables, and g is the fitted model with parameter vector θ. We measure SSD within the training sample, $\mathcal{T}$. The higher the SSD for a variable, the larger effect the variable has on the model prediction. We compute the SSD for each variable and for each model. The final importance measure of a variable is the average of its SSD values over all models. Panel (a) shows the top important variables in China. Panel (b) is copied from Kaniel et al. (2022).

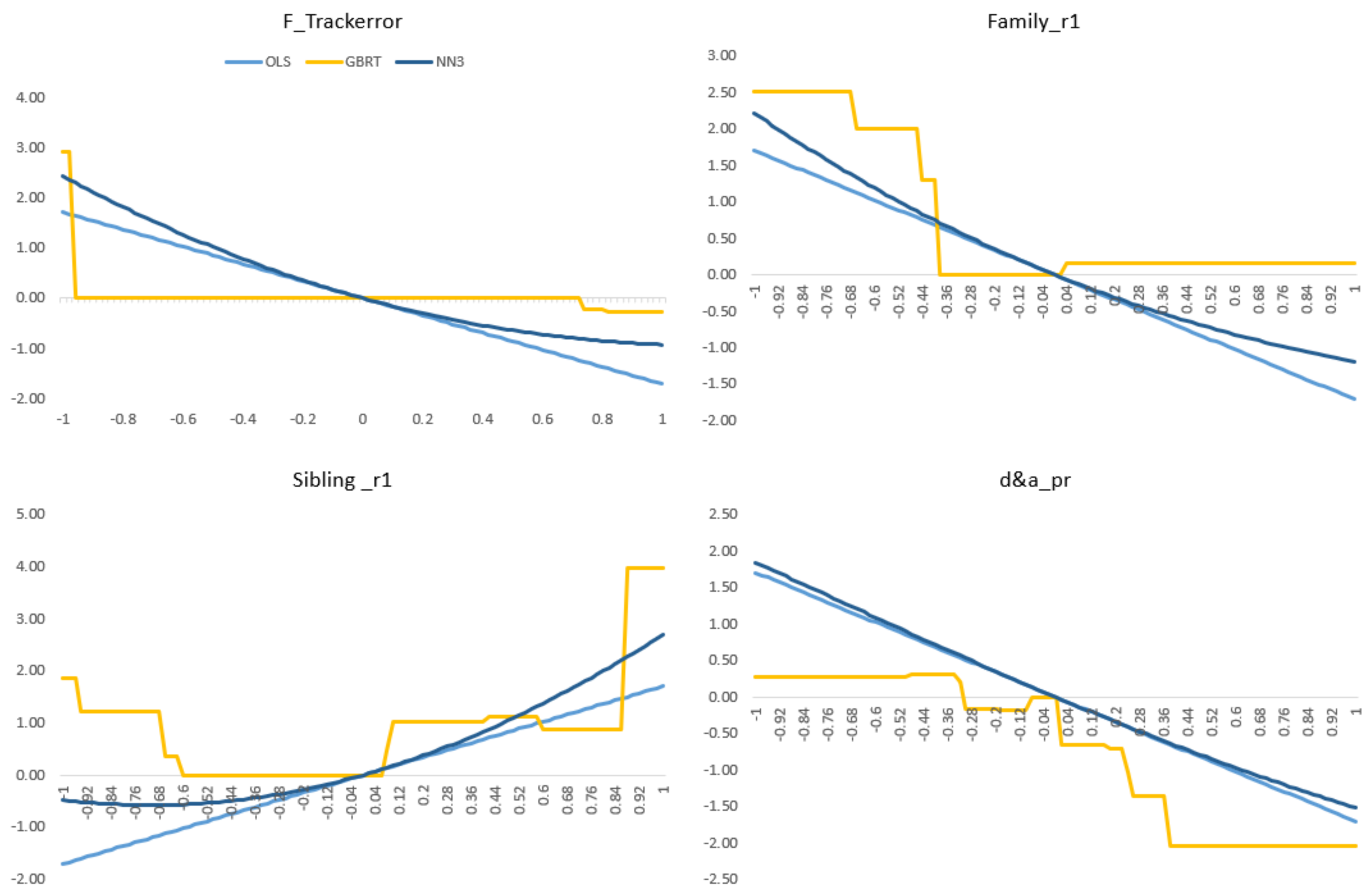


Figure 7: Model-implied marginal impact of fund characteristics on expected fund excess return

This figure shows the model-implied marginal impact of fund characteristics on expected fund excess return. The models include two nonlinear models (boosting regression trees and neural network with 3 hidden layers) and the simple linear model. Following Gu et al. (2020), the data transformation normalizes characteristics to the [-1,1], and holds all other variables fixed at their median value of zero. The vertical axis is the normalized ranking of model-predicted fund returns. We choose the most important characteristic in each information set, including fund tracking error, manager (or sibling) prior-month excess return, family prior-month excess return, and fund exposure to depreciation and amortization per share (*d&a_pr*).

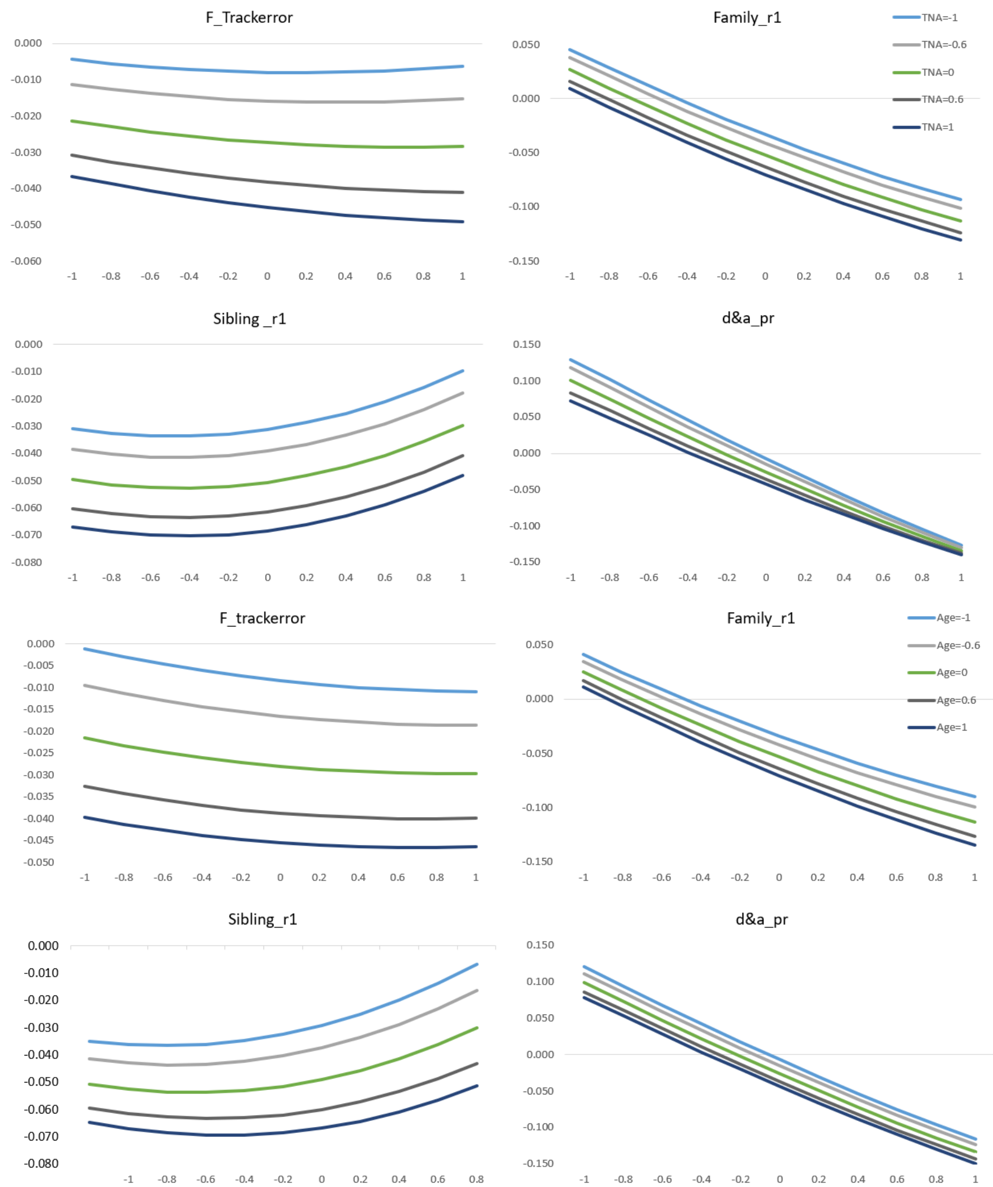


Figure 8: Model-implied marginal impact of fund characteristics on expected fund excess return at different fund size and age (NN3)

This figure shows the model-implied marginal impact of fund characteristics on expected fund excess return at the different levels of fund sizes (first four subgraphs) and fund ages (last four subgraphs). The model is the neural network with 3 hidden layers (NN3). Following Gu et al. (2020), the data transformation normalizes characteristics to the [-1,1], and holds all other variables fixed at their median value of zero. The vertical axis is the normalized ranking of model-predicted fund returns. We choose the most important characteristic in each information set, including fund tracking error, manager (or sibling) prior-month excess return, family prior-month excess return, and fund exposure to depreciation and amortization per share (*d&a_pr*).

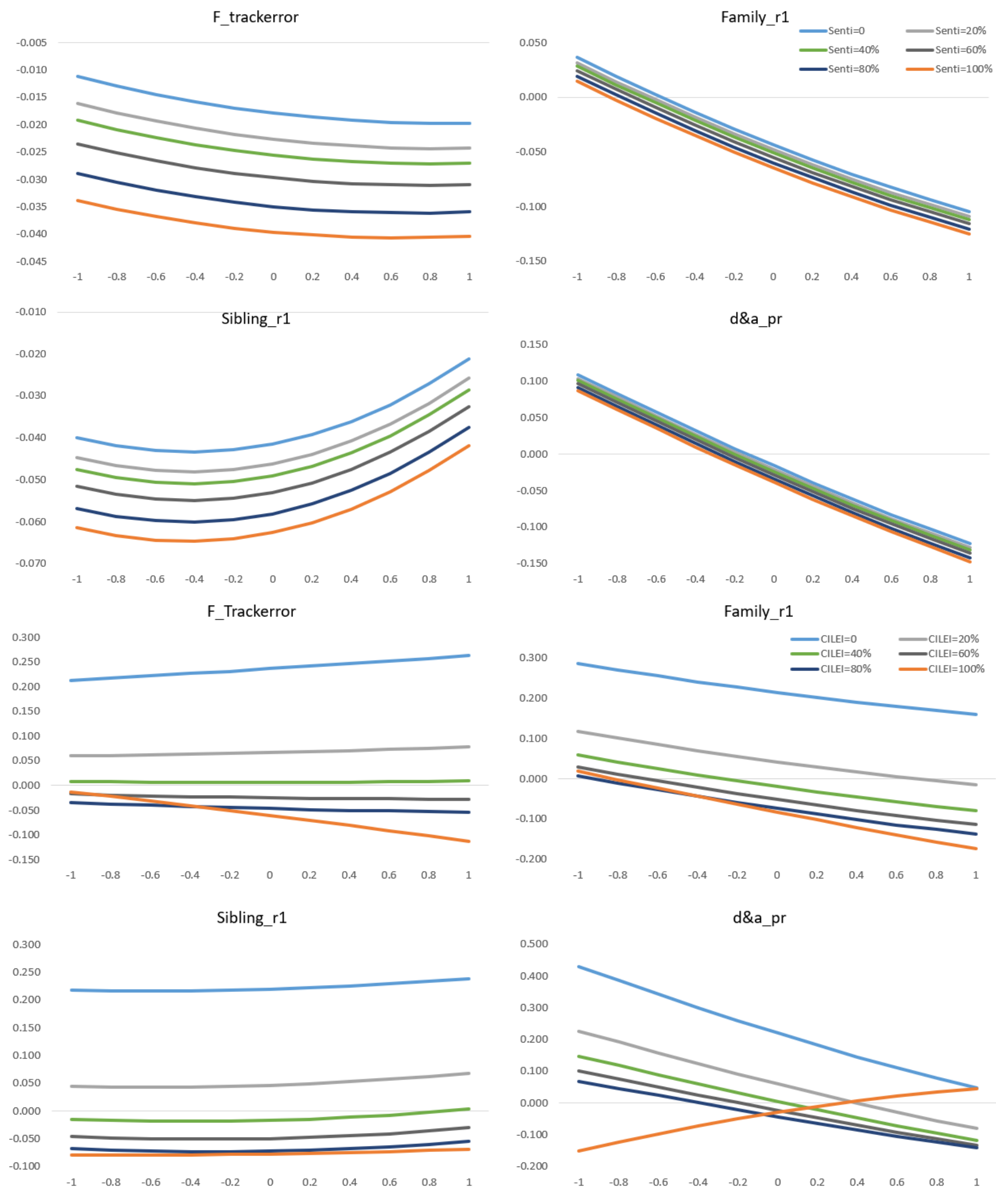


Figure 9: Model-implied marginal impact of fund characteristics on expected fund excess return at different macro state (NN3)

This figure shows the model-implied marginal impact of fund characteristics on expected fund excess return at the different investor sentiments (first four subgraphs) and macro states (last four subgraphs). The model is the neural network with 3 hidden layers (NN3). Following Gu et al. (2020), the data transformation normalizes characteristics to the [-1,1], and holds all other variables fixed at their median value of zero. The vertical axis is the normalized ranking of model-predicted fund returns. We choose the most important characteristic in each information set, including fund tracking error, manager (or sibling) prior-month excess return, family prior-month excess return, and fund exposure to depreciation and amortization per share (*d&a_pr*).

Table 1: Fund-specific and stock-specific characteristics

This table shows 33 fund-specific characteristics in panel A and 33 stock-specific characteristics in panel B.

A. Firm-specific	
ExcessRet	Realized excess return over previous month
Sharpe	Annualized sharpe ratio of monthly return over past year
Mom	Cumulative realized return over past one year (skip most recent month)
Rev	Realized return over previous month
TNA	Total net aseet
Flow	Refer to Equation
Age	Number of months since inception month
a	Alpha from FFC model over past 18 months
b_MKT_RF	Market beta from FFC model over past 18 months
b_SMB	Size beta from FFC model over past 18 months
b_HML	Value beta from FFC model over past 18 months
b_UMD	Momentum beta from FFC model over past 18 months
t_a	Alpha t-stat from FFC model over past 18 months
t_MKT_RF	Market beta t-stat from FFC model over past 18 months
t_SMB	Size beta t-stat from FFC model over past 18 months
t_HML	Value beta t-stat from FFC model over past 18 months
t_UMD	Momentum beta t-stat from FFC model over past 18 months
R2	R-square from FFC model over past 18 months
Flow_vol	Standard deviation of monthly flow over past one year
Alpha	Monthly realized alpha
ExpenseRatio	Annual expenses as a percentage of TNA
ValueAdd	RMB value extracted by fund from asset market
b_MKT_RF2	Market-squared beta from TM model over past 18 months
t_MKT_RF2	Market-squared beta t-stat from TM model over past 18 months
Stk2ttl	Stock value to total asset value
Cash2ttl	Cash ratio to total asset value
HCI	Holding percentage of top 10 stocks
TrackError	Refer to Cremers & Petsjisto (2009)
ActiveWeight	Refer to Doshi et al. (2015)
RiskShift	Refer to Huang et al. (2011)
ActiveShare	Refer to Cremers & Petsjisto (2009)
ReturnGap	Refer to Kacperczyk et al. (2008)
ICI	Industrial concentration index: refer to Kacperczyk et al. (2005)

Continued

	B. Stock-specific
size	Log of market capitalization
rev	Short-term reversal
vol	RMB trading volume
illiq	Amihud (2002)'s Illiquidity
max	Average of maximum 5-day daily return
iv	Idiosyncratic volatility per FF-3 model
beta	Dimson (1979)'s Market beta
turn	Share turnover
cf2np	Cash flow to net profit (TTM)
cf2or	Cash flow to operating revenue (TTM)
cf	Total cash flow (TTM)
cf2e	Cash flow to equity value
crr	Cash recovery rate
nocf2cl	Net operating cash flow to current liability
nocf2ibl	Net operating cash flow to interest-bearing liability
dc	Dividend cover
err	Earnings retention ratio
qgr_op	Quarterly growth rate of operating profit
qgr_or	Quarterly growth rate of operating revenue
ygr_or	Annually growth rate of operating revenue
ygr_nocf	Annually growth rate of net operating cash flow per share
ygr_fcf	Annually growth rate of financing cash flow
ygr_roe	Annually growth rate of return on equity
ygr_gp	Annually growth rate of gross profit
et	Equity turnover
nocf_pr	Net operating cash flow per share (TTM)
nfcf_pr	Net financing cash flow per share (TTM)
ffcf_pr	Firm Free cash flow per share (TTM)
efcf_pr	Equity free cash flow per share (TTM)
d&a_pr	Depreciation and amortization per share (TTM)
or_pr	Operating revenue per share
flr	Financial liability ratio
pc	Price to cash flow

Table 2: Full-sample long-short portfolios by univariate fund characteristic

This table reports the performance of long-short fund portfolios sorted by univariate fund characteristics in the full sample and in different economic states. For month $t+1$, we sort mutual funds according to a fund characteristic at month t into quintiles, then long the top-quintile funds and short the bottom-quintile funds value-weightedly and hold for one month. We report the sign and absolute value of monthly return, monthly sharpe ratio and Carhart (1997) four-factor alpha for each portfolio. The results are ordered according to the sharpe ratio. We also split the full sample into high and low economic states based on the time-series median of Composite Index of Leading Economic Indicators (CILEI) and report the results conditional on the respective state periods. For the space-saving purpose, we only report part of fund characteristics with a high sharpe ratio. For differentiation purposes, we use 'f', 'F', and 'M' to denote fund characteristics sorted into share, family, and manager information set, respectively. The stars are the significance of t-statistics for the test that the monthly return mean is different from zero. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

Predictor	Full sample				High CILEI				Low CILEI			
	sign	mean (%)	SR	FFC-alpha	sign	mean (%)	SR	FFC-alpha	sign	mean (%)	SR	FFC-alpha
F_Alpha	1	0.88**	0.15	0.81**	1	0.68	0.13	0.50	1	1.13*	0.17	0.89*
M_TNA	-1	1.15**	0.15	1.08**	-1	0.97**	0.17	0.89*	-1	1.37	0.14	0.75
F_ExcessRet	1	1.04**	0.15	0.72*	1	0.56	0.10	0.22	1	1.62**	0.19	1.27**
F_Rev	1	1.04**	0.15	0.72*	1	0.56	0.10	0.22	1	1.62**	0.19	1.27**
F_ValueAdd	1	1.48**	0.14	1.16**	1	1.56	0.13	1.10	1	1.38*	0.16	1.02
f_t_MKT_RF	-1	2.41**	0.13	2.04**	-1	2.03*	0.14	1.57	-1	2.87	0.13	1.98
M_Rev	1	1.48**	0.13	1.13**	1	1.50	0.12	1.12	1	1.44*	0.17	1.09*
M_ExcessRet	1	1.47**	0.13	1.13**	1	1.50	0.12	1.12	1	1.44*	0.17	1.09*
M_ActiveShare	-1	0.81	0.13	0.65	-1	0.73	0.13	0.54	-1	0.90	0.13	0.49
f_RiskShift	-1	2.39**	0.13	1.82*	-1	1.75	0.12	1.12	-1	3.15	0.14	1.93
f_ValueAdd	-1	2.07*	0.13	1.87	-1	1.64	0.12	1.31	-1	2.59	0.14	2.19
f_R2	-1	2.21**	0.12	1.99*	-1	1.93	0.13	1.61	-1	2.54	0.12	1.72
nocf2ibl	1	0.39	0.12	0.34	1	0.42	0.15	0.22	1	0.37	0.10	0.43
F_ExpenseRatio	-1	0.80*	0.12	0.57	-1	1.08	0.12	0.70	-1	0.45	0.13	0.32
F_TNA	-1	0.31**	0.11	0.31***	-1	0.36**	0.20	0.33***	-1	0.25	0.07	0.21
nocf_pr	1	0.63	0.11	0.61*	1	0.54**	0.23	0.30*	1	0.73	0.09	0.94
F_R2	1	1.27	0.11	1.06	1	1.63	0.12	1.31	1	0.82	0.11	0.37
f_b_MKT_RF	1	1.89**	0.11	1.54*	1	1.04	0.07	0.73	1	2.93	0.15	1.72
crr	1	0.53*	0.11	0.48**	1	0.60*	0.15	0.36*	1	0.45	0.08	0.55
f_Alpha	-1	2.03	0.11	1.68	-1	1.73	0.11	1.22	-1	2.39	0.11	1.86
f_t_HML	1	1.70*	0.11	1.30	1	1.36	0.11	0.88	1	2.11	0.10	1.31
M_cash2ttl	1	0.78	0.11	0.69	1	0.25	0.04	0.26	1	1.45	0.16	1.18
f_Flow	1	0.60*	0.10	0.52	1	0.68	0.10	0.58	1	0.49	0.14	0.33
f_cash2ttl	1	0.44	0.10	0.42	1	0.65	0.13	0.51	1	0.20	0.05	0.32
F_Mom	1	0.83	0.10	0.50	1	1.27	0.12	0.88	1	0.27	0.07	-0.05
ffcf_pr	1	0.44	0.10	0.36	1	0.39	0.13	0.04	1	0.50	0.08	0.74*
M_Flow	-1	0.95*	0.10	1.35**	-1	0.67	0.07	1.09	-1	1.30	0.13	0.93
M_t_HML	-1	1.45	0.10	1.25	-1	2.22	0.12	1.88	-1	0.57	0.07	0.17
M_b_HML	-1	1.45*	0.09	0.80	-1	1.47	0.09	0.76	-1	1.42	0.10	0.76
F_t_MKT_RF	1	0.89	0.09	0.79	1	1.44	0.12	1.15	1	0.21	0.07	0.06
max	1	0.34	0.09	0.32	1	0.11	0.04	0.23	1	0.62	0.14	0.39
f_ExcessRet	-1	1.71	0.09	1.47	-1	1.43	0.09	1.13	-1	2.08	0.10	1.68
f_Rev	-1	1.71	0.09	1.47	-1	1.43	0.09	1.13	-1	2.08	0.10	1.68
F_Sharpe	1	0.49*	0.09	0.35*	1	0.57	0.09	0.39	1	0.39	0.09	0.46
F_age	1	0.82	0.09	0.96*	1	0.72	0.11	0.82	1	0.95	0.08	0.69
F_RiskShift	1	0.65*	0.09	0.30	1	0.51	0.07	-0.01	1	0.82	0.11	0.54
pc	-1	0.26	0.09	0.26**	-1	0.44	0.15	0.27	-1	0.04	0.01	0.24
M_age	-1	0.60	0.08	0.62*	1	0.10	0.02	-0.07	-1	1.33	0.15	0.73
F_b_HML	-1	0.62	0.08	0.41	-1	0.61	0.07	0.38	-1	0.62	0.10	0.29
M_t_MKT_RF	1	1.46	0.08	1.44	1	3.02	0.13	2.63	-1	0.33	0.04	0.05
F_ReturnGap	1	0.75	0.08	0.48	1	1.48	0.12	0.96	-1	0.13	0.05	0.12
rev	1	0.31	0.08	0.20	1	0.31	0.07	0.10	1	0.31	0.10	0.35
F_t_HML	-1	0.47	0.08	0.46	-1	0.45	0.07	0.40	-1	0.49	0.08	0.28
f_t_UMD	-1	0.96	0.08	0.99	1	0.25	0.05	0.21	-1	2.43	0.14	1.95
cf2np	1	0.33	0.08	0.34*	1	0.27	0.06	0.28	1	0.41	0.11	0.36

Table 3: Out-of-sample performance of decile portfolios

This table reports the monthly out-of-sample performance of long-short fund portfolios predicted by the simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.). For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into deciles. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). Each decile portfolio is formed value-weightedly, using the normalized prediction values as weights. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022

	OLS	LASSO	PLS	BRT	NN1	NN2	NN3
D1	1.68	1.39	1.17	1.44	1.39	1.43	1.50
D2	1.52	1.45	1.41	1.61	1.59	1.61	1.59
D3	1.61	1.43	1.64	1.46	1.69	1.65	1.48
D4	1.70	1.65	1.75	1.60	1.59	1.62	1.62
D5	1.77	1.80	1.77	1.42	1.73	1.72	1.79
D6	1.76	1.95	1.79	0.72	1.77	1.76	1.70
D7	1.82	1.85	1.94	0.25	1.87	1.90	1.88
D8	1.87	1.93	1.98	0.98	1.97	1.89	1.98
D9	2.05	1.95	2.18	1.76	1.91	1.97	1.90
D10	2.09	2.65	2.26	2.43	2.21	2.41	2.31
D10-D1	0.41	1.25	1.09	0.98	0.82	0.98	0.81
t-stat	1.21	1.83	2.34	2.99	3.02	3.71	2.74

Table 4: Out-of-sample performance of long-top-short-market portfolios with respect to Carhart (1997) four-factor model

This table reports the monthly out-of-sample performance of long-top-short-market fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) with respect to Carhart (1997) four-factor model. To form a long-top-short-market portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into deciles, then long the top decile of funds value-weightedly, using the normalized prediction values as weights, and short the fund market (i.e., short all active equity funds equal-weightedly). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	Ret	α	MKT	SMB	HML	UMD	R2
OLS	0.44%***	0.39%***	0.12	0.18	0.15	0.07	0.58
	(3.86)	(2.66)	(3.21)	(4.50)	(3.68)	(1.59)	
LASSO	1.00%***	0.75%**	-0.02	0.39	0.08	0.38	0.53
	(4.00)	(2.21)	(-0.18)	(4.31)	(0.84)	(3.76)	
PLS	0.61%***	0.54%**	0.09	0.24	0.17	0.15	0.44
	(3.98)	(2.34)	(1.60)	(3.82)	(2.68)	(2.16)	
BRT	0.78%***	0.65%***	-0.02	0.18	0.04	0.24	0.40
	(4.94)	(2.66)	(-0.39)	(2.74)	(0.54)	(3.22)	
NN1	0.56%***	0.43%**	0.07	0.10	-0.03	0.03	0.29
	(5.34)	(2.46)	(1.53)	(2.18)	(-0.72)	(0.62)	
NN2	0.76%***	0.59%***	0.10	0.13	0.03	0.15	0.54
	(6.56)	(3.73)	(2.58)	(3.19)	(0.70)	(3.20)	
NN3	0.66%***	0.47%***	0.01	0.15	-0.08	0.13	0.53
	(5.02)	(2.61)	(0.20)	(3.15)	(-1.55)	(2.41)	

Table 5: Out-of-sample performance of long-top-ML-short-top-OLS portfolios

This table reports the monthly out-of-sample performance of long top-decile fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) and short top-decile fund portfolios predicted by the simple linear model (OLS). To form a long-top portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into deciles, then long the top decile of funds value-weightedly, using the normalized prediction values as weights. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	LASSO	PLS	BRT	NN1	NN2	NN3
diffOLS	0.56***	0.17*	0.34**	0.12	0.32***	0.22
t-stat	(2.60)	(1.77)	(1.99)	(0.82)	(2.54)	(1.32)

Table 6: Out-of-sample performance of long-short portfolios within one year after formations

This table reports the average monthly out-of-sample performance (excess return) of long-short decile fund portfolios predicted by models within one year after their formations. For each month $t+1$ in testing period, we sort mutual funds according to model predictions in month t into deciles, then long each group of funds value-weightedly, using the normalized prediction values as weights, and track the portfolio performance for one year ($t+1$ to $t+12$). We then average performance for $t+N$ (N=1,2,..., 12) across all formation period t. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and testing sample from June 2019 to January 2022.

		t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
OLS	D10-D1	0.28	-0.08	-0.08	0.01	0.04	0.20	-0.08	-0.08	-0.28	0.12	0.61	0.30
	t-stat	***0.86***	***-0.24***	***-0.28***	***0.03***	***0.10***	***0.56***	***-0.27***	***-0.24***	***-0.63***	***0.38***	***1.53***	***0.79***
LASSO	D10-D1	0.73	0.42	0.51	0.08	0.75	0.49	0.79	0.23	-0.33	0.43	0.55	0.42
	t-stat	***1.18***	***0.61***	***0.95***	***0.15***	***1.30***	***0.70***	***1.59***	***0.40***	***-0.67***	***0.79***	***1.01***	***0.84***
PLS	D10-D1	0.73	0.55	0.94	0.42	0.50	0.12	0.56	0.65	0.22	0.15	0.69	0.46
	t-stat	***1.73***	***1.50***	***2.52***	***0.94***	***1.05***	***0.27***	***1.59***	***1.46***	***0.46***	***0.30***	***1.27***	***1.21***
BRT	D10-D1	0.66	0.19	0.19	0.43	0.37	0.70	0.58	0.44	0.15	0.20	-0.03	-0.06
	t-stat	***2.48***	***0.72***	***0.60***	***1.47***	***1.37***	***2.97***	***1.56***	***1.48***	***0.67***	***0.83***	***-0.10***	***-0.27***
NN1	D10-D1	0.59	0.31	-0.30	0.02	0.04	0.16	-0.07	-0.23	-0.06	0.14	0.70	0.61
	t-stat	***2.25***	***0.90***	***-0.83***	***0.07***	***0.16***	***0.64***	***-0.22***	***-0.72***	***-0.20***	***0.44***	***2.11***	***2.37***
NN2	D10-D1	0.82	0.20	-0.26	-0.03	0.07	0.50	0.28	-0.03	0.02	0.20	0.88	0.39
	t-stat	***2.67***	***0.73***	***-0.82***	***-0.10***	***0.23***	***2.65***	***0.94***	***-0.11***	***0.05***	***0.65***	***2.91***	***1.45***
NN3	D10-D1	0.48	0.69	0.16	0.05	0.06	0.11	0.25	0.24	0.13	-0.10	0.70	0.70
	t-stat	***1.88***	***2.25***	***0.49***	***0.17***	***0.22***	***0.32***	***0.83***	***0.76***	***0.45***	***-0.33***	***2.00***	***2.10***

Table 7: Out-of-sample performance of long-short portfolios under different information subsets

This table reports the average out-of-sample performance of long-short portfolios over estimated models using different information subsets. For each information subset, we estimate models and average their out-of-sample performances. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

Information set	Return	Sharpe ratio
Full + Macro	6.72%	1.43
Full	4.48%	0.89
Share	3.45%	0.49
Family	0.70%	0.37
Manager	2.50%	0.57
Holding	-3.01%	-0.41

Table 8: Fund characteristics of model-predicted quintiles

This table reports the mean values of fund characteristics for quintile portfolios predicted by models. To form quintile portfolios, at the end of each month t in the testing period, we sort mutual funds according to model predictions into quintiles. Q1 (Q5) represents the quintile portfolio containing funds that are expected to perform the worst (best). Age (months), total net asset in RMB(billion), expense ratio (%), active share, active weight and return gap (%) are calculated as mean values for the quintile portfolios in each month, and then averaged across all months. The detailed definitions of each character are shown in Table (1). To save space, we only report the results for LASSO. The results for other models are similar. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	Age (months)	TNA (billion)	Expense ratio (%)	Active share	Active weight	Return gap (%)
Q1	46.97	1.29	7.58	0.54	0.90	4.06
Q2	60.13	1.23	6.36	0.54	0.90	3.06
Q3	57.18	1.20	4.96	0.54	0.90	5.01
Q4	47.24	1.08	6.48	0.55	0.91	7.24
Q5	40.17	1.04	8.09	0.55	0.92	7.95
Q5-Q1	-6.80	-0.25	0.51	0.01	0.02	3.90
t-stat	***-3.72***	***-3.55***	***1.72***	***3.44***	***4.05***	***9.44***

Table 9: Out-of-sample performance of augmented linear models

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by augmented linear models. We add quadratic terms of fund characteristics, or interaction terms between fund characteristics and investor sentiment, CILEI, fund total net asset, or fund age respectively to augment the simple linear model. To form a long-top portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 50, 200, and 200. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

Model	Ret (%)	SR	Ret (%)	SR	Ret (%)	SR
	# Group=10		# Group=50		# Group=200	
Simple	2.09	1.57	2.01	1.48	2.16	1.38
+ quadratic	1.96	1.45	1.96	1.46	1.89	1.34
+ interaction with CILEI	**2.23**	**1.59**	**2.45**	**1.49**	**2.68**	**1.50**
+ interaction with Sentiment	1.79	1.37	1.68	1.23	1.58	1.06
+ interaction with fund TNA	**2.17**	**1.59**	**1.95**	**1.56**	**2.29**	**1.70**
+ interaction with fund age	2.03	1.45	1.92	1.32	1.59	1.01

Table 10: Fund flow to model predictions

This table reports the out-of-sample panel regressions of monthly fund flow on one-month-lagged indicators. The indicators include fund ratings, CAPM alpha, Fama and French (1993) alpha, Carhart (1997) alpha and our seven model predictions. In univariate analysis, we regress fund flow on each indicator respectively, reported in columns (1)-(11). In multivariate analysis, we include all indicators as regressors, reported in column (12). All panel regressions control fixed effects of funds and months. The standard errors are clustered by fund and month. Our analysis focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the out-of-sample period spans from June 2019 to January 2022. The number of observations amounts to 54684.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
rate_JA	**0.15*****											**0.12****
	(3.12)											**(2.08)**
a_capm		**0.18*****										-0.08
		(2.74)										(-0.59)
a_ff3			**0.18*****									-0.06
			(3.13)									(-0.17)
a_ffc				**0.18*****								0.24
				(3.88)								(0.78)
OLS					-0.05							-0.09*
					(-1.20)							(-1.73)
LASSO						0.01						0.04
						(0.34)						(0.62)
PLS							0.02					0.06
							(0.42)					(1.07)
GBRT								-0.10				-0.10
								(-1.47)				(-1.51)
NN1									0.00			0.07
									(-0.03)			(1.08)
NN2										-0.03		-0.13**
										(-1.16)		(-2.23)
NN3											0.01	0.07
											(0.31)	(1.16)
R2	0.12%	0.11%	0.17%	0.19%	0.01%	0.00%	0.00%	0.03%	0.00%	0.01%	0.00%	0.35%

Table 11: Horse race of models in predicting the sign of fund flow

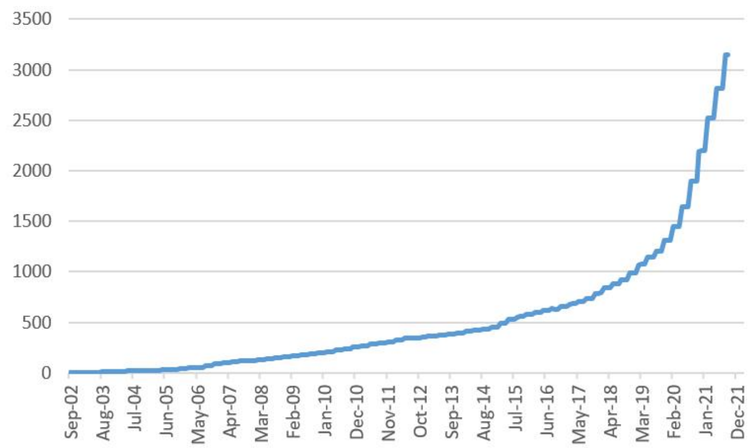
This table reports the Berk and Van Binsbergen (2016) out-of-sample horse race of models in predicting the sign of monthly fund flow. We decompose fund flow into individual flow and institutional flow. The indicators for future fund flow include fund rating, classic factor model alphas and performance predictions by simple linear model and complex machining-learning models. The first two columns are values of $\frac{\beta_1^{\mathcal{I}}+1}{2}$ where $\beta_1^{\mathcal{I}}$ is estimated from equation (2) for each model considered. The remaining columns provide statistical significance tests of the pairwise model horse races based on equation (3). Each cell reports the t-statistic of the hypothesis that $\beta^{row}>\beta^{column}$. For both univariate and pairwise tests, standard errors are double clustered by fund and time.

	$\frac{\beta_1^{\mathcal{I}}+1}{2}$	t-stat	Rate4	a_capm	a_ff3	a_ffc	OLS	LASSO	PLS	GBRT	NN1	NN2	NN3
	A. Individual flow												
Rate4	61.8%	9.78		6.24	4.89	5.53	6.99	7.84	5.68	5.87	5.52	5.97	6.96
a_capm	48.6%	-1.09			-2.66	-1.18	-0.12	-0.40	-1.84	-0.49	-1.55	-1.34	-1.09
a_ff3	50.5%	0.29				2.89	0.84	0.50	-0.70	0.53	-0.50	-0.38	-0.09
a_ffc	49.3%	-0.52					0.25	-0.06	-1.40	-0.12	-1.12	-0.95	-0.66
OLS	48.8%	-1.11						-0.51	-2.92	-0.45	-1.33	-1.26	-0.97
LASSO	49.4%	-0.54							-2.01	-0.05	-1.09	-1.00	-0.64
PLS	51.8%	1.70								1.40	0.09	0.24	0.76
GBRT	49.5%	-0.41									-1.21	-1.05	-0.60
NN1	51.6%	1.18										0.48	1.82
NN2	51.4%	1.02											1.34
NN3	50.7%	0.53											
	$\frac{\beta_1^{\mathcal{I}}+1}{2}$	t-stat	Rate4	a_capm	a_ff3	a_ffc	OLS	LASSO	PLS	GBRT	NN1	NN2	NN3
	B. Institutional flow												
Rate4	52.9%	1.81		1.76	2.20	1.90	2.62	3.29	1.42	2.44	-0.84	-1.35	-1.36
a_capm	47.6%	-1.34			1.41	0.75	0.37	1.04	-1.13	0.54	-2.48	-2.68	-3.01
a_ff3	46.2%	-2.05				-1.45	-0.26	0.46	-1.85	-0.05	-2.93	-3.13	-3.43
a_ffc	47.1%	-1.64					0.15	0.83	-1.38	0.34	-2.71	-2.91	-3.22
OLS	46.8%	-2.47						1.35	-2.89	0.20	-3.79	-4.06	-4.24
LASSO	45.2%	-3.37							-5.71	-0.54	-4.58	-5.00	-4.83
PLS	50.3%	0.28								1.92	-2.14	-2.70	-2.63
GBRT	46.3%	-1.93									-3.84	-4.11	-4.01
NN1	54.2%	3.18										-1.98	-1.31
NN2	55.0%	3.57											-0.09
NN3	55.0%	3.90											

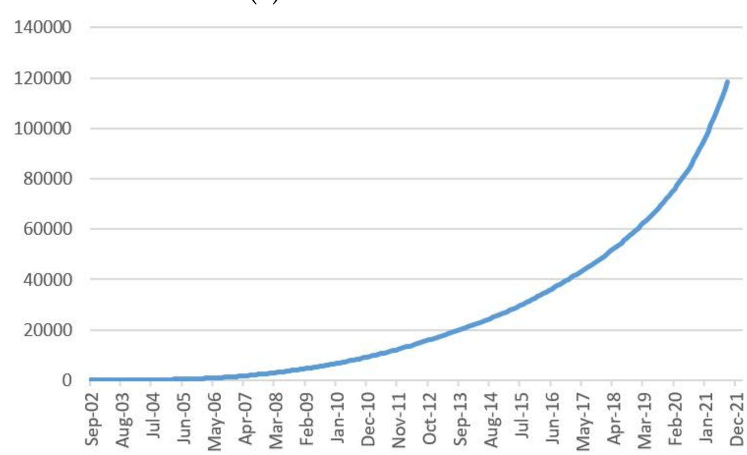
Online Appendix

A Additional Data Descriptions

Sample Observations Figure A.1 plot the time series of the number of existing actively-managed equity funds and fund-month observations. It shows that the observations have experienced exponential growth in recent years.



(a) Number of funds



(b) Number of fund-month observations

Figure A.1: Number of actively-managed equity funds and fund-month observations in the Chinese market

This figure shows the number of actively-managed equity funds and fund-month observations over time in our data sample. We focus on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022. We do not aggregate different share classes within a fund.

Summary Statistics Table A.1 reports the summary statistics of fund characteristics sorted into share, family, and manager information sets which gives us an overview of the Chinese actively-managed equity mutual fund market. Table A.2 reports the summary statistics of stock characteristics of fund holdings. We also report the percentage of fund-month observations in which the fund is under the management of a family (manager) who simultaneously runs a bunch of funds. In our sample, we have over half (53.3%) of the observations in which the fund has sibling funds and nearly all (97.5%) of observations in which the fund has family funds.

Table A.1: Summary statistics of fund characteristics sorted into share, family and manager information set

This table reports the summary statistics of fund characteristics sorted into share, family, and manager information sets. The share-level fund characteristics are constructed using the information of the focal fund itself. The family or manager-level characteristics are constructed by value-weighted averaging all funds under the management of the same family or manager, excluding the focal fund itself. For each characteristic, we winsorize at the 1st and 99th percentiles. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

	Share				Family				Manager			
	Obs	Mean	Std	Median	Obs	Mean	Std	Median	Obs	Mean	Std	Median
ExcessRet (%)	131846	0.79	6.05	0.51	125052	0.68	5.37	0.80	71850	0.74	5.94	0.65
Sharpe	98318	0.63	1.24	0.64	102052	0.51	0.99	0.52	54514	0.61	1.13	0.52
Mom (%)	98318	16.39	27.14	10.95	102052	13.24	20.22	10.03	54514	15.30	24.27	9.31
Rev (%)	131846	0.96	6.04	0.69	125052	0.86	5.36	0.98	71850	0.90	5.93	0.81
TNA (¥Billion)	121635	1.64	2.69	0.55	125052	3.95	3.85	2.76	71850	1.88	2.76	0.80
Flow (%)	112090	7.46	76.35	-4.32	115438	18.99	91.00	-0.96	64675	18.99	129.15	-3.74
Age (months)	127217	47.75	45.54	32.00	122639	66.06	32.11	65.49	71010	44.93	43.17	28.89
a (%)	98297	0.42	1.05	0.31	102041	0.46	0.93	0.34	54507	0.42	0.89	0.27
b_MKT_RF	98297	0.74	0.29	0.76	102041	0.60	0.21	0.60	54507	0.64	0.34	0.69
b_SMB	98297	0.00	0.42	-0.02	102041	0.08	0.59	-0.02	54507	-0.04	0.32	-0.02
b_HML	98297	-0.37	0.46	-0.35	102041	-0.19	0.87	-0.32	54507	-0.33	0.39	-0.28
b_UMD	98297	0.16	0.41	0.14	102041	0.14	0.29	0.13	54507	0.14	0.35	0.09
t_a	98297	0.47	1.31	0.50	102041	0.41	0.84	0.46	54507	0.49	1.14	0.41
t_MKT_RF	98297	6.64	4.14	5.82	102041	5.85	3.41	5.27	54507	5.34	4.04	4.66
t_SMB	98297	-0.15	1.59	-0.10	102041	-0.14	0.97	-0.17	54507	-0.26	1.45	-0.11
t_HML	98297	-1.72	1.77	-1.68	102041	-1.58	1.17	-1.55	54507	-1.48	1.61	-1.33
t_UMD	98297	0.75	1.51	0.71	102041	0.71	0.94	0.64	54507	0.59	1.31	0.41
R2	98297	0.81	0.15	0.85	102041	0.70	0.19	0.73	54507	0.69	0.28	0.79
Flow_vol	93865	0.47	1.45	0.12	97636	0.60	2.21	0.14	51442	0.87	3.58	0.11
Alpha (%)	95855	0.43	3.96	0.26	99621	0.14	3.12	0.20	52758	0.41	3.34	0.05
ExpenseRatio	107550	0.06	0.09	0.03	111762	0.03	0.01	0.02	61824	0.05	0.09	0.03
ValueAdd (¥Million)	95157	7.68	102.15	1.06	99445	4.83	237.17	4.38	52641	7.06	79.93	0.40
b_MKT_RF2	98297	-1.59	4.23	-0.74	102041	-1.44	2.77	-0.85	54507	-1.55	4.03	-0.61
t_MKT_RF2	98297	-0.44	1.10	-0.45	102041	-0.41	0.69	-0.40	54507	-0.38	0.98	-0.30
Stk2ttl	121636	0.82	0.13	0.86	125001	0.82	0.08	0.84	71808	0.82	0.13	0.87
cash2ttl	121669	0.11	0.08	0.09	125025	0.11	0.05	0.10	71832	0.11	0.08	0.09
HCI	121588	0.42	0.15	0.43	124770	0.43	0.10	0.43	71640	0.43	0.15	0.43
TrackErr	97035	0.04	0.03	0.04	101176	0.04	0.04	0.03	54168	0.03	0.02	0.03
ActiveShare	121270	0.55	0.04	0.55	124653	0.55	0.03	0.55	71568	0.55	0.05	0.55
ActiveWeight	121588	0.92	0.07	0.93	124770	0.92	0.05	0.92	71640	0.91	0.07	0.93
RiskShift	95718	0.00	0.03	0.00	99444	0.00	0.04	0.01	52647	0.01	0.02	0.00
ReturnGap	92268	0.04	0.09	0.03	96543	0.01	0.05	0.01	50736	0.04	0.08	0.02
ICI	121612	0.15	0.09	0.14	124734	0.15	0.06	0.14	71604	0.14	0.09	0.13

Table A.2: Summary statistics of stock characteristics of fund holdings

This table reports the summary statistics of stock characteristics of fund holdings. Fund-level characteristics are calculated as the value-weighted average of the stock characteristics held in each fund's portfolio, weighted by the funds' stock weights. For each characteristic, we winsorize at the 1st and 99th percentiles. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

	Obs	Mean	Std	Median
size	99309	1.53	0.61	1.59
rev	99309	0.00	0.36	-0.02
vol	99309	1.58	0.97	1.51
illiq	99298	-0.51	0.19	-0.53
max	99298	-0.03	0.27	-0.05
iv	99298	-0.09	0.24	-0.10
beta	99298	0.02	0.38	0.00
turn	99298	-0.34	0.19	-0.35
cf2np	99329	-0.01	0.08	-0.01
cf2or	99329	0.18	0.14	0.17
cf	99329	0.34	0.66	0.23
cf2e	99326	-0.66	0.55	-0.60
crr	99330	0.24	0.30	0.22
nocf2cl	99319	0.18	0.25	0.15
nocf2ibl	99319	0.13	0.24	0.06
dc	99315	0.05	0.19	0.03
err	99303	-0.02	0.18	0.06
qgr_op	98957	0.13	0.09	0.13
qgr_or	98957	0.00	0.16	-0.02
ygr_or	99330	0.10	0.16	0.07
ygr_nocf	99323	0.10	0.14	0.10
ygr_fcf	99322	0.00	0.23	0.01
ygr_roe	99330	0.06	0.12	0.04
ygr_gp	99330	0.08	0.15	0.05
et	99330	-0.04	0.15	-0.06
nocf_pr	99329	0.76	0.57	0.69
nfcf_pr	99330	0.04	0.41	0.04
ffcf_pr	99329	0.22	0.43	0.16
efcf_pr	99329	0.48	0.48	0.42
d&a_pr	99321	0.23	0.53	0.00
or_pr	99330	0.75	0.48	0.70
flr	99330	-0.14	0.23	-0.14
pc	99329	-0.08	0.16	-0.11

Table A.3: Percentage of funds that belong to multi-fund family or manager

This table reports the percentage of fund-month observations in which the fund is under the management of a family (manager) who simultaneously runs a bunch of funds. The number interval indicates the number of funds under management. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

A. Family						
1	(1,21]	(21,41]	(41,61]	(61,81]	(81,101]	>101
2.5%	68.9%	17.8%	6.9%	2.4%	1.0%	0.4%
B. Manager						
1	(1,3]	(3,5]	(5,7]	(7,9]	(9,11]	>11
46.7%	39.1%	9.6%	2.8%	1.2%	0.4%	0.2%

B Univariate Sorting

This section provides additional results of univariate sorting. Table B.1 reports the long-short fund portfolio performances sorted by univariate fund characteristics in the full sample and in different investor sentiments. Table B.2 offers a complete list of full-sample long-short portfolios by each univariate fund characteristic.

Table B.1: Full-sample long-short portfolios by univariate fund characteristic (Macro=investor sentiment)

This table reports the performance of long-short fund portfolios sorted by univariate fund characteristic in the full sample and in different investor sentiments. For month $t+1$, we sort mutual funds according to a fund characteristic at month t into quintiles, then long the top-quintile funds and short the bottom-quintile funds value-weighted and hold for one month. We report the sign and absolute value of monthly return, monthly sharpe ratio and Carhart (1997) four-factor alpha for each portfolio. The results are ordered according to the sharpe ratio. We also split the full sample into high and low economic states based on the time-series median of Baker and Wurgler (2006) investor sentiment and report the results conditional on the respective state period. For space-saving purposes, we only report part of fund characteristics with a high sharpe ratio. For differentiation purposes, we use 'f', 'F', and 'M' to denote fund characteristics sorted into share, family, and manager information sets, respectively. The stars are the significance of t-statistics for the test that the monthly return mean is different from zero. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

Predictor	Full sample				High sentiment				Low sentiment			
	sign	mean (%)	SR	FFC-alpha	sign	mean (%)	SR	FFC-alpha	sign	mean (%)	SR	FFC-alpha
F_Alpha	1	0.88**	0.15	0.81**	1	0.98**	0.19	0.90*	1	0.77	0.11	0.49
M_TNA	-1	1.15**	0.15	1.08**	-1	1.06**	0.19	1.10**	-1	1.26	0.13	0.69
F_ExcessRet	1	1.04**	0.15	0.72*	1	0.91**	0.17	0.52	1	1.19	0.14	0.90
F_Rev	1	1.04**	0.15	0.72*	1	0.91**	0.17	0.52	1	1.19	0.14	0.90
F_ValueAdd	1	1.48**	0.14	1.16**	1	1.63	0.14	1.28	1	1.28	0.15	0.94
f_t_MKT_RF	-1	2.41**	0.13	2.04**	-1	2.11	0.15	1.65	-1	2.76	0.13	1.89
M_Rev	1	1.48**	0.13	1.13**	1	1.57	0.12	1.08	1	1.35*	0.17	1.23*
M_ExcessRet	1	1.47**	0.13	1.13**	1	1.57	0.12	1.08	1	1.35*	0.17	1.23*
M_ActiveShare	-1	0.81	0.13	0.65	-1	0.49	0.09	0.31	-1	1.23*	0.18	1.10*
f_RiskShift	-1	2.39**	0.13	1.82*	-1	2.22*	0.15	1.53	-1	2.58	0.12	1.51
f_ValueAdd	-1	2.07*	0.13	1.87	-1	1.47	0.10	1.24	-1	2.75	0.15	2.14
f_R2	-1	2.21**	0.12	1.99*	-1	1.92	0.13	1.71	-1	2.53	0.12	1.65
nocf2ibl	1	0.39	0.12	0.34	1	0.27	0.09	0.26	1	0.54	0.15	0.50
F_ExpenseRatio	-1	0.80*	0.12	0.57	-1	1.05	0.12	0.71	-1	0.50	0.15	0.38
F_TNA	-1	0.31**	0.11	0.31***	-1	0.25	0.11	0.29	-1	0.38	0.12	0.30
nocf_pr	1	0.63	0.11	0.61*	1	0.29	0.10	0.42**	1	1.02	0.14	0.77
F_R2	1	1.27	0.11	1.06	1	1.60	0.12	1.34	1	0.85	0.11	0.55
f_b_MKT_RF	1	1.89**	0.11	1.54*	1	1.31	0.09	0.95	1	2.54	0.13	1.47
crr	1	0.53*	0.11	0.48**	1	0.39	0.10	0.39**	1	0.70	0.13	0.57
f_Alpha	-1	2.03	0.11	1.68	-1	1.41	0.09	0.99	-1	2.74	0.13	1.99
f_t_HML	1	1.70*	0.11	1.30	1	1.37	0.11	0.97	1	2.07	0.11	1.21
M_cash2ttl	1	0.78	0.11	0.69	1	0.51	0.09	0.37	1	1.11	0.12	0.89
f_Flow	1	0.60*	0.10	0.52	1	0.97	0.13	0.84	1	0.22	0.07	0.10
f_cash2ttl	1	0.44	0.10	0.42	1	0.80*	0.16	0.71*	1	0.04	0.01	0.18
F_Mom	1	0.83	0.10	0.50	1	1.21	0.11	0.82	1	0.35	0.09	0.15
ffcf_pr	1	0.44	0.10	0.36	1	0.25	0.07	0.15	1	0.67	0.12	0.57
M_Flow	-1	0.95*	0.10	1.35**	-1	0.43	0.04	1.07	-1	1.58	0.16	1.13
M_t_HML	-1	1.45	0.10	1.25	-1	2.02	0.11	1.70	-1	0.68	0.07	0.17
M_b_HML	-1	1.45*	0.09	0.80	-1	1.49	0.09	0.66	-1	1.39	0.09	0.70
F_t_MKT_RF	1	0.89	0.09	0.79	1	1.36	0.11	1.21	1	0.31	0.09	0.20
max	1	0.34	0.09	0.32	1	0.29	0.09	0.24	1	0.41	0.10	0.37
f_ExcessRet	-1	1.71	0.09	1.47	-1	1.41	0.08	1.27	-1	2.05	0.10	1.31
f_Rev	-1	1.71	0.09	1.47	-1	1.41	0.08	1.27	-1	2.05	0.10	1.31
F_Sharpe	1	0.49*	0.09	0.35*	1	0.52	0.09	0.39	1	0.44	0.10	0.46
F_age	1	0.82	0.09	0.96*	1	0.62	0.09	0.85	1	1.04	0.09	0.69
F_RiskShift	1	0.65*	0.09	0.30	1	0.24	0.04	-0.10	1	1.20	0.14	0.78
pc	-1	0.26	0.09	0.26**	-1	0.45	0.14	0.43*	-1	0.03	0.01	0.12
M_age	-1	0.60	0.08	0.62*	-1	0.09	0.02	0.11	-1	1.36	0.15	0.98
F_b_HML	-1	0.62	0.08	0.41	-1	0.78	0.09	0.49	-1	0.41	0.06	0.17
M_t_MKT_RF	1	1.46	0.08	1.44	1	2.63	0.12	2.42	-1	0.12	0.01	-0.22
F_ReturnGap	1	0.75	0.08	0.48	1	1.30	0.10	0.88	1	0.07	0.02	0.15
rev	1	0.31	0.08	0.20	1	0.69	0.14	0.46	-1	0.11	0.05	0.12
F_t_HML	-1	0.47	0.08	0.46	-1	0.61	0.10	0.59	-1	0.29	0.05	0.08
f_t_UMD	-1	0.96	0.08	0.99	1	0.13	0.02	-0.09	-1	2.18	0.13	1.62
cf2np	1	0.33	0.08	0.34*	1	0.23	0.05	0.28	1	0.46	0.14	0.30

Table B.2: Full-sample long-short portfolios by univariate fund characteristic (full list)

This table reports the performance of long-short fund portfolios sorted by univariate fund characteristic in the full sample. For month $t+1$, we sort mutual funds according to a fund characteristic at month t into quintiles, then long the top-quintile funds and short the bottom-quintile funds value-weighted and hold for one month. We report the sign and absolute value of monthly return, monthly sharpe ratio and Carhart (1997) four-factor alpha for each portfolio. The results are ordered according to the sharpe ratio. For differentiation purposes, we use 'f', 'F', and 'M' to denote fund characteristics sorted into share, family, and manager information sets, respectively. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

Predictor	sign	Ret (%)	t-stat	SR	a_ffc	t_a		sign	Ret (%)	t-stat	SR	a_ffc	t_a
	A. Share							*B. Family*					
f_t_MKT_RF	-1	2.41	2.24	0.13	2.04	1.98	F_Alpha	1	0.88	2.31	0.15	0.81	2.08
f_RiskShift	-1	2.39	2.24	0.13	1.82	1.75	F_ExcessRet	1	1.04	2.20	0.15	0.72	1.66
f_ValueAdd	-1	2.07	1.73	0.13	1.87	1.56	F_Rev	1	1.04	2.20	0.15	0.72	1.66
f_R2	-1	2.21	2.10	0.12	1.99	1.87	F_ValueAdd	1	1.48	2.03	0.14	1.16	2.02
f_b_MKT_RF	1	1.89	1.98	0.11	1.54	1.72	F_ExpenseRatio	-1	0.80	1.83	0.12	0.57	1.33
f_Alpha	-1	2.03	1.55	0.11	1.68	1.35	F_TNA	-1	0.31	2.27	0.11	0.31	2.67
f_t_HML	1	1.70	1.87	0.11	1.30	1.64	F_R2	1	1.27	1.54	0.11	1.06	1.46
f_Flow	1	0.60	1.80	0.10	0.52	1.14	F_Mom	1	0.83	1.25	0.10	0.50	1.07
f_cash2ttl	1	0.44	1.50	0.10	0.42	1.38	F_t_MKT_RF	1	0.89	1.27	0.09	0.79	1.24
f_ExcessRet	-1	1.71	1.32	0.09	1.47	1.14	F_Sharpe	1	0.49	1.81	0.09	0.35	1.79
f_Rev	-1	1.71	1.32	0.09	1.47	1.14	F_age	1	0.82	1.64	0.09	0.96	1.92
f_t_UMD	-1	0.96	1.26	0.08	0.99	1.40	F_RiskShift	1	0.65	1.61	0.09	0.30	0.82
f_b_SMB	1	1.13	1.35	0.07	1.07	1.26	F_b_HML	-1	0.62	1.48	0.08	0.41	1.20
f_TNA	1	0.53	1.03	0.07	0.53	1.08	F_ReturnGap	1	0.75	1.37	0.08	0.48	0.93
f_Flow_vol	1	0.57	1.11	0.06	0.34	0.70	F_t_HML	-1	0.47	1.51	0.08	0.46	1.40
f_TrackErr	1	0.95	1.08	0.06	0.73	1.02	F_a	1	0.56	1.27	0.08	0.64	1.36
f_HCI	-1	0.30	0.91	0.06	0.30	0.71	F_t_a	1	0.36	1.52	0.07	0.30	1.57
f_ICI	1	0.18	0.87	0.06	0.20	0.89	F_b_SMB	-1	0.82	1.17	0.07	0.74	1.09
f_b_HML	1	0.59	0.88	0.04	0.14	0.25	F_t_MKT_RF2	1	0.60	0.91	0.07	0.33	0.76
f_a	-1	0.77	0.73	0.04	0.52	0.52	F_TrackErr	-1	0.16	1.11	0.06	0.12	1.00
f_age	-1	0.31	0.80	0.04	0.03	0.11	F_ActiveShare	-1	0.30	0.70	0.05	0.23	0.49
f_Mom	1	0.24	0.65	0.04	0.04	0.12	F_t_SMB	-1	0.55	0.89	0.05	0.34	0.76
f_Stk2ttl	-1	0.21	0.65	0.04	0.44	1.14	F_Stk2ttl	1	0.24	0.81	0.05	0.01	0.03
f_ExpenseRatio	1	0.11	0.64	0.03	0.10	0.65	F_HCI	1	0.18	0.79	0.05	0.06	0.27
f_b_MKT_RF2	-1	0.46	0.49	0.03	0.36	0.43	F_Flow_vol	-1	0.47	0.83	0.05	0.67	0.90
f_t_SMB	1	0.26	0.49	0.03	0.28	0.50	F_ActiveWeight	-1	0.16	0.75	0.04	0.14	0.61
f_Sharpe	1	0.44	0.42	0.03	0.47	0.50	F_cash2ttl	1	0.15	0.65	0.04	0.29	0.93
f_t_MKT_RF2	-1	0.29	0.40	0.02	0.03	0.04	F_ICI	-1	0.07	0.27	0.02	0.13	0.44
f_ActiveWeight	-1	0.13	0.40	0.02	0.07	0.26	F_b_MKT_RF2	-1	0.04	0.18	0.01	0.00	0.01
f_ActiveShare	-1	0.11	0.30	0.02	-0.01	-0.03	F_Flow	-1	0.05	0.20	0.01	-0.16	-0.81
f_ReturnGap	-1	0.15	0.27	0.01	0.37	0.68	F_b_UMD	-1	0.07	0.21	0.01	0.10	0.29
f_t_a	1	0.15	0.21	0.01	0.20	0.30	F_b_MKT_RF	-1	0.07	0.16	0.01	0.35	1.05
f_b_UMD	-1	0.08	0.07	0.00	0.37	0.36	F_t_UMD	-1	0.04	0.12	0.01	-0.21	-0.78

(*continued*)

Continued

Predictor	sign	Ret (%)	t-stat	SR	a_ffc	t_a		sign	Ret (%)	t-stat	SR	a_ffc	t_a
	C. Manager							*D. Holding*					
	sign	Ret (%)	t-stat	SR	a_ffc	t_a		sign	Ret (%)	t-stat	SR	a_ffc	t_a
M_TNA	-1	1.15	2.38	0.15	1.08	2.05	nocf2ibl	1	0.39	1.45	0.12	0.34	1.43
M_Rev	1	1.48	1.97	0.13	1.13	2.05	nocf_pr	1	0.63	1.49	0.11	0.61	1.90
M_ExcessRet	1	1.47	1.97	0.13	1.13	2.05	crr	1	0.53	1.69	0.11	0.48	2.10
M_ActiveShare	-1	0.81	1.54	0.13	0.65	1.40	ffcf_pr	1	0.44	1.26	0.10	0.36	1.37
M_cash2ttl	1	0.78	1.62	0.11	0.69	1.46	max	1	0.34	1.61	0.09	0.32	1.58
M_Flow	-1	0.95	1.67	0.10	1.35	2.04	pc	-1	0.26	1.60	0.09	0.26	2.06
M_t_HML	-1	1.45	1.51	0.10	1.25	1.42	rev	1	0.31	1.42	0.08	0.20	1.01
M_b_HML	-1	1.45	1.77	0.09	0.80	1.29	cf2np	1	0.33	1.52	0.08	0.34	1.94
M_age	-1	0.60	1.61	0.08	0.62	1.88	ygr_fcf	-1	0.15	1.15	0.06	0.11	0.81
M_t_MKT_RF	1	1.46	1.16	0.08	1.44	1.18	beta	1	0.13	0.84	0.06	0.14	0.92
M_b_SMB	-1	1.44	1.12	0.07	1.09	1.08	err	-1	0.30	0.96	0.06	0.29	1.00
M_ICI	1	0.60	1.33	0.07	0.24	0.55	turn	-1	0.28	0.68	0.05	0.13	0.49
M_t_UMD	1	0.63	0.97	0.07	0.36	0.69	et	1	0.23	0.77	0.05	-0.06	-0.29
M_Sharpe	1	0.43	1.17	0.07	0.24	0.67	or_pr	1	0.35	0.84	0.05	-0.01	-0.04
M_Stk2ttl	-1	0.37	1.32	0.06	0.31	0.91	size	1	0.21	0.68	0.05	0.24	1.08
M_t_SMB	-1	0.89	0.92	0.06	0.82	0.97	cf	-1	0.16	0.73	0.05	0.06	0.29
M_ValueAdd	1	0.69	1.05	0.06	0.47	1.25	vol	1	0.24	0.68	0.05	0.36	1.32
M_t_MKT_RF2	1	0.93	0.91	0.06	0.52	0.71	nocf2cl	1	0.21	0.75	0.05	0.22	1.05
M_b_MKT_RF2	1	0.71	0.85	0.05	0.37	0.50	illiq	-1	0.21	0.64	0.04	0.39	1.60
M_ReturnGap	1	0.46	0.99	0.05	0.27	0.57	iv	1	0.15	0.60	0.04	0.02	0.11
M_ActiveWeight	-1	0.31	0.84	0.04	0.56	1.40	cf2e	1	0.17	0.80	0.04	0.08	0.45
M_ExpenseRatio	1	0.15	0.66	0.04	-0.04	-0.19	ygr_nocf	1	0.08	0.64	0.03	0.07	0.51
M_Flow_vol	-1	0.33	0.86	0.04	0.17	0.45	ygr_or	1	0.09	0.34	0.02	0.20	0.99
M_Alpha	1	0.30	0.61	0.03	0.26	0.68	dc	-1	0.14	0.33	0.02	0.41	1.43
M_R2	1	0.29	0.71	0.03	0.46	1.00	ygr_gp	-1	0.07	0.22	0.02	0.04	0.14
M_b_UMD	1	0.20	0.53	0.03	-0.07	-0.22	qgr_or	1	0.06	0.17	0.02	-0.01	-0.04
M_a	-1	0.18	0.51	0.02	0.23	0.79	flr	-1	0.07	0.21	0.02	-0.10	-0.39
M_Mom	1	0.09	0.36	0.02	0.28	1.26	efcf_pr	1	0.05	0.20	0.01	0.12	0.62
M_RiskShift	1	0.08	0.27	0.01	0.26	0.83	ygr_roe	1	0.04	0.19	0.01	-0.19	-1.24
M_b_MKT_RF	-1	0.19	0.26	0.01	0.47	0.98	qgr_op	-1	0.01	0.09	0.01	0.03	0.23
M_HCI	1	0.06	0.18	0.01	-0.02	-0.06	d&a_pr	-1	0.02	0.07	0.00	-0.16	-0.87
M_t_a	-1	0.08	0.20	0.01	0.00	-0.01	cf2or	-1	0.02	0.09	0.00	-0.22	-1.44
M_TrackErr	1	0.03	0.08	0.01	0.02	0.08	nfcf_pr	1	0.01	0.03	0.00	-0.06	-0.31

C Model Descriptions

Gu et al. (2020) provide an extensive description of various machine-learning models in the context of asset pricing. In this section, we briefly describe the methods that we employed. In Table C.1, we make a summary of the choice of hyperparameters for each machine learning model.

Simple Linear Model We organize our data in a panel structure, with months indexed as $t = 1, 2, \ldots T$ and share classes as $i = 1, 2, \ldots N_t$. As a benchmark, we use the simple linear model estimated via ordinary least squares (OLS):

$$\min_{\theta} \sum_{t=1}^{T-1} \sum_{i=1}^{N_t} \left(r_{i,t+1} - z_{i,t}'\theta\right)^2 \tag{C.1}$$

where $r_{i,t+1}$ is the realized fund excess return of the share class i in month $t+1$, $z_{i,t}$ is a vector of predicting variables for share class i in month t, and θ is the parameter vector.

LASSO The simple linear model is bound to fail in the presence of many predictors. LASSO [11], as a linear model as well, uses regularization to alleviate the overfitting problem and provide robust predictions. One distinctive feature of the method is setting coefficients on a subset of covariates to exactly zero, in which sense it's thought of as a variable selection method. That's also the reason we employ LASSO instead of Ridge since the latter just shrinkage the coefficients but does not impose exact zeros anywhere. The objective function of LASSO takes the form of :

$$\min_{\theta} \sum_{t=1}^{T-1} \sum_{i=1}^{N_t} \left(r_{i,t+1} - z_{i,t}'\theta\right)^2 + \lambda\|\theta\|_1 \tag{C.2}$$

where $\|\theta\|_1 = \sum_{k=1}^{K} |\theta_k|$ is the 1-norm of the parameter vector θ, and λ is hyperparameter controlling the degree of sparsity of the estimated parameter vector θ.

PLS Partial least square, known as a dimension-reduction technique, takes the idea of predictor

[11] Abbreviation of Least Absolute Sum of Squares Operator.

averaging as opposed to predictor selection, which helps reduce noise to better isolate the signal in predictors and decorrelate highly dependent predictors. We choose PLS rather than another classic dimension-reduction method namely principle components analysis (PCA) due to the latter failing to incorporate the ultimate objective of forecasting returns in the dimension-reduction step. See Gu et al. (2020) for more details about the objective function and computational algorithm. The hyperparameter of PLS is the number of linear combinations of predictors.

Boosting Regression Trees Regression trees have become a popular machine-learning approach that incorporates multi-way predictor interactions. Therefore, this method is born as a nonlinear model. The advantages of the tree model are that it is invariant to the monotonic transformation of predictors, that it accommodates categorical and numerical data in the same model, and that it can approximate potentially severe nonlinearities. However, their flexibility meanwhile makes the method prone to overfit. Boosting regression trees, known as an ensemble learning method, can combine forecasts from many different trees into a single forecast. Unlike random forests which aggregate independent decision trees, BRT aggregates trees sequentially in order to give more influence to those observations that are poorly predicted by previous trees. In this fashion, boosting achieves improved predictions by reducing not only prediction variance, but also the prediction bias (Schapire and Freund, 2012). The hyperparameters include the learning rate which determines the weight the ensemble gives to the most recent decision tree, the number of decision trees aggregated, the depth and the number of nodes of each tree, and the minimum number of observations in a leaf node tuned for better regularization.

Neural Network Another employed nonlinear method is the artificial neural network, arguably the most powerful modeling device in machine learning. It has theoretical underpinnings as universal approximators for any smooth predictive associations (Hornik et al., 1989; Cybenko, 1989). We focus our analysis on traditional feed-forward networks. To construct the neural network, there are many choices to make, including the number of hidden layers, the number of neurons in each layer, and which units are connected. Instead of searching over uncountably many architectures, we fix a variety of network architectures ex-ante with up to three hidden layers (denoted as NN1$\sim$NN3). Tuned on the validation sample, our final choice of neuron number for each neural network is: NN1 having one hidden layer of 64 neurons, NN2 having two hidden layers with 32 and 16 neurons, NN3 having three hidden layers with 32, 16, and 8 neurons. All architectures are fully connected.

Another choice for neural networks is the nonlinear activation function. As most of the literature do, we choose a popular functional form known as the rectified linear unit (ReLU), defined as:

$$\mathrm{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{otherwise} \end{cases} \tag{C.3}$$

Our choice of regularization techniques in the model estimation follows Gu et al. (2020), including early stopping, batch normalization, learning rate shrinkage, and ensembles.

Table C.1 makes a summary of our choices of machine-learning model hyper-parameters.

Table C.1: Hyperparameters for all machining learning models

This table shows the set of hyperparameters that we tune in each machine-learning model. The optimal parameters are selected on the validation data.

	LASSO	PLS	GBRT	NN1∼NN3
Hyperparameters	Degree of sparsity (λ)	Number of linear combinations (K)	Learning rate (LR), Number of decision trees, Depth of tree	Number of hidden units in each layer (HU), Learning rate, Batch size
Candidates	$\lambda \in (10^{-4}, 10^{-1})$	$K \in 2, 3, 4$	$LR \in (10^{-2}, 10^{-1})$, #Tree=1∼300, Depth=1∼5	HU=2^{6-i} or 2^{7-i} for i=1 to # of hidden layers, LR∈{ 0.0001, 0.001, 0.01}, Batch size∈{512, 1024, 2048}
Optimal	λ =0.01	K=2	LR=0.09, #Tree=100, Depth=3	NN1's HU=(64,), NN2's HU=(32,16), NN3's HU=(32,16,8), LR=0.0001, Batch size=512
Others				Batch normalization=True, Early stopping =True, Ensemble=8, Epochs=100, L2 penalty=0.0001, Activation=ReLU, Solver=Adam, Patience=10

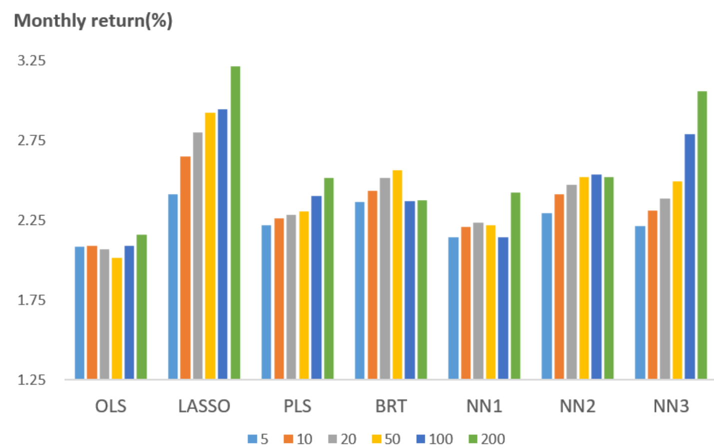
D Additional results of model out-of-sample performances

Number of Groups To assuage concerns that our results are sensitive to the number of groups that we divide into, we consider multiple numbers including 5, 10, 20, 50, 100 and 200. Table D.1 reports the out-of-sample performance of long-top fund portfolios predicted by each model. It shows that, with the increasing group numbers that we divide into, the performance of the long-only top group by LASSO and neural network (NN3 in particular) improves. For example, the top-quintile portfolio by LASSO earns a monthly return of 2.08 percent ($t - stat$=2.77) with an annual sharpe ratio of 1.60 and alpha of 1.27 percentage ($t - stat$=3.90). As a comparison, the top-0.5% portfolio by LASSO achieves a monthly return of 3.21 percent ($t - stat$=3.16) with an annual sharpe ratio of 1.83 and alpha of 2.23 percentage ($t - stat$=3.32). This finding hence further confirms the predictive power of machine learning tools since they predict a robust monotonic pattern of future fund returns. The corresponding results are also vividly shown in Figure D.1. In Table D.2, we report the out-of-sample monthly Carhart (1997) four-factor alphas of multiple long-top fund portfolios predicted by models.

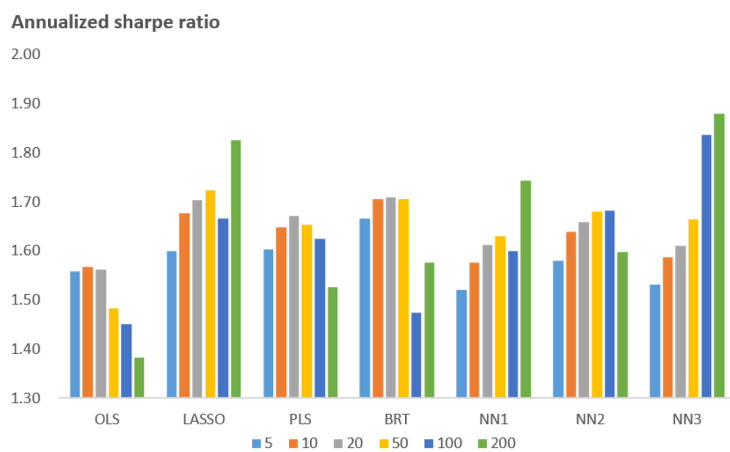
Table D.1: Out-of-sample performance of long-top portfolios

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.). For each month $t + 1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. We report the monthly return, annualized sharpe ratio, and Carhart (1997) four-factor alpha for each portfolio. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	Ret	SR	t-stat	a_ffc	t_a	Ret	SR	t-stat	a_ffc	t_a
			# Group=5					# Group=10		
OLS	2.08	1.56	2.70	1.09	4.91	2.09	1.57	2.71	1.10	4.78
LASSO	2.41	1.60	2.77	1.27	3.90	2.65	1.68	2.90	1.47	3.86
PLS	2.22	1.60	2.78	1.19	4.41	2.26	1.65	2.85	1.25	4.23
BRT	2.36	1.67	2.89	1.29	5.51	2.43	1.70	2.95	1.36	4.98
NN1	2.14	1.52	2.63	1.08	5.19	2.21	1.58	2.73	1.15	5.27
NN2	2.30	1.58	2.74	1.20	5.54	2.41	1.64	2.84	1.31	5.53
NN3	2.21	1.53	2.65	1.10	5.75	2.31	1.59	2.75	1.19	5.41
			# Group=20					# Group=50		
OLS	2.07	1.56	2.70	1.10	4.37	2.01	1.48	2.57	1.05	3.65
LASSO	2.80	1.70	2.95	1.59	3.56	2.92	1.72	2.99	1.78	3.22
PLS	2.28	1.67	2.89	1.29	4.01	2.30	1.65	2.86	1.31	3.59
BRT	2.51	1.71	2.96	1.42	4.36	2.56	1.71	2.95	1.45	3.66
NN1	2.23	1.61	2.79	1.18	5.04	2.22	1.63	2.82	1.19	4.97
NN2	2.47	1.66	2.87	1.36	5.30	2.52	1.68	2.91	1.41	4.91
NN3	2.38	1.61	2.79	1.24	4.79	2.49	1.66	2.88	1.35	4.29
			# Group=100					# Group=200		
OLS	2.09	1.45	2.51	1.11	3.23	2.16	1.38	2.39	1.14	2.64
LASSO	2.95	1.67	2.88	1.82	2.93	3.21	1.83	3.16	2.23	3.32
PLS	2.40	1.62	2.81	1.35	3.44	2.51	1.53	2.64	1.41	2.85
BRT	2.37	1.47	2.55	1.20	2.39	2.37	1.58	2.73	1.26	3.73
NN1	2.14	1.60	2.77	1.14	4.71	2.42	1.74	3.02	1.40	4.88
NN2	2.53	1.68	2.91	1.47	4.00	2.52	1.60	2.77	1.46	3.06
NN3	2.79	1.84	3.18	1.65	4.11	3.06	1.88	3.26	1.93	3.43



(a) Monthly return



(b) Annualized sharpe ratio

Figure D.1: Out-of-sample performance of long-top portfolios under different grouping numbers This figure shows the out-of-sample performance (monthly return in panel (a) and annualized sharpe ratio in panel (b)) of long-top fund portfolios predicted by simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.). For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

Table D.2: Out-of-sample performance of long-top portfolios with respect to Carhart (1997) four-factor model

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) with respect to Carhart (1997) four-factor model. To form a long-top portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2
			# Group=5						# Group=10						# Group=20			
OLS	0.011	0.867	0.011	-0.246	0.272	0.941	0.011	0.883	0.044	-0.215	0.274	0.937	0.011	0.897	0.060	-0.187	0.260	0.923
t-stat	*4.910*	*15.274*	*0.192*	*-4.103*	*4.086*		*4.778*	*15.004*	*0.712*	*-3.446*	*3.963*		*4.367*	*13.940*	*0.886*	*-2.739*	*3.435*	
LASSO	0.013	0.772	0.150	-0.324	0.475	0.902	0.015	0.748	0.260	-0.282	0.587	0.878	0.016	0.704	0.334	-0.276	0.653	0.843
t-stat	*3.902*	*9.302*	*1.722*	*-3.688*	*4.870*		*3.857*	*7.721*	*2.551*	*-2.755*	*5.155*		*3.557*	*6.172*	*2.780*	*-2.289*	*4.878*	
PLS	0.012	0.849	0.082	-0.237	0.351	0.920	0.013	0.857	0.103	-0.193	0.353	0.902	0.013	0.869	0.124	-0.161	0.339	0.882
t-stat	*4.408*	*12.395*	*1.138*	*-3.262*	*4.361*		*4.234*	*11.362*	*1.302*	*-2.418*	*3.989*		*4.008*	*10.571*	*1.430*	*-1.855*	*3.507*	
BRT	0.013	0.776	-0.015	-0.324	0.391	0.946	0.014	0.739	0.047	-0.324	0.440	0.922	0.014	0.712	0.087	-0.340	0.476	0.896
t-stat	*5.812*	*13.551*	*-0.248*	*-5.343*	*5.810*		*4.979*	*10.590*	*0.643*	*-4.387*	*5.366*		*4.356*	*8.579*	*0.994*	*-3.875*	*4.879*	
NN1	0.011	0.833	-0.053	-0.400	0.242	0.954	0.011	0.832	-0.030	-0.394	0.237	0.949	0.012	0.813	-0.017	-0.394	0.237	0.940
t-stat	*5.188*	*15.719*	*-0.947*	*-7.137*	*3.883*		*5.269*	*15.007*	*-0.514*	*-6.714*	*3.640*		*5.038*	*13.572*	*-0.266*	*-6.220*	*3.366*	
NN2	0.012	0.853	-0.032	-0.362	0.321	0.953	0.013	0.867	0.002	-0.330	0.356	0.946	0.014	0.879	0.028	-0.296	0.397	0.938
t-stat	*5.536*	*15.398*	*-0.547*	*-6.169*	*4.938*		*5.527*	*14.403*	*0.036*	*-5.178*	*5.028*		*5.303*	*13.468*	*0.403*	*-4.289*	*5.179*	
NN3	0.011	0.791	-0.022	-0.438	0.304	0.963	0.012	0.773	0.021	-0.435	0.335	0.952	0.012	0.750	0.065	-0.427	0.383	0.935
t-stat	*5.754*	*16.200*	*-0.425*	*-8.489*	*5.303*		*5.413*	*13.830*	*0.350*	*-7.363*	*5.108*		*4.794*	*11.364*	*0.938*	*-6.113*	*4.933*	
		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2
			# Group=50						# Group=100						# Group=200			
OLS	0.010	0.942	0.084	-0.134	0.271	0.906	0.011	1.007	0.114	-0.049	0.340	0.880	0.011	1.065	0.141	0.013	0.414	0.839
t-stat	*3.654*	*12.871*	*1.094*	*-1.736*	*3.152*		*3.226*	*11.490*	*1.232*	*-0.528*	*3.302*		*2.641*	*9.706*	*1.222*	*0.112*	*3.213*	
LASSO	0.016	0.586	0.333	-0.400	0.626	0.783	0.016	0.528	0.319	-0.510	0.579	0.739	0.015	0.382	0.324	-0.527	0.663	0.622
t-stat	*2.960*	*4.199*	*2.262*	*-2.706*	*3.817*		*2.472*	*3.295*	*1.886*	*-3.007*	*3.073*		*1.831*	*1.811*	*1.455*	*-2.357*	*2.672*	
PLS	0.013	0.888	0.190	-0.135	0.343	0.856	0.014	0.979	0.236	-0.117	0.316	0.851	0.014	1.133	0.257	-0.077	0.270	0.810
t-stat	*3.589*	*9.574*	*1.944*	*-1.375*	*3.147*		*3.444*	*9.779*	*2.238*	*-1.100*	*2.682*		*2.850*	*8.992*	*1.936*	*-0.576*	*1.823*	
BRT	0.015	0.697	0.148	-0.359	0.465	0.853	0.012	0.804	0.211	-0.365	0.360	0.802	0.008	0.866	0.195	-0.295	0.362	0.788
t-stat	*3.658*	*6.891*	*1.392*	*-3.356*	*3.915*		*2.387*	*6.398*	*1.596*	*-2.744*	*2.435*		*1.619*	*6.613*	*1.410*	*-2.128*	*2.349*	
NN1	0.012	0.789	-0.025	-0.399	0.222	0.935	0.011	0.818	-0.037	-0.387	0.164	0.931	0.014	0.879	-0.048	-0.397	0.102	0.910
t-stat	*4.969*	*12.929*	*-0.384*	*-6.174*	*3.099*		*4.705*	*13.267*	*-0.572*	*-5.926*	*2.261*		*4.881*	*12.029*	*-0.619*	*-5.131*	*1.189*	
NN2	0.014	0.875	0.032	-0.270	0.425	0.922	0.015	0.883	-0.011	-0.264	0.380	0.875	0.015	0.882	-0.092	-0.328	0.311	0.807
t-stat	*4.910*	*11.929*	*0.413*	*-3.482*	*4.930*		*3.997*	*9.440*	*-0.111*	*-2.667*	*3.457*		*3.055*	*7.250*	*-0.720*	*-2.546*	*2.176*	
NN3	0.013	0.699	0.129	-0.422	0.436	0.908	0.017	0.599	0.197	-0.440	0.472	0.852	0.019	0.497	0.258	-0.468	0.523	0.749
t-stat	*4.288*	*8.746*	*1.528*	*-4.994*	*4.644*		*4.105*	*5.841*	*1.824*	*-4.051*	*3.917*		*3.429*	*3.475*	*1.713*	*-3.092*	*3.109*	

Table D.3 reports the out-of-sample performance of long-short fund portfolios predicted by each model. Again, we consider multiple numbers to group funds. We find that no matter how many groups that we divide into, the long-short fund portfolio exhibits economically and statistically significant positive Carhart (1997) four-factor alphas.

Weighting Schemes We show that weighting the portfolios using model predicting values outperforms weighting equally or weighting using the funds' total net assets. In all of our analyses, we form the fund portfolios using model predictions as weights. Table D.4 reports the out-of-sample performances of long-top portfolios formed equal-weightedly and TNA-weightedly.

Abnormal Performance Table D.5 reports the out-of-sample performance differences between long-top fund portfolios predicted by models and fund market portfolio (equal-weighted and TNA-weighetd) as well as performance differences between long-top fund portfolios predicted by machining-learning models and long-top fund portfolios predicted by simple linear model. Again, we consider multiple numbers to group funds. In Table D.6, we provide the corresponding long-short portfolios' Carhart (1997) four-factor alphas and risk exposures.

Performance Persistence Table D.7 reports the average monthly out-of-sample performance (excess return) of decile (D1D̃10) fund portfolios predicted by models within one year after formations. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). In Table D.8, we also report the corresponding Carhart (1997)'s alphas of D1D̃10 fund portfolios predicted by each model.

Figure D.2 shows the out-of-sample performance persistence of decile portfolios predicted by models. Cell (i, j) of the transition matrix represents the probability a fund in decile i in month t transfers to decile j in month $t + N$ (N=3, 6, 12).

Table D.3: Out-of-sample performance of long-short portfolios with respect to Carhart (1997) four-factor model

This table reports the monthly out-of-sample performance of long-short fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) with respect to Carhart (1997) four-factor model. To form a long-short portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top and short the bottom group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2
	# Group=5						# Group=10						# Group=20					
OLS	0.005	0.060	0.211	0.180	0.076	0.444	0.004	0.092	0.266	0.229	0.062	0.466	0.004	0.092	0.285	0.267	0.042	0.453
t-stat	*2.423*	*1.096*	*3.639*	*3.080*	*1.169*		*1.555*	*1.320*	*3.634*	*3.107*	*0.756*		*1.220*	*1.125*	*3.294*	*3.073*	*0.434*	
LASSO	0.008	-0.088	0.482	0.106	0.408	0.426	0.010	-0.108	0.643	0.174	0.525	0.485	0.011	-0.103	0.715	0.187	0.591	0.445
t-stat	*1.601*	*-0.719*	*3.743*	*0.817*	*2.838*		*1.807*	*-0.764*	*4.334*	*1.163*	*3.169*		*1.697*	*-0.601*	*3.973*	*1.033*	*2.945*	
PLS	0.008	0.055	0.345	0.213	0.272	0.380	0.010	0.081	0.398	0.248	0.271	0.388	0.010	0.139	0.418	0.297	0.221	0.399
t-stat	*2.188*	*0.588*	*3.529*	*2.165*	*2.496*		*2.436*	*0.780*	*3.645*	*2.257*	*2.221*		*2.219*	*1.260*	*3.598*	*2.539*	*1.707*	
BRT	0.008	-0.006	0.171	0.109	0.247	0.337	0.010	-0.058	0.150	0.117	0.282	0.313	0.010	-0.032	0.188	0.146	0.300	0.295
t-stat	*2.956*	*-0.085*	*2.456*	*1.561*	*3.172*		*3.258*	*-0.773*	*1.897*	*1.479*	*3.200*		*3.112*	*-0.373*	*2.088*	*1.618*	*2.996*	
NN1	0.005	0.005	0.137	-0.057	0.043	0.205	0.007	0.027	0.154	-0.048	0.042	0.202	0.008	0.008	0.159	-0.088	-0.017	0.173
t-stat	*1.937*	*0.073*	*2.005*	*-0.837*	*0.568*		*2.592*	*0.383*	*2.087*	*-0.651*	*0.511*		*2.569*	*0.099*	*1.817*	*-1.002*	*-0.173*	
NN2	0.006	0.055	0.139	-0.009	0.129	0.389	0.008	0.069	0.198	-0.008	0.148	0.434	0.009	0.101	0.214	0.068	0.219	0.385
t-stat	*3.177*	*1.107*	*2.658*	*-0.170*	*2.206*		*3.467*	*1.205*	*3.276*	*-0.128*	*2.203*		*3.233*	*1.406*	*2.840*	*0.901*	*2.609*	
NN3	0.005	-0.024	0.180	-0.116	0.125	0.565	0.006	-0.056	0.213	-0.147	0.128	0.577	0.006	-0.073	0.260	-0.150	0.166	0.552
t-stat	*2.370*	*-0.474*	*3.433*	*-2.208*	*2.143*		*2.715*	*-1.005*	*3.601*	*-2.468*	*1.942*		*2.311*	*-1.067*	*3.598*	*-2.060*	*2.066*	
		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2
	# Group=50						# Group=100						# Group=200					
OLS	0.002	0.070	0.391	0.359	0.074	0.435	0.006	0.083	0.502	0.514	0.227	0.494	0.007	0.262	0.451	0.561	0.239	0.474
t-stat	*0.550*	*0.620*	*3.265*	*2.985*	*0.553*		*1.180*	*0.648*	*3.726*	*3.793*	*1.506*		*1.333*	*1.898*	*3.104*	*3.844*	*1.476*	
LASSO	0.011	-0.199	0.811	0.388	0.768	0.353	0.009	-0.022	0.736	0.494	0.863	0.308	0.014	-0.027	0.886	0.791	0.968	0.351
t-stat	*1.107*	*-0.820*	*3.170*	*1.508*	*2.690*		*0.854*	*-0.082*	*2.627*	*1.754*	*2.761*		*1.209*	*-0.093*	*2.899*	*2.577*	*2.839*	
PLS	0.010	0.187	0.508	0.332	0.231	0.389	0.010	0.275	0.530	0.283	0.210	0.319	0.016	0.507	0.542	0.352	0.180	0.376
t-stat	*1.890*	*1.378*	*3.548*	*2.310*	*1.445*		*1.567*	*1.636*	*2.992*	*1.591*	*1.063*		*2.222*	*2.714*	*2.756*	*1.780*	*0.821*	
BRT	0.010	-0.050	0.246	0.146	0.230	0.175	0.006	0.099	0.327	0.113	-0.017	0.172	0.009	0.092	0.199	0.160	-0.090	0.171
t-stat	*2.074*	*-0.430*	*1.992*	*1.174*	*1.666*		*0.999*	*0.652*	*2.049*	*0.702*	*-0.096*		*1.732*	*0.662*	*1.358*	*1.091*	*-0.552*	
NN1	0.007	-0.110	0.267	-0.040	0.037	0.191	0.009	-0.127	0.265	-0.019	-0.038	0.173	0.013	-0.107	0.297	0.003	-0.031	0.149
t-stat	*1.468*	*-0.946*	*2.188*	*-0.326*	*0.275*		*1.690*	*-0.969*	*1.922*	*-0.136*	*-0.245*		*2.184*	*-0.705*	*1.854*	*0.020*	*-0.175*	
NN2	0.008	0.103	0.298	0.139	0.306	0.362	0.005	0.056	0.241	0.116	0.246	0.174	0.006	-0.021	0.157	-0.014	-0.021	0.048
t-stat	*2.046*	*1.063*	*2.924*	*1.355*	*2.693*		*0.963*	*0.451*	*1.853*	*0.890*	*1.697*		*1.145*	*-0.149*	*1.047*	*-0.090*	*-0.126*	
NN3	0.006	-0.180	0.360	-0.102	0.196	0.450	0.009	-0.451	0.429	-0.119	0.264	0.513	0.010	-0.483	0.477	-0.103	0.380	0.530
t-stat	*1.621*	*-1.846*	*3.509*	*-0.989*	*1.712*		*1.812*	*-3.630*	*3.279*	*-0.907*	*1.804*		*1.889*	*-3.574*	*3.354*	*-0.718*	*2.398*	

Table D.4: Out-of-sample performance of the long-short portfolio (equal-weighted and value-weighted)

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by the simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.). For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds equal-weightedly or value-weightedly, using the normalized fund total net asset as weights. We consider multiple group numbers including 5, 10, 20, 50, 100 and 200. We report the monthly return, annualized sharpe ratio, and Carhart (1997) four-factor alpha for each portfolio. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022

	Equal-weighted							Value-weighted					
	Ret	SR	t-stat	Ret	SR	t-stat		Ret	SR	t-stat	Ret	SR	t-stat
	# Group=5			# Group=10				# Group=5			# Group=10		
OLS	2.06	1.53	2.49	2.06	1.54	2.52	OLS	1.75	1.34	2.19	1.64	1.23	2.00
LASSO	2.11	1.52	2.48	2.18	1.59	2.59	LASSO	1.81	1.28	2.09	2.03	1.46	2.37
PLS	2.16	1.55	2.52	2.20	1.59	2.58	PLS	2.15	1.48	2.41	2.14	1.44	2.35
GBRT	2.01	1.48	2.41	2.05	1.52	2.48	GBRT	1.60	1.20	1.96	1.51	1.17	1.91
NN1	2.03	1.44	2.35	2.19	1.54	2.51	NN1	1.78	1.24	2.02	1.92	1.26	2.06
NN2	2.14	1.49	2.44	2.30	1.59	2.58	NN2	1.87	1.25	2.04	2.10	1.39	2.26
NN3	2.10	1.45	2.37	2.22	1.55	2.52	NN3	1.74	1.20	1.95	1.94	1.29	2.11
	# Group=20			# Group=50				# Group=20			# Group=50		
OLS	2.11	1.57	2.56	2.00	1.54	2.51	OLS	1.70	1.28	2.08	1.37	0.98	1.60
LASSO	2.22	1.59	2.59	2.31	1.60	2.61	LASSO	2.01	1.39	2.26	2.48	1.57	2.56
PLS	2.30	1.67	2.72	2.26	1.67	2.72	PLS	2.24	1.53	2.49	2.50	1.69	2.75
GBRT	2.00	1.47	2.40	1.82	1.32	2.14	GBRT	1.51	1.14	1.86	1.69	1.19	1.93
NN1	2.20	1.56	2.55	2.18	1.55	2.53	NN1	2.10	1.42	2.32	2.35	1.53	2.49
NN2	2.47	1.68	2.73	2.52	1.71	2.78	NN2	2.38	1.54	2.50	2.45	1.59	2.59
NN3	2.28	1.56	2.55	2.29	1.52	2.48	NN3	2.01	1.33	2.18	1.99	1.23	2.01
	# Group=100			# Group=200				# Group=100			# Group=200		
OLS	2.05	1.52	2.48	1.96	1.39	2.26	OLS	1.74	1.10	1.80	1.90	1.17	1.91
LASSO	2.43	1.62	2.64	2.62	1.70	2.76	LASSO	2.39	1.55	2.53	2.72	1.70	2.78
PLS	2.25	1.66	2.70	2.48	1.70	2.77	PLS	2.43	1.68	2.73	2.75	1.72	2.81
GBRT	1.59	1.15	1.87	2.08	1.48	2.42	GBRT	1.60	1.14	1.85	1.94	1.42	2.31
NN1	2.07	1.50	2.45	2.05	1.51	2.47	NN1	2.39	1.46	2.38	2.81	1.75	2.85
NN2	2.48	1.65	2.68	2.38	1.61	2.63	NN2	2.44	1.47	2.39	2.13	1.24	2.02
NN3	2.36	1.59	2.59	2.62	1.79	2.92	NN3	2.30	1.38	2.25	2.64	1.55	2.53

Table D.5: Out-of-sample performance of machining-learning models with respect to OLS and fund market

This table reports the monthly out-of-sample performance (monthly return and annualized sharpe ratio) of long top fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) and short top fund portfolios predicted by the simple linear model (OLS). To form a long-top portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. We also compare the out-of-sample performance between model-predicted long-top portfolios and the fund market (long all funds equal-weighted or value-weighted). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	diffOLS	t	diffEW	t	diffVW	t	diffOLS	t	diffEW	t	diffVW	t
	# Group=5						# Group=10					
OLS	0.00		0.44	4.67	0.68	4.97	0.00		0.44	3.86	0.68	4.33
LASSO	0.33	1.93	0.76	3.90	1.01	4.18	0.56	2.60	1.00	4.00	1.25	4.23
PLS	0.13	1.48	0.57	4.16	0.82	4.35	0.17	1.77	0.61	3.98	0.86	4.21
BRT	0.28	2.01	0.72	5.18	0.96	5.23	0.34	1.99	0.78	4.94	1.03	5.15
NN1	0.06	0.49	0.50	5.33	0.74	6.34	0.12	0.82	0.56	5.34	0.81	6.12
NN2	0.21	2.05	0.65	6.72	0.89	7.25	0.32	2.54	0.76	6.56	1.01	6.85
NN3	0.13	0.93	0.57	5.22	0.81	5.92	0.22	1.32	0.66	5.02	0.91	5.50
	# Group=20						# Group=50					
OLS	0.00		0.42	3.10	0.67	3.73	0.00		0.37	2.11	0.61	2.85
LASSO	0.73	2.66	1.15	3.85	1.39	4.12	0.91	2.70	1.27	3.55	1.52	3.76
PLS	0.21	1.83	0.63	3.73	0.88	4.02	0.29	1.87	0.66	3.28	0.90	3.66
BRT	0.44	1.96	0.87	4.35	1.11	4.61	0.55	1.89	0.92	3.86	1.16	4.14
NN1	0.17	0.91	0.59	5.00	0.83	5.67	0.20	0.90	0.57	4.59	0.82	5.35
NN2	0.40	2.60	0.83	5.99	1.07	6.19	0.50	2.74	0.87	5.61	1.12	5.83
NN3	0.31	1.52	0.74	4.57	0.98	4.97	0.48	1.83	0.85	4.18	1.09	4.50
	# Group=100						# Group=200					
OLS	0.00		0.45	2.05	0.69	2.70	0.00		0.51	1.90	0.75	2.50
LASSO	0.85	2.35	1.30	3.36	1.54	3.61	1.06	2.97	1.57	3.58	1.81	3.81
PLS	0.31	1.57	0.76	3.20	1.00	3.58	0.26	1.31	0.87	2.78	1.11	3.19
BRT	0.19	0.55	0.70	2.47	0.93	2.86	0.22	0.74	0.73	3.53	0.97	4.03
NN1	0.05	0.18	0.50	3.64	0.74	4.64	0.26	0.89	0.77	4.84	1.02	5.81
NN2	0.44	2.14	0.89	5.12	1.13	5.54	0.36	1.42	0.87	4.10	1.11	4.84
NN3	0.69	2.11	1.14	4.38	1.38	4.61	0.90	2.08	1.41	4.05	1.66	4.31

Table D.6: Out-of-sample performance of long-top-short-market portfolios with respect to Carhart (1997) four-factor model

This table reports the monthly out-of-sample performance of long-top-short-market fund portfolios predicted by machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) with respect to Carhart (1997) four-factor model. To form a long-top-short-market portfolio, for each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights, and short the fund market (i.e., short all active equity funds equal-weighted). We consider multiple group numbers including 5, 10, 20, 50, 100 and 200. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2	α	MKT	SMB	HML	UMD	R2
	# Group=5						# Group=10						# Group=20					
OLS	0.004	0.103	0.144	0.113	0.068	0.579	0.004	0.120	0.177	0.145	0.069	0.584	0.004	0.133	0.193	0.173	0.055	0.542
t-stat	*3.150*	*3.370*	*4.460*	*3.486*	*1.886*		*2.661*	*3.206*	*4.502*	*3.677*	*1.587*		*2.124*	*2.863*	*3.924*	*3.509*	*1.007*	
LASSO	0.006	0.008	0.283	0.036	0.270	0.476	0.008	-0.016	0.393	0.077	0.382	0.534	0.009	-0.060	0.466	0.083	0.449	0.526
t-stat	*1.971*	*0.111*	*3.739*	*0.473*	*3.199*		*2.212*	*-0.182*	*4.307*	*0.844*	*3.756*		*2.147*	*-0.576*	*4.255*	*0.758*	*3.671*	
PLS	0.005	0.086	0.215	0.123	0.147	0.448	0.005	0.094	0.236	0.167	0.149	0.439	0.006	0.106	0.256	0.198	0.134	0.447
t-stat	*2.324*	*1.660*	*3.946*	*2.252*	*2.415*		*2.343*	*1.596*	*3.823*	*2.685*	*2.163*		*2.305*	*1.652*	*3.802*	*2.924*	*1.786*	
BRT	0.006	0.012	0.118	0.036	0.186	0.381	0.007	-0.024	0.180	0.036	0.236	0.401	0.007	-0.052	0.220	0.019	0.271	0.378
t-stat	*3.078*	*0.252*	*2.281*	*0.693*	*3.237*		*2.660*	*-0.389*	*2.743*	*0.539*	*3.221*		*2.260*	*-0.651*	*2.625*	*0.230*	*2.906*	
NN1	0.004	0.070	0.080	-0.041	0.037	0.348	0.004	0.068	0.103	-0.034	0.033	0.294	0.005	0.049	0.116	-0.034	0.032	0.230
t-stat	*2.443*	*1.828*	*1.990*	*-1.010*	*0.834*		*2.462*	*1.531*	*2.178*	*-0.723*	*0.620*		*2.286*	*0.936*	*2.102*	*-0.622*	*0.525*	
NN2	0.005	0.089	0.101	-0.002	0.117	0.576	0.006	0.104	0.135	0.030	0.151	0.536	0.006	0.116	0.160	0.063	0.193	0.505
t-stat	*3.914*	*2.801*	*3.005*	*-0.056*	*3.123*		*3.754*	*2.584*	*3.188*	*0.698*	*3.204*		*3.340*	*2.353*	*3.096*	*1.217*	*3.337*	
NN3	0.004	0.027	0.111	-0.079	0.100	0.575	0.005	0.009	0.153	-0.076	0.131	0.526	0.005	-0.013	0.198	-0.068	0.178	0.505
t-stat	*2.762*	*0.759*	*2.939*	*-2.081*	*2.368*		*2.607*	*0.198*	*3.150*	*-1.548*	*2.410*		*2.344*	*-0.228*	*3.272*	*-1.111*	*2.641*	
		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2		MKT	SMB	HML	UMD	R2
	# Group=50						# Group=100						# Group=200					
OLS	0.003	0.178	0.217	0.225	0.067	0.505	0.004	0.244	0.246	0.311	0.136	0.513	0.004	0.302	0.274	0.373	0.210	0.473
t-stat	*1.373*	*2.870*	*3.313*	*3.422*	*0.910*		*1.306*	*3.159*	*3.030*	*3.801*	*1.495*		*1.092*	*3.056*	*2.634*	*3.567*	*1.808*	
LASSO	0.009	-0.177	0.465	-0.040	0.422	0.471	0.008	-0.235	0.451	-0.151	0.375	0.430	0.008	-0.381	0.456	-0.167	0.458	0.360
t-stat	*1.830*	*-1.400*	*3.495*	*-0.301*	*2.840*		*1.463*	*-1.602*	*2.921*	*-0.971*	*2.174*		*1.039*	*-1.934*	*2.198*	*-0.801*	*1.980*	
PLS	0.006	0.124	0.322	0.225	0.138	0.478	0.006	0.216	0.369	0.243	0.111	0.510	0.007	0.369	0.389	0.283	0.065	0.467
t-stat	*2.052*	*1.688*	*4.168*	*2.891*	*1.602*		*1.946*	*2.579*	*4.181*	*2.744*	*1.129*		*1.533*	*3.196*	*3.202*	*2.315*	*0.481*	
BRT	0.007	-0.067	0.281	0.001	0.261	0.332	0.004	0.041	0.342	-0.005	0.158	0.248	0.001	0.103	0.326	0.065	0.160	0.212
t-stat	*1.907*	*-0.678*	*2.706*	*0.006*	*2.251*		*0.868*	*0.330*	*2.642*	*-0.036*	*1.096*		*0.159*	*0.800*	*2.402*	*0.477*	*1.056*	
NN1	0.005	0.025	0.108	-0.039	0.018	0.158	0.004	0.054	0.095	-0.027	-0.041	0.121	0.007	0.116	0.085	-0.037	-0.102	0.177
t-stat	*2.091*	*0.439*	*1.768*	*-0.636*	*0.259*		*1.674*	*0.842*	*1.404*	*-0.394*	*-0.537*		*2.380*	*1.575*	*1.099*	*-0.479*	*-1.187*	
NN2	0.007	0.112	0.164	0.089	0.220	0.429	0.008	0.119	0.122	0.096	0.175	0.237	0.007	0.118	0.040	0.032	0.106	0.095
t-stat	*2.995*	*1.875*	*2.625*	*1.418*	*3.152*		*2.504*	*1.559*	*1.508*	*1.180*	*1.949*		*1.853*	*1.155*	*0.375*	*0.295*	*0.885*	
NN3	0.006	-0.065	0.261	-0.063	0.232	0.480	0.009	-0.164	0.330	-0.080	0.268	0.446	0.012	-0.266	0.391	-0.109	0.318	0.386
t-stat	*2.172*	*-0.872*	*3.352*	*-0.801*	*2.663*		*2.438*	*-1.673*	*3.190*	*-0.773*	*2.322*		*2.230*	*-1.921*	*2.679*	*-0.741*	*1.955*	

Table D.7: Out-of-sample performance of decile portfolios within one year after formations

This table reports the average monthly out-of-sample performance (excess return) of decile fund portfolios predicted by models within one year after their formations. For each month $t+1$ in testing period, we sort mutual funds according to model predictions in month t into deciles, then long each group of funds value-weightedly, using the normalized prediction values as weights, and track the portfolio performance for one year ($t+1$ to $t+12$). We then average performance for $t+N$ (N=1,2,..., 12) across all formation period t. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and testing sample from June 2019 to January 2022.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
						OLS						
D1	2.75	2.71	2.80	2.84	2.89	2.83	2.73	2.46	2.60	2.72	2.03	1.63
D2	2.61	2.52	2.79	2.84	2.99	2.94	2.54	2.48	2.18	2.56	2.21	1.64
D3	2.84	2.52	2.71	3.11	3.04	3.00	2.59	2.24	2.24	2.65	1.99	1.46
D4	2.95	2.60	2.89	2.94	2.94	2.92	2.66	2.42	2.34	2.68	2.37	1.50
D5	2.98	2.64	2.93	3.01	3.01	3.00	2.69	2.41	2.34	2.81	2.11	1.68
D6	3.00	2.79	2.82	3.11	3.09	2.83	2.75	2.23	2.16	2.78	2.31	1.54
D7	3.03	2.80	2.90	2.96	3.06	2.80	2.57	2.29	2.16	2.84	2.25	1.72
D8	3.12	2.84	2.81	3.03	3.05	2.98	2.63	2.36	2.22	2.70	2.32	1.67
D9	3.30	2.87	2.89	3.03	3.00	2.94	2.71	2.46	2.47	2.59	2.47	1.65
D10	3.03	2.64	2.72	2.85	2.93	3.03	2.65	2.38	2.31	2.83	2.64	1.93
D10-D1	0.28	-0.08	-0.08	0.01	0.04	0.20	-0.08	-0.08	-0.28	0.12	0.61	0.30
t-stat	***0.86***	***-0.24***	***-0.28***	***0.03***	***0.10***	***0.56***	***-0.27***	***-0.24***	***-0.63***	***0.38***	***1.53***	***0.79***
						LASSO						
D1	2.83	2.71	2.83	2.93	3.00	2.95	2.64	2.42	2.61	2.79	2.17	1.48
D2	2.71	2.47	2.49	2.97	2.65	2.71	2.60	2.39	2.23	2.63	1.98	1.52
D3	2.62	2.40	2.31	2.55	2.59	2.66	2.52	2.36	2.15	2.49	2.12	1.74
D4	2.83	2.54	2.72	2.82	2.62	2.96	2.55	2.31	2.13	2.54	2.32	1.50
D5	2.95	2.65	2.67	2.84	2.91	2.87	2.70	2.23	2.31	2.69	2.31	1.55
D6	3.14	2.72	2.76	2.99	2.97	2.84	2.62	2.43	2.46	2.80	2.25	1.73
D7	3.00	2.73	2.92	3.21	3.21	3.22	2.77	2.44	2.26	2.85	2.32	1.86
D8	2.91	2.68	2.71	3.05	3.09	3.20	2.84	2.63	2.25	2.85	2.42	1.89
D9	2.96	2.84	3.08	3.35	3.14	3.31	2.75	2.38	2.14	2.71	2.38	1.77
D10	3.55	3.12	3.34	3.01	3.75	3.43	3.44	2.65	2.28	3.22	2.72	1.90
D10-D1	0.73	0.42	0.51	0.08	0.75	0.49	0.79	0.23	-0.33	0.43	0.55	0.42
t-stat	***1.18***	***0.61***	***0.95***	***0.15***	***1.30***	***0.70***	***1.59***	***0.40***	***-0.67***	***0.79***	***1.01***	***0.84***
						PLS						
D1	2.41	2.37	2.14	2.66	2.77	2.70	2.25	1.96	2.25	2.72	2.01	1.54
D2	2.67	2.45	2.37	2.67	2.50	3.00	2.60	2.43	2.32	2.45	2.21	1.69
D3	2.90	2.46	2.79	2.78	2.77	3.09	2.48	2.29	2.23	2.51	2.11	1.56
D4	3.12	2.70	2.68	2.98	2.91	3.13	2.59	2.46	2.26	2.81	2.18	1.77
D5	2.97	2.68	2.82	2.97	2.99	3.10	2.80	2.44	2.41	2.87	2.36	1.70
D6	3.04	2.79	2.86	3.16	3.08	3.10	2.99	2.58	2.39	2.96	2.58	1.56
D7	3.04	2.85	2.97	3.19	3.06	2.95	2.95	2.45	2.39	2.94	2.36	1.85
D8	3.15	2.83	3.17	3.06	3.41	3.16	3.03	2.73	2.32	2.91	2.46	1.67
D9	3.26	2.96	3.04	3.20	3.45	3.20	2.86	2.51	2.38	2.78	2.48	1.87
D10	3.13	2.92	3.08	3.08	3.26	2.81	2.81	2.60	2.47	2.87	2.70	1.99
D10-D1	0.73	0.55	0.94	0.42	0.50	0.12	0.56	0.65	0.22	0.15	0.69	0.46
t-stat	***1.73***	***1.50***	***2.52***	***0.94***	***1.05***	***0.27***	***1.59***	***1.46***	***0.46***	***0.30***	***1.27***	***1.21***

Continued

						BRT						
D1	2.66	2.49	2.69	2.71	2.66	2.51	2.09	1.99	2.31	2.73	2.38	1.78
D2	2.83	2.87	2.73	2.88	3.03	2.73	2.45	2.32	2.34	2.93	2.21	1.62
D3	2.80	2.86	2.95	2.45	2.47	2.52	2.65	2.21	2.38	2.84	2.31	1.75
D4	2.70	3.06	2.85	2.48	2.64	3.04	2.58	2.35	1.48	1.80	2.07	2.31
D5	2.70	2.06	1.41	2.49	2.98	2.40	1.85	1.67	0.85	1.59	2.00	0.73
D6	1.25	0.70	1.71	2.98	2.30	1.17	1.29	0.60	1.39	1.97	0.71	-0.54
D7	1.20	0.70	1.61	1.72	1.98	1.78	2.07	1.24	0.67	1.21	1.03	0.19
D8	1.87	0.96	2.33	1.91	1.67	2.12	2.70	1.75	2.11	1.28	1.26	1.21
D9	2.59	2.38	2.31	2.40	3.15	2.99	2.51	2.08	2.21	2.46	2.04	1.49
D10	3.32	2.68	2.88	3.14	3.02	3.20	2.67	2.43	2.47	2.93	2.35	1.72
D10-D1	0.66	0.19	0.19	0.43	0.37	0.70	0.58	0.44	0.15	0.20	-0.03	-0.06
t-stat	***2.48***	***0.72***	***0.60***	***1.47***	***1.37***	***2.97***	***1.56***	***1.48***	***0.67***	***0.83***	***-0.10***	***-0.27***
						NN1						
D1	2.61	2.46	3.10	2.92	2.97	2.77	2.70	2.49	2.38	2.62	1.91	1.18
D2	2.86	2.61	2.82	2.99	2.98	2.74	2.77	2.50	2.29	2.79	2.07	1.56
D3	2.83	2.82	2.77	2.91	2.91	3.00	2.70	2.50	2.21	2.65	2.25	1.53
D4	2.75	2.77	2.66	3.06	3.05	2.85	2.48	2.28	2.39	2.86	2.35	1.62
D5	2.93	2.73	2.83	3.06	3.05	3.04	2.92	2.45	2.42	2.88	2.30	1.71
D6	3.00	2.68	2.78	2.96	2.85	2.92	2.62	2.40	2.37	2.85	2.32	1.79
D7	2.99	2.65	2.89	3.05	2.99	3.25	2.60	2.35	2.26	2.62	2.52	1.87
D8	3.18	2.59	2.80	2.93	3.10	3.06	2.56	2.36	2.30	2.81	2.40	1.80
D9	2.99	2.69	2.76	2.92	3.07	2.94	2.63	2.46	2.37	2.79	2.47	1.85
D10	3.20	2.76	2.80	2.94	3.01	2.93	2.63	2.25	2.33	2.76	2.61	1.79
D10-D1	0.59	0.31	-0.30	0.02	0.04	0.16	-0.07	-0.23	-0.06	0.14	0.70	0.61
t-stat	***2.25***	***0.90***	***-0.83***	***0.07***	***0.16***	***0.64***	***-0.22***	***-0.72***	***-0.20***	***0.44***	***2.11***	***2.37***
						NN2						
D1	2.57	2.61	3.12	3.04	3.09	2.60	2.49	2.45	2.37	2.57	1.87	1.50
D2	2.75	2.68	2.89	2.93	2.87	2.80	2.56	2.45	2.30	2.71	2.19	1.49
D3	2.86	2.73	2.77	2.88	3.04	2.83	2.61	2.52	2.27	2.76	2.35	1.61
D4	2.76	2.82	2.73	2.94	2.93	2.94	2.80	2.40	2.21	2.85	2.18	1.66
D5	2.88	2.60	2.75	3.16	3.00	2.94	2.77	2.47	2.37	2.71	2.38	1.67
D6	2.96	2.75	2.83	3.02	3.05	2.92	2.71	2.37	2.36	2.86	2.33	1.70
D7	3.12	2.60	2.78	2.96	2.97	3.18	2.82	2.43	2.26	2.84	2.26	1.71
D8	3.11	2.59	2.79	2.94	2.97	3.17	2.65	2.48	2.45	2.83	2.31	1.85
D9	3.21	2.76	2.86	2.99	3.09	3.04	2.61	2.14	2.34	2.81	2.60	1.81
D10	3.39	2.81	2.86	3.02	3.16	3.10	2.77	2.42	2.39	2.77	2.75	1.89
D10-D1	0.82	0.20	-0.26	-0.03	0.07	0.50	0.28	-0.03	0.02	0.20	0.88	0.39
t-stat	***2.67***	***0.73***	***-0.82***	***-0.10***	***0.23***	***2.65***	***0.94***	***-0.11***	***0.05***	***0.65***	***2.91***	***1.45***
						NN3						
D1	2.71	2.21	2.78	2.95	3.08	2.80	2.52	2.30	2.24	2.80	1.85	1.20
D2	2.78	2.53	2.89	2.94	2.90	2.81	2.66	2.50	2.26	2.85	1.98	1.58
D3	2.71	2.65	2.45	2.97	2.91	2.83	2.69	2.48	2.35	2.74	2.31	1.54
D4	2.79	2.64	2.75	3.03	2.90	2.79	2.64	2.41	2.22	2.84	2.27	1.66
D5	2.93	2.57	2.81	3.12	2.87	2.88	2.84	2.39	2.44	2.91	2.30	1.65
D6	2.87	2.63	2.70	2.95	2.96	3.04	2.67	2.32	2.23	2.61	2.37	1.64
D7	3.10	2.66	2.79	2.93	2.97	3.12	2.65	2.29	2.31	2.77	2.38	1.83
D8	3.17	2.85	2.92	2.90	3.22	3.15	2.61	2.40	2.33	2.75	2.43	1.71
D9	3.05	2.83	3.02	2.99	3.09	3.12	2.62	2.26	2.46	2.72	2.66	1.89
D10	3.19	2.90	2.94	3.00	3.14	2.91	2.77	2.54	2.37	2.69	2.56	1.90
D10-D1	0.48	0.69	0.16	0.05	0.06	0.11	0.25	0.24	0.13	-0.10	0.70	0.70
t-stat	***1.88***	***2.25***	***0.49***	***0.17***	***0.22***	***0.32***	***0.83***	***0.76***	***0.45***	***-0.33***	***2.00***	***2.10***

Table D.8: Out-of-sample performance (Carhart (1997) four-factor alpha) of decile portfolios within one year after formations

This table reports the average monthly out-of-sample performance (Carhart (1997) four-factor alpha) of decile fund portfolios predicted by models within one year after formations. For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into deciles, then long each group of funds value-weighted, using the normalized prediction values as weights, and track the portfolio performance for one year ($t+1$ to $t+12$). We then average performance for $t+N$ (N=1,2,..., 12) across all formation period t. D1 (D10) represents the decile portfolio containing funds that are expected to perform the worst (best). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
OLS												
D1	0.76	1.03	1.13	0.99	1.01	0.98	1.20	1.10	1.15	0.97	0.66	0.82
D2	0.62	0.86	1.18	1.09	1.18	1.01	0.95	1.06	0.60	0.59	0.74	0.76
D3	0.76	0.88	1.03	1.30	1.16	1.13	1.01	0.80	0.70	0.78	0.58	0.56
D4	0.84	0.89	1.18	1.14	1.03	1.07	1.05	0.96	0.77	0.74	0.79	0.55
D5	0.97	0.96	1.16	1.15	1.11	1.11	1.02	0.93	0.76	0.83	0.61	0.70
D6	0.85	1.17	1.07	1.22	1.15	0.89	1.11	0.75	0.58	0.80	0.75	0.59
D7	1.01	1.14	1.16	1.00	1.14	0.89	0.94	0.83	0.62	0.90	0.71	0.77
D8	1.01	1.22	1.10	1.13	1.15	1.09	1.04	0.96	0.59	0.69	0.85	0.75
D9	1.26	1.18	1.17	1.08	1.06	1.04	1.07	1.03	0.85	0.62	0.97	0.69
D10	1.07	1.03	1.03	0.98	1.07	1.13	1.01	0.94	0.70	0.86	1.12	0.94
D10-D1	0.32	0.00	-0.09	-0.01	0.06	0.15	-0.19	-0.15	-0.45	-0.10	0.46	0.12
t-stat	***0.99***	***0.00***	***-0.35***	***-0.02***	***0.17***	***0.37***	***-0.54***	***-0.40***	***-1.06***	***-0.35***	***1.25***	***0.38***
LASSO												
D1	0.90	1.29	1.18	1.20	1.08	1.08	1.01	1.07	1.10	0.88	0.75	0.55
D2	0.89	1.09	0.76	1.14	0.89	0.92	0.93	1.04	0.75	0.82	0.50	0.67
D3	0.85	0.91	0.76	0.84	0.89	0.91	1.03	1.01	0.69	0.61	0.71	0.86
D4	0.93	1.01	1.05	1.02	0.85	1.09	1.00	0.95	0.62	0.66	0.93	0.64
D5	0.85	1.00	0.91	0.93	1.00	0.95	1.02	0.76	0.65	0.69	0.77	0.67
D6	0.99	1.04	0.98	1.04	1.04	0.93	0.93	0.94	0.78	0.70	0.70	0.77
D7	0.77	0.99	1.10	1.24	1.19	1.20	1.09	0.98	0.62	0.81	0.68	0.92
D8	0.75	0.87	0.98	1.06	1.02	1.22	1.09	1.07	0.56	0.77	0.90	0.93
D9	0.81	0.97	1.30	1.39	1.08	1.22	0.99	0.79	0.48	0.70	0.83	0.83
D10	1.31	1.13	1.40	0.82	1.58	1.05	1.36	0.86	0.40	1.11	1.02	0.93
D10-D1	0.41	-0.17	0.21	-0.38	0.51	-0.03	0.35	-0.20	-0.71	0.23	0.28	0.37
t-stat	***0.65***	***-0.30***	***0.38***	***-0.80***	***0.78***	***-0.04***	***0.71***	***-0.40***	***-1.52***	***0.42***	***0.52***	***0.75***
PLS												
D1	0.65	1.04	0.67	1.05	1.08	0.98	0.76	0.78	0.97	1.18	0.81	0.81
D2	0.85	0.98	0.78	1.08	0.79	1.20	1.12	1.10	0.89	0.62	0.82	0.84
D3	0.82	0.87	1.09	1.00	0.83	1.24	0.91	0.91	0.70	0.61	0.70	0.64
D4	1.03	1.03	0.91	1.11	0.99	1.25	0.90	0.95	0.69	0.80	0.67	0.88
D5	0.84	1.00	1.06	1.05	0.98	1.12	1.03	0.92	0.77	0.86	0.87	0.77
D6	0.76	1.12	1.05	1.24	1.12	1.14	1.30	1.04	0.69	0.89	0.94	0.57
D7	0.90	1.11	1.15	1.21	1.06	0.82	1.25	0.88	0.69	0.87	0.69	0.85
D8	1.12	1.02	1.39	0.98	1.43	1.15	1.14	1.19	0.60	0.83	0.84	0.69
D9	1.13	1.16	1.25	1.17	1.43	1.12	1.08	0.94	0.62	0.63	0.85	0.87
D10	1.17	1.20	1.35	1.06	1.23	0.79	1.13	1.07	0.82	0.83	1.16	1.03
D10-D1	0.51	0.16	0.69	0.01	0.15	-0.18	0.36	0.29	-0.15	-0.35	0.35	0.21
t-stat	***1.10***	***0.58***	***1.85***	***0.02***	***0.30***	***-0.41***	***0.92***	***0.66***	***-0.31***	***-0.84***	***0.96***	***0.84***

Continued

						BRT						
D1	0.80	0.90	1.10	1.02	0.97	0.89	0.80	0.72	0.81	0.86	0.94	0.87
D2	0.78	1.26	1.13	1.08	1.18	0.99	0.97	0.97	0.78	0.93	0.75	0.69
D3	0.87	1.33	1.35	0.74	0.73	0.60	1.10	0.90	0.95	0.66	0.84	0.81
D4	0.64	1.42	1.38	0.71	0.89	1.46	1.04	0.96	0.31	0.44	0.63	1.46
D5	1.12	1.01	0.23	0.57	1.57	0.95	0.39	0.88	0.46	0.58	1.18	0.71
D6	0.36	-0.03	0.45	1.66	1.01	-0.50	0.50	0.29	0.68	1.24	0.59	-0.82
D7	0.07	-0.14	0.35	0.78	0.66	0.26	0.78	0.49	0.02	0.15	0.93	-0.05
D8	1.34	0.02	0.67	0.81	0.38	0.16	1.55	0.50	0.66	0.17	0.63	0.38
D9	1.20	0.68	0.88	0.51	1.18	1.19	0.85	0.60	0.73	0.57	0.75	0.62
D10	1.26	0.93	0.94	1.16	0.95	1.17	0.89	0.89	0.81	0.95	0.83	0.82
D10-D1	0.46	0.03	-0.16	0.13	-0.02	0.27	0.09	0.17	0.00	0.09	-0.11	-0.05
t-stat	***1.46***	***0.12***	***-0.60***	***0.48***	***-0.08***	***1.67***	***0.31***	***0.62***	***0.01***	***0.34***	***-0.42***	***-0.26***
						NN1						
D1	0.60	0.97	1.45	1.08	1.11	0.91	1.14	1.12	0.89	0.89	0.59	0.33
D2	0.88	1.08	1.19	1.14	1.21	0.81	1.14	1.09	0.74	0.94	0.70	0.75
D3	0.91	1.21	1.15	1.04	1.12	1.18	1.09	1.02	0.63	0.73	0.86	0.65
D4	0.75	1.13	0.98	1.13	1.25	0.93	0.86	0.81	0.81	0.95	0.90	0.73
D5	0.86	1.03	1.09	1.16	1.12	1.11	1.21	0.96	0.76	0.93	0.87	0.76
D6	0.95	0.98	1.09	1.09	0.96	0.97	1.06	1.00	0.84	0.87	0.79	0.86
D7	0.86	0.95	1.08	1.16	0.95	1.28	0.92	0.88	0.69	0.68	0.98	0.93
D8	1.13	0.90	0.97	1.03	1.10	1.11	0.93	0.91	0.76	0.81	0.88	0.83
D9	0.92	0.96	1.02	0.97	1.06	0.94	0.95	1.05	0.74	0.80	0.95	0.91
D10	1.21	1.02	1.02	1.03	1.05	0.97	0.91	0.88	0.77	0.81	1.10	0.81
D10-D1	0.61	0.05	-0.43	-0.05	-0.06	0.07	-0.23	-0.24	-0.11	-0.08	0.51	0.48
t-stat	***2.21***	***0.17***	***-1.13***	***-0.14***	***-0.24***	***0.22***	***-0.73***	***-0.84***	***-0.47***	***-0.23***	***1.61***	***2.02***
						NN2						
D1	0.65	1.07	1.51	1.09	1.16	0.74	0.90	1.10	0.86	0.87	0.63	0.73
D2	0.75	1.06	1.29	1.03	1.03	0.89	0.95	1.05	0.77	0.85	0.77	0.59
D3	0.78	1.10	1.08	1.03	1.16	0.94	0.95	1.03	0.70	0.79	0.91	0.70
D4	0.74	1.20	1.04	1.06	1.06	0.94	1.12	0.95	0.58	0.96	0.73	0.75
D5	0.88	0.96	0.97	1.27	1.11	0.98	1.14	0.98	0.75	0.65	0.91	0.81
D6	0.89	1.03	1.16	1.12	1.10	0.97	1.04	0.92	0.82	0.92	0.83	0.79
D7	1.06	0.89	1.00	1.05	1.03	1.23	1.17	0.94	0.68	0.82	0.73	0.74
D8	0.96	0.86	0.99	1.08	1.03	1.27	1.00	1.00	0.82	0.80	0.74	0.83
D9	1.09	1.03	1.07	1.11	1.15	1.05	0.93	0.72	0.69	0.83	0.97	0.84
D10	1.26	1.06	1.03	1.04	1.14	1.13	1.05	0.98	0.81	0.79	1.25	0.89
D10-D1	0.61	-0.02	-0.47	-0.05	-0.02	0.38	0.15	-0.12	-0.04	-0.08	0.62	0.16
t-stat	***1.97***	***-0.07***	***-1.49***	***-0.15***	***-0.05***	***2.09***	***0.51***	***-0.42***	***-0.16***	***-0.24***	***2.35***	***0.90***
						NN3						
D1	0.79	0.72	1.15	1.06	1.16	0.93	0.94	0.96	0.76	1.04	0.62	0.37
D2	0.85	0.94	1.24	1.05	1.11	1.06	1.02	1.12	0.75	0.99	0.58	0.70
D3	0.77	1.06	0.80	1.13	1.09	0.95	1.14	1.02	0.79	0.86	0.96	0.70
D4	0.83	1.08	1.09	1.14	1.06	0.85	0.98	0.96	0.58	0.91	0.80	0.76
D5	0.89	0.90	1.09	1.21	0.94	0.89	1.18	0.90	0.76	0.98	0.80	0.75
D6	0.78	0.98	0.97	1.06	1.03	1.05	0.99	0.84	0.69	0.65	0.85	0.66
D7	0.96	0.96	1.01	1.03	0.98	1.13	0.94	0.84	0.74	0.79	0.90	0.87
D8	0.98	1.10	1.14	0.95	1.22	1.19	0.92	0.92	0.70	0.72	0.85	0.78
D9	0.91	1.04	1.19	1.04	1.03	1.08	0.97	0.80	0.87	0.75	1.13	0.93
D10	1.04	1.12	1.12	1.09	1.15	0.87	0.99	1.09	0.75	0.61	0.92	0.91
D10-D1	0.25	0.40	-0.03	0.03	-0.01	-0.07	0.04	0.14	-0.02	-0.43	0.30	0.55
t-stat	***1.26***	***1.67***	***-0.09***	***0.09***	***-0.05***	***-0.16***	***0.13***	***0.47***	***-0.05***	***-1.34***	***1.01***	***1.81***

OLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.40	0.18	0.12	0.08	0.06	0.05	0.04	0.03	0.02	0.02
2	0.20	0.16	0.14	0.13	0.10	0.08	0.07	0.06	0.05	0.04
3	0.13	0.16	0.15	0.11	0.11	0.09	0.08	0.06	0.05	0.05
4	0.10	0.15	0.13	0.13	0.10	0.09	0.09	0.08	0.07	0.06
5	0.08	0.11	0.11	0.12	0.11	0.11	0.11	0.10	0.10	0.07
6	0.06	0.10	0.11	0.11	0.12	0.11	0.11	0.11	0.09	0.09
7	0.05	0.08	0.09	0.09	0.11	0.12	0.11	0.12	0.12	0.11
8	0.04	0.06	0.09	0.09	0.09	0.11	0.11	0.13	0.14	0.14
9	0.03	0.06	0.05	0.07	0.08	0.10	0.12	0.12	0.18	0.20
Winner	0.02	0.04	0.04	0.05	0.06	0.08	0.09	0.13	0.18	0.32

LASSO

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.16	0.13	0.10	0.07	0.05	0.05	0.07	0.09	0.12	0.14
2	0.12	0.12	0.11	0.09	0.08	0.07	0.09	0.11	0.11	0.10
3	0.10	0.10	0.12	0.12	0.10	0.09	0.10	0.10	0.09	0.08
4	0.06	0.09	0.11	0.14	0.14	0.12	0.11	0.08	0.07	0.06
5	0.06	0.08	0.10	0.13	0.16	0.14	0.11	0.08	0.06	0.05
6	0.06	0.07	0.09	0.13	0.15	0.15	0.14	0.09	0.07	0.05
7	0.07	0.08	0.09	0.11	0.13	0.13	0.13	0.11	0.08	0.07
8	0.10	0.09	0.08	0.09	0.10	0.11	0.11	0.12	0.10	0.10
9	0.12	0.11	0.09	0.08	0.06	0.06	0.08	0.11	0.14	0.14
Winner	0.13	0.10	0.09	0.06	0.05	0.04	0.07	0.10	0.14	0.21

PLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.42	0.20	0.12	0.07	0.05	0.04	0.03	0.02	0.02	0.02
2	0.21	0.21	0.15	0.11	0.09	0.07	0.05	0.05	0.03	0.03
3	0.13	0.17	0.15	0.13	0.12	0.09	0.08	0.06	0.05	0.04
4	0.09	0.13	0.14	0.13	0.11	0.11	0.10	0.08	0.07	0.05
5	0.07	0.11	0.12	0.12	0.13	0.11	0.12	0.10	0.08	0.07
6	0.06	0.08	0.11	0.12	0.13	0.12	0.12	0.11	0.10	0.08
7	0.05	0.06	0.09	0.11	0.11	0.12	0.12	0.13	0.12	0.11
8	0.04	0.06	0.07	0.09	0.10	0.11	0.12	0.14	0.14	0.13
9	0.02	0.04	0.06	0.07	0.08	0.10	0.13	0.13	0.17	0.20
Winner	0.02	0.03	0.04	0.05	0.06	0.07	0.10	0.14	0.19	0.33

BRT

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.12	0.08	0.06	0.04	0.02	0.01	0.02	0.02	0.03	0.03
2	0.07	0.07	0.06	0.05	0.03	0.02	0.02	0.02	0.04	0.03
3	0.05	0.05	0.04	0.05	0.03	0.03	0.03	0.03	0.04	0.04
4	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.04
5	0.03	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.06	0.04
6	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.07	0.04	0.04
7	0.02	0.02	0.02	0.03	0.03	0.05	0.03	0.03	0.08	0.04
8	0.03	0.04	0.03	0.03	0.03	0.09	0.07	0.08	0.05	0.07
9	0.04	0.05	0.04	0.05	0.03	0.04	0.06	0.04	0.10	0.08
Winner	0.04	0.04	0.04	0.04	0.06	0.03	0.04	0.06	0.06	0.10

NN1

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.24	0.15	0.12	0.10	0.09	0.07	0.07	0.06	0.05	0.05
2	0.16	0.14	0.13	0.11	0.11	0.09	0.07	0.08	0.07	0.06
3	0.13	0.12	0.12	0.11	0.10	0.10	0.09	0.08	0.08	0.07
4	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.07
5	0.10	0.11	0.11	0.11	0.11	0.10	0.11	0.10	0.10	0.08
6	0.08	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.11	0.10
7	0.08	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.11	0.12
8	0.07	0.08	0.09	0.10	0.09	0.10	0.11	0.11	0.12	0.14
9	0.06	0.08	0.08	0.09	0.10	0.10	0.10	0.12	0.13	0.16
Winner	0.06	0.06	0.06	0.07	0.08	0.09	0.09	0.12	0.15	0.24

NN2

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.28	0.17	0.12	0.10	0.08	0.06	0.05	0.06	0.05	0.04
2	0.17	0.14	0.14	0.11	0.10	0.09	0.08	0.07	0.06	0.06
3	0.13	0.13	0.13	0.12	0.10	0.09	0.09	0.08	0.07	0.05
4	0.10	0.12	0.12	0.12	0.11	0.10	0.09	0.09	0.08	0.07
5	0.09	0.11	0.11	0.12	0.11	0.10	0.10	0.10	0.10	0.08
6	0.08	0.10	0.10	0.10	0.11	0.11	0.11	0.10	0.11	0.09
7	0.07	0.09	0.09	0.10	0.10	0.11	0.11	0.11	0.11	0.10
8	0.07	0.08	0.08	0.09	0.10	0.10	0.12	0.11	0.12	0.12
9	0.06	0.07	0.07	0.08	0.09	0.11	0.10	0.12	0.14	0.17
Winner	0.04	0.06	0.06	0.07	0.08	0.08	0.09	0.11	0.15	0.27

(a) Horizon = 3 months

OLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.31	0.17	0.12	0.08	0.07	0.06	0.05	0.05	0.04	0.04
2	0.18	0.16	0.13	0.11	0.09	0.08	0.07	0.07	0.07	0.05
3	0.14	0.14	0.13	0.11	0.10	0.09	0.08	0.08	0.07	0.06
4	0.12	0.14	0.12	0.11	0.11	0.09	0.08	0.09	0.08	0.07
5	0.10	0.12	0.11	0.11	0.11	0.09	0.09	0.10	0.10	0.08
6	0.10	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.09	0.09
7	0.08	0.10	0.10	0.10	0.10	0.11	0.11	0.10	0.11	0.11
8	0.06	0.08	0.08	0.09	0.10	0.11	0.11	0.11	0.12	0.14
9	0.06	0.07	0.08	0.08	0.09	0.09	0.10	0.12	0.14	0.18
Winner	0.05	0.06	0.06	0.07	0.07	0.08	0.09	0.11	0.16	0.27

LASSO

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.19	0.14	0.10	0.07	0.04	0.05	0.06	0.08	0.12	0.14
2	0.12	0.13	0.13	0.09	0.07	0.06	0.08	0.10	0.10	0.10
3	0.09	0.10	0.14	0.14	0.11	0.07	0.08	0.09	0.09	0.07
4	0.07	0.08	0.11	0.17	0.17	0.11	0.09	0.08	0.06	0.06
5	0.05	0.07	0.10	0.14	0.18	0.15	0.10	0.06	0.06	0.06
6	0.06	0.07	0.08	0.11	0.16	0.18	0.15	0.09	0.07	0.05
7	0.05	0.07	0.09	0.09	0.12	0.14	0.16	0.11	0.09	0.08
8	0.09	0.09	0.08	0.09	0.08	0.09	0.13	0.13	0.12	0.10
9	0.10	0.10	0.09	0.08	0.07	0.07	0.10	0.12	0.13	0.13
Winner	0.13	0.11	0.09	0.06	0.05	0.05	0.07	0.11	0.14	0.19

PLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.36	0.19	0.11	0.08	0.06	0.06	0.04	0.04	0.03	0.03
2	0.19	0.19	0.15	0.11	0.10	0.07	0.06	0.05	0.04	0.04
3	0.14	0.15	0.13	0.12	0.11	0.09	0.09	0.07	0.06	0.05
4	0.11	0.13	0.13	0.11	0.11	0.10	0.09	0.08	0.07	0.07
5	0.09	0.11	0.12	0.11	0.12	0.10	0.10	0.10	0.08	0.08
6	0.07	0.09	0.10	0.12	0.11	0.11	0.11	0.11	0.10	0.09
7	0.07	0.08	0.10	0.10	0.10	0.11	0.12	0.11	0.11	0.11
8	0.06	0.07	0.09	0.09	0.09	0.10	0.11	0.12	0.13	0.14
9	0.06	0.06	0.07	0.08	0.09	0.09	0.12	0.12	0.15	0.17
Winner	0.04	0.05	0.06	0.06	0.07	0.09	0.10	0.12	0.16	0.27

BRT

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.08	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.03	0.03
2	0.06	0.05	0.04	0.04	0.03	0.02	0.02	0.02	0.04	0.05
3	0.05	0.05	0.04	0.03	0.03	0.02	0.02	0.02	0.04	0.05
4	0.04	0.04	0.04	0.03	0.03	0.03	0.02	0.02	0.04	0.04
5	0.03	0.03	0.03	0.02	0.02	0.01	0.03	0.02	0.03	0.05
6	0.03	0.03	0.03	0.03	0.03	0.05	0.02	0.03	0.02	0.03
7	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.08	0.04
8	0.03	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.07
9	0.04	0.05	0.05	0.05	0.03	0.04	0.03	0.07	0.06	0.07
Winner	0.06	0.05	0.04	0.04	0.05	0.02	0.04	0.04	0.07	0.07

NN1

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.21	0.13	0.12	0.10	0.09	0.08	0.07	0.07	0.07	0.06
2	0.15	0.13	0.12	0.10	0.09	0.08	0.10	0.08	0.07	0.07
3	0.12	0.12	0.12	0.11	0.10	0.10	0.09	0.09	0.09	0.08
4	0.11	0.12	0.11	0.11	0.11	0.10	0.10	0.09	0.08	0.09
5	0.10	0.12	0.11	0.10	0.10	0.10	0.10	0.09	0.10	0.10
6	0.10	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.10	0.10
7	0.09	0.10	0.10	0.10	0.10	0.09	0.10	0.11	0.12	0.11
8	0.08	0.08	0.09	0.08	0.10	0.10	0.11	0.12	0.11	0.12
9	0.07	0.08	0.08	0.08	0.10	0.09	0.10	0.12	0.14	0.15
Winner	0.07	0.07	0.07	0.08	0.08	0.09	0.10	0.11	0.13	0.22

NN2

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.25	0.15	0.12	0.10	0.08	0.06	0.07	0.06	0.06	0.05
2	0.16	0.13	0.13	0.10	0.10	0.08	0.09	0.08	0.07	0.06
3	0.13	0.13	0.12	0.11	0.10	0.09	0.09	0.08	0.09	0.08
4	0.10	0.11	0.12	0.11	0.10	0.10	0.10	0.09	0.09	0.08
5	0.10	0.11	0.11	0.12	0.10	0.11	0.09	0.09	0.08	0.09
6	0.09	0.10	0.11	0.10	0.10	0.11	0.10	0.10	0.10	0.09
7	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.10	0.11
8	0.08	0.09	0.09	0.09	0.09	0.10	0.10	0.12	0.12	0.12
9	0.07	0.08	0.07	0.08	0.10	0.10	0.10	0.12	0.13	0.15
Winner	0.06	0.07	0.07	0.07	0.08	0.09	0.09	0.10	0.13	0.23

(b) Horizon = 6 months

(continued)

OLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.25	0.15	0.10	0.08	0.08	0.07	0.06	0.07	0.07	0.07
2	0.17	0.15	0.12	0.10	0.09	0.08	0.08	0.08	0.07	0.08
3	0.15	0.14	0.12	0.11	0.09	0.09	0.08	0.07	0.08	0.09
4	0.13	0.14	0.10	0.11	0.11	0.09	0.08	0.09	0.08	0.09
5	0.11	0.13	0.11	0.10	0.09	0.10	0.09	0.08	0.09	0.11
6	0.11	0.12	0.11	0.10	0.10	0.09	0.09	0.09	0.09	0.11
7	0.12	0.10	0.11	0.09	0.09	0.09	0.10	0.10	0.10	0.09
8	0.10	0.10	0.10	0.09	0.10	0.09	0.09	0.10	0.10	0.12
9	0.09	0.09	0.09	0.09	0.08	0.10	0.10	0.10	0.12	0.15
Winner	0.08	0.09	0.08	0.08	0.08	0.07	0.09	0.11	0.14	0.19

LASSO

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.17	0.13	0.09	0.08	0.05	0.05	0.07	0.09	0.11	0.14
2	0.13	0.11	0.11	0.10	0.09	0.06	0.07	0.08	0.11	0.11
3	0.09	0.11	0.13	0.13	0.12	0.09	0.08	0.09	0.09	0.07
4	0.07	0.08	0.11	0.15	0.18	0.12	0.09	0.07	0.07	0.05
5	0.05	0.07	0.09	0.15	0.18	0.14	0.10	0.07	0.05	0.05
6	0.05	0.06	0.08	0.12	0.18	0.16	0.14	0.09	0.06	0.06
7	0.06	0.06	0.08	0.11	0.14	0.14	0.14	0.10	0.08	0.08
8	0.09	0.08	0.08	0.09	0.09	0.12	0.13	0.12	0.10	0.10
9	0.11	0.11	0.09	0.08	0.07	0.08	0.10	0.10	0.13	0.11
Winner	0.12	0.10	0.09	0.06	0.06	0.05	0.09	0.10	0.14	0.18

PLS

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.35	0.15	0.12	0.09	0.06	0.06	0.05	0.05	0.04	0.04
2	0.20	0.17	0.13	0.10	0.09	0.07	0.06	0.07	0.07	0.06
3	0.16	0.16	0.13	0.11	0.10	0.08	0.08	0.07	0.06	0.07
4	0.12	0.13	0.11	0.10	0.11	0.09	0.10	0.09	0.07	0.09
5	0.12	0.12	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.08
6	0.10	0.11	0.11	0.11	0.10	0.09	0.10	0.10	0.09	0.10
7	0.08	0.09	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.11
8	0.07	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.11	0.13
9	0.06	0.08	0.08	0.09	0.09	0.10	0.11	0.10	0.13	0.16
Winner	0.05	0.06	0.08	0.07	0.09	0.08	0.10	0.11	0.14	0.23

BRT

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.06	0.06	0.04	0.03	0.04	0.01	0.02	0.03	0.04	0.04
2	0.06	0.05	0.04	0.04	0.04	0.02	0.02	0.03	0.04	0.04
3	0.05	0.04	0.04	0.03	0.03	0.02	0.03	0.03	0.04	0.04
4	0.04	0.04	0.03	0.03	0.03	0.02	0.02	0.03	0.04	0.03
5	0.04	0.04	0.03	0.02	0.04	0.02	0.03	0.03	0.03	0.03
6	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.02	0.03	0.05
7	0.03	0.03	0.02	0.02	0.03	0.01	0.02	0.08	0.01	0.02
8	0.04	0.03	0.03	0.04	0.05	0.04	0.03	0.02	0.11	0.08
9	0.05	0.05	0.04	0.03	0.03	0.08	0.04	0.05	0.03	0.09
Winner	0.06	0.06	0.05	0.05	0.04	0.05	0.06	0.03	0.05	0.05

NN1

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.15	0.13	0.10	0.11	0.09	0.08	0.07	0.09	0.09	0.10
2	0.14	0.11	0.10	0.10	0.09	0.10	0.09	0.08	0.09	0.09
3	0.13	0.12	0.11	0.09	0.10	0.09	0.09	0.09	0.10	0.08
4	0.11	0.11	0.10	0.11	0.11	0.10	0.10	0.09	0.10	0.09
5	0.10	0.09	0.10	0.09	0.12	0.09	0.11	0.10	0.11	0.11
6	0.10	0.10	0.10	0.10	0.09	0.09	0.10	0.10	0.10	0.11
7	0.11	0.09	0.11	0.09	0.10	0.10	0.10	0.10	0.10	0.11
8	0.11	0.10	0.11	0.11	0.09	0.09	0.09	0.10	0.11	0.11
9	0.10	0.10	0.09	0.08	0.10	0.09	0.10	0.09	0.11	0.13
Winner	0.11	0.10	0.09	0.08	0.08	0.09	0.08	0.10	0.12	0.15

NN2

	Loser	2	3	4	5	6	7	8	9	Winner
Loser	0.19	0.13	0.11	0.10	0.09	0.08	0.08	0.07	0.07	0.08
2	0.15	0.14	0.11	0.10	0.09	0.09	0.08	0.08	0.09	0.08
3	0.13	0.13	0.11	0.10	0.10	0.09	0.09	0.09	0.07	0.09
4	0.12	0.11	0.11	0.10	0.10	0.10	0.09	0.10	0.09	0.09
5	0.11	0.10	0.10	0.10	0.11	0.10	0.11	0.10	0.10	0.09
6	0.10	0.11	0.11	0.10	0.10	0.10	0.09	0.10	0.09	0.10
7	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.08	0.11	0.11
8	0.10	0.11	0.10	0.10	0.09	0.09	0.10	0.10	0.10	0.11
9	0.09	0.09	0.08	0.08	0.09	0.10	0.09	0.11	0.12	0.14
Winner	0.10	0.09	0.09	0.08	0.09	0.09	0.08	0.11	0.13	0.16

(c) Horizon = 12 months

Figure D.2: Out-of-sample performance persistence (3, 6, and 12 months) of decile portfolios predicted by models

This figure shows the out-of-sample performance persistence of decile portfolios predicted by models. For each model, we draw a transition matrix in which the cell (i, j) represents the probability a fund in decile i in month t transfers to decile j in month $t + N$ (N=3, 6, 12). Specifically, at the end of each month t in the testing period, we sort mutual funds according to model predictions into deciles. We then calculate how many percentages of funds in decile i of the month t fall into decile j of the month $t + N$ (N=3, 6, 12). Finally, we obtain the value of cell (i, j) by averaging the corresponding values across all months. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

Characteristics of Superior Funds TableD.9 reports the mean values of fund characteristics of quintile portfolios predicted by each model.

Table D.9: Fund characteristics of model-predicted quintiles

This table reports the mean values of fund characteristics for quintile portfolios predicted by models. To form quintile portfolios, at the end of each month *t* in the testing period, we sort mutual funds according to model predictions into quintiles. Q1 (Q5) represents the quintile portfolio containing funds that are expected to perform the worst (best). Age (months), total net asset (¥billion), expense ratio (%), active share, active weight and return gap (%) are calculated as mean values for the quintile portfolios in each month, and then averaged across all months. The detailed definitions of each character are shown in Table (1). Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	Age (months)	TNA (¥billion)	Expense ratio (%)	Active share	Active weight	Return gap (%)
			OLS			
Q1	59.77	1.49	6.85	0.54	0.91	2.72
Q2	53.65	1.23	6.37	0.54	0.90	4.41
Q3	48.58	1.13	6.21	0.55	0.91	5.43
Q4	46.45	1.03	6.35	0.55	0.91	6.23
Q5	44.78	0.96	7.24	0.55	0.91	8.55
Q5-Q1	-14.99	-0.53	0.39	0.01	0.00	5.84
t-stat	***-8.17***	***-10.70***	***1.65***	***4.92***	***0.93***	***15.14***
			LASSO			
Q1	46.97	1.29	7.58	0.54	0.90	4.06
Q2	60.13	1.23	6.36	0.54	0.90	3.06
Q3	57.18	1.20	4.96	0.54	0.90	5.01
Q4	47.24	1.08	6.48	0.55	0.91	7.24
Q5	40.17	1.04	8.09	0.55	0.92	7.95
Q5-Q1	-6.80	-0.25	0.51	0.01	0.02	3.90
t-stat	***-3.72***	***-3.55***	***1.72***	***3.44***	***4.05***	***9.44***
			PLS			
Q1	74.01	1.79	5.04	0.55	0.92	0.39
Q2	56.17	1.31	5.77	0.54	0.91	3.59
Q3	44.64	1.17	6.33	0.54	0.90	6.18
Q4	40.01	0.93	6.95	0.55	0.91	7.77
Q5	36.11	0.60	9.28	0.55	0.90	10.82
Q5-Q1	-37.90	-1.19	4.24	0.00	-0.01	10.43
t-stat	***-16.83***	***-13.44***	***17.20***	***0.30***	***-2.95***	***20.37***
			BRT			
Q1	55.02	1.22	8.17	0.54	0.90	5.61
Q2	48.16	1.10	7.61	0.55	0.91	5.71
Q3	46.53	1.24	6.70	0.55	0.91	5.95
Q4	46.79	1.12	6.18	0.55	0.91	5.58
Q5	45.42	1.16	6.82	0.55	0.91	5.98
Q5-Q1	-9.61	-0.06	-1.35	0.01	0.01	0.37
t-stat	***-3.55***	***-1.04***	***-2.56***	***3.24***	***3.13***	***0.66***
			NN1			
Q1	54.80	1.27	6.84	0.54	0.91	4.42
Q2	53.17	1.18	6.16	0.54	0.91	4.72
Q3	50.05	1.18	6.23	0.55	0.91	5.13
Q4	47.87	1.12	6.48	0.55	0.91	5.77
Q5	47.54	1.10	7.24	0.55	0.91	6.93
Q5-Q1	-7.26	-0.17	0.40	0.01	0.01	2.51
t-stat	***-2.88***	***-1.98***	***1.45***	***5.85***	***2.37***	***3.80***
			NN2			
Q1	56.60	1.34	6.92	0.54	0.26	3.42
Q2	55.93	1.15	6.12	0.54	0.15	4.06
Q3	49.92	1.13	6.14	0.55	0.01	5.14
Q4	46.15	1.15	6.51	0.55	0.05	6.57
Q5	44.29	1.09	7.36	0.55	0.07	8.06
Q5-Q1	-12.31	-0.26	0.44	0.01	-0.19	4.65
t-stat	***-5.17***	***-3.39***	***1.72***	***3.54***	***-4.24***	***9.49***
			NN3			
Q1	55.82	1.29	6.74	0.54	0.90	4.15
Q2	56.29	1.22	6.04	0.55	0.90	4.04
Q3	50.87	1.16	6.05	0.55	0.91	5.23
Q4	47.05	1.16	6.59	0.55	0.91	6.12
Q5	42.92	1.01	7.58	0.55	0.92	7.68
Q5-Q1	-12.90	-0.28	0.84	0.00	0.01	3.54
t-stat	***-6.70***	***-3.82***	***2.80***	***2.76***	***3.30***	***6.92***

E Robustness results

Dynamic Implementation Approach Considering that the relation between fund return and fund characteristics could change over time, the dynamic implementation approach can accommodate such changes and make a robustness test of our findings. To begin, we use the first 9 years of data to train models. Then, we use the estimated models for the next year. That is, for each month in the following 12 months, we reuse the trained models to predict fund returns and form a long-only portfolio of funds in the top group of the predicted performance distribution. The portfolio is rebalanced monthly. For every remaining year, we expand the trained sample forward one year, retrain the models and make new predictions every month for the following 12 months. This way, we conduct a time series of monthly out-of-sample returns of the long-top portfolio. The results (shown in Table E.1) are robust, with slightly less statistical significance though.

Longer Holding Periods Our main findings are also robust to longer portfolio holding periods. Different from Kaniel et al. (2022) who hold overlapping portfolios, we rebalance the fund investment, for example, every three months, if we expand the portfolio holding period to three months, which has the advantage of saving transaction costs. The main findings still remain that the models which exploit multiple fund characteristics outperform the naïve strategy of long all active equity funds, and that machine learning models can be employed to beat the simple linear model, as expanding the holding period from one-month to three-month and six-month. To save space, we put the detailed results in Table E.2.

Transaction Costs To assess the economic significance of the long-only portfolio's performance that delivers to the fund investors, we ultimately have to account for transaction costs in our approach. The transaction cost in the fund market consists of a purchase fee when buying funds and a redemption fee when selling funds charged by fund sales channels [12]. Instead of charging fees as a fixed proportion of the transaction amount as in the stock market, the transaction fees charged by fund sales channels depend on the holding period and amount. A typical charge method for pur-

[12] We do not consider conversion fee paid to switch investments between different open-ended funds managed by the same fund management company, which is usually smaller than the simple sum of redemption fee and purchase fee. That is, we assume that our monthly turnover is 100%.

Table E.1: Out-of-sample performance of the long-top portfolio (dynamic approach)

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) based on the dynamic implementation approach. To begin, we use the first 9 years of data to train models. Then, we use the estimated models for the next one year, i.e., for each month in the following 12 months, we reuse the trained models to sort mutual funds according to model predictions and long the top group of funds value-weighted, using the normalized prediction values as weights. For every remaining year, we expand the trained sample forward one year, retrain the models and make new predictions every month for the following 12 months. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. We report the monthly return, annualized sharpe ratio, and Carhart (1997) four-factor alpha for each portfolio. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022

	Ret	t-stat	SR	a_ffc	t_a	diffOLS	t	diffEW	t	diffVW	t
						# Group=5					
OLS	1.42	2.63	0.83	0.80	5.09	0.00		0.09	0.45	0.02	0.04
LASSO	1.54	2.75	0.87	0.90	5.21	0.12*	1.69	0.21*	1.71	0.14	0.26
PLS	1.47	2.67	0.84	0.82	5.52	0.04	0.40	0.13	0.55	0.06	0.10
BRT	1.70	2.66	0.86	1.06	2.68	0.23*	1.70	0.32*	1.82	0.24*	1.69
NN1	1.57	2.67	0.84	0.92	3.43	0.15*	1.68	0.24*	1.79	0.17	0.42
NN2	1.44	2.55	0.81	0.81	4.71	0.02	0.20	0.11	0.58	0.04	0.08
NN3	1.52	2.67	0.84	0.88	4.15	0.10	0.67	0.19*	1.65	0.12	0.26
						# Group=10					
OLS	1.41	2.57	0.81	0.78	4.29	0.00		0.07	0.35	0.01	0.01
LASSO	1.60	2.81	0.89	0.95	5.01	0.19*	1.86	0.26*	1.89	0.19	0.37
PLS	1.48	2.69	0.85	0.82	5.20	0.07	0.54	0.15	0.59	0.08	0.13
BRT	1.94	2.63	0.83	1.29	2.36	0.53*	1.80	0.61**	1.97	0.54***	2.87
NN1	1.66	2.75	0.87	0.99	3.40	0.25*	1.82	0.32**	1.99	0.25*	1.65
NN2	1.45	2.53	0.80	0.82	4.05	0.04	0.30	0.12	0.56	0.05	0.09
NN3	1.62	2.78	0.88	0.97	3.98	0.21*	1.77	0.28**	1.96	0.21	0.48
						# Group=20					
OLS	1.39	2.51	0.79	0.76	3.63	0.00		0.06	0.25	-0.01	-0.02
LASSO	1.63	2.84	0.90	0.98	4.85	0.23*	1.90	0.29*	1.77	0.22	0.39
PLS	1.49	2.69	0.85	0.82	4.92	0.09	0.56	0.15	0.58	0.08	0.14
BRT	2.04	2.62	0.83	1.37	2.28	0.65*	1.84	0.71**	1.96	0.64***	2.62
NN1	1.74	2.66	0.84	1.06	2.67	0.34*	1.80	0.40*	1.68	0.33*	1.68
NN2	1.39	2.36	0.75	0.75	3.05	0.00	-0.02	0.05	0.21	-0.01	-0.02
NN3	1.68	2.84	0.90	1.02	3.75	0.28*	1.78	0.34**	2.04	0.27*	1.66

(*continued*)

Continued

	Ret	t-stat	SR	a_ffc	t_a	diffOLS	t	diffEW	t	diffVW	t
						# Group=50					
OLS	1.46	2.57	0.81	0.82	3.34	0.00		0.12	0.44	0.05	0.09
LASSO	1.64	2.81	0.89	1.00	4.47	0.19*	1.66	0.31*	1.70	0.24	0.38
PLS	1.53	2.74	0.87	0.88	3.93	0.08	0.31	0.19*	1.66	0.13	0.23
BRT	2.08	2.77	0.88	1.34	2.42	0.55*	1.81	0.67**	1.98	0.60**	2.10
NN1	1.62	2.23	0.71	0.93	1.79	0.17	0.33	0.29*	1.65	0.22	0.46
NN2	1.32	2.09	0.66	0.67	1.95	-0.13	-0.37	-0.01	-0.04	-0.08	-0.13
NN3	1.45	2.27	0.72	0.76	1.96	0.00	-0.01	0.12	0.34	0.05	0.09
						# Group=100					
OLS	1.52	2.41	0.76	0.84	2.18	0.00		0.18	0.48	0.11	0.18
LASSO	1.63	2.85	0.90	1.01	4.33	0.11	0.30	0.29*	1.74	0.22	0.36
PLS	1.50	2.58	0.82	0.85	2.79	-0.01	-0.03	0.17	0.57	0.10	0.18
BRT	2.96	2.68	0.85	2.16	2.20	1.44*	1.84	1.62**	2.14	1.56***	3.07
NN1	1.10	1.34	0.42	0.38	0.61	-0.41	-0.68	-0.23	-0.40	-0.30	-0.42
NN2	1.18	1.74	0.55	0.56	1.23	-0.34	-0.61	-0.16	-0.35	-0.23	-0.34
NN3	1.18	1.72	0.54	0.46	0.96	-0.33	-1.06	-0.15	-0.33	-0.22	-0.35
						# Group=200					
OLS	1.81	2.56	0.93	1.08	2.89	0.00		0.52*	1.74	0.77**	1.97
LASSO	2.15	2.76	1.00	1.38	3.79	0.34*	1.68	0.87***	2.57	1.11***	2.97
PLS	1.54	2.31	0.84	0.97	2.58	-0.26	-0.52	0.26	0.63	0.50*	1.69
BRT	2.19	2.64	0.97	1.47	3.23	0.33*	1.65	0.89**	2.04	1.12**	2.49
NN1	1.71	2.38	0.86	0.99	3.16	-0.10	-0.20	0.42*	1.83	0.66**	2.14
NN2	1.70	2.65	0.96	1.05	3.88	-0.10	-0.26	0.42*	1.76	0.66**	2.45
NN3	1.67	2.57	0.93	1.01	3.20	-0.13	-0.29	0.39*	1.68	0.63*	1.88

Table E.2: Out-of-sample performance of the long-top portfolio (longer holding periods)

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by the simple linear model (OLS) and machining models (LASSO, PLS, boosting regression trees and neural networks with 1 through 3 hidden layers.) with longer holding periods (or less frequency of rebalance) based on dynamic implementation approach. Different from Kaniel et al. (2022) who hold overlapping portfolios, we rebalance the fund investment, for example, every three months, if we expand the portfolio holding period to three months, which has the advantage of saving transaction costs. For space-saving purposes, we only consider group numbers 20 and 200. We report the monthly return, annualized sharpe ratio, and Carhart (1997) four-factor alpha for each portfolio. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022.

	Ret	t-stat	SR	a_ffc	t_a	diffOLS	t	diffEW	t	diffVW	t
						A. Holding period=3 months					
						# Group=20					
OLS	1.28	2.25	0.71	0.65	3.29	0.00		-0.05	-0.23	-0.12	-0.22
LASSO	1.65	2.85	0.90	1.01	5.28	0.37**	2.15	0.32*	1.80	0.25	0.46
PLS	1.52	2.74	0.87	0.91	6.53	0.24*	1.73	0.18	0.74	0.11	0.19
BRT	1.59	2.75	0.88	0.88	3.67	0.16	0.62	0.13	0.56	0.05	0.09
NN1	1.84	2.44	0.77	1.13	2.05	0.56*	1.82	0.51*	1.90	0.44**	2.29
NN2	1.54	2.51	0.80	0.87	2.87	0.26*	1.85	0.20*	1.74	0.13	0.35
NN3	1.80	2.66	0.84	1.13	2.60	0.52*	1.90	0.47*	1.89	0.40*	1.72
						# Group=200					
OLS	1.27	1.81	0.66	0.62	1.68	0.00		0.00	0.00	0.24	0.61
LASSO	2.16	2.63	0.96	1.38	3.66	0.89**	1.96	0.89**	2.36	1.13***	2.79
PLS	2.04	2.67	0.98	1.35	3.55	0.77**	1.97	0.77**	2.04	1.01***	2.62
BRT	2.22	2.41	1.02	1.34	3.22	0.72*	1.70	0.73*	1.72	0.99**	2.25
NN1	2.01	2.67	0.98	1.31	3.26	0.69*	1.77	0.74**	2.02	0.97***	2.55
NN2	1.61	2.31	0.84	0.93	2.85	0.34*	1.65	0.34*	1.70	0.58**	1.97
NN3	1.82	2.39	0.88	1.06	3.35	0.51*	1.71	0.55*	1.84	0.78**	2.17
						B. Holding period=6 months					
						# Group=20					
OLS	1.19	2.04	0.65	0.55	2.73	0.00		-0.15	-0.61	-0.22	-0.38
LASSO	1.62	2.76	0.87	0.96	5.02	0.43***	2.62	0.28*	1.72	0.21	0.39
PLS	1.41	2.53	0.80	0.79	5.34	0.23*	1.82	0.08	0.31	0.01	0.02
BRT	1.79	2.22	0.70	1.03	1.77	0.60*	1.70	0.45*	1.83	0.38*	1.67
NN1	1.80	2.41	0.76	1.09	2.00	0.61*	1.73	0.46*	1.87	0.39**	2.16
NN2	1.47	2.38	0.75	0.80	2.71	0.28*	1.68	0.13*	1.68	0.06	0.17
NN3	1.73	2.59	0.82	1.07	2.48	0.55*	1.78	0.40*	1.84	0.33*	1.72
						# Group=200					
OLS	1.20	1.84	0.67	0.59	1.74	0.00		-0.07	-0.20	0.17	0.47
LASSO	2.04	2.55	0.93	1.32	3.38	0.84**	1.97	0.78**	2.02	1.01***	2.59
PLS	1.68	2.12	0.78	0.95	2.94	0.48*	1.72	0.41*	1.80	0.65**	1.97
BRT	3.05	2.16	1.03	1.54	2.75	1.20*	1.78	1.20**	2.00	1.47**	2.26
NN1	1.49	1.99	0.73	0.79	2.13	0.25	0.49	0.22	0.66	0.46*	1.74
NN2	1.81	2.44	0.89	1.06	3.39	0.61*	1.82	0.55*	1.82	0.78**	2.25
NN3	1.42	1.83	0.67	0.69	2.00	0.17	0.33	0.14	0.45	0.38*	1.66

chase is stepped-like depending on purchase amount, for example, 1.5% (of purchasing amount) when the purchase amount is less than 1 million yuan, 1% when between 1 million and 3 million yuan, 0.8% when between 3 million and 5 million. For redemption, the transaction fees depend on the holding period, for example, 1.5% of (redemption amount) when the holding period is less than 7 days, 0.75% when between 7 days and 30 days, 0.5% when between 30 days and 1 year, and zero when holding for more than 1 year.

We download the transaction fee charge rules of each fund from WIND database. Each fund has different levels of purchase fee ratio and redemption fee ratio depending on the holding period and amount. To simplify the computation, for each fund, we choose the maximum level among its all purchase fee ratios which is more realistic for retail investors considering that a lower fee ratio usually requires at least one million capital. Regarding redemption, for each fund, we use the median of all its redemption fee ratios. We then take the average of fee ratios across funds in our sample. Specifically, the purchase fee ratio is 0.92% on average and the redemption fee ratio is 0.46%. In our analysis, we further consider the fee discount in actual fund charges. For example, the third-party fund sales platform will give a 90% discount for the purchase fee. We consider three situations in which the discount levels for purchase fees are 70%, 80% and 90% respectively, that is, the total transaction fee ratios for a portfolio rebalance are then 0.55% (0.92%*0.1+0.46%), 0.64% (0.92%*0.2+0.46%) and 0.73% (0.92%*0.3+0.46%), respectively.

It is unsurprising, as shown in Table E.3, that the severe fund transaction costs would erode a non-negligible fraction of profits earned by strategies. Nonetheless, all portfolios can still earn significant abnormal returns with respect to the four-factor model. However, we also notice that with large transaction costs it is harder to beat the average fund market (i.e., equal-weighted long all active equity funds) recalling that the monthly return of average fund market is 1.7% [13]. For example, the long-top portfolio predicted by the simple linear model (OLS) earns only 1.53% of monthly excess return when the transaction fee ratio is 0.53%, compared to 2.08% under a no transaction cost environment. To our relief, machine-learning models such as LASSO and neural networks maintain the excellent ability to select funds that beat the fund market even with expensive transaction fees.

To avoid the burden of transaction costs, we next consider a longer holding period. A longer

[13] The consolation is that there is no *index* that tracks the average performance of funds in the market yet.

Table E.3: Out-of-sample performance of long-top portfolios with transaction cost

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by models with transaction costs. For each month $t+1$ in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. We report the monthly return and Carhart (1997) four-factor alpha for each portfolio. We consider several levels of transaction fee ratios including 0.55%, 0.64%, and 0.73%, which are charged each time of portfolio rebalancing. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	# Group=10		# Group=20		# Group=50		# Group=100			# Group=10		# Group=20		# Group=50		# Group=100	
	Transaction cost=0									*Transaction cost=0.64%*							
	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc		Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc
OLS	2.09	1.10	2.07	1.10	2.01	1.05	2.09	1.11	OLS	1.44	0.46	1.42	0.46	1.37	0.40	1.45	0.46
t-stat	*2.71*	*4.78*	*2.70*	*4.37*	*2.57*	*3.65*	*2.51*	*3.23*	***t-stat***	*1.77*	*1.98*	*1.76*	*1.81*	*1.65*	*1.41*	*1.65*	*1.35*
LASSO	2.65	1.47	2.80	1.59	2.92	1.78	2.95	1.82	LASSO	2.00	0.82	2.15	0.95	2.19	0.98	2.15	0.91
t-stat	*2.90*	*3.86*	*2.95*	*3.56*	*2.99*	*3.22*	*2.88*	*2.93*	***t-stat***	*2.08*	*2.16*	*2.15*	*2.11*	*2.11*	*1.78*	*1.97*	*1.45*
PLS	2.26	1.25	2.28	1.29	2.30	1.31	2.40	1.35	PLS	1.61	0.61	1.63	0.65	1.66	0.66	1.76	0.71
t-stat	*2.85*	*4.23*	*2.89*	*4.01*	*2.86*	*3.59*	*2.81*	*3.44*	***t-stat***	*1.93*	*2.05*	*1.96*	*2.01*	*1.95*	*1.81*	*1.95*	*1.80*
BRT	2.43	1.36	2.51	1.42	2.56	1.45	2.37	1.20	BRT	1.79	0.72	1.87	0.77	1.92	0.81	1.65	0.49
t-stat	*2.95*	*4.98*	*2.96*	*4.36*	*2.95*	*3.66*	*2.55*	*2.39*	***t-stat***	*2.05*	*2.62*	*2.08*	*2.37*	*2.09*	*2.03*	*1.70*	*1.00*
NN1	2.21	1.15	2.23	1.18	2.22	1.19	2.14	1.14	NN1	1.56	0.50	1.59	0.54	1.57	0.54	1.50	0.49
t-stat	*2.73*	*5.27*	*2.79*	*5.04*	*2.82*	*4.97*	*2.77*	*4.71*	***t-stat***	*1.83*	*2.30*	*1.88*	*2.29*	*1.90*	*2.27*	*1.83*	*2.04*
NN2	2.41	1.31	2.47	1.36	2.52	1.41	2.53	1.47	NN2	1.76	0.66	1.83	0.71	1.87	0.77	1.89	0.82
t-stat	*2.84*	*5.53*	*2.87*	*5.30*	*2.91*	*4.91*	*2.91*	*4.00*	***t-stat***	*1.97*	*2.80*	*2.01*	*2.78*	*2.05*	*2.67*	*2.06*	*2.24*
NN3	2.31	1.19	2.38	1.24	2.49	1.35	2.79	1.65	NN3	1.67	0.54	1.74	0.60	1.85	0.70	2.14	1.01
t-stat	*2.75*	*5.41*	*2.79*	*4.79*	*2.88*	*4.29*	*3.18*	*4.11*	***t-stat***	*1.88*	*2.47*	*1.93*	*2.30*	*2.02*	*2.23*	*2.31*	*2.50*
	Transaction cost=0.55%									*Transaction cost=0.73%*							
	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc		Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc
OLS	1.53	0.55	1.51	0.55	1.46	0.50	1.54	0.56	OLS	1.35	0.37	1.33	0.37	1.28	0.31	1.36	0.37
t-stat	*1.84*	*2.38*	*1.83*	*2.18*	*1.72*	*1.73*	*1.71*	*1.62*	***t-stat***	*1.66*	*1.58*	*1.65*	*1.45*	*1.54*	*1.09*	*1.54*	*1.08*
LASSO	2.09	0.91	2.24	1.04	2.28	1.07	2.24	1.00	LASSO	1.91	0.73	2.06	0.85	2.10	0.89	2.06	0.82
t-stat	*2.12*	*2.40*	*2.19*	*2.32*	*2.14*	*1.95*	*2.01*	*1.59*	***t-stat***	*1.98*	*1.92*	*2.06*	*1.91*	*2.02*	*1.61*	*1.89*	*1.30*
PLS	1.71	0.70	1.73	0.74	1.75	0.75	1.85	0.80	PLS	1.52	0.52	1.54	0.56	1.57	0.57	1.66	0.62
t-stat	*1.99*	*2.37*	*2.02*	*2.29*	*2.01*	*2.07*	*2.00*	*2.04*	***t-stat***	*1.82*	*1.74*	*1.85*	*1.72*	*1.84*	*1.56*	*1.85*	*1.57*
BRT	1.88	0.81	1.96	0.87	2.01	0.90	1.74	0.58	BRT	1.69	0.63	1.77	0.68	1.83	0.71	1.55	0.40
t-stat	*2.11*	*2.96*	*2.13*	*2.66*	*2.14*	*2.26*	*1.76*	*1.19*	***t-stat***	*1.95*	*2.29*	*1.98*	*2.09*	*1.99*	*1.80*	*1.61*	*0.81*
NN1	1.65	0.59	1.68	0.63	1.66	0.64	1.59	0.59	NN1	1.47	0.41	1.50	0.45	1.48	0.45	1.40	0.40
t-stat	*1.89*	*2.73*	*1.94*	*2.68*	*1.96*	*2.66*	*1.90*	*2.42*	***t-stat***	*1.72*	*1.88*	*1.77*	*1.90*	*1.78*	*1.89*	*1.72*	*1.66*
NN2	1.86	0.75	1.92	0.81	1.96	0.86	1.98	0.91	NN2	1.67	0.57	1.73	0.62	1.78	0.68	1.80	0.73
t-stat	*2.02*	*3.19*	*2.06*	*3.14*	*2.10*	*2.99*	*2.10*	*2.49*	***t-stat***	*1.87*	*2.41*	*1.91*	*2.42*	*1.95*	*2.35*	*1.96*	*1.99*
NN3	1.76	0.63	1.83	0.69	1.94	0.79	2.23	1.10	NN3	1.57	0.45	1.65	0.51	1.76	0.61	2.05	0.92
t-stat	*1.93*	*2.89*	*1.98*	*2.66*	*2.07*	*2.52*	*2.35*	*2.73*	***t-stat***	*1.77*	*2.05*	*1.82*	*1.95*	*1.92*	*1.94*	*2.21*	*2.27*

holding period helps reduce the transaction costs by a large by astricting the number of transactions and shrinking the transaction price. Specifically, we expand the holding period to one year (since most of the funds charge no redemption fee when the holding period lasts over one year), that is, we keep the portfolio unchanged since its formation for a year and then reconstitute. In our out-of-sample analysis, we only rebalance 2 times due to the short sample horizon (32 months). In Table E.4, we set the purchase fee ratio as 28 bps (70% discount of the average level of 0.92%) which is charged each time of portfolio rebalance, and ignore the redemption fee since most funds charge no redemption fee when the holding period lasts over one year. The results are exhilarating. On the one hand, nearly all portfolios beat the average fund market. On the other hand, it reflects that the long-top portfolio predicted by our models has persistent superior performance which does not reverse (a lot) after its formation.

Table E.4: Out-of-sample performance of long-top portfolios with holding period of one-year

This table reports the monthly out-of-sample performance of long-top fund portfolios predicted by models with a holding period of one year. Specifically, in the testing period, we sort mutual funds according to model predictions in month t into a number of groups, then long the top group of funds value-weighted, using the normalized prediction values as weights. We then hold the portfolio for one year with no transaction during the period until $t + 12$. We consider multiple group numbers including 5, 10, 20, 50, 100, and 200. We report the monthly return and Carhart (1997) four-factor alpha for each portfolio. We set the purchase fee ratio as 28 bps (70% discount of the average level of 0.92%) which is charged each time of portfolio rebalancing. We ignore redemption fees since most funds charge no redemption fee when the holding period lasts over one year. Our data sample focuses on the Chinese actively-managed equity mutual funds ranging from January 2003 to January 2022, among which the training sample spans from January 2003 to May 2019 and the testing sample from June 2019 to January 2022.

	# Group=5		# Group=10		# Group=20		# Group=50		# Group=100		# Group=200	
	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc	Ret	a_ffc
OLS	1.89	0.92	1.94	0.98	1.93	1.02	1.98	1.12	1.89	1.04	1.82	1.03
t-stat	2.35	5.34	2.41	5.37	2.48	5.53	2.66	5.92	2.57	4.46	2.43	3.38
LASSO	2.20	0.99	2.23	0.98	2.08	0.78	1.67	0.40	1.29	0.11	1.10	-0.08
t-stat	2.25	3.45	2.19	3.15	1.96	2.18	1.57	0.93	1.27	0.21	0.96	-0.11
PLS	2.01	0.96	1.95	0.94	1.96	0.98	1.86	0.85	1.86	0.85	2.25	1.15
t-stat	2.37	5.56	2.38	5.26	2.45	5.30	2.24	3.59	2.12	2.69	2.31	2.95
BRT	1.95	0.87	1.93	0.82	2.07	0.90	2.13	0.90	2.31	1.04	2.32	1.08
t-stat	2.23	4.00	2.15	3.25	2.22	3.16	2.18	2.79	2.26	2.96	2.31	3.29
NN1	1.97	0.91	1.97	0.89	1.94	0.83	1.62	0.55	1.35	0.25	1.16	0.13
t-stat	2.29	5.00	2.26	4.64	2.19	3.93	1.87	2.14	1.53	0.92	1.34	0.38
NN2	2.01	0.95	2.14	1.07	2.15	1.05	2.06	1.00	2.39	1.32	2.60	1.56
t-stat	2.33	5.21	2.47	5.32	2.44	4.48	2.38	3.70	2.73	5.55	2.93	4.81
NN3	2.01	0.90	2.04	0.91	2.16	0.98	2.21	0.99	2.12	0.90	2.02	0.77
t-stat	2.27	4.83	2.28	4.69	2.32	4.12	2.26	3.33	2.04	2.07	1.89	1.40

F Variable Importance

This section provides a complete list of variable importance with the most influential characteristics on top and the least influential on the bottom.

In Table F.1, we report the number of common fund characteristics among the most important 20 characteristics identified by each pair of models. LASSO and PLS identify similar important fund characteristics. Neural networks with different numbers of hidden layers detect similar important fund characteristics. Surprisingly, we find that simple linear model is more close to non-linear neural networks in identifying important fund characteristics than advanced linear models (LASSO and PLS).

Table F.1: Number of common characteristics among most important 20 characteristics identified by each pair of models

This table reports the number of common fund characteristics among the most important 20 characteristics identified by each pair of models

	OLS	LASSO	PLS	BRT	NN1	NN2	NN3
OLS	20						
LASSO	6	20					
PLS	8	11	20				
BRT	7	7	8	20			
NN1	13	5	9	10	20		
NN2	14	5	7	9	16	20	
NN3	11	5	9	11	17	14	20

	OLS	LASSO	PLS	BRT	NN1	NN2	NN3
d&a_pr	134	133	130	131	134	134	134
turn	133	115	124	82	122	125	125
M_t_MKT_RF	131	111	110	117	117	120	114
M_ExcessRet	47	134	128	130	124	123	126
M_t_UMD	128	103	62	82	133	133	132
beta	115	118	114	82	116	109	119
rev	104	105	98	99	119	119	122
f_TrackErr	97	132	107	125	108	91	100
F_ExcessRet	126	1	133	117	127	130	124
M_Stk2ttl	113	126	115	128	89	95	90
F_Rev	127	1	134	114	123	128	128
F_b_SMB	114	127	119	82	104	108	94
M_ValueAdd	61	124	84	125	110	117	110
M_ReturnGap	89	113	121	108	106	93	99
f_Rev	108	1	132	119	130	110	121
M_Sharpe	116	1	100	119	129	124	130
f_Sharpe	95	107	109	104	100	99	102
f_ExcessRet	106	1	131	119	126	111	117
M_t_SMB	122	1	102	99	128	132	127
M_Flow_vol	78	116	73	124	101	97	112
F_R2	129	129	90	1	114	118	115
F_Mom	101	1	113	93	125	127	131
M_R2	130	1	117	106	97	114	111
M_Mom	94	1	96	132	113	112	118
M_Rev	41	1	129	115	121	122	120
M_t_HML	93	125	81	106	76	66	97
M_b_UMD	121	1	7	115	132	131	129
M_b_SMB	117	1	55	99	120	126	113
ygr_or	132	120	122	82	59	64	44
f_RiskShift	111	128	126	93	55	57	49
M_b_MKT_RF2	8	121	85	119	98	105	83
M_t_a	124	1	33	111	118	121	106
F_ReturnGap	102	122	123	1	87	87	89
M_ActiveWeight	119	1	67	93	94	103	108
F_RiskShift	125	119	118	1	72	71	68
F_Sharpe	46	1	105	82	112	107	116
f_Mom	43	1	64	110	109	113	123
M_ICI	53	109	88	99	75	61	76
M_b_HML	109	1	53	82	99	100	104
f_ReturnGap	105	130	125	82	34	39	31
vol	112	1	99	1	115	102	107
crr	103	1	34	93	95	96	105
M_TrackErr	7	1	108	129	103	98	79
M_a	118	1	23	113	83	106	75

(continued)

	OLS	LASSO	PLS	BRT	NN1	NN2	NN3
F_b_MKT_RF2	18	110	80	1	107	90	92
F_t_HML	76	123	91	1	58	70	72
M_Alpha	10	1	60	112	102	101	103
err	59	1	93	72	91	78	91
M_t_MKT_RF2	84	1	18	123	84	86	85
f_t_MKT_RF2	90	1	89	72	81	75	70
M_Flow	91	1	25	98	90	81	87
M_ExpenseRatio	1	1	31	99	111	116	109
qgr_op	107	1	116	1	82	84	73
flr	110	112	94	1	44	49	42
illiq	123	1	15	1	92	115	101
M_b_MKT_RF	58	1	28	93	79	89	96
M_TNA	50	1	106	82	52	76	69
size	31	1	83	82	62	92	78
F_Alpha	75	1	63	1	105	94	86
f_R2	21	1	103	72	61	80	84
f_b_MKT_RF	88	1	26	127	64	55	60
F_ExpenseRatio	100	1	16	1	93	104	98
f_t_MKT_RF	52	1	92	1	80	83	95
F_b_MKT_RF	120	1	36	1	85	79	82
f_b_MKT_RF2	62	1	70	72	69	58	62
f_t_a	37	117	51	1	70	62	51
F_t_MKT_RF	72	1	65	1	67	72	88
M_RiskShift	30	1	104	1	88	74	65
F_t_SMB	74	1	76	1	63	82	61
iv	98	1	13	1	74	85	80
f_age	70	1	82	104	24	36	34
F_ActiveWeight	44	1	54	1	78	77	93
f_t_HML	60	106	59	1	28	37	53
F_TrackErr	51	1	97	1	73	54	67
f_ActiveShare	87	104	101	1	16	19	14
max	71	1	19	1	77	88	74
f_b_HML	64	1	41	72	36	53	59
et	28	1	43	1	96	73	81
or_pr	17	1	79	1	86	67	71
M_ActiveShare	36	1	69	108	39	28	35
M_HCI	14	1	68	82	60	50	40
F_Flow_vol	56	1	27	72	54	41	54
F_age	99	1	87	1	23	46	46
F_ValueAdd	34	1	56	1	71	60	77
ygr_roe	82	1	72	1	53	51	36
F_ICI	27	108	78	1	20	34	25
F_Stk2ttl	15	114	112	1	13	13	15
nocf2cl	83	1	17	1	65	47	58

(continued)

	OLS	LASSO	PLS	BRT	NN1	NN2	NN3
f_t_SMB	39	1	71	72	18	30	38
F_t_UMD	86	1	3	1	48	63	63
F_ActiveShare	69	1	95	72	4	9	12
pc	79	1	86	1	30	38	21
f_b_UMD	65	1	58	1	38	52	39
f_TNA	68	1	111	1	21	20	30
F_a	92	1	6	1	43	59	50
nocf_pr	66	1	1	1	46	69	64
qgr_or	2	1	120	1	49	35	37
f_t_UMD	40	1	24	1	57	68	52
M_cash2ttl	26	1	11	1	68	65	66
f_ActiveWeight	77	1	44	1	22	48	43
F_b_UMD	96	1	9	1	42	42	45
M_age	42	1	20	72	32	31	32
F_b_HML	13	1	49	1	47	56	55
F_t_a	19	1	30	1	66	44	57
cf2e	32	1	35	1	50	45	48
f_a	29	1	32	1	45	43	56
f_Alpha	25	1	77	1	40	29	29
cf	38	1	50	1	37	25	41
f_Stk2ttl	45	1	48	72	7	8	6
ygr_gp	81	1	21	1	35	32	16
cf2or	22	1	40	1	51	21	47
F_TNA	11	1	75	1	26	40	28
F_Flow	85	1	39	1	19	16	20
ygr_fcf	63	1	47	1	25	27	17
cf2np	54	1	52	1	29	18	18
F_HCI	73	1	61	1	10	10	9
dc	49	1	57	1	12	17	23
f_ValueAdd	16	1	74	1	27	11	27
F_t_MKT_RF2	4	1	37	1	56	23	33
f_b_SMB	3	1	66	1	31	26	22
nfcf_pr	35	1	22	1	41	15	26
efcf_pr	6	1	45	1	17	33	24
ffcf_pr	12	1	29	1	33	24	19
f_ExpenseRatio	80	1	10	1	6	7	5
f_cash2ttl	48	1	42	1	3	3	3
nocf2ibl	57	1	14	1	8	5	7
f_ICI	23	1	38	1	11	6	8
f_HCI	33	1	46	1	2	2	2
ygr_nocf	24	1	4	1	15	14	10
f_Flow_vol	9	1	8	1	14	22	13
F_cash2ttl	20	1	2	1	9	12	11
f_Flow	5	1	12	1	5	4	4

Figure F.1: Characteristic importance

This figure shows the variable importance of all fund characteristics identified by each model. Characteristics are ordered based on the sum of rankings over all models, with the most influential characteristics on top and the least influential on the bottom. Columns correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (white) characteristics. For differentiation purposes, we use 'f', 'F', and 'M' to denote fund characteristics sorted into share, family, and manager groups.