What Beauty Brings? Managers' Attractiveness and Fund Performance*

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Abstract

In this paper, we study the relationship between stock fund managers' facial attractiveness and fund outcomes. Utilizing the state-of-art deep learning technique to quantify facial attractiveness, we find that funds with facial unattractive managers outperform funds with attractive managers by over 2% per annum. We next show that good-looking managers attract significant higher fund flow especially if the funds are available on Fintech platforms where their photos are accessible to investors. Good-looking managers also have greater chance of promotion and tend to move to small firms. The potential explanations for their underperformance include inadequate ability, insufficient effort, overconfidence and inefficient site visits.

Keywords: Mutual fund, Facial attractiveness, Fund flow, Manager career, Skill

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1 Introduction

We human being, whether intentionally or subconsciously, are keen to infer people's traits from their facial appearance. We ask the question: would it be beneficial if we take a look at mutual fund managers' photo before we invest? Despite the fact that purchasing mutual fund shares is becoming more and more fashionable for ordinary investors in China, we focus on Chinese market for two reasons. The regulations require mutual fund managers to disclose identification photos, which reduces the impact of image retouch. Secondly, the recent fast development of mutual fund Fintech adoption makes managers' photo easily accessible to fund investors.

In this paper, we study the relationship between mutual fund performance and fund manager facial attractiveness. We obtain identification-type photographs of 1677 Chinese active stock mutual fund managers from the website of Asset Management Association of China (AMAC), Choice database and Sina. We use face detection technique to extract faces from photos to avoid the influence of apparel and haircut. To quantify the facial attractiveness of fund managers, we utilize the cutting-edge deep learning models. We rely on the pre-trained deep neural networks of Liang et al. (2018) from the computer vision field. The model takes managers' photos as inputs and outputs scores which measure the facial attractiveness. Previous economics researches (Hamermesh and Biddle (1994), Scholz and Sicinski (2015) and Ruffle and Shtudiner (2015)) rely on very few human raters to quantify the facial attractiveness of the subjects or the interviewees. Their approaches are suffered from the subjectivity of the rater and the high cost of hiring raters. Our method achieves a higher level of objectivity and economical affordability. To our best knowledge, this is the first study in economics academia using deep learning model to quantify facial attractiveness.

In the empirical analysis, we take fund managers' facial attractiveness to examine the fund performance, and find facially unattractive managers display better performance. We begin our analysis by sorting stock mutual funds into value-weighted quintile portfolios based on their managers' facial attractiveness scores. The results show that funds in the bottom portfolio (run by unattractive managers) outperform those in the top portfolio (run by attractive managers) by 0.17% in excess return per month (t-stat = 2.6). We further show that the return differences are still significant even after adjusting systematic risks (CAPM, Fama-French 3-factor, Fama-French 5-factor) and the results are also robust to various holding horizons.

We next examine the performance persistence of the hedging portfolio, which longs funds whose manager has the lowest attractiveness score and shorts funds whose manager has the highest attractiveness score. We plot the cumulative Fama-French 3-factor adjusted return of a monthly rebalanced hedging portfolio from 2005 to 2020, and find that value-weighted portfolio is persistently profitable in general. It generates an additional cumulative abnormal return of 30% in our sample period. The cumulative abnormal return of equal-weighted portfolio is relatively lower but has a similar pattern. This persistent profitability is partially due to the low turnover of fund managers. Based on the transition matrix of fund manager score ranks, 74% quintile 1 funds remain in quintile 1 after 12 months and 35% would still remain in quintile 1 even 60 months after formation. In brief, the funds' manager attractiveness score can capture certain time-invariant fund level characteristics.

We then turn to regression-based analysis. Specifically, we regress the performance measure, Fama-French 3-factor alpha, on fund manager facial attractiveness score and a host of control variables on fund characteristics and manager characteristics. The regressions reveal a negative relationship between fund performance and manager attractiveness. Our results become stronger if we only focus on the large funds. Specially, one grade increase in attractiveness score leads to 0.57% decrease in next quarter 3-factor alpha (t-stat = -2.39). In general, regression-based analysis provides further evidence supporting our argument that lesser-looking managers deliver better performance.

While comely managers display worse performance, they actually attract more fund inflows. Following previous studies, we calculate fund flow as net growth in fund total net assets. We then regress fund flow on fund manager attractiveness scores. Indeed, the results show a significant positive relationship between fund manager attractiveness and fund flow under various specifications. We also explore the channels through which managers' beauty lure flows. We find that funds not only perform well in the past but also have good-looking managers can attract more inflows, indicating that there exists higher performance chasing for funds with good-looking managers. We then consider the Fintech adoption effect (Hong et al. (2020)), as fund managers' photo become easily accessible to investors on Fintech platforms. We consider two scenarios: 1. whether the funds are signed up on two major platforms: Ant financial and Tiantian. 2. whether the year is after 2012 when Fintech platform distributions of mutual funds share become proved. In both scenarios, we find that Fintech adoption provides more advantages for the good-looking managers on attracting inflows.

We next study the career prospect of the managers and ask the question whether attractive managers enjoy more chance of promotion. We define promotion as the increase of the number of funds assigned. In various setups, attractive managers do have higher chance of promotion after controlling their past performance and fund flow. In addition, we find attractive managers serve more firms as well, indicating that they have more bargaining power in the labor market. We also find that good-looking managers tend to move to small fund companies. The reason behind this phenomenon could be that small firms have higher priority in attracting fund flows where good-looking managers have stronger advantages. This is consistent with our result that the profitability difference is more prominent in large firms.

At last, we ask what could be the reasons for the outperformance of the unattractive managers? We first focus on potential labor market discrimination of unattractive workers, as good-looking managers could be hired for marketing while plain-looking managers can only be hired for their ability. To measure managers' skillness, we first propose three indicators measuring the concentration of the holding portfolio. We expect that skilled managers will invest more capital in their best ideas, rather than hedging their bets across a large number of securities. Consistent with our intuition, we find plain-looking managers have more concentrated portfolios. We also calculate the conventional timing and selectivity measures of Kacperczyk et al. (2014) and Daniel et al. (1997) for each fund. The results suggest that plain-looking managers have higher skill of market timing and stock selecting.

Secondly, we show that that plain-looking managers exert higher effort as measured by active share (Cremers and Petajisto (2009)) and R^2 (Amihud and Goyenko (2013)). By comparing fund holding to the hypothesized average fund, we also report evidence that good-looking managers display stronger herding behaviors.

Next, we study the psychological channel. we find that good-looking managers trade more excessively, prefer lottery-like assets and stocks with higher return volatility. They also exhibit more optimism when conducting market analysis in their periodic reports. These facts imply that good-looking managers could suffer overconfidence.

Lastly, we turn our attention to information acquisition channel. Previous literature shows the importance of site visit on fund performance (Chen et al. (2022)) and good-looking analysts posses advantages during site visits (Cao et al. (2020)). Inspired by these works, we investigate whether good-looking managers have advantages as well. However, the results show that they lack efficiency and tend to buy stocks with low future alpha and sell stocks with high future alphas after the visits.

Related Literature This paper is related to works on predicting fund performance by manager characteristics. In an early work by Chevalier and Ellison (1999a), they examine various manager characteristics, including age, average SAT score of manager's undergraduate institution, MBA degree. They find that after adjusting for selection bias, managers from higher-SAT undergraduate institutes have higher excess returns. Li et al. (2011) find similar results in the hedge fund industry. Hedge fund managers who attended higher-SAT undergraduate institutes are more likely to have higher both raw and risk-adjusted returns. A recent work by Chuprinin and Sosyura (2018) investigates the relationship between the family of origin and mutual fund manager performance. They find that managers born in poor families have better performance. The reason is that the poor-born manager face larger entry barriers and get promoted only if they perform well. Interestingly, Bai et al. (2019) document the 'relative age effect' on manager performance. As the result of the cutoff date of school entry, children born just after the cutoff date are relatively older. For instance, children born in September are relative older than their August born peers although they attend school in the same year. Bai et al. (2019) report that the relatively older managers outperforms the relatively younger managers because the former are more confident. More closely, our paper is related to Lu and Teo (2021) who study the facial structure of hedge fund managers. They find that the wide-face managers underperform their thin-face peers. Lu and Teo (2021) explain their results by testosterone which impacts facial width-to-height ratio and masculine behaviors in males. Our paper contributes to the literature by showing that the performance of a fund can be predicted by its managers' facial attractiveness.

Our paper is also related to studies on the association between facial appearance and economic outcomes. One of the early work is Hamermesh and Biddle (1994) who find that good-looking people earn more than plain-looking counterparts and the effect is independent to gender and occupation. Their results suggest employer discrimination. Scholz and Sicinski (2015) report a similar result using longitudinal data of male high school graduates. Ruffle and Shtudiner (2015) find that physically attractive male are more likely to receive interview invitations than unattractive male but this beauty premium does not exist for female. A closely related work is Cao et al. (2020) who study the financial analysts' beauty and performance. They find that physically attractive sell-side analysts display better performance in terms of the forecasting accuracy and the profitability of recommended stocks. Cao et al. (2020) provide evidence that attractive analysts have advantage in accessing information. Several studies focus on other aspects of physical appearance. Duarte et al. (2012) consider the trustworthiness of borrowers based on their photos. They find a positive relationship between the probability of loans funded and the photo-appeared trustworthiness. Persico et al. (2004) document a 'height premium' that taller workers receive higher wages. Our paper contributes to the literature by showing that 'beauty premium' exist in mutual fund industry that good-looking managers attract higher fund inflows and enjoy higher chance of promotion. We also contribute to the literature by introducing to the economics academia a new technique of quantifying appearance based only photographs.

Psychology studies reveal that human are very keen to judging people by their facial appearance. Willis and Todorov (2006) show that 0.1 second is sufficient enough for people to make inferences about other people's trait only by looking at them. People attribute positive and negative traits to a physically attractive person. Early works such as Dion et al. (1972) show that physical attractive persons are believed to be more socially desirable. Human prefer beauty from a very early stage of life. Langlois et al. (1991) report that even infants display preference to attractive faces. In this paper, we dig into mutual fund industry and find it would be beneficial if we take mangers' appearance into consideration before we invest their funds.

The rest of the paper proceeds as follow: Section 2 introduces the data of Chinese stock mutual funds and the deep learning model of quantifying fund managers' facial attractiveness. Section 3 shows the main results on the relationship between manager attractiveness and fund performance. Section 4 reports the results of fund flow and manager career. Section 5 analyze potential channels that could explain the performance difference. Section 6 concludes.

2 Data and Attractiveness Score

2.1 Chinese Stock Mutual Funds

We obtain our mutual fund data from Wind database, a leading Chinese financial data provider. We focus on open-ended stock funds and hybrid stock funds which are actively managed. The index funds, initial funds and principal guaranteed funds are excluded from our analysis. The sample period is from January 2005 to December 2020. To be included in our sample, we require the ratio of the equity holdings to total net assets of each fund to be greater than 60%. To further ensure data quality, we restrict the fund age to be greater than 12 months and the total net assets to be greater than RMB 1 million. After applying all these filtering procedures, we end up with 1402 unique fund shares and the corresponding 1677 managers. The sample is free of survivorship bias.

For each of the fund in our sample, we collect fund-level characteristics such as fund names, fund managers, returns, total net assets, expense ratio among others. Following Sirri and Tufano (1998), fund flow is calculated as the net growth in fund assets over the last quarter. To alleviate any concern about outliers, flow is winsorized at 1% and 99% levels. We report summary statistics of fund characteristics by year from 2005 to 2020 in table 1. One observation is that Chinese equity mutual fund industry is growing, with the total number of equity funds steadily increasing from fewer than 50 in 2005 to close to 1500 by 2020. The average fund size reached the highest level of 8.20 billion yuan in 2007 and has a decreasing pattern afterwards, which is driven by large initiations of new and smaller funds over our sample period. Due to the same reason, fund age also decreases steadily from 202 months to 73 months. Funds on average have a monthly return of 1.61%, with the standard deviation of 6.31%. The turnover rate is calculated as the minimum value between total sales or purchases, divided by the average 12-month total net assets (TNA) of the funds. The average turnover ratio for stock funds is 3.12, and had the highest value of 5.37 in 2015. There are flows in and out the equity fund industry throughout our sample period, with the largest outflow of -12.7% in 2006 and largest inflow of 41.12% in 2007. After 2015, fund flow remains positive. In addition, the management fee shows a slightly decrease from 1.50% to 1.47% in the recent years.

Besides, each funds has 1.24 managers at the same time on average, and average manager tenure is 33.5 months. For the 1677 managers in our sample, there are 267 female managers and 1410 male managers. Most (1398) managers have master's degrees, 60 managers have bachelor's degrees and 219 managers have doctor's degrees.

[Insert Table 1 Here.]

2.2 Attractiveness Score and Fund Manager Photos

We quantify fund managers facial attractiveness based the cutting-edge beauty prediction technique by Liang et al. (2018). They utilize a deep learning model to make facial beauty prediction. Concretely, they collect a large and diverse dataset containing photos of 2000 Asian males, 2000 Asian females, 750 Caucasian males and 750 Caucasian females. They then ask 60 human volunteers to grade each of these photos in a range from 1 to 5 points where 5 points represents the highest attractiveness. Therefore, each photo will have 60 graders and the average score will be the final score for that photo. Liang et al. (2018) train a convolutional neural network[1] which takes the photos as the inputs and the scores as the labels. This process is essentially similar to supervised learning. The trained neural network is able to replicate the grading results of human raters. Once the neural network is trained, it can be used to predict the beauty score of photos beyond its training set.

For our study, we use the trained model by Liang et al. (2018) to grade mutual fund managers. Previous works rely on human judges and interviewer to quantify attractiveness (Hamermesh and Biddle (1994) Ruffle and Shtudiner (2015)). Compared with earlier studies, our deep learning method is more convenient and economical because hiring interviewer

[1]The pretrained model and the training set of Liang et al. (2018) are available at their Github: `https://github.com/HCIILAB/SCUT-FBP5500-Database-Release` The best-performed architecture of their convolutional neural network is the wildly used ResNeXt50 by Xie et al. (2017). We use their ResNeXt50 model for our study.

can be costly. We only need the photos of managers and the trained model would evaluate their attractiveness. As the model is able to replicate the results of 60 human raters, our method provides more objective predictions of manager's actual attractiveness.

The photos of mutual fund managers are mainly collected from the Asset Management Association of China (AMAC). AMAC has an information disclosure system where one can find high resolution document photos of fund managers. We have two additional data source: Choice database and SINA. These two databases provide photos of managers who have left the funds or the asset management industry. We also gather photos via an Internet search. We try to collect frontal faces with expressions as natural as possible. We use face detection technique to extract faces from the photos to avoid the effect of haircuts and wearings.

We report the summary statistics of the facial attractiveness score of fund managers in table 2. The average score is 2.88 points, with the standard deviation of 0.51 points. We also demonstrate examples of high/low score male and female managers' photos.

[Insert Table 2 Here.]

3 Fund Performance and Attractiveness Score

In this section, we reveal the relationship between fund performance and manager facial attractiveness. We first sort funds into portfolios by their managers' score and then, turn to regression-based analysis.

3.1 Portfolios Sorting

We begin our analysis on the relationship between fund manager facial attractiveness and fund performance by forming portfolios. Concretely, at the end of each month, we sort all stock mutual funds into quintile portfolios based on their managers' facial attractiveness score. The scores are obtained according to the deep learning method of Liang et al. (2018). For funds with multiple managers, we use the average score of these managers as the score of the fund. The results are robust no matter we use the maximum or minimum score of the managers in funds with multiple managers, as shown in appendix table A1. Portfolios are rebalanced every month and are held for 0, $1-3$, and $4-12$ months respectively. As portfolios are formed every month but held for multiple months, we follow Jegadeesh and Titman (1993) to deal with the overlapping months. We adopt monthly excess return of the risk-free rate, CAPM alpha, Fama-French 3-factor alpha and Fama-French 5-factor alpha as our performance measures. We form both equal-weighted and value-weighted portfolios and report the results in table 3.

[Insert Table 3 Here.]

Panel A of table 3 reports the results of value-weighted portfolios. Quintile 1 contains funds whose managers' facial attractiveness score fall into the lowest 20% interval while quintile 5 contains funds whose managers' attractiveness score fall into the highest 20% interval. We also form a hedging portfolio by longing the low attractiveness score funds and shorting the high attractiveness score funds. The 'Formation Month' category in Panel A of table 3 shows the portfolio's abnormal return for the formation month 0. We can find that, in the formation month, the hedging portfolio earns 0.17% return, and the t statistic of 2.6 indicates that the return difference is significant from zero. The alphas of the hedging portfolio are statistically significant as well: the CAPM alpha, Fama-French three factor alpha and Fama-French five factor alpha are 0.17%, 0.17% and 0.16% respectively. The monthly return difference between low-score funds and high-score funds is 0.16% (t-stat = 2.49) when the holding period is from month 1 to month 3 and is 0.13% (t-stat = 2.28) when the holding period is from month 4 to month 12, indicating that low-score funds persistently outperform the high-score funds. The magnitude of our results are comparable to previous studies such as the "active share" effect by Cremers and Petajisto (2009), the "return gap" effect by Kacperczyk et al. (2008) and the "relative age" effect by Bai et al. (2019). Besides, when comparing with mutual fund industry average monthly return (1.61% in table 1), the economic magnitude of our hedging portfolio's return is also large.

The panel B of table 3 reports the results of equal-weighted portfolios. The results also show that the funds with low facial attractiveness scores outperform funds with high facial attractiveness scores. The outperformance holds for all the performance measures, although the results are not significant. The inconsistency of t statistics between value-weighted portfolios and equal-weighted portfolios suggests that our attractiveness effect is more significant on large funds. In appendix table A2, we dependently sort funds into a three-by-three matrix first by fund size then by fund attractiveness score. We find that low-score large funds have significantly higher returns than high-score large funds, while high-score small funds have insignificantly higher returns than low-score small funds. We also distinguish large funds from the whole fund sample in the regression-based analysis in the following subsection.

3.2 Persistence of the Portfolios

We next study the time series pattern of the performance of our hedging portfolio through the sample period from 2005 to 2020. At the end of each month, we sort funds into quintile portfolios by their last month fund managers' attractiveness score and construct the hedging portfolio by longing the bottom quintile (low-score) portfolio while shorting the top quintile (high-score) portfolio. The hedging portfolio is held for one month and is rebalanced at the end of each month. We form both equal- and value-weighted portfolios. We plot the cumulative Fama-French 3-factor adjusted return of the hedging portfolio from 2005 to 2020 in figure 1, and we find that value-weighted hedging portfolio is persistently profitable, except that it jumped a little during 2013-2015 and 2019. It generates an additional cumulative abnormal return of 30% in our sample period. The cumulative abnormal return of equal-weighted portfolio is relatively lower but has a similar pattern. In addition, in appendix figure A1, we report the cross-trade average cumulative return of the hedging portfolio if we hold the hedging portfolio fixed for three years. We find a monotonic increasing return pattern for both value-weighted and equal-weighted portfolios. Overall, our results provide strong evidence that our hedging strategy is profitable and the profitability is very persistent.

[Insert Figure 1 Here.]

To investigate the persistence of the fund manager attractiveness score, we construct a transition matrix of fund manager score ranks. As shown in table 4, 74% quintile 1 funds remain in quintile 1 after 12 months and 35% would still remain in quintile 1 even 60 months after formation. Only 4% funds from top quintile 1 migrate to quintile 5 in the next 12 months. In appendix figure A2, we also report the migration of facial attractiveness score rank for each portfolio. Funds in the top quintile (quintile = 5) have a quintile rank of 3.85 in 3 years, and funds in the bottom quintile have an average quintile rank of 2.2 after three years from formation. In brief, the low fluctuation of funds' manager attractiveness score could capture certain time-invariant fund level characteristics and help us select unique type of funds.

[Insert Table 4 Here.]

3.3 Regression-based Analysis

We now utilize regression-based method to study the relationship between fund performance and managers' facial attractiveness. Specially, we consider the following predictive regression:

$$\text{Performance}_{i,t+1} = \beta_0 + \beta_1 \text{Score}_{i,t} + \beta_2 X_{i,t} + \epsilon_{i,t+1} \tag{1}$$

where i is the index for funds. We take the 3-factor alpha as our performance measures on the left-hand side of the regressions. The 3-factor alpha is the intercept term of regressing fund excess returns against Fama-French 3 factors. We use a 24-months rolling-window regression to estimate fund alphas and convert alphas to quarterly frequency[1]. The control variables $X_{i,t}$ include fund characteristics and manager characteristics. We control for fund size which is equal to the natural logarithm of fund total net assets, fund age which is the number of months since fund inception. We also control fund quarterly flow, turnover and fund past performance measure which is the average fund past 12 month return. We include management fee as well. As Fintech platform distributions of mutual funds grow fast in China and have a very large impact on mutual fund performance (Hong et al. (2020)), we add a *Platform* dummy which equals one if the fund is available on two major Chinese mutual fund platform: Ant financial and Tiantian. For the manager characteristics, we include manager tenure, gender and education level. We also consider the facial characteristics of managers. Specially, we control for facial width-to-height ratio (*fWHR*)[2]. As reported by Lu

[1]We mainly use quarterly panel regression because some funds only report fund shares at a quarterly frequency.
[2]Given manager photos, facial width-to-height ratio can be easily calculate with facial landmark predictor of dlib library.

and Teo (2021), high-fWHR managers deliver worse performance due to testosterone which affects both fWHR and risk-taking behaviors of the manager.

We consider panel regression and control for both fund fixed effect and year fixed effect and the results are reported in table 5. Column (1) - (4) of table 5 show results using full sample and column (5) - (8) show results using the subsample of large funds. We find a significantly negative relationship between manager attractiveness and fund performance. The coefficients of attractiveness scores are significant at 5% level in 6 of 8 regression settings. In the full sample regressions, one point increase of attractiveness score leads to 0.26 to 0.3 decreases in quarterly alphas. Comparing column (3) to column (1), the coefficient of attractiveness score is still significant after other manager-level characteristics are controlled, indicating that manager attractiveness score provide additional information that is not captured by manager education, tenure, gender and other known facial characteristics.

[Insert Table 5 Here.]

In the section of portfolio sorting, we find that the return differences are more significant for value-weighted portfolios than equally-weighted portfolios. Therefore, we pay extra attention to the large funds whose total net assets falls into the top one third of our sample funds, and we find that the results indeed become stronger. Column (5) - (8) of table 5 show that the negative relationship between fund performance and manager attractiveness is significant no matter we control for fund characteristics or manager characteristics. One point increase of attractiveness score leads to 0.53 to 0.57 decreases in quarterly alphas. In addition, in column (7) and (8) of table 5, we find also find evidence supporting Lu and Teo (2021) that high facial width-to-height ratio (fWHR) manager deliver worse performance [1]. Overall, the regression-based analysis further supports the finding that funds with unattractive managers outperform funds with attractive managers.

To capture the heterogeneous impact of fund manager facial attractiveness score, we further look into the subsamples of fund managers and report the results in appendix table A3. We divide the whole sample based on managers' gender and education levels respectively. As shown in the left panel, we find that, only for male fund managers, the facial attractiveness

[1] In appendix table A1, we show that the hedging portfolio constructed based on fWHR has no significant underperformance.

score has significantly negative impact on fund performance. For female managers, there's no significant performance difference between good-looking and plain-looking managers. It's also interesting to find that, among all education levels, good-looking managers with bachelor's degree significantly underperform. While for managers with doctor's degree, facial attractiveness score has less impact.

4 Manager Attractiveness and Economic Outcomes

4.1 Fund Flow

So far, we have shown that facial unattractive managers outperform facial attractive managers. Then, a natural question is whether fund investors realize this and invest more money to funds with unattractive managers? However, in the meanwhile, previous studies show that physically attractive persons are more preferred by human (Dion et al. (1972),Langlois et al. (1991)), indicating that good-looking managers may have more advantages in attracting fund flows.

In this subsection, we study the relationship between fund flow and manager attractiveness using a regression-based method. We follow previous studies (Chevalier and Ellison (1997) and Sirri and Tufano (1998)) and calculate fund flow as follows:

$$\text{Flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}\left(1 + \text{Ret}_{i,t}\right)}{\text{TNA}_{i,t-1}} \tag{2}$$

Specially, we consider the following regression:

$$\text{Flow}_{i,t+1} = \beta_0 + \beta_1 \text{Score}_{i,t} + \beta_2 \text{Score}_{i,t} \times \{\text{MOM}_{i,t}, \text{Platform}_{i,t}, \text{Post}_t, \text{Log(size)}_{i,t}\} + \beta_3 X_{i,t} + \epsilon_{i,t+1} \tag{3}$$

where $Flow_{i,t+1}$ is the fund flow for fund i in quarter $t+1$. $Score_{i,t}$ is the facial attractiveness score of the fund manager. We also explore two channels through which manager attractiveness affects fund flow by introducing three variables. Firstly, we use $MOM_{i,t}$ (fund i's' past 12 months average return) to study the performance chasing of investors. Secondly, Fintech platform distributions of mutual funds not only bring fund managers' photos available to investor, but also have a large effect on China mutual funds. Therefore, we include two dummy variables to study this impact: $Platform_{i,t}$ is a dummy variable which equals to 1 if fund i is available on Ant Financial and Tiantian platform in the beginning of quarter t; $Post_t$ is a dummy variable which equals to 1 if the calendar time is after 2012 when policy in China begins to allow Fintech platform directly sell fund shares to investors. Hong et al. (2019)). We also add an interaction term of score and Log(size) to investigate the fund size effect on the relationship of manager attractiveness with fund flow. Our control variables $X_{i,t}$ includes fund characteristics (size, age, fee, turnover), manager characteristics (gender, education, tenure, fWHR) and last quarter flow. We conduct our analysis controlling firm fixed effect and year fixed effect.

[Insert Table 6 Here.]

We report our results in table 6. In the first column, we find that one grade increase of manager attractiveness score leads to a 1.86% (t-stat = 2.69) increase in fund flow. Controlling fund characteristics and manager characteristics even strengthen our result as in the second column. These results indicate that good-looking managers have advantages in attracting fund flows. We also find a positive relationship between fund past return and future inflow, which echos previous studies that mutual investors chase past performance (Sirri and Tufano (1998), Chevalier and Ellison (1997)). In our third regression, we then add an interaction term $(\text{Score}_{i,t} \times \text{MOM}_{i,t})$, and its coefficient captures the interactive effect between manager attractiveness and fund past performance. The interaction coefficient is 0.67 (t-stat = 3.18), indicating that good-looking managers who have better performance before can attract more inflows. The coefficient of score is still significant, showing investors' preference over good-looking managers regardless of their performance.

Then we turn to study the Fintech adoption effect for mutual fund managers. Through Fintech distribution of mutual funds, the photos of fund managers can be easily viewed by investors. Therefore, there is a great possibility that fund investors have preference over the manager appearance when they buy fund shares. To study this impact, we add an interaction term $(\text{Score}_{i,t} \times \text{Platform}_{i,t})$ in our third regression. The result in column (4) illustrates that for funds which signed up on the two major Fintech platform: Ant Financial and Tiantian platform, they can attract extra 2.74% inflow (t-stat = 2.23) if their managers facial attractiveness score increase one grade.

In addition, we regard 2012 as a major event year of mutual fund industry as the China Securities Regulatory Commission (CSRC) begin to allow Fintech platforms to distribute mutual fund shares. We study this effect by adding an interaction term ($\text{Score}_{i,t} \times \text{Post}_t$) in to the fifth regression. Since we control the year fixed effect, we do not add the dummy variable (Post_t) along in the regression. Column (5) reports a significant positive coefficient (2.69 with t-stat = 2.19) of the interaction term, meaning that after the Fintech adoption, funds with high-score managers attract more fund inflows. In the column (4) and (5), the coefficients of score became insignificant. Therefore, Fintech platform could be the channel through which manager appearance begin to affect fund flows.

In column (6), we add an interaction term of score and fund size ($\text{Score}_{i,t} \times \text{Log(size)}_t$). The coefficient is significantly negative (-0.98 with t-stat = -2.2), indicating that, good-looking managers in large funds have less power to attract fund inflows. This result is also consistent with our previous result showing that good-looking managers in large funds have even worse performance than plain-looking managers. Investors may realize the performance gap when purchase shares of large funds.

At last, we investigate the relationship between manager attractiveness score and fund flow based on the subsample of fund managers. As shown in the right panel of appendix table A3, we find that good-looking male fund managers can attract more capital inflows, while people care less about manager attractiveness score for female managers. Besides, there are more inflows to good-looking managers with higher education levels.

4.2 Manager Career

In this subsection, we study the career prospects of the fund managers and examine the role of facial attractiveness. We first consider the promotion of fund managers. Many aspects can be used to define promotion and a quantitatively-evaluated and easily-calculated measure is preferred. To this end, we regard the promotion of a manager as the increase of number of fund assigned (Barber et al. (2017)). We regress promotion to manager facial attractiveness score as follow:

$$\#\text{Promotion}_{j,t+1} = \beta_0 + \beta_1 \text{Score}_j + \beta_2 \text{Performance}_{j,t} + \beta_3 \text{Flow}_{j,t} + \beta_4 X_{j,t} + \epsilon_{j,t+1} \quad (4)$$

where $\#Promotion_{j,t+1}$ is the number of promotion of manager j in year $t+1$. We count the frequency of additional fund assignments. If a manager is assigned one or more funds in a month, we count it as one promotion. We then add up the number of promotion in that year as our explained variable. Co-managed fund is treated the same as sole-managed fund.

We also examine two important elements determining manager promotion: performance and fund flow. We use fund 3-factor alpha in year t as our performance measure, and the average fund quarterly flow in year t as our flow measure. If a manager runs multiple funds, we calculate fund size value-weighted average alpha and fund flow for all the funds. We control manager's education, gender and average management fee. Year fixed effect and firm fixed effect are considered as well.

The first three columns of table 7 report the results of regression (4). The results reveal a significant positive relationship between manager's promotion and facial attractiveness. The magnitude of the coefficient is comparable to the mean value (about 0.7) of the explained variable. Similar to Chevalier and Ellison (1999b), we only find weak effect of past performance over management responsibilities. Fund flow is still an important factor in promotion decisions as the coefficient of fund flow is significant in two of the three specifications. The reason behind this phenomenon could be that China mutual fund industry is growing and thus attracting fund flow has priority to fund companies. In addition, male manager tend to be assigned more funds.

We next consider the entire career experience of the fund managers and run regressions at manager level. Concretely, we consider the following cross-sectional regression:

$$Y_j = \beta_0 + \beta_1 \text{Score}_j + \beta_2 \text{Performance}_j + \beta_3 \text{Flow}_j + \beta_3 X_j + \epsilon_j \quad (5)$$

where j is the index for managers. We take three variables as the explained variable. The first one *#Promotion/#Year* is the total number of promotions divided by the number of years in mutual fund industry of the fund manager. The second variable *#Company/#Year* is the number of company that a manager served normalized by the number of year of his experience. The last variable *Move to Big Co.* is a dummy variable that equals 1 if the manager moves to a larger company, equals 0 if the manager does not change the company, equals -1 if the manager moves to a smaller company afterwards. If a manager moves more than once, we compare the size of the first and the last last company he served. The results are reported in the last three columns of table 7.

[Insert Table 7 Here.]

The forth column of table 7 echoes our previous results that attractive manager are more likely to be promoted. In this setup, a manager's advancement can also be attributed to his superior performance. In column (5), it shows that the attractive managers serve more companies. This result suggests good-looking managers have more bargaining power in the mutual fund industry.

The last column of table 7 manifests that attractive managers tend to move to small fund companies. The reason is that small fund companies tend to have higher priority in attracting fund flow where good-looking managers have more advantages. In addition, we find that male managers have a greater chance moving to large firms as well.

5 Value Channels

In the previous sections, we show that funds operated by good-looking managers underperform funds operated by plain-looking managers. In this section, we try to explore channels that could contribute to performance gap between attractive managers and unattractive managers. We first study the ability channel that plain-looking managers possess stronger ability as only high-ability manager could overcome the stringent selection. The second channel posits that good-looking managers exert less effort and could enjoy the 'quiet life' (Bertrand and Mullainathan (2003)). While the first two channels are not completely exclusive and mainly focus on potential labor market discrimination, we next consider the psychological channel that the underperformance of good-looking managers is the result of their overconfidence. Lastly, we investigate whether good-looking managers posses superiority during site visits.

5.1 Ability

Labor economics literature has shown that good-looking people are more likely to find jobs and get higher paid (Hamermesh and Biddle (1994), Scholz and Sicinski (2015), Ruffle and Shtudiner (2015)). In our previous section, we show that good-looking managers are more likely to be promoted, in terms of the number of funds assigned. Leaving aside job market discrimination, fund firms could hire good-looking mangers to attract investors as we shown in section 4. However, plain-looking mangers could only be hired for their ability of investment. As the result, mutual fund managers are good-looking people and plain-looking high-ability people. In this subsection, we examine the hypothesis that the outperformance of plain-looking manager is because of their superior investment ability.

Firstly, we propose three easily-calculated indicators to measure managerial ability of stock selecting. The logic is simple: a skilled manager always picks the best stocks for each subdivided industry and neglects stocks in the second place. Therefore, his portfolio should be concentrated rather than diversified. To measure the concentration of portfolio, we use i. the number of stocks in the portfolio (*#Stocks*); ii. the Herfindahl–Hirschman Index (*HHI*) which is the sum of the squared stock weights; iii. the total market value of the top 10 stocks invested as a percentage of the net asset value of the fund (*Navratio*). We report the results in the first three columns of table 8. We find significant evidence that good-looking managers hold a greater number of stocks in their portfolios and their portfolios are more diversified. This result indicates that good-looking managers lack the ability of stock picking, and hedge their bets across a large number of securities.

We then adopt the classic measures of manager's market timing skill and stock selecting skill proposed by Kacperczyk et al. (2014) and Daniel et al. (1997). A manager is regarded to possess market timing ability (*Timing*) if he could overweight stocks that have high betas and is regarded to possess stock picking ability (*Picking*) if he could overweight stocks that have higher subsequent idiosyncratic returns (Kacperczyk et al. (2014)). As for measures of Daniel et al. (1997), a manager with higher characteristic selectivity (*CS*) ability could pick stocks that beats the characteristic-based benchmark portfolios. A manager who switches to profitable style strategy is regarded to possess the ability of characteristic timing (*CT*). Specially, we construct these measures as follows:

$$Timing_t = \sum_{i=1}^{N} (w_{i,t} - w_{i,t}^m)\beta_{i,t} R_{t+1}^m \quad (6)$$

$$Picking_t = \sum_{i=1}^{N} (w_{i,t} - w_{i,t}^m)(R_{t+1}^i - \beta_{i,t} R_{t+1}^m) \quad (7)$$

where $w_{i,t}$ is the weight of stock i in the fund and $w_{i,t}^m$ is the weight of the stock i in the market portfolio. $\beta_{i,t}$ measures the covariance of stock i's return with market return using monthly return from $t - 12$ to $t - 1$. Therefore, before the market return rises (declines), a fund with a high timing ability overweights (underweights) assets that have high market betas. Similarly, a fund with a high picking ability overweights (underweights) assets that have subsequently high (low) idiosyncratic returns.

$$CS_t = \sum_{j=1}^{N} w_{j,t-1}(R_{j,t} - R_t^{b_{j,t-1}}) \quad (8)$$

$$CT_t = \sum_{j=1}^{N} (w_{j,t-1} R_t^{b_{j,t-1}} - w_{j,t-13} R_t^{b_{j,t-13}}) \quad (9)$$

where $w_{j,t-1}$, and $w_{j,t-13}$ is the portfolio weight of stock j at the end of month $t - 1$ and $t - 13$ respectively, $R_{j,t}$ is the return for stock j at month t , and $R_t^{b_{j,t-1}}$ ($R_t^{b_{j,t-13}}$) is the month t return of the characteristic-based passive portfolio that is matched to stock j during month $t - 1$ ($t - 13$). Therefore, funds with higher CS have good skills in picking stocks that outperform their benchmark portfolios, and funds with higher CT have good skills in switching their benchmark portfolios. In addition, Daniel et al. (1997) consider two dimensions of a stock: size and book-to-market ratio. The data of benchmark portfolios and assignments is from CSMAR database.

[Insert Table 8 Here.]

The results are reported in the last four columns of table 8. We include the next 6 and 12 months' monthly average values for Market Timing and Characteristic Selectivity measures. The coefficients of attractiveness score against Timing are significant beyond 5% level and the coefficients of score against CS are significant at 10% level. Therefore, plain-looking managers indeed have better market timing and characteristic selectivity skills. The results for Picking and CT are not shown, as we did not find significant coefficients, although the directions of the coefficients are consistent with those of Timing and CS.

5.2 Effort

In this subsection, we examine the hypothesis that good-looking managers underperform because they work less hard. To measure the effort that a manager exerted, firstly, we follow previous literature and calculate the *Active Share* as in Cremers and Petajisto (2009) and R^2 as in Amihud and Goyenko (2013) for our fund sample. These two indicators measures the extent to which a fund manager deviates from his benchmark index. Lower Active Share and higher R^2 imply that a manager makes less effort in researching stocks and just closely follows the benchmark index. The first two columns of table 9 illustrate that funds run by good-looking managers have significantly lower active share and higher R^2. This result reveals that plain-looking managers work harder than their good-looking peers.

Lazy managers could follow other managers and thus, display herding behavior. To measure the extend to which a fund manager follows other managers, we calculate i. the correlation between changes in fund holdings (number of stock shares) and the corresponding changes in the holdings of a hypothetical average fund in the style (*Herding*); ii. the sum of squared portfolios weight differences between fund and the corresponding average fund (*Dispersion*). Therefore, higher Herding and lower Dispersion manifest that a fund follows other funds more closely. These two measures were used in previous literature as well (Chuprinin and Sosyura (2018), Kacperczyk et al. (2014)). Column (3) and (4) in table 9 report the results of managerial herding behaviors. We find that good-looking managers display stronger herding behaviors, and for both regressions, the coefficients of attractiveness score are significant at 5% level. Overall, our findings reveal that good-looking managers are less hard-working than their plain-looking peers.

[Insert Table 9 Here.]

5.3 Overconfidence

In the experiment of Mobius and Rosenblat (2006), they find that good-looking workers are more confident about their productivity. Psychological studies also find evidence that good-looking people tend to be more confident (Jackson and Huston (1975)). However, the boundary between confidence and overconfidence may not be clear and it is hard to tell ex ante whether an individual is confident or overconfident. Overconfidence is a common recognition bias on financial market where investors overestimate the market or their skills. In this subsection, we test whether good-looking managers are more overconfident.

Measuring overconfidence directly is difficult and there is no wildly accepted indicators in the literature. Thus, we infer whether a manager is overconfident by his trading behaviors, holdings and market analysis. In the seminal work of Barber and Odean (2001), they show that overconfidence results in excessive trading volumes and reduced returns. Therefore, our first measure of overconfidence is fund turnover ratio (*Turnover*), which is also used by Puetz and Ruenzi (2011), Chow et al. (2011) and Adebambo and Yan (2016). In the meanwhile, overconfident managers demonstrate overoptimism and tend to buy lottery-like assets who have experienced extreme high returns. Inspired by Bali et al. (2011), our second measure of overconfidence (*Lottery*) is calculated as the maximum daily stock return over the past one month averaged across stocks held in the fund. In addition, we examine whether good-looking managers prefer stocks with high return volatility (*Ret Vol*). Lastly, we consider manager's textual sentiment towards the market. We count the number of positive words and negative words from the market analysis session of fund periodic reports. *Sentiment* is calculated as the difference between the number of positive words and negative words divided by the sum number of them (Luo et al. (2022)).

We report the results of managerial overconfidence in the last four columns of table 9. We find significantly negative relationships between managers attractiveness and the overconfidence measures. The coefficient of attractiveness score against turnover measure is significant at 1% level, showing that good-looking managers trade more frequently. Good-looking managers also prefer lottery-like assets and stocks with high return volatility. And when they conduct market analysis, they have more positive perspectives than plain-looking managers. In sum, these results suggest that the interior performance of good-looking manager could be due to their overconfidence.

5.4 Site Visits

Site visit is one of the most important sections for mutual fund managers to make investment decisions. During site visits, fund managers directly acquire information about the investigated firms. Chen et al. (2022) report a positive link between site visits and mutual fund performance. Through direct communication, managers could potentially obtain 'soft information' that is not provided by financial reports. Face-to-face meeting could benefit good-looking managers more. Cao et al. (2020) find that good-looking sell-side financial analyst receive preferential treatment during site visits and partially because of that, their forecasts are more accurate. Inspired by their works, we examine whether good-looking managers possess advantages during site visits in this subsection.

The institutional background in China provides us unique advantages in researching managers' site visits. Financial intermediaries and retail investors are permitted to visit listed firms. During the visits, investors can communicate with the management team and take field tours of the production processes as well as firm's operation. Shenzhen Stock Exchange (SZSE) require the listed firms to record and disclose the names and affiliations of their visitors in the periodic reports. Chen et al. (2022) provide more detailed background information. Wind database provide data on mutual fund site visits and we merge it to our fund holding data by fund family names and manager names.

If good-looking managers have advantages during site visits, their visit-and-buy (visit-and-sell) stocks should exhibit higher (lower) ex post alphas than their plain-looking peers. To formally test this assumption, we calculate the stock position changes in the fund holdings from the begin to the end of period t, and we focus on stocks with none-zero position changes. For stocks with increased number of shares, we classify it as 'buy' stocks and, vice the verse, stocks with decreased number of shares as 'sell' stocks. We calculate stock 3-factor alphas in the period $t + 1$ and regress them to managers' visits as regression (10). Stocks held by different funds are treated as different observations.

$$\alpha_{i,t+1} = \beta_0 + \beta_1 \text{Visit}_{j\to i,t} + \beta_2 \text{Score}_{j,t} + \beta_3 \text{Visit}_{j\to i,t} \times \text{Score}_{j,t} + \text{Controls}_t + \epsilon_{i,t+1} \quad (10)$$

We first construct a dummy of site visit: $\text{Visit}_{j\to i,t} = 1$ if managers in fund j visited company i during the period t. To study whether good-looking managers posses superiority during visits, we add an interactive term of site visits and manager attractiveness score $\text{Visit}_{j\to i,t} \times \text{Score}_{j,t}$. If good-looking managers have advantages during site visits, the coefficient of the interactive term should be positive for 'buy' stocks and negative for 'sell' stocks. [1] Control variables includes fund characteristics, manager characteristics which are aforementioned. Fund manager visits might potentially impact stock prices. Therefore, we also control for stock characteristics including stock market capitalization, turnover, ROA, asset-liability ratio and past 6-month returns. We report the results in table 10.

[Insert Table 10 Here.]

In table 10, the sign of the interactive terms are opposite to our expectation. Column (2) and (4) shows that good-looking managers incline to visit and buy (sell) firms with lower (higher) alphas in the following periods. In the regressions, attractiveness could only have effects when interacted with site visits. Therefore, we explain our results as the lack of 'soft-skills' rather than the lack of selecting skill for good-looking managers.

The sign of the coefficient of visit in all regressions shows the usefulness of field investigation. For the stocks that a manager increase positions, the visited firms have higher alphas than the non-visited firms. Managers are more likely to sell low-alpha stocks if they have visited the firms. One concern is that managers tend to visit firms which they have already formed expectations. We add control variables at firm level to partially pin down this explanation.

In addition, we find that good-looking managers visit less of firms which they have already hold in the portfolios. This result suggest that good-looking managers exert less effort in researching their holdings.

[1] To study manager's skill during site visits, one could either focus on the alphas of visit-and-buy(sell) stocks or focus on the visit-and-buy(sell) action of high(low) alpha stocks. We take the former method to avoid potential data mining on defining high(low)-alpha stocks.

6 Conclusion

In this paper, we study the relationship between stock fund managers' facial attractiveness and fund outcomes. We start our paper by introducing the state-of-art deep learning technique to quantifying facial attractiveness. Using the deep learning model to evaluate attractiveness is able to achieve a high level of objectivity at a low cost. Our main finding is that funds run by facial unattractive managers are actually outperforming funds run by attractive managers. It is persistently profitable by longing funds whose managers are unattractive while shorting funds whose managers are attractive.

We find that good-looking managers attract more fund inflows especially if they have good past performance. Fintech platforms where managers' photos are available to investors give more advantage to good-looking managers in attracting fund flows. We also study the career prospect of managers and find that good-looking managers have larger chances of promotion. Moreover, good-looking managers tend to move to small firms where attracting fund flow is of higher priority.

To explain the performance differences, we provide evidences that plain-looking managers possess higher ability of stock selecting and market timing. We show that good-looking managers exert less effort to their work and display more overconfident behaviors. We also find that good-looking managers lack efficiencies during site visits. Overall, the relationship between facial appearance and investment outcomes could be an interesting topic for further studies.

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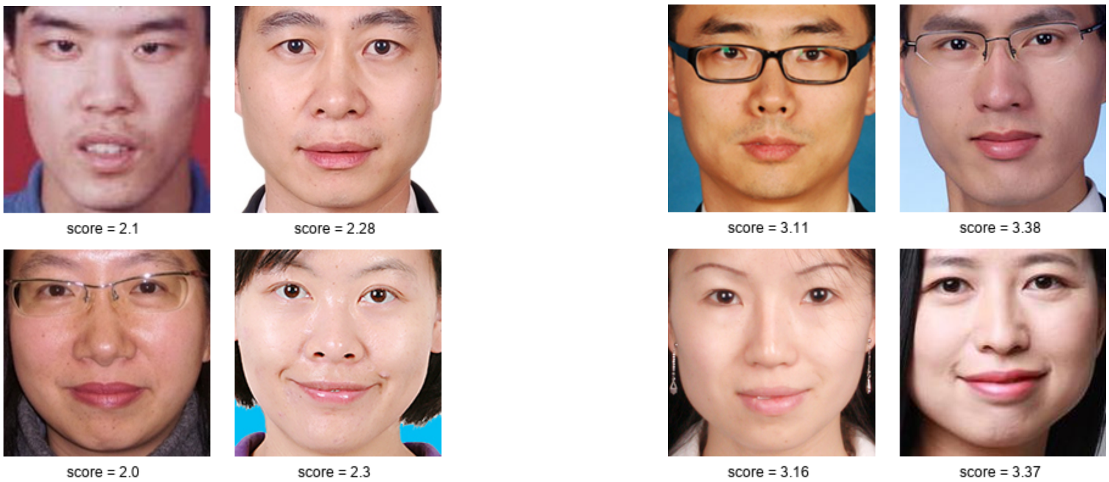
Table 1: **Summary Statistics** This table reports the summary statistics for actively managed equity funds year by year. #Funds is the average number of unique fund shares in each year. TNA is average fund size in billions of dollars. Return is average fund monthly return in percentage. STD is the standard deviation of fund monthly returns in percentage, calculated for each fund and then averaged across all funds in the year. Age is number of months since a fund's inception. Turnover is computed as the minimum value between total sales or purchases, divided by the average 12-month total net assets (TNA). Flow is fund quarterly flow in percentage, calculated as Sirri and Tufano (1998). Fee is fund management fee in percentage. #Managers is the number of managers of the fund. The sample period is from 2005 to 2020.

Year	#Fund	TNA ($Billion)	Return (%)	STD (%)	Age (Months)	Turnover	Flow (%)	FEE (%)	#Manager
2005	42	1.56	0.30	4.04	202	1.75	-8.17	1.50	1.18
2006	78	1.66	7.04	7.13	194	2.88	-12.70	1.50	1.14
2007	134	8.20	7.28	9.44	183	2.59	41.12	1.50	1.29
2008	169	7.29	-5.19	8.03	177	1.97	-1.54	1.49	1.27
2009	206	5.72	4.77	8.45	171	3.45	-2.33	1.50	1.22
2010	256	4.84	0.43	5.60	163	2.93	-1.90	1.49	1.24
2011	321	3.65	-2.17	4.85	156	2.45	-1.78	1.49	1.23
2012	386	2.57	0.57	6.15	150	2.58	-4.30	1.50	1.26
2013	424	2.38	1.38	5.59	145	3.14	-3.26	1.50	1.29
2014	463	1.99	1.84	4.71	140	3.36	-1.78	1.50	1.25
2015	560	2.01	3.93	12.55	129	5.37	-5.04	1.50	1.27
2016	658	1.29	-0.85	8.49	120	3.72	3.67	1.50	1.26
2017	745	1.22	1.19	3.29	111	3.38	3.21	1.49	1.24
2018	910	1.01	-2.15	4.35	98	3.57	0.33	1.48	1.24
2019	1148	0.91	3.26	5.07	83	3.62	2.82	1.48	1.22
2020	1334	1.24	4.12	7.18	73	3.22	5.42	1.47	1.20
All	1402	2.97	1.61	6.31	143	3.12	0.86	1.49	1.24

Table 2: **Fund Manager Facial Attractiveness Score** We quantify fund managers facial attractiveness based on the cutting-edge beauty prediction technique by Liang et al. (2018). They utilize a deep learning model to make facial beauty prediction. The model is able to replicate the results of 60 human raters. We collect mutual fund managers' photos from the Asset Management Association of China (AMAC), Choice database and SINA. This table shows the summary statistic of facial attractiveness score of actively managed equity fund managers, along with examples of high/low score male and female managers' photos.

Variable	N	Mean	Std	Min	Q1	Median	Q3	Max
Facial Attractiveness Score	1677	2.88	0.51	1.36	2.57	2.89	3.19	4.43



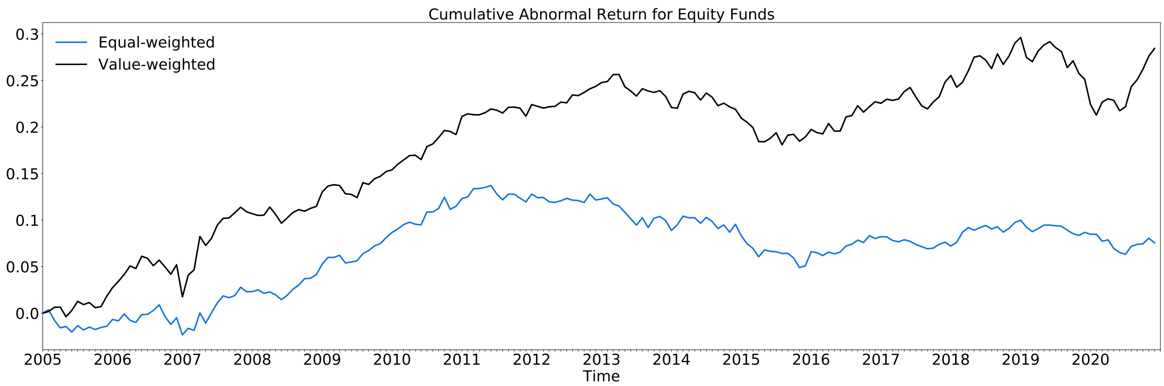


Figure 1: **Equity Fund Performance by Facial Attractiveness Score** The figure plots the cumulative three-factor adjusted abnormal return of equity funds from 2005 to 2020. We form calendar-time equal-weighted and value-weighted portfolios by sorting all mutual funds into quintiles based on manager last month facial attractiveness score, then we examine the portfolio performance. We plot the cumulative abnormal return for the hedging portfolio which longs quintile 1 and shorts quintile 5.

Table 3: **Portfolio Returns Ranked by Facial Attractiveness Score** This table reports calendar-time returns to portfolios ranked by facial attractiveness score. At the end of each month, we form calendar-time portfolios by sorting all mutual funds into quintiles based on fund manager average facial attractiveness score. The portfolios are rebalanced every month and are held for corresponding time periods. The two panels report the value-weighted and equal-weighted monthly portfolio returns in percent. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. Monthly returns with different risk adjustments are reported: the return in excess of the risk-free rate, the CAPM alpha, 3-factor alpha, 5-factor alpha. Market factors are collected from CSMAR.

Panel A: Value-Weighted Portfolios

	Month 0 (Formation Month.)				Month 1-3				Month 4-12			
Quintile	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5
1 (low)	1.30	0.39	0.37	0.20	1.27	0.45	0.42	0.26	1.34	0.51	0.44	0.30
2	1.12	0.23	0.22	0.06	1.13	0.32	0.29	0.12	1.27	0.43	0.34	0.20
3	1.17	0.26	0.24	0.07	1.12	0.28	0.25	0.07	1.23	0.37	0.31	0.14
4	1.16	0.26	0.24	0.07	1.15	0.32	0.29	0.12	1.23	0.40	0.32	0.17
5 (high)	1.13	0.22	0.20	0.04	1.11	0.29	0.25	0.08	1.22	0.37	0.30	0.15
low-high	0.17	0.17	0.17	0.16	0.16	0.16	0.17	0.18	0.13	0.14	0.14	0.15
t-stat	2.60	2.61	2.69	2.48	2.49	2.56	2.81	2.89	2.28	2.43	2.54	2.59

Panel B: Equal-Weighted Portfolios

	Month 0 (Formation Month.)				Month 1-3				Month 4-12			
Quintile	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5
1 (low)	1.37	0.48	0.43	0.28	1.35	0.54	0.48	0.31	1.42	0.58	0.48	0.33
2	1.31	0.42	0.37	0.19	1.27	0.47	0.40	0.21	1.39	0.55	0.42	0.27
3	1.30	0.39	0.35	0.19	1.26	0.43	0.37	0.19	1.33	0.48	0.38	0.22
4	1.29	0.39	0.33	0.18	1.25	0.42	0.35	0.18	1.35	0.50	0.40	0.25
5 (high)	1.34	0.44	0.38	0.22	1.30	0.48	0.41	0.23	1.38	0.54	0.44	0.27
low-high	0.04	0.05	0.05	0.07	0.05	0.06	0.07	0.08	0.04	0.05	0.04	0.06
t-stat	0.69	0.86	0.98	1.21	1.04	1.20	1.43	1.68	0.85	1.02	0.94	1.35

Table 4: **Transition Matrix of Facial Attractiveness Score Rank** This table reports the transition matrix of facial attractiveness score rank for equity funds. The numbers in the table indicate the probability of the facial attractiveness score rank become in the next 12, 24, 36 and 60 months. All figures are reported in percentage.

	$t = 12$						$t = 24$				
Quintile	1	2	3	4	5	Quintile	1	2	3	4	5
1	74	11	6	6	4	1	57	14	11	11	6
2	14	64	11	6	5	2	18	47	14	10	10
3	6	13	64	11	5	3	10	19	45	15	10
4	6	7	14	60	12	4	12	10	21	42	15
5	3	4	6	14	73	5	7	7	10	19	58

	$t = 36$						$t = 60$				
Quintile	1	2	3	4	5	Quintile	1	2	3	4	5
1	47	17	14	12	10	1	35	19	15	16	16
2	21	37	15	13	14	2	21	26	20	17	16
3	13	23	36	16	12	3	17	24	26	18	15
4	14	13	23	35	15	4	22	16	21	27	14
5	11	9	13	20	48	5	14	16	18	22	30

Table 5: **Manager Facial Attractiveness and Fund Performance** This table reports the results of multivariate OLS regressions of fund performance on facial attractiveness score and a host of control variables. The dependent variable is fund 3-factor alpha (%) in quarter $t + 1$. Alpha is the intercept from regressing the fund's monthly excess returns against Fama-French 3-factors. A rolling window of 24 months is used, and alphas are converted to quarterly frequency. The independent variables are quarter t end Score (facial attractiveness score), Log(size), Age (the number of months since fund inception), Turnover, Flow, MOM (fund past 12 months average return), Management fee, Male (equals one if fund manager is a male), Education (equals 0 for bachelors, equals 1 for masters, equals 2 for doctors), Tenure (the number of month of manager tenure), Platform (equals one if the fund is available for sale as of the beginning of quarter through the two major platforms: Ant Financial and Tiantian), fWHR (manager's facial width-to-height ratio). Large funds is the subsample consisting of fund whose total net assets falls into the top one third of the all funds. Year fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	Three-factor alpha$_{t+1}$							
	All Funds				Large Funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score	-0.275**	-0.281*	-0.302**	-0.260*	-0.531**	-0.578**	-0.552**	-0.568**
	(-2.04)	(-1.94)	(-2.16)	(-1.77)	(-2.36)	(-2.46)	(-2.37)	(-2.39)
Log(size)		-0.906***		-0.918***		-1.954***		-2.027***
		(-11.48)		(-11.47)		(-8.21)		(-8.64)
Age		-0.176		-0.175		-0.241		-0.232
		(-1.21)		(-1.20)		(-1.15)		(-1.10)
Turnover		0.151***		0.154***		0.385***		0.398***
		(5.96)		(6.05)		(7.25)		(7.52)
Flow		0.407***		0.414***		0.117		0.14
		(2.94)		(2.98)		(0.37)		(0.45)
MOM		-0.204***		-0.204***		-0.254***		-0.253***
		(-7.87)		(-7.86)		(-6.32)		(-6.28)
Management fee		-1.6		-1.55		3.311		3.502*
		(-0.66)		(-0.63)		(1.50)		(1.72)
Platform		0.453*		0.457*		0.497		0.505
		(1.73)		(1.74)		(1.18)		(1.19)
Tenure			-0.060*	0.042			-0.036	0.094*
			(-1.82)	(1.23)			(-0.79)	(1.90)
Education			-0.064	-0.138			-0.103	-0.027
			(-0.42)	(-0.82)			(-0.38)	(-0.09)
Male			-0.031	0.05			-0.061	-0.022
			(-0.16)	(0.23)			(-0.18)	(-0.06)
fWHR			-0.577	-0.563			-1.734**	-2.132**
			(-1.07)	(-0.97)			(-2.14)	(-2.27)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	26,666	26,666	26,666	26,666	9,367	9,367	9,367	9,367
R-squared	17.2%	18.5%	17.2%	18.5%	18.2%	20.6%	18.3%	20.7%

Table 6: **Manager Facial Attractiveness and Fund Flow** This table reports the results from multivariate OLS regressions of investors' flow on facial attractiveness score and a host of control variables. The dependent variable is fund Flow (%) in quarter $t+1$ is calculated following Sirri and Tufano (1998). The control variables are the same as table 5. We also include the interaction terms of facial attractiveness score with MOM (fund past 12 months average return), Platform (equals one if at of the beginning of quarter, the fund is available for sale through the two major third-party platforms: Ant Financial and Tiantian), Post (equals to one if the calendar time is after 2012), and Log(size). Year fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	Flow_{t+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
Score	1.855***	2.404***	1.583**	0.380	0.347	8.838***
	(2.69)	(3.02)	(2.02)	(0.33)	(0.30)	(2.69)
MOM×Score			0.668***			
			(3.18)			
Platform×Score				2.739**		
				(2.23)		
Post×Score					2.691**	
					(2.19)	
Log(size)×Score						-0.976**
						(-2.20)
Log(size)		-13.455***	-13.47***	-13.459***	-13.461***	-10.690***
		(-25.73)	(-25.78)	(-25.79)	(-25.79)	(-7.99)
Age		-0.49	-0.525	-0.524	-0.529	-0.534
		(-0.87)	(-0.93)	(-0.93)	(-0.94)	(-0.95)
Turnover		-0.219*	-0.21	-0.221*	-0.220*	-0.221*
		(-1.69)	(-1.61)	(-1.70)	(-1.70)	(-1.71)
Flow		8.220***	8.196***	8.205***	8.210***	8.227***
		(8.29)	(8.25)	(8.27)	(8.28)	(8.30)
MOM		2.361***	0.475	2.362***	2.362***	2.363***
		(18.52)	(0.79)	(18.56)	(18.55)	(18.56)
Management fee		1.636	1.277	1.553	1.510	1.763
		(0.13)	(0.10)	(0.13)	(0.12)	(0.14)
Platform		-1.268	-1.197	-8.870**	-1.263	-1.262
		(-1.08)	(-1.02)	(-2.46)	(-1.08)	(-1.08)
Tenure		0.464***	0.478***	0.486***	0.485***	0.463***
		(2.77)	(2.83)	(2.88)	(2.88)	(2.75)
Education		0.156	0.156	0.215	0.205	0.236
		(0.15)	(0.15)	(0.20)	(0.19)	(0.22)
Male		2.194*	2.157*	2.143*	2.128*	2.224*
		(1.93)	(1.89)	(1.88)	(1.86)	(1.95)
fWHR		-0.199	-0.082	-0.161	-0.197	-0.092
		(-0.07)	(-0.03)	(-0.05)	(-0.07)	(-0.03)
Year FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	28,331	28,331	28,331	28,331	28,331	28,331
R-squared	11.3%	18.0%	18.0%	18.0%	18.0%	18.0%

Table 7: **Manager Facial Attractiveness and Career Trajectory** This table reports the results from pooled-OLS regression and OLS regression of manager career trajectory on facial attractiveness score. For column (1) to (3), the dependent variable is #Promotion$_{t+1}$ (number of promotions in year $t+1$). The career change is considered as a promotion if the number of funds that a manager manages increases (following Barber et al. (2017)). The independent variables are manager facial attractiveness score, education level, gender, year t 3-Factor Alpha (computed using value-weighted fund returns), value-weighted Flow and average Management fee. Fixed effects are included as shown. Standard errors are double-clustered at the year level and company level. #Promotion/#Year in column (4) is the number of promotions divided by years of manager's experience. #Company/#Year in column (5) is the number of management companies that the manager has served divided by years of manager's experience. Move to Big Co. is a dummy variable that equals 1 if the manager moves to a larger company, equals 0 if the manager does not change the company, equals -1 if the manager moves to a smaller company afterwards. From column (4) to (6), 3-Factor Alpha is estimated for each manager using all observations. Flow, Management fee and Family size are averaged across time. Standard errors are adjusted for heteroskedasticity. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	#Promotion			#Promotion/#Year	#Company/#Year	Move to Big Co.
	(1)	(2)	(3)	(4)	(5)	(6)
Score	0.025**	0.047***	0.020*	0.063***	0.033***	-0.019*
	(2.47)	(3.54)	(1.95)	(2.94)	(4.68)	(-1.92)
3-Factor Alpha	0.061*	0.053	0.059*	0.072***	-0.024**	0.007
	(1.93)	(1.16)	(2.01)	(2.94)	(-2.27)	(1.01)
Flow	0.073**	0.058	0.071**	0.023	-0.009	0.003
	(2.22)	(1.41)	(2.35)	(0.71)	(-0.70)	(0.38)
Education	0.005	0.004	-0.002	0.046	0.001	-0.004
	(0.12)	(0.10)	(-0.06)	(0.86)	(0.04)	(-0.16)
Male	0.098*	0.094**	0.112***	0.102*	-0.002	-0.055**
	(2.03)	(2.20)	(3.13)	(1.74)	(-0.08)	(-2.51)
fWHR	-0.018	-0.009	-0.009	-0.158	-0.066	0.103
	(-0.99)	(-0.43)	(-0.48)	(-0.95)	(-1.17)	(1.46)
Management fee	-0.053***	-0.039*	-0.034	-0.132***	-0.024***	0.01
	(-3.41)	(-1.78)	(-1.59)	(-4.25)	(-3.14)	(1.55)
Year FE	Y		Y			
Company FE		Y	Y			
Observations	4,305	4,291	4,291	1,525	1,525	1,525
R-squared	6.5%	7.4%	12.3%	3.9%	3.1%	0.7%

Table 8: **Manager Facial Attractiveness and Ability** This table reports the results from multivariate OLS regressions of managers' ability measures on facial attractiveness score and a host of control variables. Dependent variables of ability measures include: Concentration, Market Timing from Kacperczyk et al. (2014) and Characteristic Selectivity from Daniel et al. (1997), Concentration measures include log(#Stock) (logarithmic of the number of stocks in the fund), HHI (holding concentration index), and Navratio (total market value of the top 10 stocks invested as a percentage of the net asset value of the fund). We include the next 6, 12 months' monthly average values for Market Timing and Characteristic Selectivity measures. The control variables are the same as table 5. Year fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	Concentration			Market Timing		Characteristics Selectivity	
	#stock	HHI	Navratio	Timing (6m)	Timing (12m)	CS (6m)	CS (12m)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Score	0.056***	-0.143***	-1.182**	-9.050**	-6.434**	-2.451*	-2.958*
	(2.81)	(-3.06)	(-2.37)	(-2.02)	(-2.12)	(-1.66)	(-1.80)
Log(size)	0.063***	0.032	0.325	-29.842***	-5.966***	-4.483***	-4.706***
	(6.61)	(1.45)	(1.33)	(-11.22)	(-4.19)	(-5.27)	(-5.52)
Age	0.012	0.005	-0.057	-39.713***	41.967***	35.123***	-0.03
	(0.99)	(0.20)	(-0.19)	(-6.26)	(10.08)	(9.24)	(-0.03)
Turnover	0	-0.010*	-0.107*	-3.084***	1.187**	0.307	0.22
	(0.04)	(-1.71)	(-1.79)	(-4.07)	(2.57)	(0.91)	(0.88)
Flow	0.028***	0.003	-0.028	25.089***	-1.8	-3.240**	1.305
	(2.66)	(0.13)	(-0.10)	(4.12)	(-0.62)	(-2.05)	(1.07)
MOM	0.013***	0.068***	0.655***	-68.328***	-14.619***	3.119***	-3.066***
	(5.30)	(11.02)	(9.75)	(-37.05)	(-23.93)	(6.99)	(-9.62)
Management fee	-0.047	-0.063	3.013	50.207	41.141	-27.726	-8.579
	(-0.16)	(-0.09)	(0.35)	(0.90)	(1.02)	(-1.25)	(-0.46)
Platform	-0.017	0.046	1.202*	-4.842	9.013*	-4.691	-3.268
	(-0.65)	(0.73)	(1.72)	(-0.66)	(1.75)	(-1.48)	(-1.01)
Tenure	0.005	0.008	0.157	4.537***	1.434**	-1.081***	-1.185***
	(1.02)	(0.73)	(1.42)	(4.31)	(2.10)	(-2.77)	(-2.76)
Education	-0.039*	0.021	0.074	-3.941	-0.947	-1.085	-1.381
	(-1.72)	(0.36)	(0.12)	(-0.69)	(-0.26)	(-0.70)	(-0.84)
Male	0.017	0.135**	1.487**	15.765**	10.846***	-0.458	0.071
	(0.61)	(2.31)	(2.32)	(2.41)	(2.84)	(-0.23)	(0.03)
fWHR	-0.139*	0.395**	3.681*	36.312**	22.683**	-2.601	2.225
	(-1.90)	(2.15)	(1.90)	(2.07)	(2.26)	(-0.48)	(0.39)
Year FE	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y
Observations	12,809	12,809	11,366	12,777	12,777	11,324	11,324
R-squared	63.3%	57.2%	58.2%	60.3%	75.2%	27.3%	32.4%

Table 9: **Effort and Overconfidence** This table reports the results from multivariate OLS regressions of managers' effort measures and overconfidence measures on facial attractiveness score and a host of control variables. Effort measures include: Active share (Cremers and Petajisto (2009)); R^2 is estimated from regressing fund excess return against Fama-French three factor and momentum factor as in Amihud and Goyenko (2013); Herding is the correlation of position changes between fund and the hypothetical average fund in the same style; Dispersion is the sum of squared portfolio weight difference between fund and the hypothetical average fund in the same style (Kacperczyk et al. (2014)). Overconfidence measures include: fund turnover; Lottery is the maximum daily stock return over the past one month averaged across stocks held in the fund as in Bali et al. (2011); Ret Vol is the past 24 months stock return volatility averaged across stocks held in the fund; Sentiment measures manager's textual sentiment and is calculated as the difference between the number of positive words and negative words divided by the sum number of them (Luo et al. (2022)). The control variables are the same as table 5. Year fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	Effort				Overconfidence			
	Active Share	R^2	Herding	Dispersion	Turnover	Lottery	Ret Vol	Sentiment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score	-0.696**	0.929***	1.049**	-0.153***	0.259***	5.958**	0.116**	1.901**
	(-2.29)	(2.88)	(2.46)	(-3.44)	(3.43)	(2.04)	(1.99)	(2.51)
Log(size)	0.126	0.369**	0.452	0.018	-0.439***	-3.416**	0.196***	-0.418
	(0.87)	(1.97)	(1.63)	(0.79)	(-10.59)	(-2.48)	(7.28)	(-1.14)
Age	0.575***	-1.066***	-0.821	0.045*	4.075***	-1.178	-0.188***	-0.154
	(2.95)	(-5.39)	(-1.59)	(1.74)	(13.23)	(-0.47)	(-3.52)	(-0.25)
Turnover	0.142***	-0.207***	-0.077	-0.002	0.179***	2.901***	0.101***	-0.006***
	(4.52)	(-5.00)	(-1.21)	(-0.44)	(8.12)	(7.08)	(11.37)	(-4.63)
Flow	-0.22	-0.342*	0.205	-0.036	0.188***	6.128***	-0.058	1.651***
	(-1.32)	(-1.72)	(0.40)	(-1.45)	(3.37)	(2.74)	(-1.21)	(3.00)
MOM	0.427***	-0.516***	0.320***	0.050***	-0.044***	-8.967***	-0.064***	-0.534***
	(10.99)	(-11.17)	(2.91)	(8.49)	(-4.12)	(-18.08)	(-6.56)	(-4.65)
Management fee	-0.783	2.207	-3.166	-0.4	-0.792	66.532*	-0.721	-5.815
	(-0.30)	(0.67)	(-0.71)	(-0.69)	(-0.72)	(1.93)	(-1.01)	(-0.55)
Platform	0.205	0.374	-1.215	0.105	-0.145	-14.375***	-0.051	2.234*
	(0.45)	(0.66)	(-1.38)	(1.62)	(-1.00)	(-2.88)	(-0.53)	(1.65)
Tenure	0.094	0.096	-0.048	0.005	-0.038**	0.216	-0.01	-0.128
	(1.39)	(1.22)	(-0.44)	(0.53)	(-2.49)	(0.35)	(-0.81)	(-0.67)
Education	0	-0.278	-0.639	0.059	0.048	-0.928	-0.038	-0.47
	0.00	(-0.71)	(-1.14)	(1.05)	(0.50)	(-0.25)	(-0.53)	(-0.42)
Male	-0.024	-0.699	0.792	0.094*	0.223*	-10.675***	-0.069	1.769
	(-0.06)	(-1.43)	(1.19)	(1.67)	(1.73)	(-2.91)	(-0.89)	(1.59)
fWHR	2.083*	-0.064	4.230**	0.334**	0.395	10.4	-0.255	0.387
	(1.87)	(-0.05)	(2.24)	(1.98)	(1.41)	(0.97)	(-1.14)	(0.13)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	12,744	12,119	11,951	11,956	12,809	12,778	12,777	27,141
R-squared	63.2%	66.3%	18.7%	55.9%	60.4%	67.4%	83.6%	30.1%

Table 10: **Manager Facial Attractiveness and Site Visits** This table reports the results from multivariate OLS regressions of managers' site visit activities and outcomes on facial attractiveness score and a host of control variables. Stocks in fund portfolios are classified as *Buy* and *Sell* based on share number changes. Stocks in different funds are treated as different observations. Alpha[1,3] is the cumulative 3-factor alpha of the next three months. #Visit/#Stock is the total number of stocks site visited by fund managers in each semi-annual period divided by the total number of stocks held in a fund. #Hold&Visit/#Stock is the total number of stocks with initial position that are site-visited by fund managers in each semi-annual period divided by the total number of stocks held in a fund. The control variables for characteristics of fund and manager are the same as table 5. Stock Controls are stock market capitalization, turnover, ROA, asset-liability ratio and past 6-month returns. Year fixed effects and fund fixed effects are included. Standard errors are clustered at the fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	Buy, Alpha[1,3]		Sell, Alpha[1,3]		#Visit/#Stock	#Hold&Visit/#Stock
	(1)	(2)	(3)	(4)	(5)	(6)
Visit	0.334	4.828**	-0.433	-10.838***		
	(0.95)	(2.23)	(-0.73)	(-3.66)		
Visit×Score		-1.583**		3.709***		
		(-2.13)		(3.55)		
Score		0.147		-0.067	-0.478	-0.245**
		(0.57)		(-0.15)	(-1.00)	(-2.25)
Log(size)	-0.934***	-0.936***	-0.811***	-0.813***	-0.625***	0.1047*
	(-7.35)	(-7.34)	(-3.92)	(-3.93)	(-3.15)	(1.84)
Age	4.841***	4.835***	7.187***	7.184***	0.709**	0.383***
	(11.60)	(11.53)	(11.51)	(11.46)	(2.02)	(3.20)
Turnover	-0.002***	-0.002***	-0.003***	-0.003***	0.000	0.000
	(-4.76)	(-4.76)	(-4.99)	(-4.98)	(0.93)	(-1.33)
Flow	-0.245	-0.246	-0.051	-0.047	-0.173	-0.068
	(-1.06)	(-1.06)	(-0.14)	(-0.13)	(-0.60)	(-0.64)
MOM	-0.375***	-0.374***	-0.635***	-0.636***	-0.150*	0.161***
	(-5.98)	(-5.98)	(-6.11)	(-6.11)	(-1.87)	(5.84)
Management fee	0.761	0.767	-10.969**	-10.922**	12.675***	3.283***
	(0.16)	(0.16)	(-2.09)	(-2.08)	(3.08)	(2.85)
Platform	-1.042***	-1.043***	-1.0717*	-1.0667*	1.319**	-0.307*
	(-2.77)	(-2.77)	(-1.76)	(-1.75)	(2.15)	(-1.77)
Tenure	-0.022	-0.018	-0.016	-0.017	-0.271***	-0.071***
	(-0.37)	(-0.30)	(-0.17)	(-0.18)	(-3.24)	(-2.81)
Education	-0.163	-0.16	0.191	0.192	-0.005	-0.208
	(-0.63)	(-0.62)	(0.38)	(0.39)	(-0.01)	(-1.54)
Male	0.389	0.428	1.096**	1.092*	0.010	-0.113
	(1.32)	(1.39)	(1.98)	(1.94)	(0.02)	(-0.73)
fWHR	-0.505	-0.515	1.495	1.544	0.392	-0.697*
	(-0.54)	(-0.56)	(0.97)	(1.00)	(0.29)	(-1.86)
Stock Control	Y	Y	Y	Y		
Year FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	307,943	307,943	73,589	73,589	6,590	6,590
R-squared	2.6%	2.6%	4.5%	4.6%	41.9%	37.7%

Appendix for "What Beauty Brings? Managers' Attractiveness and Fund Performance"

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This appendix contains additional tables and figures supplementing original article.

Results associated with profitability persistence are reported in figure A1 and A2. In figure A1, we report the cross-trade average cumulative return of the hedging portfolio if we hold the hedging portfolio fixed for three years. We find a monotonic increasing return pattern for both value-weighted and equal-weighted portfolios. In figure A2, we report the migration of facial attractiveness score rank for each portfolio, and find a low fluctuation of funds' manager attractiveness score.

In table A1, we report portfolio sorting results using the maximum or minimum score of the managers in funds with multiple managers, and managers' facial width-to-height ratio (fWHR). The results are robust no matter we use the maximum or minimum score. Meanwhile, the hedging portfolio constructed based on fWHR has no significant underperformance as documented in Lu and Teo (2021). In table A2, we dependently sort funds into a three-by-three matrix first by fund size then by fund attractiveness score. We find that the outperformance of low-score funds is more prominent for large funds. In table A3, we investigate the relationship between manager attractiveness score and fund alpha (flow) based

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on the subsample of fund managers. We find that the outperformance of low-score funds is more significant for funds with male managers and managers with bachelor's degree. For female managers or managers with doctor's degree, facial attractiveness score has less impact. Besides, we find there are more inflows to high-score funds with male managers and managers with higher education level.

References

Jegadeesh, Narasimhan and Sheridan Titman (1993) "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 48 (1), 65–91.

Lu, Yan and Melvyn Teo (2021) "Do alpha males deliver alpha? Facial width-to-height ratio and hedge funds," *Journal of Financial and Quantitative Analysis*, 1–44.

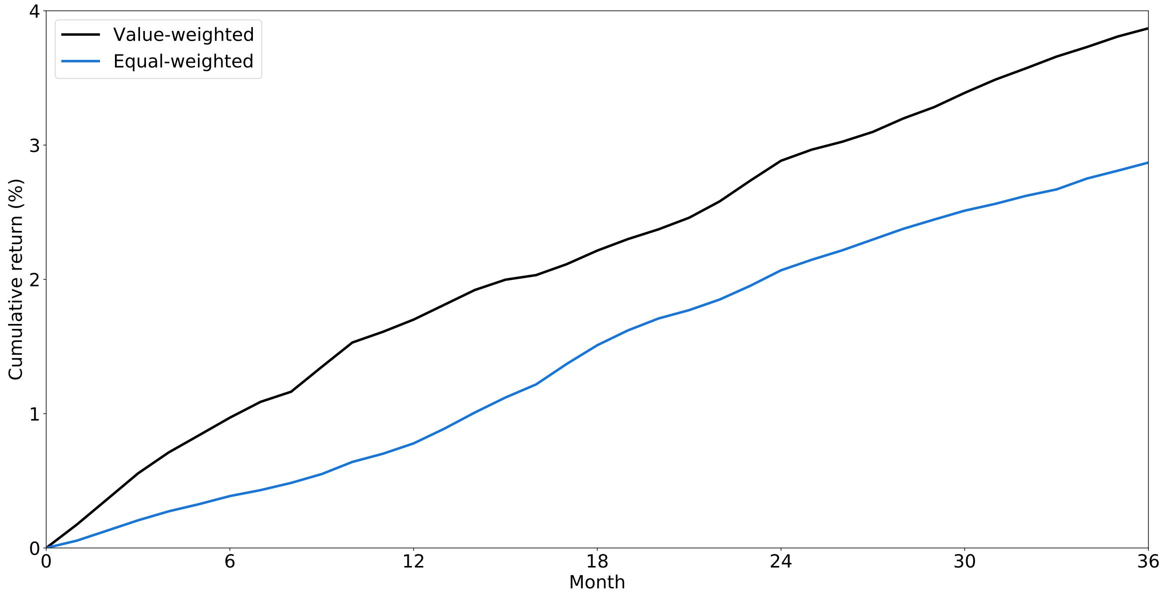

Figure A1: **Cumulative Returns for the Hedging Portfolios** This figure plots the cumulative returns for the hedging portfolios ranked by mutual fund manager facial attractiveness score. At the end of each month, all the mutual funds are sorted into quintiles based on facial attractiveness score. These quintile portfolios are then rebalanced every month and are held for three years. Mutual funds in the bottom quintile are equal/value-weighted to form the long portfolio, and funds in the top quintile are equal/value-weighted to form the short portfolio. Here we require funds exist for at least three years after the formation month.

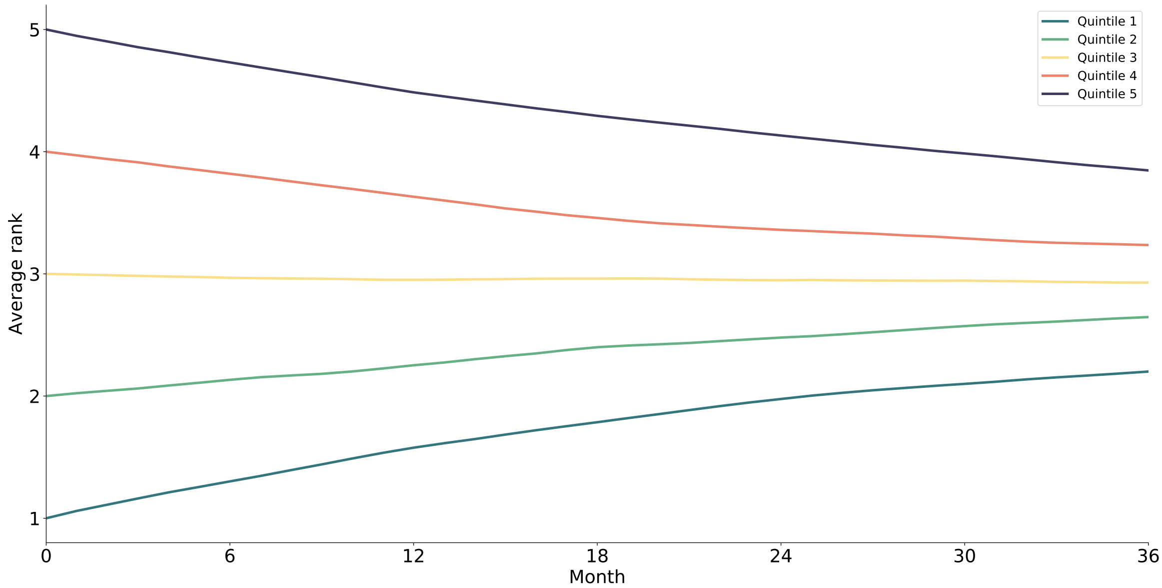

Figure A2: **The Migration of Facial Attrctiveness Score Rank** This figure tracks the average mutual fund manager facial attractiveness score quintile rank after event time, where month zero is the portfolio formation period. For each month, we form quintile portfolios by ranking mutual funds based on their current month end manager facial attractiveness score. Then we compute the average facial attractiveness score rank for each portfolio, for the next 36 months, holding the portfolios fixed.

Table A1: **Portfolio Returns Ranked by Facial Attractiveness Score** This table reports calendar-time returns to portfolios ranked by facial attractiveness score. At the end of each month, we form calendar-time portfolios by sorting all mutual funds into quintiles based on the minimum or maximum facial attractiveness score of managers in the fund, and the managers' facial width-to-height ratio (fWHR. The portfolios are rebalanced every month and are held for corresponding time periods. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. Monthly returns with different risk adjustments are reported: the return in excess of the risk-free rate, the CAPM alpha, 3-factor alpha, 5-factor alpha.

Panel A. Value-Weighted Portfolios, Ranked by Minimum Attractiveness Score												
	Month 0 (Formation Month.)				Month 1-3				Month 4-12			
Quintile	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5
1 (low)	1.22	0.33	0.32	0.16	1.22	0.41	0.39	0.22	1.31	0.48	0.41	0.27
2	1.19	0.29	0.26	0.11	1.14	0.33	0.28	0.12	1.26	0.42	0.33	0.21
3	1.18	0.26	0.25	0.07	1.14	0.31	0.28	0.11	1.26	0.41	0.34	0.17
4	1.20	0.28	0.25	0.09	1.17	0.33	0.28	0.12	1.24	0.38	0.30	0.15
5 (high)	1.13	0.22	0.20	0.04	1.12	0.29	0.26	0.08	1.22	0.38	0.31	0.16
low-high	0.09	0.11	0.12	0.12	0.10	0.12	0.13	0.14	0.10	0.11	0.10	0.12
t-stat	1.62	2.02	2.32	2.12	2.00	2.45	2.77	2.73	2.02	2.27	2.19	2.46

Panel B. Value-Weighted Portfolios, Ranked by maximum Attractiveness Score												
	Month 0 (Formation Month.)				Month 1-3				Month 4-12			
Quintile	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5
1 (low)	1.28	0.38	0.35	0.19	1.27	0.45	0.41	0.26	1.36	0.52	0.45	0.31
2	1.22	0.32	0.31	0.14	1.18	0.36	0.33	0.16	1.30	0.45	0.37	0.23
3	1.18	0.25	0.23	0.07	1.15	0.30	0.27	0.10	1.26	0.40	0.33	0.18
4	1.04	0.15	0.13	-0.05	1.05	0.23	0.20	0.01	1.13	0.30	0.22	0.06
5 (high)	1.18	0.28	0.25	0.10	1.14	0.33	0.29	0.13	1.23	0.40	0.32	0.18
low-high	0.11	0.10	0.10	0.09	0.13	0.12	0.13	0.13	0.13	0.12	0.13	0.14
t-stat	1.46	1.31	1.44	1.25	1.77	1.64	1.85	1.85	2.07	2.02	2.28	2.24

Panel C. Value-Weighted Portfolios, Ranked by fWHR												
	Month 0 (Formation Month.)				Month 1-3				Month 4-12			
Quintile	Ex Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5	Ex. Ret	CAPM	FF3	FF5
1 (low)	0.33	0.31	0.34	0.15	0.39	0.35	0.38	0.19	0.39	0.31	0.33	0.16
2	0.19	0.20	0.23	0.04	0.27	0.26	0.29	0.09	0.45	0.40	0.41	0.26
3	0.27	0.24	0.28	0.08	0.32	0.28	0.31	0.11	0.40	0.33	0.34	0.18
4	0.37	0.34	0.38	0.16	0.40	0.36	0.39	0.18	0.43	0.35	0.36	0.20
5 (high)	0.27	0.25	0.28	0.09	0.34	0.29	0.33	0.12	0.42	0.34	0.35	0.18
low-high	-0.05	-0.06	-0.06	-0.06	-0.05	-0.06	-0.06	-0.06	0.03	0.02	0.02	0.02
t-stat	-0.87	-1.03	-0.98	-0.98	-0.87	-0.99	-0.94	-1.01	0.69	0.49	0.49	0.39

Table A2: **Double sorted by TNA and Score** In this table, mutual funds are sorted into a three-by-three matrix first by fund size, then by manager appearance score. The portfolios are rebalanced every month and are held for 3 or 12 months afterwards. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. Monthly returns with different risk adjustments are reported: the return in excess of the risk-free rate, and the Fama-French three-factor alpha.

			Sorted by Appearance Score							
			Month 1-3				Month 1-12			
			Low	2	High	H-L	Low	2	High	H-L
Sorted by Fund Size	Excess Return	Small	20.72	20.12	21.23	0.51	20.61	19.76	21.38	0.76
			(2.94)	(2.80)	(2.88)	(0.57)	(2.87)	(2.73)	(2.89)	(0.94)
		2	21.22	20.34	20.40	-0.81	21.07	20.74	20.03	-1.05
			(2.85)	(2.70)	(2.75)	(-1.18)	(2.84)	(2.75)	(2.70)	(-1.41)
		Large	19.19	17.95	17.69	-1.50***	18.65	18.11	17.47	-1.18**
			(2.56)	(2.39)	(2.34)	(-2.88)	(2.52)	(2.43)	(2.35)	(-2.31)
	3-factor Alpha	Small	7.51	6.77	8.14	0.62	7.23	6.27	8.29	1.06
			(3.87)	(3.38)	(3.58)	(0.78)	(3.68)	(3.10)	(3.82)	(1.42)
		2	8.09	7.18	7.28	-0.81	7.81	7.56	7.00	-0.81
			(3.89)	(3.35)	(3.38)	(-1.17)	(3.81)	(3.49)	(3.21)	(-1.20)
		Large	6.40	5.02	4.85	-1.55***	5.88	5.32	4.74	-1.15**
			(3.17)	(2.50)	(2.33)	(-3.00)	(3.07)	(2.71)	(2.32)	(-2.20)

Table A3: **Subsamples of Fund managers** This table looks into the subsamples of fund managers to investigate the relationships between manager facial attractiveness with fund performance and flow. The dependent variables are 3-factor alpha (%) in quarter $t+1$ and fund flow (%) in quarter $t+1$. Then independent variables are the same as in table 5. For easiness of interpretation, for each subsample, all the continuous independent variables are standardized with a mean of zero and standard deviation of one. Year fixed effects and fund fixed effects are included. Standard errors are double-clustered at the time level and fund level. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	3Factor Alpha					Fund Flow				
	Male	Female	Bachelor	Master	Doctor	Male	Female	Bachelor	Master	Doctor
Score	-0.285*	0.066	-3.761***	-0.317*	0.173	2.437**	-0.240	-3.907	2.592***	5.532
	(-1.69)	(0.06)	(-4.51)	(-1.82)	(0.23)	(2.55)	(-0.05)	(-0.83)	(2.93)	(1.02)
Log(size)	-0.997***	-1.322***	-2.128***	-0.933***	-1.675***	-14.165***	-19.012***	-21.225***	-14.122***	-21.572***
	(-11.05)	(-3.84)	(-3.12)	(-9.85)	(-5.39)	(-24.03)	(-9.28)	(-7.76)	(-23.43)	(-10.74)
Age	-0.139	-0.314	-0.085	-0.009	-1.207**	-0.522	-2.382	-3.884	-0.858	-1.743
	(-0.87)	(-0.60)	(-0.08)	(-0.06)	(-1.99)	(-0.85)	(-1.25)	(-0.82)	(-1.46)	(-0.62)
Turnover	0.172***	0.234***	0.033	0.177***	0.122	-0.263*	-0.587	-0.399	-0.220	-0.931*
	(6.14)	(2.60)	(0.22)	(6.10)	(1.37)	(-1.81)	(-1.44)	(-0.57)	(-1.62)	(-1.82)
Flow	0.420***	0.638	1.303	0.321**	0.581	8.061***	5.366**	12.649**	8.391***	-0.239
	(2.69)	(1.36)	(1.49)	(2.05)	(1.18)	(7.28)	(1.99)	(2.06)	(7.54)	(-0.09)
MOM	-0.223***	-0.253***	-0.299**	-0.195***	-0.379***	2.401***	2.321***	3.870***	2.191***	3.431***
	(-7.71)	(-2.84)	(-2.07)	(-6.68)	(-4.06)	(17.18)	(5.35)	(3.90)	(15.96)	(7.92)
Management fee	-1.047	-8.063	-6.608	0.388	-7.669*	-10.222	82.793***	54.412	-6.022	0.947
	(-0.38)	(-1.02)	(-1.36)	(0.11)	(-1.66)	(-0.73)	(3.72)	(0.97)	(-0.34)	(0.04)
Platform	0.371	1.133	0.640	0.654**	0.760	-1.192	0.955	-6.730	0.047	-8.220**
	(1.21)	(1.17)	(0.62)	(2.40)	(0.75)	(-0.85)	(0.26)	(-1.41)	(0.03)	(-2.22)
Tenure	0.042	0.294	0.451*	0.051	0.223	0.406**	-0.382	3.972**	0.565***	0.417
	(1.11)	(1.60)	(1.71)	(1.31)	(1.39)	(2.08)	(-0.34)	(2.04)	(3.15)	(0.39)
Education	-0.286	-0.477				0.925	4.317			
	(-1.55)	(-0.43)				(0.77)	(1.13)			
Male			6.784***	-0.053	2.026			7.700	1.883	12.589
			(2.75)	(-0.22)	(1.20)			(0.51)	(1.49)	(1.30)
fWHR	-0.666	3.142	15.223	-0.702	-1.522	2.470	3.659	-54.455	-0.138	-1.354
	(-0.98)	(0.70)	(1.33)	(-1.02)	(-0.50)	(0.71)	(0.16)	(-0.53)	(-0.04)	(-0.07)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	21,976	2,943	713	21,563	2,759	23,321	3,141	741	22,890	2,949
R-squared	18.7%	26.8%	23.5%	19.3%	24.5%	18.8%	26.0%	27.4%	18.8%	30.8%