Do Investors Pay Less Attention to Women (Fund Managers)?

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Abstract

Using individual-level fund data from a fintech platform in China, we document that individual mutual fund investors chase performance, are prone to a gender bias away from women when choosing to invest in funds, but, conditional on having invested in a female managed fund, are less sensitive to fund performance, although there is no significant difference in the performance of male and female managers. The effect persists after controlling for managerial characteristics and fund objectives, as well as individual investor fixed effects. Simply put, conditional on investing in a female-managed fund, investors react less to the performance of their managers.

Keywords: Behavioral finance, household finance, mutual funds, flow-performance relationship, attention bias, gender bias, fintech, inclusive finance, psychology, Natural Language Processing

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1. Introduction

Using aggregate mutual fund flow data, Sirri and Tufano (1998) and Del Guercio and Tkac (2002), among others, document that at the aggregate level, there is a positive correlation between prior mutual fund performance and subsequent fund flow, commonly termed the flow-performance sensitivity of the fund. Money chases after the best performing funds in the previous month, leaving funds with poor performance. In addition, again using data at the aggregate level, the fund performance-flow relationship appears to be affected by gender-driven biases. Atkinson, Baird, and Frye (2003) find that although male- and female-managed funds do not differ significantly in terms of performance, risk, and other fund characteristics, net asset flows into fixed income funds managed by females are lower than for males. Similarly, Niessen-Ruenzi and Ruenzi (2018) document significantly lower inflows into female-managed funds than male-managed funds at the aggregate annual fund level.

Examining the extent of gender bias in the investment management industry is important. In 2019, for example, women accounted for 37.5% of all lawyers, 49% of judges, 34.5% of economists, 19% of surgeons, and 26% of chief executives, according to the U.S. Census Bureau.[1] In contrast, the percentage of funds managed by women has barely changed. It was 10.3% in 2016 and 11% in 2020.[2] While there are several explanations for the employment gap between men and women in various industries[3], Niessen-Ruenzi and Ruenzi (2018) propose a customer-based discrimination explanation specifically for the mutual fund industry. Because mutual fund investors appear to direct significantly lower flows to female-managed mutual funds than to male-managed funds, they argue that, in response, rational fund companies might choose to hire fewer women since fund companies generate their profits from fees charged on assets under management. Hence, they argue that *individual* investor biases against women fund managers causes *aggregate* discrimination against women in the fund industry.

Relative to the rest of the finance industry, it is relatively straightforward to measure the relation between effort and reward in the investment management industry. In general, when many executives contribute to a firm's value, it is difficult to establish how much performance depends on an individual executive's skill and effort. However, in the investment management industry, for mutual funds with a single manager, it is relatively straightforward to attribute

[1] Data available at the US Census Bureau.
[2] Data available at Citywire Alpha Female Report, 2020.
[3] Examples include including hiring discrimination against women (Goldin and Rouse, 2000), occupational choice by women into other professions (Polachek, 1981) gender differences in the willingness to compete (Sutter and Gätzle-Rützler, 2014), or career discontinuities (Bertrand, Goldin, and Katz, 2010).

performance to managerial effort and to relate investment flows (rewards) to performance (effort). However, because of a lack of data on investor-level fund flows, it has proven difficult to establish whether individual fund investors reward effort (rewarding funds that perform well), let alone whether their performance-chasing behavior is affected by a gender bias.

In this paper, in contrast to the previous literature, we examine whether the flow-performance sensitivity for *individual investors* is affected by managerial gender, using a unique dataset provided by a large fintech platform in China. The fintech platform allows users to make and receive payments to and from other people and businesses, and also provides in-app access to a variety of saving and investment products with different risk levels. The investment products offered on the platform include open-ended mutual funds managed by fund managers affiliated to fund management companies independent of the platform. The app allows the investors to rank funds based on raw returns over the prior one-, three-, six-, and 12-month return horizons.

Importantly, the app provides clear information on the gender of the fund managers (including a photograph in a large number of cases) to the investors at the time of investment. Prior papers that have examined the effect of gender on fund flows are unable to establish that fund investors are even aware of who is managing their fund. In China, this information is almost the first piece of information investors receive when choosing to invest on the app.

Our data is based on a random sample of investors drawn from the platform and consisting of 172,672 retail investors' monthly investment positions in 253 domestic stock funds over the period from August 2017 to July 2019, for a total of 2.35 million user-fund-month observations. The database contains monthly data on each individual investor's fund investment and redemption amounts and details of capital gains or losses for every fund owned by the investor in that month. It also contains individual characteristics of each investor on the platform, such as their gender, ages, monthly payment amounts, places of residency, and risk aversion levels (surveyed through a questionnaire upon users' registration on the platform).

We first document that the flow-performance sensitivity for individual investors in China is similar to patterns documented in the prior literature for funds elsewhere in the world. Our fund-flow and performance measures are similar to those defined by Sirri and Tufano (1998), except that our measures are defined at the investor-month level, while their measures are defined at the fund-year level. Our findings are consistent with those documented by Hong, Lu, and Pan (2020), who use public Chinese fund data to document that the Chinese fund market is also characterized by performance chasing behavior at the aggregate level which markedly increases after the introduction of fintech platforms in China. We find strong evidence that *even at the individual level*, mutual fund investors in China appear to chase performance, directing flows to funds that perform well in the past while reducing flows to funds that perform poorly.

We next document that there appears to be a gender effect among individual investors. Inconsistent with Niessen-Ruenzi and Ruenzi (2018), we find no aggregate gender effect on mutual fund flows. However, the effect appears when we examine individual fund flows. Specifically, when we examine a sub-sample of all *first*-time investors, at the time of their first investment, investors are significantly less likely to invest in female-managed funds for the same level of performance.

Finally, we document the existence of a new, different, and previously unstudied type of gender bias in individual investor behavior, that we term gender-based attention bias. Gender-based attention bias refers to the tendency to pay less attention to women than men. The literature in psychology and the social sciences on gender issues argues that this type of attention bias is manifested at both the personal and professional levels. At the personal level, the literature documents that boys and girls receive differential attention in families, especially in developing countries. For example, Barcellos, Carvalho, and Lleras-Muney (2014) find that boys receive more childcare time than girls, they are breastfed longer, and they get more vitamin supplements in India. At the professional level, Cortina (2008), for example, argues that women are more likely to be ignored or interrupted or experience their contributions being belittled than men within organizations. This type of bias has been shown to exist among attorneys (Cortina et al., 2002), university faculty (Richman et al., 1999), and court employees (Cortina et al., 2001). Bigelow et al. (2014) report that attention bias also seems to exist in women-led initial public offerings. They show that female CEOs are disproportionately disadvantaged in their ability to attract growth capital, perceived as less capable than their male counterparts, and their firms are considered less attractive.

Interacting the flow-performance sensitivity term with a gender dummy variable, we show that flow-performance sensitivity is significantly weaker for female-managed funds. We document decreased flow sensitivity to performance for women across all the raw return horizons, from one- to 12-months, the platform allows the investor to sort over. Simply put, when female-managed funds do well, they experience significantly lower fund inflows than male-managed funds. However, when these funds perform poorly, they experience relatively lower fund outflows than male-managed funds. The attention bias is reduced when performance drops, suggesting that investors pay less attention to female than male managers when performance increases but punish both sets of managers when performance drops. Using piecewise regressions, we show that the decrease in flow sensitivity appears to exist across all levels of performance for female managers except for the very top managers.

Our results are robust to controlling for fixed effects at the investor level, allowing us to address potential omitted variable concerns arising from differing investor backgrounds or personalities. The results are also robust to including time fixed effects, reducing a potential omitted variable bias caused by common economic shocks. All the regressions also control for manager characteristics, such as their educational backgrounds and their length of tenures as managers for the funds, and for fund characteristics such as fund objectives, fund size, and fees. In addition, a placebo treatment test where we replicate the core analysis with a randomly assigned managerial gender shows no significant impact of gender on performance sensitivity, suggesting that our results do not reflect random error, misspecification, confounding, or something else.

Our results also do not appear to be driven by several alternative explanations. For example, an alternative rational explanation for the muted flow-performance sensitivity for female managers is that male managers' past performance is a better predictor of their future performance. Hence investors rationally invest in what they believe will be better-performing funds. We show, however, that past performance does not predict future performance for Chinese fund managers and, moreover, that there is no gender difference in the predictive ability for future performance. In addition, controlling for managerial characteristics and time fixed effects, we find that female fund managers perform significantly better (at the 10% level) than male fund managers when computing rankings at the one-month period. In other words, investors appear to believe without evidence that better-performing male managers are more likely to perform well than female managers.

A second alternative explanation is that female managers are less likely to take risks and hence investors who do not adequately adjust for risk direct more flows to (risky) male managers. Regressing a battery of risk measures on manager gender, controlling for managerial characteristics and time fixed effects, we find no significant differences in levels of idiosyncratic or systematic risk or risk-adjusted performance between female and male-managed mutual funds. Evans and Sun (2020) show that retail investors use simple risk-adjustment heuristics to direct fund flows. We show that the differential flow-performance relationship continues to exist when we rank funds based on plausible heuristics such as risk-adjusted returns measured by Jensen's Alpha (Jensen, 1968).

A third alternative explanation is that female managers are more trustworthy. Gul, Srinidhi, and Ng (2011) show that firms with women on their boards increase public disclosure which in turn, increases stock price informativeness. If female mutual fund managers are similarly more transparent, it is possible that investors pay less attention to women managers because they do not need to monitor them. In contrast, male managers need to be monitored because signals of managerial ability as reflected in fund performance are noisier for male than for female managers. However, our evidence on first-time investors being less likely to invest in women managed funds appears inconsistent with the hypothesis that investors find women to be more trustworthy.

A fourth alternative explanation is that female fund managers are difficult to find. The Chinese sample of fund managers is similar to the data studied in other countries in that only 15% of the sample of managers are female. For example, Niessen-Ruenzi and Ruenzi (2018) analyze the gender-fund flow relationship in a sample where only 13.8% of the mutual fund manager sample is female. Hence, we investigate if the attention bias arises because investors face higher search costs when searching for female fund managers. For example, an investor who is actually gender-neutral towards the choice of fund manager might appear biased because of the high search costs involved in finding female managers. We note that, in univariate two-sample p-tests, female-managed funds consistently outperform male-managed funds over 1-, 3-, 6-, and 12-month horizons, suggesting that female-managed funds tend to be ranked higher on the app.

To explicitly address the visibility problem, we use two approaches. First, we match each female manager to a similar male manager in each month using a propensity-score matching (PSM) approach using a host of managerial and fund characteristics as proxies for manager visibility. Although PSM does not allow us to establish causality, the covariates of managerial and fund characteristics are well balanced in the matched sample. Attention bias continues to be significant in this matched fund sample, where search costs for male and female managers are likely to be approximately similar.

Second, we use a Natural Language Processing (NLP) technique to extract names from 400,000 financial news articles in Chinese and count the frequency of each manager's name appearance in the article each month. We show that the level of attention bias is unaffected by the level of media coverage. We also measure the frequencies of positive and negative media mentions of each fund manager through sentiment analysis based on a variant of the Transformer model (Vaswani et al., 2017) in machine learning. We show that, while the sign of the media mention does not appear to affect the level of attention bias, positive mentions of fund manager names in the news strengthens the flow-performance relationship on average. However, we continue to find evidence that, controlling for performance and positive media mentions, female manager performance is less sensitive to investor flows than male manager performance.

One might reasonably assume that female investors may be less subject to this attention bias than male investors, as the prior literature (Lovén, Herlitz, and Rehnman, 2011) suggests that female investors will more naturally identify with and be less biased away from female fund managers. We find weak evidence that female investors exhibit less gender bias towards female managers than male investors. Similarly, users from smaller cities appear more subject to the gender attention bias than users from larger cities. In contrast, gender bias seems to be unrelated to user age or risk aversion.

Is there a causal relationship between the gender identity of female managers and investor fund flows? To examine this question, we employ a three-stage instrumental variable regression approach suggested by Wooldridge (2001). We use two different instrumental variables, the first being the proportion of illiterate women amongst all women in the municipal district that the investor resides in, and the second being the proportion of female new-borns amongst all new-borns in the municipal district that the investor resides in. Both instrumental variables do not instrument for fund manager per se, but for the specific investor's choice of a fund manager. The instruments do not directly drive investors' fund flow decisions but are likely to be related to investors' biases on gender identities, conditional on investors' characteristics that we control for.

Specifically, in the first stage, we estimate a logit regression where we model the choice of fund manager gender using the instrumental variables, the proportion of illiterate women and the proportion of female new-borns as explanatory variables. In the second stage, we compute the fitted probability of choosing a female manager from the first-stage logit. In the third stage, we use the fitted probability to instrument for manager gender and interact with performance of the fund. Our instrumental variable regressions confirm the existence of gender-based attention biases away from female managers, which cause investors to pay less attention to female-managed funds.

Finally, we formally run a regression testing the difference of individual fund flow volatilities between male- and female-managed funds. Our results show that individuals holding female-managed funds exhibit lower fund flow volatilities throughout our sample period. For mutual fund companies therefore, employing a female manager may have the desirable impact of lowering the volatility of flows into the fund.

The literature that documents the existence of gender bias in executive performance (such as CEOs) suffers from the handicap that it is impossible to clearly attribute firm-level performance to individual executive efforts. In contrast, in the mutual fund industry, the performance of a sole-managed mutual fund is clearly attributable to the manager. However, in the absence of data on fund flows from specific individuals to specific funds, it is again not possible to relate fund flow at the user level to performance at the fund level. With its unique dataset matching user-level flows to specific funds, this paper is the first to document the existence of an individual investor-level gender-based attention bias away from women in the professional finance industry.

Our study makes four additional contributions to the finance literature. To the best of our knowledge, this is the first paper to document return chasing behavior among mutual fund investors at the individual level. We are also the first to show an effect of gender on fund flows at the individual investor level. Our paper hence contributes to a rich literature on gender differences in individual investor investment behaviour. Early research in this area focuses mainly on the difference in performance between male and female investors. We add to this literature by documenting gender-based investment differences among investors.

Second, this study complements the literature on mutual fund flows associated with search costs and manager heterogeneities. Chevalier and Ellison (1999) show that mutual fund managers who attended higher SAT undergraduate institutions have systematically higher risk-adjusted excess returns. Huang and Wang (2015) show that manager fixed effects predict future fund performance, and investors reward managers with higher fixed effects by directing flows to the funds they manage. Our research complements their study by showing that manager gender, tenure, and education backgrounds, which are included in manager fixed effects, also have significant impacts on fund flows in our sample. However, those managerial factors are independent of the attention bias also documented in this paper.

Third, this study complements the existing literature on the mutual fund performance-flow relationship. Berk and Green (2004) show that investors learn from fund managers' past performance and allocate funds accordingly. Sirri and Tufano (1998) show that investors chase after funds with higher relative performance in the previous year. Bailey, Kumar, and Ng (2011) show that mutual fund investors are subject to behavioral biases. Though Atkinson, Baird, and Frye (2003) and Niessen-Ruenzi and Ruenzi (2018) also document significantly differential flows to male and female-managed funds using aggregate annual fund level data, these papers are unable to directly establish that investors are even aware of who is managing their funds, let alone that investors focus on the gender of these managers. In our setting, in contrast, manager identity and gender are extremely salient when the investor is making the investment decision. In addition, given that the gender composition in our sample is similar to that in other settings, it seems reasonable to believe these results would extend elsewhere, with the caveat that this would assume that there are no significant differences in gender biases across countries and cultures.

Most important, this study adds to the existing literature on gender issues in the finance industry. Adams and Kirchmaier (2016) document that there is a lower fraction of women on the board for firms in the STEM and Finance sectors than in the non-STEM sector. Rau, Sandvik, and Vermaelen (2022) show that initial public offerings by firms with gender diverse boards suffer significantly greater underpricing at the offering than firms with only male boards. Adams and Funk (2012) show that, unlike the well-documented fact that women are more risk-averse in the general population, women in the boardroom are more risk-loving and less security-oriented than their male counterparts. Niessen-Ruenzi and Ruenzi (2018) argue that rational fund companies might choose to hire fewer women since fund companies generate their profits from fees charged on assets under management. However, we show that the attention bias works both ways. Though investors may be less willing to invest in female managed funds, they appear less sensitive to fund performance when the fund manager is female. Moreover, the sensitivity is bi-directional. Investors who choose to invest in female managed funds are also less sensitive to underperforming female managers. For mutual fund companies, this appears to have the beneficial effect of lowering the volatility of flows into the fund.

The remainder of the paper is organized as follows. Section 2 documents the literature in psychology and the social sciences on gender-based attention biases. Section 3 describes our data and the measure of fund flows and fund performance. Section 4 presents our main empirical analyses. Section 5 concludes.

2. Literature on attention bias

There are three strands of literature in the psychology and social sciences on gender issues that are related to attention bias.

The first strand examines whether boys and girls in families receive different levels of attention, especially in developing countries. Barcellos, Carvalho, and Lleras-Muney (2014) find that boys receive more childcare time than girls, they are breastfed longer, and they get more vitamin supplements in India. Park and Rukumnuaykit (2004) use nutrient intake data from the China Health and Nutrition Survey to show that rural fathers, especially less educated men, favour sons while rural mothers do not. These findings suggest that there are geographic differences in the level of gender bias.

The second strand examines gender stereotypes and biases in households and corporations. Hannum, Kong, and Zhang (2009) use survey data to show that the vast majority of mothers in their sample expect to reply on sons for support in their old age, and nearly one in five mothers do not expect girls to go to school in rural China, suggesting one reason why more attention is paid to boys than girls. They also show that parents view boys as having greater talent than girls. In a random experiment on judgments of fame, Banaji and Greenwald (1995) show that subjects were more likely to assign fame to male than female names. At the professional level, Cortina (2008) argues that women are more likely to be being ignored or interrupted or experience their contributions being belittled than men within organizations. Neumark and Bank (1996) show that men and women are treated differently in job applications and women are less likely to be hired. Newton and Simutin (2015) show that CEOs pay executives of the opposite gender less than executives of their own gender, and older and male CEOs exhibit the greatest propensity to differentiate based on gender.

The final strand examines gender-based double standards. Botelho and Abraham (2017) use lab-based evidence to show that double standards disadvantage women when evaluators face heightened search costs related to the number of candidates being compared to or higher levels of uncertainty stemming from variation in the amount of pertinent information available. Botelho and Gertsberg (2020) use a quasi-natural experiment to show that women are disadvantaged in the evaluative process and are given lower ratings on Yelp. Given the low number of female to male managers in the mutual fund space, the search costs for female managers are likely to be higher than those for male managers. Hence, when evaluating female fund managers' performance, investors may believe the lack of female managers in the profession is a sign that female managers are less competent than male managers.

3. Data

Our research is based on a random sample of user investments into stock funds supplied by a large anonymous fintech platform based in China. The fintech platform allows users to make and receive payments to and from other people and businesses though a smartphone application (app) interface, and also provides in-app access to a variety of saving and investment products with different risk levels.

The fintech platform does not have in-house fund managers itself. It only serves as a portal to fund investments with significantly lower (typically a tenth of) transaction fees than traditional brokers. Investors can choose from a variety of fund types, including stock funds, currency funds, index funds, hybrid funds, and Qualified Domestic Institutional Investor

(QDII) funds. The lower risk investment products available on the app include zero-interest and risk-free savings as well as low-interest currency funds, while the higher risk investment products include open-ended mutual funds managed by fund managers affiliated to fund management companies independent of the platform.

In this paper, we focus on investments by actively managed stock mutual funds because of the wealth of extant research on the fund-flow relationship in actively managed stock funds and to avoid biases caused by differential liquidities and risks among the different types of underlying assets. The app provides information on the fund managers (including a photograph in a large number of cases) to the investors and allows the investors to rank funds on the basis of raw returns over the prior one-, three-, six- and 12-month raw return horizons.

Figures 1 and 2 provide screenshots of the typical user experience when they access the smartphone app.[4] When investors open the app to invest, the app presents to them a page listing funds ranked by past performance. Investors can choose to rank fund performance by their objectives and over the past 1-, 3-, and 6-month horizons, as shown in Figure 1 panels A, B, and C, respectively. When investors scroll down to the bottom of the list, a second page is automatically loaded by the platform and presented to investors immediately, an experience termed an “infinite scroll”. While the platform does not alter fund rankings through fund advertisements or promotions, investors can search for a fund’s name and bypass the infinite scroll list if they learn the fund’s name through advertising elsewhere on the internet. If investors click on a specific fund on the list, they will be further shown a second fund profile page, where they can read a short description of each fund manager listing the name, gender, education background, tenure at the fund, and company. Most managers also have photographs on their profile pages, as shown in Figure 2 Panels A and B. It is also fairly easy for investors to infer the fund manager’s gender from Chinese names in the extremely rare cases where both the fund manager description and profile images are not available. We note that prior literature on gender biases on mutual fund flows are unable to directly establish that investors are aware of who is managing their funds, let alone focus on the gender of these managers. For example, Niessen-Ruenzi and Ruenzi (2018) rely on a controlled laboratory experiment to establish that gender bias exists in the experimental setting and extrapolate the results to the general population. Figure 2 Panels A and B show that, in our setting, manager identity and gender are extremely salient when the investor is making the investment decision. The fund profile page

[4] The translations in the figures are provided by the authors.

also presents the detailed ranking of a fund among funds within the same objective or category over past 1-, 3-, 6-, and 12-month horizons, as shown in Figure 2 Panel C.

The random sample we acquire from the fintech platform is largely representative of the mainland Chinese population. Figure 3 Panels A and B depict the geographic distributions of the sample and the Chinese population in mainland China. Most investors in our sample are concentrated in the three major economic regions in mainland China: The Beijing-Tianjin-Hebei Economic Zone, the Yangtze River Delta region and the Pearl River Delta region, which is consistent with the Chinese population distribution.

3.1 Sample construction

Our sample consists of two main databases supplied by the platform. The first database documents monthly investment positions in 253 stock funds for 172,672 retail investors on the platform over the period from August 2017 to July 2019. Over this period, the Shanghai stock index rose by 6.3% between July 2017-January 2018, dropped by 25.7% over the year 2018, and rose by 11.7% from January 2019 to the end of our sample period.

The investment position database contains each individual investor's invested amount in each fund, capital gains or losses experienced over the month, and investment and redemption amount for each fund at the end of each month. We exclude hybrid funds, index funds, and other fund types from the sample, focusing only on actively managed stock funds. We also exclude funds that are co-managed by multiple fund managers. Finally, we eliminate funds where there is only a single female manager across the sample in that fund objective. Fund objectives identify the core stocks that a fund manager targets when forming the portfolio. For example, income funds target stocks that pay high dividends, while growth funds target stocks that are likely to increase in value over time. Appreciation funds target stocks that both pay high dividends and increase in value over time. Our final sample consists of funds with the following objectives: Appreciation, Stable Growth, Growth, and Income.

The second database documents individual characteristics of each investor on the platform, such as their gender, age, monthly payment amount, place of residency and risk tolerance levels. [5] We match the two databases by investors' unique (anonymized) IDs as well as fund codes.

Next, we match this sample to three China Stock Market & Accounting Research (CSMAR) databases: the fund finance database, the fund manager database, and the fund

[5] The randomized raw data sample is only accessible through the fintech platform and cannot be downloaded by researchers. It is impossible for researchers to identify the true identity of any specific investor from the data.

evaluation database. The fund finance database documents the balance sheets and income statements of funds, including management fees, sales fees, and transaction fees at the fund level. The fund manager database documents the start and end dates of each manager's tenure at each fund. It also includes managers' characteristics, such as their gender and degree of education. The fund evaluation database documents the monthly Net Asset Value (NAV) for each fund, adjusted for dividends, splits and reinvestments. The fund evaluation database also provides CAPM risk-adjusted returns of funds, also known as alphas. We merge the platform database to the fund finance and the fund evaluation databases through fund codes and trading months. We merge the platform database to the fund manager database based on fund code if the trading month falls between the start and end dates of the manager's tenure at the fund.

Finally, to create our instrumental variables, we merge our data with the National Bureau of Statistics of China (NBSC)'s Census Data (2011) on the proportion of illiterate women amongst all women and the proportion of female new-borns amongst all new-borns in different municipal districts. We merge the census data with the primary municipal districts of residence of the platform users in our sample.

3.2 Measures of fund flow and fund performance

We construct our measure of fund flow using individual-level data provided by the platform. Our definition of fund flow is similar to the definition by Sirri and Tufano (1998), except that our fund-flow is defined at the individual level:

$$Flow_{i,f,t} = \frac{Fund\ Amount_{i,f,t} - Fund\ Amount_{i,f,t\text{-}1} - Capital\ Gain\ or\ Loss_{i,f,t}}{Fund\ Amount_{i,f,t\text{-}1}} \qquad (1)$$

where i indexes investors, f indexes funds, and t indexes time. $Fund\ Amount_{i,f,t}$ represents investor i's position in fund f at the end of the current month t, while $Fund\ Amount_{i,f,t\text{-}1}$ is the same variable lagged by one month. $Capital\ Gain\ or\ Loss_{i,f,t}$ is the capital gain or loss that investor i incurred in fund f and month t at the end of the current month.[6] To remove outliers arising from fund conversions, we winsorize fund flows at the 99.9% level and the 0.1% level.

[6] Most researchers follow Sirri and Tufano (1998) and compute flow as the percentage growth of the fund in excess of the growth that would have occurred had no new funds flowed in and had all dividends been reinvested. To compute the growth had no new funds flowed in, the literature has typically used the fund return over the previous year, assuming that the flow occurs over the end of the period. In our case, since our data is at the investor-month level, we use the actual capital gain or loss incurred by the investor over the month and assume that the investor flow occurs at the end of the month.

Because investors are able to make investments and redemptions frequently during the month, and we only have month-end data on individual fund holdings, it is impossible to calculate their actual return on investments using their month-end capital gains or losses. Therefore, we follow Bollen and Busse (2005) and compute funds' adjusted NAV returns as proxies for investors' prior returns on investments:

$$NAV\ Return_{f,t\text{-}1,1\text{-month}} = \frac{NAV_{f,t\text{-}1} - NAV_{f,t\text{-}2}}{NAV_{f,t\text{-}2}} \tag{2}$$

where f indexes funds, and t indexes time. The adjusted NAV represents the fund's Net Asset Value, the unit price of one share of the fund, after adjusting the fund NAV for dividends paid over the month.

Fund rankings are displayed on the platform as "infinite scrolls", as shown in Figure 1. As users scroll down the list, more funds are loaded on the screen instantly. According to their preferences, users can choose to display fund rankings by past 1-month, 3-month or 6-month returns (though not 12-month returns). Over the period of our analysis, the default ranking was one month. However, users can also view individual fund rankings amongst funds of the same category or objective by past 1-month, 3-month, 6-month, or 12-month returns.

We follow Sirri and Tufano (1998) in ranking fund performance within each fund objective. To check the robustness of our results, we also create three performance metrics over longer investment horizons for our performance-flow panel regressions, including 3-, 6-, and 12-month fund returns ranked among funds with the same objectives, calculated as follows:

$$Rank_{f,t\text{-}1,3\text{-month}} = Percentage\ Rank\left(\frac{NAV_{f,t\text{-}1} - NAV_{f,t\text{-}4}}{NAV_{f,t\text{-}4}}\right) \tag{3}$$

$$Rank_{f,t\text{-}1,6\text{-month}} = Percentage\ Rank\left(\frac{NAV_{f,t\text{-}1} - NAV_{f,t\text{-}7}}{NAV_{f,t\text{-}7}}\right) \tag{4}$$

$$Rank_{f,t\text{-}1,12\text{-month}} = Percentage\ Rank\left(\frac{NAV_{f,t\text{-}1} - NAV_{f,t\text{-}13}}{NAV_{f,t\text{-}13}}\right) \tag{5}$$

where f indexes funds, and t indexes time. *Percentage Rank* is a function that ranks each fund's performance into percentiles, with 0 being the worst-performing fund and 1 being the best performing fund.

We then follow Sirri and Tufano (1998) and create three variables based on each fund's performance percentile: the bottom performance quintile is defined as $Min(RANK_{f,t\text{-}1,1\text{-month}}, 0.2)$, while the combined middle three performance quintiles are defined as $Min(RANK_{f,t\text{-}1,1\text{-month}} - BOTPERF_{f,t\text{-}1,1\text{-month}}, 0.6)$, and the top performance quintile is defined as $RANK_{f,t\text{-}1,1\text{-month}}$

- $BOTPERF_{f,t-1,1\text{-}month}$ - $MIDPERF_{f,t-1,1\text{-}month}$. Funds that fall into the top performance quintile appear first when users start to scroll down the fund list in the platform, and funds that fall into the bottom performance quintile appear last when users reach the end of the list in the platform. Funds that appear in the middle three quintiles are mediocre funds that appear in an intermediate position. We also carry out robustness checks in several alternative piecewise regressions, progressively shrinking the top and bottom sections to decile, vingtile, and percentile rankings. All these fund rankings are dynamic in the sense that they are regenerated every month.

3.3 Descriptive statistics

Table 1 Panel A.1 reports summary statistics for fund variables. There are 3,515 manager-fund-month observations, with 591 manager-fund-month observations (16.8%) being funds managed by female managers. The proportion is higher than the sample in Niessen-Ruenzi and Ruenzi (2018) (13.8%). Female-managed funds have significantly higher monthly relative performance ranks than male-managed funds over all return horizons (1-, 3-, 6-, and 12-months), implying that female-managed funds are displayed higher in the app rankings on average than male-managed funds. Standard deviations of funds' returns are approximately similar between male- and female-managed funds across all these return horizon periods. Consistent with Niessen-Ruenzi and Ruenzi (2018), fund flow is significantly higher for male- than for female-managed funds. The standard deviation of fund flow is, however, lower for female than male-managed funds.

Female-managed funds are also smaller (Total Net Asset values) than their male counterparts though the funds have similar ages. Relative to U.S. fund managers, both male and female managers have relatively low tenures in our Chinese sample on average, as the mutual fund industry in China is relatively young. Male managers, however, have longer tenures than female managers on average.

Fund sales, fund management, and fund transaction fees are obtained from CSMAR's annual fund balance sheet data. Female-managed funds have significantly lower management fees and transaction fees than do male-managed funds. This suggests that female managers have lower salary expenses but perform at least as well as male managers in terms of overall fund NAV returns and slightly better than male managers in terms of fund monthly relative performance. Female-managed funds are associated with higher sales expense fees than their male counterparts, suggesting that female managers require higher promotion efforts to increase their visibility to investors. The relative lack of visibility is also seen in the media mention frequency ranks. Female managers are mentioned less frequently in the media than male managers, and the difference is statistically significant. When mentioned, both the number of positive and negative mentions are lower for female than for male managers.

Table 1 Panel A.2 shows the number of funds with different fund objectives. For funds managed by male managers, the top fund objectives are Appreciation Funds (1,484) and Income Funds (605). Similarly, for funds managed by female managers, the top fund objectives are Appreciation Funds (220) and Growth Funds (195). Panel A.3 reports summary statistics for our manager variables. Both male and female managers are highly educated on average, with most male managers and all female managers reporting at least a master's degree or above.

Table 1 Panel B reports summary statistics for our user variables. There are 2,345,875 user-fund-month observations, with 255,718 observations consisting of funds held by female users. The average overall fund holding is 5,893 CNY (approximately US$910), showing that most investors on the platform are micro-investors with relatively small investments into stock funds. Male investors have significantly higher average fund holdings than female investors do, and male investors also have higher average fund inflows on average. Although both male and female investors exhibit negative average monthly capital gains, female investors appear to perform slightly better than male investors, though the difference is not statistically significant. Male investors spend similar amounts to female investors on the platform per month on average. Male investors also appear to be slightly older, reside in larger cities, and report lower levels of risk tolerance (or equivalently, higher levels of risk aversion) than female investors, on average.

4. Results

4.1 Do individual investors chase performance?

We first examine if the flow-performance sensitivity for individual investors in China is similar to patterns documented in the prior literature for funds elsewhere in the world. We employ the following panel OLS regression model:

$$Flow_{i,f,t}=\alpha+\beta_1\ Rank_{f,t\text{-}1}+\beta_2 Manager\ Gender_{i,f,t}+\mu M_{f,t}+\psi F_{f,t}+\lambda U_{i,t}+\theta O_f+\gamma_i+\delta_t+\epsilon_{i,f,t} \qquad (6)$$

where i indexes investors, f indexes funds, and t indexes time. γ and δ denote individual and time fixed effects. ϵ is the error term. We follow Niessen-Ruenzi and Ruenzi (2018) and cluster our standard errors at the entity (user) level.

The dependent variable, *Flow*, is the percentage change in fund amount for a particular user's investment in a specific fund. *Rank* is the relative performance rank of funds in the previous month, with 0 being the worst-performing fund and 1 being the best performing fund. *Manager Gender* is a dummy variable that equals 1 if the fund manager is female and 0 if the fund manager is male. *M* is a vector of fund manager control variables, including a fund manager's education background and tenure duration. *F* is a vector of fund control variables that have been found to affect fund flows in the previous literature (Sirri and Tufano, 1998, Barber, Odean, and Zheng, 2005), including fund management fees, fund transaction fees and fund sales fees, which are normalized by fund total assets, respectively. We control for the fund size, measured by the logarithm of Total Net Assets in the previous quarter. We also control for fund age (the logarithm of the number of months since the fund's inception), fund risk (the standard deviation of fund's daily returns over the past month), and the aggregate level fund flow in the previous quarter. *U* is a vector of user control variables, including a user's average spending and standard deviation of spending for the previous 6 months, which are proxies for a user's income level and stability, respectively. *O* is a vector of fund objective dummy variables.

Table 2 Panel A presents the results for our baseline models. The models use various relative fund performance rankings within the same fund objective as the main regressor. As documented in the prior literature, performance matters. Model (1) does not include managerial gender. Consistent with the prior literature, there is a significant and positive association between a fund's relative performance ranking in the previous month and the current month fund in-flow. An increase in relative performance ranking of a fund by 1% over the previous month is associated with an increase in current month fund flow of 0.36% at the individual investor level.

Model (2) shows that the positive relationship between a fund's previous month return ranking and fund in-flow persists with similar significance and magnitude, across all the return horizons, even after adding manager gender as an explanatory variable. However, in contrast to Niessen-Ruenzi and Ruenzi (2018), we do not find significant gender biases at the monthly individual investor level, as the manager gender term is insignificant across all the ranking measures.

Turning to fund characteristics, we divide fund sales, fund management, and fund transaction fees by fund total assets to obtain the fund sales expense ratio, fund management expense ratio, and fund transaction fee ratio, respectively. The sales expense ratio is positively and significantly correlated with fund flows in all our model specifications in Table 2. This is consistent with the results on search cost and fund flows in Sirri and Tufano (1998). While the platform does not adjust rankings based on the fund payments to the platform, investors can locate funds directly by searching for them. If the sales fee is a proxy for fund expenditure on advertising, it is plausible that investors become aware of the fund and search for the fund name directly, bypassing the list of ranked funds on the platform.

A higher management fee expense ratio is associated with significantly lower fund-inflows. The negative correlation between fund management fee expense ratio and fund flow is consistent with Christoffersen (2001), who finds that fund managers voluntarily waive their management fees to improve the net performance of their funds, which is strongly and positively correlated with fund-inflows. Managerial tenure at the current fund is also significantly positively related to fund inflows. Our findings are consistent with Christoffersen and Sarkissian (2009), who show that funds managed by more experienced managers deliver high returns, and hence have higher fund inflows. Finally, the negative sign on the relationship between transaction fee expense ratio and fund flow is consistent with the literature on transaction costs and fund underperformance (Rakowski, 2010, Grinblatt and Titman, 1989, Chalmers, Edelen, and Kadlec, 2001, Edelen, 1999, and Wermers, 2000) though in our sample, the effect is statistically insignificant.

In Table 2 Panel B, we follow Niessen-Ruenzi and Ruenzi (2018) and examine if there is a gender bias at the aggregate fund level. As before, past performance is significantly positively related to fund flows. Although the coefficient on manager gender is negative, suggesting that female managers receive lower aggregate fund flows on average, the coefficient is statistically insignificant. Therefore, inconsistent with Niessen-Ruenzi and Ruenzi (2018), in China at least, there does not appear to be a gender bias at the quarterly aggregate fund level. One explanation is that the gender bias does not show up at shorter horizons than the annual aggregate levels studied by Niessen-Ruenzi and Ruenzi (2018).

To detect gender bias in our sample, we therefore examine investors who are investing for the *first* time on the platform. Specifically, we run a logistic regression with the following specification:

$$Manager\ Gender_{i,f,t} = Logit(\alpha + \beta_1\ Rank_{f,t\text{-}1} + \mu M_{f,t} + \psi F_{f,t} + \lambda U_{i,t} + \theta O_f + \epsilon_{i,f,t})$$

where i indexes investors, f indexes funds, and t indexes time. ϵ is the error term.

Table 3 presents the results. Models 1-2 report regression coefficients including only user characteristics (Model 1), and user, fund, and manager characteristics (Model 2). In model (2), managerial tenure is negatively related to the likelihood of investing in a female-managed fund. Across both Models (1) and (2) however, controlling for managerial, fund, and user characteristics, performance is negatively related to the propensity to invest in female-managed funds. Even when investing for the first time, they direct lower flows to women for the same level of performance. Hence, the results suggest that at the individual level, Chinese investors do display a similar type of gender bias as those documented by Niessen-Ruenzi and Ruenzi (2018).

Overall, however, our results suggest that Chinese investors display broadly similar behavior to investors as documented elsewhere in the world. They chase performance and display gender biases in their investment behavior.

4.2 Is the flow-performance relationship affected by gender-based attention bias?

In this section, we examine whether the flow-performance sensitivity differs by gender. We employ the following panel-OLS regression model:

$$Flow_{i,f,t}=\alpha+\beta_0\ Rank_{f,t-1}+\beta_1\ Rank_{f,t-1}\times Manager\ Gender_{i,f,t}+\beta_2 Manager\ Gender_{i,f,t}+\mu M_{f,t} +\psi F_{f,t}+\lambda U_{i,t}+\theta O_f+\gamma_i+\delta_t+\epsilon_{i,f,t} \quad (7)$$

where i indexes investors, f indexes funds, and t indexes time. γ and δ denote individual and time fixed effects. ϵ is the error term. As before, we follow Niessen-Ruenzi and Ruenzi (2018) and cluster our standard errors at the entity (user) level. Our variable of interest, *Rank × Manager Gender* is the interaction term between fund relative performance ranking and manager gender. M, F, U, and O are the vectors of fund manager control variables, fund control variables, user control variables, and fund objective dummy variables, respectively, described in the previous section.

Table 4 presents the results. In model (1), we interact the manager gender dummy variable with the relative performance ranking of funds in the previous month, controlling for user, month, manager education, and fund objective fixed effects. Interestingly, the coefficient on managerial gender is significantly positive, suggesting that, without conditioning on performance, female managers enjoy significantly larger fund inflows than male managers. As before, the current month's fund flow is significantly positively correlated with the prior month's relative performance of the fund. The coefficient on the fund relative performance is 0.39 and statistically significant at the 1% level, suggesting that the greater the prior relative performance, the higher the current month's fund inflow. The sensitivity of fund flows to short horizon performance has typically been documented at annual horizons.[7] This paper is the first

[7] One of the few exceptions is Ferreira, et al. (2012) who examine the flow-performance relationship using aggregate quarterly data.

to document evidence of performance-flow sensitivity at the monthly level on an individual investor basis.

However, the effect is significantly smaller for a female fund manager. The interaction term between manager gender and relative performance of funds has a statistically significant (at the 1% level) coefficient of -0.33. This suggests that, for a male manager, if the relative performance ranking of the fund in the previous month increases by 1%, the fund flow increases subsequently by 0.39%. However, for a female manager, the same relative performance ranking increase increases monthly fund inflows by only 0.06% (=0.39% – 0.33%).

In economic terms, the monthly difference in the monthly performance-flow relationship between male and female managers for the average user is 19.45 CNY (approximately US$3.01), or US$36.12 in annual terms when the performance ranking of the fund increases by 1% each month for 12 months. While this effect may seem small at the investor level, we note that the number of subscribers to each fund is substantial. Table 1 Panel A.1 shows that the average TNA for a male-managed fund is 1.02 billion CNY (approximately US$158.14 million), while the average TNA for a female-managed fund is 0.78 billion CNY (approximately US$254.8 million). Hence, the attention bias at the individual investor level translates to a difference in the monthly fund-level performance-flow relationship between male and female managers of approximately 2.57 million CNY (approximately US$0.40 million) for an average female-managed fund per month, or US$ 4.8 million in annual terms when the performance ranking of the fund increases by 1% each month over a 12-month period.

Table 4 Models 2-4 show that the attention bias continues to exist for all the other rankings available on the platform including the 3-, 6- and 12-month return horizons. In each case, the interaction term between manager gender (female) and 3-, 6-, and 12-month return ranking is negative and significant. The magnitude of the (negative) coefficient on the interaction term is considerably larger than the (positive) coefficient on managerial gender across all the models, turning the overall effect of gender on flow negative.[8]

Our results therefore suggest the presence of a significant attention bias in the flow–performance sensitivity away from female funds. If a male-managed fund performs well over the previous month, the fund inflows are higher than at a female-managed fund. However, if a female-managed fund performs poorly in the previous month, the monthly fund outflow will

[8] In untabulated regressions, we subtract automatic fund investments from the numerator of our fund flow measure, and our results remain unchanged.

also be lower than at a male-managed fund. Simply put, conditional on investing in a female-managed fund, investors appear to pay less attention to performance.

If investors are rational and their goals are to maximize their returns on investments, there should not be any systematic differences in the flow-performance relationship based on gender. One explanation is that people have double standards toward females (Botelho and Abraham, 2017, and Botelho and Gertsberg, 2020). To receive the same attention as male managers, female managers must perform better than mediocre male managers. Another explanation is the deeply rooted cultural norm whereby girls get less attention in their families than boys when growing up, which leads to less attention being paid to females in general (Barcellos, Carvalho, and Lleras-Muney, 2014, and Park and Rukumnuaykit, 2004). It is also possible that people project stereotypes onto female managers which bias them against trusting their funds to female managers if the performance is short of excellent (Neumark and Bank, 1996, Newton and Simutin, 2015, Hannum, Kong, and Zhang, 2009, Banaji and Greenwald, 1995).

An alternative, rational, explanation to the muted flow-performance sensitivity for female managers is that male managers' past performance is a better predictor of their future performance than for female managers. Hence, investors rationally invest in what they believe will be better performing funds and divest away when performance declines. We therefore examine whether past performance predicts future performance for Chinese fund managers and whether there is a gender difference in the predictive ability for future performance. This is related to the hot hands effect, first documented by Hendricks, Patel, and Zeckhauser (1993), who find that the relative performance of no-load and growth-oriented mutual funds persists in the near term. Carhart (1997) argues that persistence in mutual fund returns is mostly driven by the one-year momentum effect of Jegadeesh and Titman (1993) and finds no evidence for the hot hands effect. Nevertheless, if investors believe that male fund managers are more likely to have hot hands, then an increase in short-term performance might be consistent with rational investor behavior in directing flows to these funds. Hence, the differential gender sensitivity of flow to performance might be an outcome of rational choices by investors.

We regress the current month fund return ranking on the future 3-, 6-, and 12-month return rankings, respectively. Table 4 Panel B shows the coefficients of the regression estimates. Current month fund return ranking appears to be negatively and significantly correlated with the future 3-, 6- and 12-month return rankings, inconsistent with the hypothesis that Chinese mutual fund managers have hot hands. In addition, since the coefficient of the manager gender dummy variable is insignificant, there is no evidence that male managers are more likely to have hot hands than female managers.

We then examine whether the gender attention effect is also subject to the tendency of fund investors, documented using US data (see for example, Sirri and Tufano, 1998, or Del Guercio and Tkac, 2002) to buy past winners more intensely than they sell past losers. Huang et al. (2007) show that the magnitude of this relationship has declined over time for US mutual funds. Ferreira et al. (2012) find marked differences in in the flow-performance relationship across countries, suggesting that US findings do not apply directly to other countries. In particular, for less developed countries, they find little evidence of convexity at the individual country level. China is not included in their sample.

We test if attention bias affects the tendency of Chinese investors to preferentially buy winning funds while avoiding sell losing funds based on the gender of the fund manager. For example, investors might react asymmetrically to winners and losers based on performance, directing flows preferentially towards high-performing male fund manager while being faster to direct flows away from poorly performing female fund managers.

Specifically, we divide our sample into two subsamples where the first includes only funds whose returns have increased in the previous month compared to two months ago (winners), and the second includes funds whose returns have decreased in the previous month relative to two months ago (losers). We then create a dummy variable that indicates if the fund is a winner or a loser and formally test whether there is a gender-based differential performance chasing effect between male- and female-managed funds. Table 4 Panel C reports the coefficients for these regressions.

Columns 1-2 show that, while both subsamples exhibit significant attention bias, the magnitude of the attention bias coefficient is around five times the size for the winners than the losers, suggesting that investors pay significantly less attention to women when the funds are performing particularly well and more attention to them when the funds are performing poorly. Column (3) formally tests the difference in magnitude of the attention bias between the two subsamples, using a triple interaction term (Return increase dummy × Manager gender × Fund performance ranking). The triple interaction term is significantly negative, suggesting that the well-documented asymmetric flow-performance relationship is also affected by attention bias.

Finally, we follow Sirri and Tufano (1998) in using piecewise regression approaches in Table 4 Panel D. The first specification uses the Sirri-Tufano specification, cutting the funds on the top quintile, the mid-three quintiles and the bottom quintile of performance. The gender attention bias appears to be concentrated in the mid- and bottom quintiles of performance. In the top quintile, there is no evidence of gender bias in the interaction term. However, it is possible that the top quintile is too coarse a specification if the very top female managers do not experience a gender bias. Hence, in the subsequent specifications, we progressively shrink the size of the top section from quintiles to deciles to percentiles. The attention bias continues to exist in the mid and bottom sections across all our cuts, suggesting that progressively refining the definition of top performing fund managers does not change the results. A gender bias appears in the top 1% and 5% sections as well, though the extremely small numbers of female managers in these sections implies that these findings are noisy.

4.3 Placebo test: Do the results reflect random error?

A concern with the empirical results so far is that they simply reflect a random error or misspecification. Hence, in this section, we conduct a placebo treatment effect where we replicate the core analysis with a different treatment variable. This placebo test is informative about flaws in the core analysis if we believe that the placebo treatment does not affect the outcome (or does not affect it through the mechanism postulated in the core analysis) but the purported flaw operates in a similar way (Eggers, Tuñón, and Dafoe, 2021).

Specifically, we randomly assign managerial gender (male and female) to funds in our data in the ratio of 9:1 (which is approximately the actual ratio of male vs female managers) and rerun the core regression in Table 4 Panel A, model (1). Table 5 reports the coefficients of this regression analysis. While fund performance ranking remains significant, we note that neither managerial gender nor the interaction term between gender and performance are significant, suggesting our results are not driven by random errors.

4.4 Alternative Performance Metrics

So far, our performance metrics are based on the objective-adjusted rankings reported by the platform. However, it could be argued that investors do not use these platform-provided rankings but adjust for risks in other ways. Evans and Sun (2020) show that U.S. retail investors use simple risk-adjustment heuristics provided by Morningstar to direct fund flows. Specifically, using Morningstar's 2002 rating methodology change, they show that before the change, flows are strongly correlated with CAPM alphas. After the change, when funds are ranked by size and book-to-market groups, flows become more sensitive to 3-factor alphas (FF3).

To check the robustness of our results, we use two simple alternative heuristics that investors might consider for our performance-flow panel regressions. We compute the Jensen's Alpha (Jensen, 1968), calculated from funds' daily returns over the past month. Jensen's Alpha assumes that the CAPM (Sharpe, 1964) model is correct and calculates the risk-adjusted return for investors. We obtain Jensen's Alpha for each fund from CSMAR which computes it from the following regression equation with funds' daily returns during the past month:

$$\alpha_{i,t} = R_{i,t} - R_{f,t} + \beta_{i,t} \times \left(R_{m,t} - R_{f,t}\right) \tag{8}$$

where *i* indexes for funds, t indexes for days, R_i is the daily return of fund *i*, R_f is the risk-free rate and R_m is the market return. We then rank the alphas into percentiles by month.

The second performance metric that we use is the arithmetic average of daily returns for the fund over the past month, which is calculated as follows:

$$\overline{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{i,t} \tag{9}$$

where *i* indexes for funds, t indexes for days, *T* is the number of days in the past month, and *R* is the daily fund return. We then rank the daily average returns into percentiles by month. We then use these performance metrics in the same panel-OLS regression model as in equation 7. Both these heuristics are relatively simple to calculate and it is plausible that an investor might use them as alternatives to the rankings provided by the platform.

Table 6 presents the results. Model (1) and (2) use the Jensen's Alpha rank for the past month as the performance metric, while Model (3) and (4) use the daily fund performance rank for the past month as the performance metric. Our results across all four models are consistent with our previous results in Table 2 and Table 4.

Models (1) and (2) show a positive and significant correlation between prior month's risk-adjusted return and current month's fund flow. In addition, the interaction term between risk-adjusted return and fund manager gender is negative and statistically significant. If the relative Jensen's Alpha ranking of a male-managed fund increases by 1% in the previous month, the current month fund flow increases by 0.37%. In economic terms, for an average user with a fund amount of 5,893 CNY (approximately US$910), the fund flow increases by 21.80 CNY (approximately US$3.37) per month. In contrast, the fund flow to female-managed funds increases only by 0.06% (0.40% – 0.34%). This is equivalent to a difference of 2.65 million CNY (approximately US$ 410,141) in the performance-flow relationship between male- and female-managed funds at the monthly fund level. A similar pattern exists when we use the average daily returns for funds in the past month in models (3) and (4).

4.5 Do female managers take less risks than male managers?

An alternative explanation is that female managers are less likely to take risks and hence investors who do not adequately adjust for risk direct more flows to (risky) male managers. In this section, we examine whether there is a difference in performance and risk between male and female managers using a multiple regression approach on all stock funds covered by CSMAR. We employ the following regression model:

$$Performance/Risk_{f,t} = \alpha + \beta_1 Manager\ Gender_{f,t} + \mu M_{f,t} \\ + \psi F_{f,t} + \theta O_f + \gamma_i + \delta_t + \epsilon_{f,t} \qquad (10)$$

where *f* indexes funds, and *t* indexes time. γ and δ denote individual and time fixed effects. ϵ is the error term. We cluster our standard errors at the fund level. The dependent variable, *Performance/Risk* is drawn from a battery of fund performance, idiosyncratic risk, systematic risk, stock selection ability and market timing ability measures.

Table 7 reports the results. Models 1-4 report regression coefficients for regressions where the dependent variables are the 1-, 3-, 6-, and 12-month return rankings, respectively. Model (5) reports coefficients for a regression where the dependent variable is the daily return standard deviation, to proxy for the idiosyncratic risk that the fund bears. Model (6) reports coefficients for a regression where the dependent variable is the Sharpe (1965) ratio, which measures the excess return per unit of idiosyncratic risk that the fund bears. Models 7-8 report coefficients where dependent variables are betas and alphas of the Sharpe (1964) CAPM model. The CAPM beta proxies for the systematic risk that the fund bears against the market, while the CAPM alpha proxies for the ability of the fund to beat the market portfolio. Model (9) reports the coefficients where the dependent variable is the Treynor (1965) Index, which measures the excess return per unit of systematic risk that the fund bears. Models 10-11 use the Treynor and Mazuy (1966) model's measure of market timing and stock selection abilities as dependent variables, respectively. Models 12-15 use the Chang and Lewellen (1984) model's measure of bear- and bull-market timing as well as stock selection abilities as dependent variables.

Across all fund performance specifications (except for the 1-month return ranking measure), manager gender is not significantly related to fund return rankings after controlling for manager tenure, education, the previous quarter fund size and aggregate-level flow, fund sales fee, fund transaction fee, fund management fee and fund objectives. When measuring fund performance in terms of 1-month fund performance, female managers perform 4.24

percentage points better than male managers, which is statistically significant at the 1% level. We do not detect significant differences in idiosyncratic or systematic risks or excess returns per unit of systematic or idiosyncratic risk between funds managed by male and female managers. Furthermore, male-managed funds do not exhibit superior stock selection or market timing abilities (other than the TM model). Overall, gender appears to be unrelated to the fund's performance, risk, market timing ability or stock selection ability. It is therefore difficult to explain the differential performance chasing behaviour between male- and female-managed funds using a rational asset pricing framework. It appears more likely that this is due to investor preferences for male-managed funds.

4.6 Do investors assume that female managers are more trustworthy than male managers?

Yet another explanation is that female managers are more trustworthy. Several papers show that female managers are less likely to be associated with fraud. For example, Gao et. al. (2017) show that female directors are faster to leave firms that commit financial fraud. Wang, Yu, and Gao (2022) show that firms with female corporate leaders in China have a lower propensity to engage in fraud. Gul, Srinidhi, and Ng (2011) show that firms with women on their boards increase public disclosure which in turn, increases stock price informativeness. If female mutual fund managers are similarly more transparent, it is possible that investors pay less attention to women managers because they do not need to monitor them. In contrast, male managers need to be monitored because signals of managerial ability as reflected in fund performance are noisier for male than for female managers. However, inconsistent with this hypothesis, we note that the results in Table 3 show that after controlling for managerial, fund, and user characteristics, performance is negatively related to the propensity to invest in female-managed funds. This suggests that first-time investors do not view female managers as inherently more trustworthy than male managers. They direct lower flows to women for the same level of performance.

A second possibility is that consistent with Table 3, first-time investors are initially biased against women. However, once they invest, they learn that women are more trustworthy and stop paying attention to them and monitor male managers relatively more intensively. However, this explanation is inconsistent with our results in Table 4 Panel C which documents an asymmetry in responses to increases and decreases in performance. The magnitude of the attention bias coefficient in this table is around five times the size for the winners than the losers, suggesting that when funds perform poorly, investors pay significantly more attention to women managers than when their funds are performing well.

4.7 Is attention bias driven by the lack of female fund managers in the sample?

Table 1 shows that there are more male managers than female managers in our sample. Therefore, a natural question to ask is if the attention bias exists because of the sheer number of male managers, which captures most of the investors' attention. In other words, do investors exhibit attention bias away from female managers simply because there are fewer female managers who are difficult to find? We note that univariate two-sample t-tests in Table 1 show that female managers perform significantly better in terms of 1-, 3-, 6-, and 12-month returns, suggesting that users see female-managed funds higher in the app rankings, on average, than male-managed funds, implying that female-managed funds are more visible than male-managed funds.

Nevertheless, to explicitly eliminate the effect of the difference in the number of male and female managers in our sample, we use two approaches. In this section, we report results from a propensity score matching (PSM) approach where we show that attention bias still exists even after matching the male and female managers on a host of managerial and fund characteristics. While the PSM approach does not address causality, it balances manager and fund covariates in our sample and mitigates concerns that higher search costs for female managers affect the attention bias of investors.

We use a logistic regression to calculate the propensity score of a fund choosing a female manager and control for variables that affects a fund's visibility to the investors. Panel A of Table 8 shows the results of a logistic regression where we regress a fund's choice of manager gender on past 1-, 3-, 6-, and 12-month returns ranked within each fund objective, fund fees, fund size, fund age, fund return standard deviation, aggregate level fund flow, manager tenure, and manager education (whether the manager has at least an undergraduate degree).[9] We then estimate propensity scores at the fund level and match each female manager to a male manager by month using a PSM with nearest neighbour matching. Panel B of Table 8 shows the difference-in-means of the independent variables for male managers versus female managers for both the unmatched and matched samples, respectively. T–statistics for the difference–in–means test indicate that all variables differ significantly for the unmatched sample. In contrast, the corresponding difference-in-means tests indicate that the variables do not differ significantly for the matched sample, and there is a good covariate balance across the matched variables.

[9] Table 1 Panel C.1. shows that all the female managers have at least an undergraduate degree while some male managers stop at the undergraduate degree level.

Using the matched fund sample, we merge individual investor data to the matched funds and re-run the regression with the same control variables and fixed effects as in equation (7). The results are reported in Table 8 Panel C. Model (1) shows the regression coefficients when we use the prior 1-month fund returns as the performance measure. The current month's fund flow continues to be significantly positively correlated with the prior month's relative fund performance. The relative performance coefficient is 0.37 and statistically significant at the 1% level, suggesting that higher relative performance increases the current month's fund flow. However, as before, the effect is significantly smaller for a female fund manager. The interaction term between manager gender and relative performance of funds has a coefficient of -0.20, which is also statistically significant at the 10% level. Hence, investors still appear to exhibit an attention bias even in a sample matched on performance and visibility. Models 2-4 report regression coefficients when we use the 3-, 6-, and 12-month fund returns as the performance measure, respectively. In all models, the interaction term is negative and significant, with model 2-3 significant at the 1% level and model 4 significant at the 10% level. Overall, our PSM results suggest that attention bias does not appear to be driven by higher search costs of finding female managers.

4.8 Do investors pay less attention to women fund managers because of a lack of media attention?

In the second approach, we examine if attention bias is related to difference in media coverage or sentiment between male and female fund managers. Da, Engelberg, and Gao (2011) propose a new measure of retail investor attention using search frequency in Google and find that investor attention predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year. Ben-Rephael, Da and Israelsen (2017) measure institutional investor attention using news searching and news reading activity on Bloomberg terminals and find that institutional attention responds more quickly to major news events, leads retail attention, and facilitates permanent price adjustment. It is possible, therefore, that more frequent coverage or more positive coverage of male managers than female managers in the news may lead to investors paying more attention to male managers than to female managers.

To control for media coverage on fund managers, we collect approximately 1.2 million Chinese news articles from CSMAR and filter out approximately 400,000 news articles within the financial news category. We do not conduct a plain search of managers' names in the news articles, as some Chinese names are also common phrases (such as the word "trillion", which is both a typical Chinese name and an expression of numerical count in Chinese) and may lead to large levels of noise in the frequency count of media coverage on managers' names. Instead, we use spaCy, a state-of-the art natural-language-processing model based on convolutional neural networks, to extract people's names from the news articles through part-of-speech tagging and named-entity-recognition. We then count the frequency of each manager's name in news articles each month and rank the frequency by fund objectives into percentiles. The resulting variable, media mention frequency rank, proxies for media's coverage on fund managers in each month. Table 1 Panel A shows that female managers are mentioned less frequently in the media than male managers, and the difference is statistically significant.

To further distinguish between positive mentions and negative mentions of each manager in the news, we apply sentiment analysis to each sentence that includes a manager's name. We employ the SKEP (Sentiment Knowledge Enhanced Pre-training for Sentiment Analysis) model proposed by Tian et al. (2020) for sentiment analysis. SKEP is a variant of the Transformer model (Vaswani et al. 2017) that incorporates sentiment knowledge by self-supervised learning. Specifically, we apply the state-of-the-art SKEP model pre-trained based on ERNIE (Enhanced Language Representation with Informative Entities) proposed by Zhang et al. (2019).[10] Each sentence is classified as either positive or negative sentiment by the SKEP model. We then count the frequencies of sentences of positive sentiments and negative sentiments, respectively, for each manager and each month. Next, we normalize the frequencies by the total number of sentences that mention each manager in each month. Finally, we rank the normalized frequencies by month and fund objective and obtain our measure of positive and negative mentions of managers in the news. Table 1 Panel A shows that there are more positive mentions than negative mentions in our sample. In addition, whether in terms of positive or negative mentions, male managers are mentioned more frequently than female managers.

We then add media mention frequency, positive and negative media mentions as control variables in Table 9. Column (1) includes the overall media mention frequency as the control variable and shows that the gender bias remains negative and significant after controlling for media coverage. Column (2) disentangles the overall media mention frequency into positive and negative media mention frequencies based on sentiment analysis and show that, while gender bias remains significant, negative (positive) mentions in the media reduces (increases) fund flows. Column (3) interacts positive and negative media mention frequencies with fund

[10] We run the SKEP model on 2,409,963 sentences with 8 Nvidia-Ampere GPUs, a process that takes approximately six hours to finish.

performance and shows that positive mentions in the media strengthen the flow-performance sensitivity, though the gender bias still stays significant. Column (4) triple interacts positive and negative media mention frequencies with fund performance and fund manager gender and shows that the gender bias exists only for the female fund managers who are mentioned positively in the news. In other words, relative to another male fund manager with identical performance and positive mentions in the news, the female manager earns lower fund flows. The results from Columns 1-3 suggest that the gender bias is unlikely to be the result of different levels of media coverage or sentiments between male and female managers. Although the evidence in Column (4) is relatively weak (there are very few negative mentions of female managers in our sample), it suggests that the bias is stronger when a female manager is given positive media coverage in the news, as investors still pay less attention to them than to an equivalent male manager with identical performance and a positive mention in the news.

4.9 What type of users are prone to attention bias?

We next examine cross-sectional evidence on attention bias based on four user characteristics: user gender, age, city of residency and risk tolerance. We pick these four characteristics based on evidence in the literature that shows different levels of gender biases across these characteristics. For example, considering gender, experimental evidence (see for example, Lovén, Herlitz, and Rehnman, 2011) shows that women remember more female than male faces, whereas men do not seem to display an own-gender bias in face recognition memory. Similarly, for age, Das Gupta and Shuzhuo (1999), among others, argue that the wars and famine experienced in China over the last century led to the prioritization of female children over male children in terms of nutrition and education. We conjecture therefore, that older investors are more likely to be affected by attention bias. For city of residency, the literature on gender biases argues that in smaller cities or rural areas in developing countries, female children are given less resources and paid less attention in families (e.g., Barcellos, Carvalho, and Lleras-Muney, 2014, Hannum, Kong, and Zhang, 2009, and Park and Rukumnuaykit, 2004). We conjecture that attention bias is likely to be higher in smaller cities. We define big cities as tier-1 cities in China, which include Beijing, Shanghai, Guangzhou and Shenzhen. The rest of the cities with higher tiers fall into our definition of small cities. Finally, the platform assesses users' risk tolerance based on a questionnaire, and each user is classified into a risk band, with values ranging from 0 to 6. The smaller the value, the less risk-tolerant the user. We define users with a risk band value below or equal to 2 as risk-averse, and users with a risk band value greater than 2 as risk-tolerant.

We interact each of the four user characteristics with manager gender and fund performance. Table 10 presents the results for each of the four triple-interaction regressions where fund performance is measured as fund returns over the past 1-month horizon.

Table 10 Column (1) suggests that female users tend to direct lower flows to funds as well as displaying a weaker flow-performance relationship than male users. However, the triple interaction term of user gender, manager gender, and fund performance is positive and statistically significant, suggesting that female users have a lower degree of gender bias than male users. Column (2) suggests that older users tend to have higher fund flows and a stronger flow-performance relationship than younger users, but the degree of gender bias is insignificant among users of different ages. Column (3) suggests that users from smaller cities tend to have higher fund flows, a stronger flow-performance relationship, and a stronger gender bias than users from larger cities. Finally, Column (4) does not show significant results relating the degree of user risk aversion to flow-performance sensitivity. Overall, female investors and investors from larger cities appear to have lower levels of gender attention bias than male investors or investors from smaller cities respectively.

4.10 Is there a causal relationship between gender bias and fund flows?

Our main variable of interest, manager gender, could be subject to endogenous and unobserved factors in the error term. Therefore, we next use two instrumental variables to establish a causal relationship between manager gender and fund flows. These instruments do not instrument for fund manager per se, but for the specific investor's choice of a fund manager. We first discuss the economic arguments supporting the validity of the two different instrumental variables.

The first instrumental variable is the proportion of illiterate women in the entire female population at the municipal district level in 2010 based on Census data released by the National Bureau of Statistics of China. Since the Song Dynasty (960), the Chinese imperial examinations, or *Keju*, have been used as a civil service examination system for selecting candidates for the state bureaucracy. However, the examination system did not allow female candidates to participate, and for almost a thousand years, a typical social norm was that females should not receive formal education and should remain illiterate. The situation has been greatly improved since the establishment of the PRC, who introduced a compulsory education law which mandates free education for both male children and female children below the 9th grade since 1986. Before the introduction of the compulsory education law, families could choose to send their children to school for basic education by paying tuition fees. Families who did not possess enough resources to send all their children to school might prioritize boys over girls, leaving a proportion of illiterate women.

The motivation for this instrument is that people from districts with a higher proportion of illiterate women might exhibit a stronger gender bias towards men, as their parents, grandparents or friends might have directed educational resources towards boys over girls before 1986. Since the literature shows that culture (values, knowledge and practices) that are prevalent in one generation are transferred to the next generation, it is likely that some gender biases are transferred intergenerationally as well. However, it is unlikely that the proportion of illiterate women in a local district will influence investors' decisions on fund flows through channels other than gender biases, after controlling for investor income and other characteristics, implying that the proportion of illiterate women is a suitable instrumental variable.

The second instrumental variable is the proportion of female new-borns amongst all new-borns at the municipal district level in 2010. In 2003, the regulations in China banned foetal gender identification for non-medical needs and any artificial termination of pregnancy for gender selection purposes. Though the act is a legal requirement to increase gender equality in all provinces, some illegal enterprises continued to conduct foetal gender identification and artificial termination of pregnancy in the first few years after the law was introduced. Those activities were commonly known as "the two-illegal activities" in China.[11] While gender identification and artificial termination have both been significantly reduced by law enforcement officials today, as of the 2010 census, some provinces continue to display a degree of gender imbalance relative to world averages. Therefore, it is plausible that the proportion of female new-borns at the local district level reflects the level of local gender bias in the area. However, the proportion of female new-borns is unlikely to be directly related to people's fund flow controlling for people's income, as there is no statistical evidence that there is a significant price difference in medical costs when giving birth to a male or female child. Therefore, the proportion of female new-borns is an ideal candidate for an exogenous instrument.

Our endogenous variable, manager gender, is a binary variable. Although the traditional 2SLS estimator is still consistent for binary endogenous variables, it is not necessarily efficient. Therefore, we follow Adams, Almeida, and Ferreira (2009) in carrying out a three-stage

[11] The phrase is used commonly in government issued (Chinese) news releases (see for example, http://www.gov.cn/xinwen/2015-05/07/content_2857935.htm). The government has repeatedly tried to crack down on these gender discrimination activities (see Hou, Liqiang and Shan, Juan, 2014, Joint forces to curb illegal abortions, *China Daily*, 4 September 2014).

procedure in identifying the causal effects. In the first stage, we estimate the following Logit model:

$$Manager\ Gender_{i,f,t} = Logit(\alpha + \beta_0 Instrumental\ Variable_i + \beta_1\ Rank_{f,t-1} + \mu M_{f,t} + \psi F_{f,t} + \lambda U_{i,t} + \theta O_f + \epsilon_{i,f,t}) \quad (12)$$

where i indexes investors, f indexes funds, and t indexes time. ϵ is the error term. $Instrumental\ Variable_i$ is the proportion of illiterate women in the female population or the proportion of female new-borns among all newly born children at the local district where the investor resides. M, F, U, and O are the vectors of fund manager control variables, fund control variables, user control variables, and fund objective dummy variables described in the previous section.

In the second stage of the procedure, we then compute the fitted probability of choosing female managers, $\widehat{Manager\ Gender}$, from the Logit regression above. In the third stage of the procedure, we use $\widehat{Manager\ Gender}$ to instrument for *Manager gender*, and $\widehat{Manager\ Gender} \times Rank$ to instrument for Manager gender × Rank, respectively, in the following equation using a standard 2SLS procedure:

$$Flow_{i,f,t} = \alpha + \beta_0\ Rank_{f,t-1} + \beta_1\ Rank_{f,t-1} \times Manager\ Gender_{i,f,t} + \beta_2 Manager\ Gender_{i,f,t} + \mu M_{f,t} + \psi F_{f,t} + \lambda U_{i,t} + \theta O_f + \gamma_i + \delta_t + \epsilon_{i,f,t} \quad (13)$$

where i indexes investors, f indexes funds, and t indexes time. ϵ is the error term. We cluster our standard errors at the user level.

As Wooldridge (2001) notes, the advantage of the above procedure is that it delivers consistent estimates in the third stage while allowing for the presence of non-linearities in the first stage. Furthermore, the consistency guarantee of the procedure does not require a correct specification of the functional form in the first stage regression, and although fitted values from the first stage are used in the third stage as inputs to the standard 2SLS procedure, the standard IV standard errors are still asymptotically valid.

Table 11 shows the results of our three-stage instrumental variable estimation procedures.[12] Table 11 Panel A shows the coefficient estimates of the first stage Logit model. Model (1) shows that the proportion of female new-borns at the district level is positively and significantly correlated with the probability of an investor choosing a female manager. This is consistent with our earlier hypothesis that the larger the proportion of female new-borns versus

[12] We reject the null hypothesis that the model is over-identified using several over-identification tests including the Anderson-Rubin Test, the Sargan test, the Basmann test, and the Wooldridge test. In addition, the first (or second in the three-stage IV process) stage have F-statistics of over 360, rejecting the null hypothesis that our instrument is weak.

male new-borns, the lower the gender bias in the local district and the more likely that investors from that local district are going to invest in a female manager. Model (2) shows that the proportion of illiterate females amongst all females at the district level is negatively and significantly correlated with the probability of an investor choosing a female manager. Again, this is consistent with our earlier hypothesis that the larger the proportion of illiterate females at the district level, the higher the gender bias in the local district and the less likely that investors from that local district are going to invest in a female manager. Both of our instruments are highly statistically significant in both models, suggesting that they are strong predictors of the probability of choosing a female manager. We note that these results are also consistent with Niessen-Ruenzi and Ruenzi (2018) in that investors in areas that are more biased towards males are less likely to invest in female-managed funds.

Table 11 Panel B shows the coefficient estimates of the third stage 2SLS model. Consistent with our previous OLS estimates, both model (1) and (2) show a significant and positive correlation between past-month fund performance and current month fund flows. Most importantly, the coefficient of manager gender, our instrumented variable, is positive and significant, while the coefficient of the interaction term between manager gender and previous-month fund performance is negative and significant. The coefficients in our instrumental variable regressions therefore confirm our earlier hypothesis that gender bias towards female managers has a causal influence on investors' fund flow decisions.

4.11 Do female-managed funds have lower individual fund flow volatilities?

Table 1 Panel A shows that female-managed funds have lower aggregate-level monthly volatilities on the fintech platform. Our main results also show that investors respond less to female managers' performance than male managers' performance due to an attention induced gender bias. Do individuals holding female-managed funds indeed have lower fund flow volatilities?

In the final part of the paper, we compute individual fund flow volatilities by measuring the standard deviation of fund flows for each individual and each fund during our entire sample period. We use individual fund flow volatilities as the dependent variable, and managerial, fund and user characteristics as the explanatory variables. Table 12 reports the results. The manager gender term has a negative and significant (at the 10% level) coefficient, implying that, at the individual user level, fund volatilities are lower for female-managed funds than for male-managed funds. For mutual fund companies, this may have the desirable impact of lowering the volatility of flows into the fund.

5. Conclusions

The prior literature has argued that individual investors chase performance while discriminating against women, with the consequence that there are relatively few female mutual fund managers in the industry. However, these conclusions are based on aggregate flows. Using a unique sample of individual investor flows into individual funds in China, we show that investors chase performance at the individual level, they exhibit gender bias away from female managers while investing in mutual funds and they are more sensitive to the performance of male managed-funds than for female-managed funds.

The bias exists across all the return horizons where the platform app allows sorting of fund returns, as well in simple heuristics for performance such as Jensen's alpha and daily average returns. There are also significant cross-sectional differences between investors. Female users appear to display lower levels of gender bias away from female-managed funds. Similarly, users living in smaller cities display higher levels of gender bias away female-managed funds. The attention bias uncovered in the sample appears to be irrational and cannot be explained by the difference in performance between male and female managers or the difference in media coverage between male and female managers.

Niessen-Ruenzi and Ruenzi (2018) argue that because mutual fund investors appear to direct significantly lower flows to female-managed mutual funds than to male-managed funds, rational fund companies might choose to hire fewer women since fund companies generate their profits from fees charged on assets under management. Our paper shows that while investors may indeed direct lower flows to female managed funds, the attention bias works both ways. Though investors appear more sensitive to fund performance when the fund manager is male, the sensitivity is bi-directional. Investors who choose to invest in female managed funds are also less flow-sensitive to underperforming female managers. For mutual fund companies, this may have the desirable impact of lowering the volatility of flows into the fund.

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Appendix. Variable Definitions

Variable	Description	Source
User Variables		
Current month spending	Total amount paid out from the platform account in the current month (in thousands CNY).	Platform User Table
User age	User age.	Platform User Table
User gender	User gender.	Platform User Table
User city size	The tier of the user's city of residency. 1 is the biggest city (Beijing, Shanghai, etc.), and 6 is the smallest city.	Platform User Table
User risk band	User risk band, from 0 - 5, where 0 represents the highest level of risk aversion and 5 represents the lowest.	Platform User Table
User fund amount	Fund holding amount (in CNY).	Platform Fund Table
User monthly capital gain or loss	Monthly capital gain or loss of the user's current fund holding relative to the value of the position as of the previous month (in CNY).	Platform Fund Table
User fund flow	The fund flow for non-first-time investors.	Platform Fund Table
Female new-born ratio	The proportion of female new-borns amongst all new-borns in 2010 at the local district level.	China Census 2010
Female illiteracy ratio	The proportion of illiterate females in the female population at the local district level.	China Census 2010
Manager Variables		
Manager gender	Fund manager gender (0 for male and 1 for female).	CSMAR Fund Manager Database
Manager degree	Manager's education background.	CSMAR Fund Manager Database
Manager tenure	The number of years the manager has been managing the current fund.	CSMAR Fund Manager Database
Media mention frequency rank	The ranking of the number of times each manager's name is mentioned in the news in each month.	CSMAR News Database
Positive (negative) mention frequency rank	The ranking of the number of times each manager's name is positively (negatively) mentioned in the news in each month.	CSMAR News Database
Fund Variables		
Fund risk	Fund's standard deviation of daily returns.	CSMAR Fund Finance Database
Log(TNA)	Logarithm of Total Net Assets	CSMAR Fund Finance Database
Log(Fund age)	Logarithm of the number of months since fund's inception.	CSMAR Fund Finance Database
Aggregate fund flow	The aggregate level fund flow at the quarterly level.	CSMAR Fund Finance Database
Fund sales fee (%)	Fund's annual selling service fee (standardized by dividing by the fund's annual total asset value).	CSMAR Fund Finance Database
Fund management fee (%)	Fund's annual remuneration of managers (standardized by dividing by the fund's annual total asset value).	CSMAR Fund Finance Database
Fund transaction fee (%)	Fund's annual transaction fee (standardized by dividing by the fund's annual total asset value).	CSMAR Fund Finance Database
Fund 1-month NAV return	Previous-month fund-level NAV return (adjusted for splits and dividends) in decimals.	CSMAR Fund Evaluation Database

Fund 1-month NAV return rank	Previous-month fund level NAV return ranked on a percentile basis, with 0 being the worst performing fund and 1 being the best.	CSMAR Fund Evaluation Database
Fund 3-month NAV return rank	Previous 3-month fund level NAV return ranked on a percentile basis, with 0 being the worst performing fund and 1 being the best.	CSMAR Fund Evaluation Database
Fund 6-month NAV return rank	Previous 6-month fund level NAV return ranked on a percentile basis, with 0 being the worst performing fund and 1 being the best.	CSMAR Fund Evaluation Database
Fund 12-month NAV return rank	Previous 12-month fund level NAV return ranked on a percentile basis, with 0 being the worst performing fund and 1 being the best.	CSMAR Fund Evaluation Database
Alpha rank	Fund's alpha calculated using the CAPM on past-month daily returns ranked into percentiles.	CSMAR Fund Evaluation Database
Daily return rank	Fund's average daily return for the past month ranked into percentiles.	CSMAR Fund Evaluation Database
Sharpe ratio	Fund's Sharpe ratio calculated using daily returns in the current month.	CSMAR Fund Evaluation Database
CAPM beta	The beta coefficient from the CAPM model calculated using daily returns in the current month.	CSMAR Fund Evaluation Database
CAPM alpha	The alpha coefficient from the CAPM model calculated using daily returns in the current month.	CSMAR Fund Evaluation Database
Treynor index	Fund's Treynor index calculated using daily returns in the current month.	CSMAR Fund Evaluation Database
CL-Model bear market timing	Chang and Lewellen (1984)'s measure of the fund's market timing ability in bear markets.	CSMAR Fund Evaluation Database
CL-Model bull market timing	Chang and Lewellen (1984)'s measure of the fund's market timing ability in bull markets.	CSMAR Fund Evaluation Database
CL-Model stock selection	Chang and Lewellen (1984)'s measure of stock selection ability.	CSMAR Fund Evaluation Database

Figure 1. Illustration of Fund Ranking Information Available to Investors on the platform

Fund rankings on the platform are displayed as “infinite scrolls”. As users scroll down the list, more funds instantly appear at the bottom. Users can choose to rank funds by their past 1-month, 3-month or 6-month returns, shown in panels A, B, and C, respectively.

A B C

Figure 2. Illustration of Fund Manager Information Available to Investors on the platform

Panels A and B show the profile pages for a female and a male fund manager, respectively, on the platform. Each panel shows the manager's profile image, tenure, and reviews. Panel C shows the ranking of the historical performance of a fund on the platform by its past 1-, 3-, 6-, and 12-month returns.

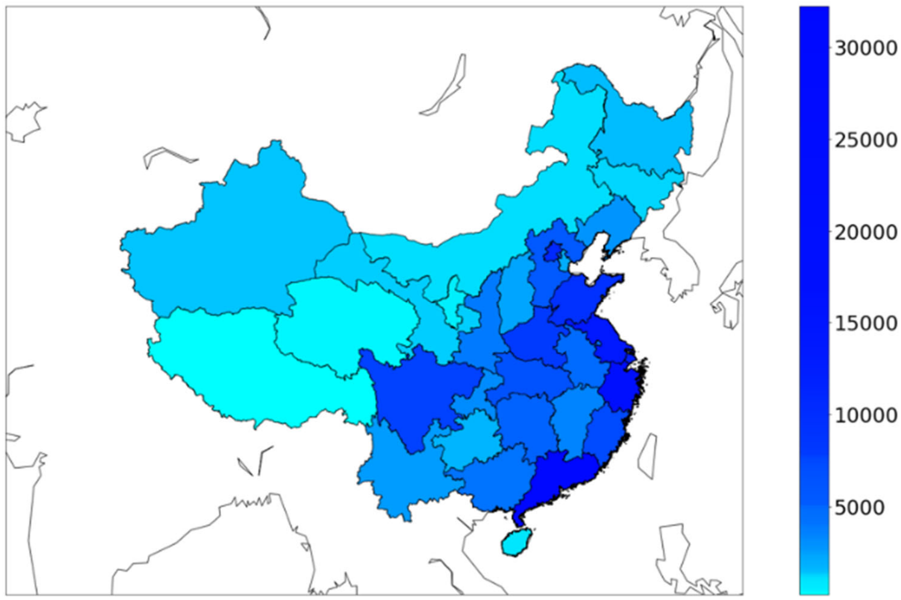
A

B

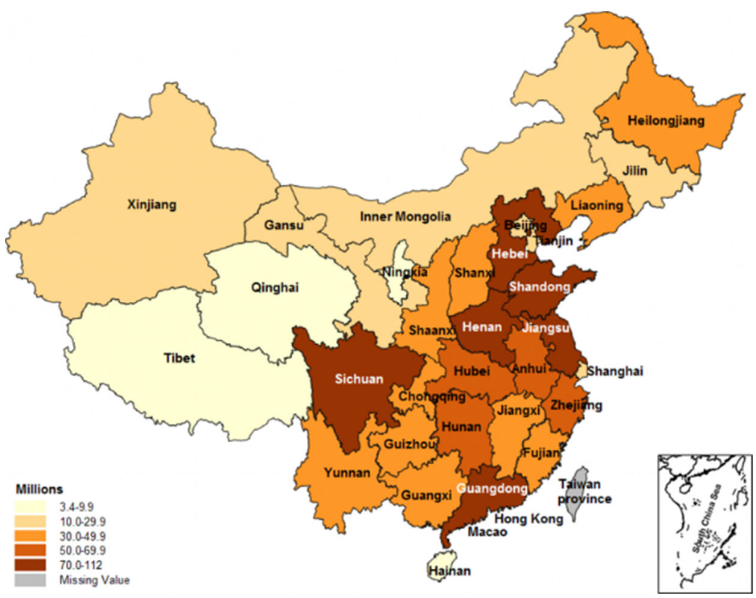
C

Figure 3. Geographic Distribution of Stock Fund Users

Panel A shows the geographic distribution of the number of stock fund users in mainland China provided by the tech platform. The deeper the color, the more users there are in the province relative to other provinces. Panel B shows the geographic distribution of the population in China.[13] The deeper the color, the higher the number of people who reside in the province relative to other provinces.



A



B

[13] Source: United Nations Children's Emergency Fund. URL: https://www.unicef.cn/en/figure-13-population-density-province-2017

Table 1. Sample Descriptive Statistics

This table reports summary statistics for the funds, users, and managers. Panel A reports the mean, standard deviation, and the number of observations for fund and manager characteristics. Panel B reports the mean, standard deviation, and the number of observations for the platform users' fund investments and characteristics, respectively. All fees, fund amounts, user monthly capital gain/loss, and user monthly spending amount are in CNY. Return ranks are in percentiles.

Panel A.1 Fund characteristics

	Entire sample		**Male Managers**		**Female Managers**		**Two Sample T-test**
	N (Fund-Months) = 3,515		**N (Fund-Months) = 2,924**		**N (Fund-Month) = 591**		
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**p-value**
Fund 1-month NAV return rank	0.51	0.29	0.50	0.29	0.53	0.27	0.02
Fund 3-month NAV return rank	0.51	0.29	0.50	0.29	0.54	0.28	0.01
Fund 6-month NAV return rank	0.51	0.29	0.50	0.29	0.54	0.29	0.00
Fund 12-month NAV return rank	0.51	0.29	0.49	0.29	0.56	0.29	0.00
Fund Flow	0.67	10.64	0.69	10.81	0.50	9.12	0.00
Fund TNA (thousands CNY)	981,601.40	1,388,371.00	1,022,803.00	1,462,619.00	777,752.60	912,182.50	0.00
Fund age (Months)	41.15	20.26	40.98	18.59	41.99	27.05	0.27
Manager tenure (in years)	2.12	1.35	2.19	1.38	1.70	1.08	0.00
Sales fee	0.01%	0.00	0.01%	0.00	0.02%	0.00	0.00
Management fee	1.69%	0.01	1.71%	0.01	1.57%	0.00	0.00
Transaction fee	1.04%	0.01	1.07%	0.01	0.89%	0.01	0.00
Media mention frequency (rank)	0.11	0.28	0.11	0.28	0.08	0.23	0.00
Positive mention frequency rank	0.10	0.27	0.11	0.28	0.08	0.23	0.01
Negative mention frequency rank	0.03	0.14	0.04	0.15	0.02	0.09	0.01

Panel A.2 Fund objectives

Variable	Entire sample	Male Managers	Female Managers	
	Fund-Month Count	Fund-Month Count	Fund-Month Count	Percentage
Fund Objective - Appreciation	1,704	1,484	220	12.91%
Fund Objective - Stable Growth	307	263	44	14.33%
Fund Objective - Growth	767	572	195	25.42%
Fund Objective - Income	737	605	132	17.91%

Panel A.3. Manager education (fund-month counts)

	Entire sample	Male Managers	Female Managers
Manager Degree - Undergraduate	86	86	0
Manager Degree - Master	3,459	2,924	535
Manager Degree - MBA / EMBA	36	36	0
Manager Degree - Doctoral	331	265	66

Panel B. User data

Variable	Entire sample N (User-Months) = 2,345,875		Male Users N (User-Months) = 2,090,157		Female Users N (User-Months) = 255,718		Two Sample T-test
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	p-value
Fund Amount	5,893.31	24,928.60	5,963.80	25,308.92	5,317.15	21,561.50	0.00
Fund Flow	0.67	10.66	0.69	10.83	0.51	9.13	0.00
User Monthly Capital Gain/Loss (CNY)	-3.94	1,546.76	-4.01	1,575.02	-3.36	1,292.82	0.84
User Monthly Spending Amount (thousands CNY)	5.30	20.07	5.31	20.39	5.27	17.20	0.33
User Age	32.40	8.31	32.41	8.32	32.36	8.22	0.01
User City Size	2.43	1.25	2.43	1.25	2.44	1.26	0.00
User Risk Tolerance	3.16	1.06	3.16	1.06	3.19	1.06	0.00

Table 2

This table reports coefficients from panel-OLS regressions for the effect of funds' prior months' performance on users' current month fund flow for the period between August 2017 to July 2019. In Panel A, the dependent variable is each user's fund flow, defined as the difference between the user's current month fund amount and the prior month fund amount (adjusting for capital gains or losses), divided by previous month fund amount. The 1-, 3-, 6-, and 12-month return rankings are the fund's NAV return over the respective 1-, 3-, 6- and 12-months ranked into percentiles. Columns 1-2 use the funds' prior month NAV return ranked within funds with the same fund objective as the measure of fund performance. Columns 3-5 use the funds' past 3-, 6- and 12- NAV returns ranked within funds with the same fund objective as the measure of fund performance, respectively. The rolling average spending over the past 6 months is computed as the rolling average of each user's spending on the fintech platform over the past 6 months and the rolling spending deviation over the prior 6 months is the standard deviation of each user's spending on the fintech platform over the past 6 months. Both the rolling average and rolling standard deviations are standardized to avoid extremely large or extremely small coefficients. Panel B reports coefficients for the effects of previous-quarter fund performance on quarterly level fund flows. Fund flows are aggregated at the quarterly level and are winsorized at the 99% level. All other variables are defined in the Appendix. The panel-OLS regressions in Panel A include user, month, fund objective and manager degree fixed effects, whose coefficients are suppressed. The panel-OLS regressions in Panel B include fund, month, fund objective and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, clustered at the user level in Panel A and at the fund level in Panel B, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Fund flow sensitivity to performance at the individual investor level

	Lagged alternative performance measures (Independent Variables) Return ranking over				
	1-month	1-month	3-month	6-month	12-month
	(1)	(2)	(3)	(4)	(5)
Fund performance					
Fund performance ranking	0.3562 ***	0.3559 ***	0.4589 ***	0.4881 ***	0.2652 ***
	(0.0251)	(0.0251)	(0.0262)	(0.0286)	(0.0302)
Managerial characteristics					
Manager gender (Female)		0.0296	0.0142	-0.0078	0.0186
		(0.0284)	(0.0284)	(0.0285)	(0.0294)
Manager tenure	0.0447 ***	0.0464 ***	0.0443 ***	0.0386 ***	0.0406 ***
	(0.0066)	(0.0070)	(0.0070)	(0.0070)	(0.0071)
Fund characteristics					
Fund risk (Previous month)	0.3588 ***	0.3596 ***	0.3714 ***	0.3567 ***	0.4490 ***
	(0.0314)	(0.0314)	(0.0312)	(0.0314)	(0.0329)

Log(Fund age)	0.0245	0.0182	0.0257	0.0388	0.0355
	(0.0282)	(0.0292)	(0.0292)	(0.0295)	(0.0334)
Log(TNA) (previous quarter)	0.0504 ***	0.0521 ***	0.0530 ***	0.0386 ***	0.0303 ***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0095)
Aggregate fund flow (previous quarter)	-0.0214 ***	-0.0214 ***	-0.0244 ***	-0.0296 ***	0.0133
	(0.0038)	(0.0038)	(0.0037)	(0.0038)	(0.0120)
Fund sales fee (%)	0.7368 ***	0.7478 ***	0.8423 ***	0.7666 ***	0.8080 ***
	(0.2529)	(0.2529)	(0.2523)	(0.2539)	(0.2689)
Fund management fee (%)	-0.1928 ***	-0.1944 ***	-0.1535 ***	-0.1338 ***	-0.1659 ***
	(0.0199)	(0.0199)	(0.0202)	(0.0202)	(0.0207)
Fund transaction fee (%)	-0.0220	-0.0208	-0.0246	-0.0179	-0.0186
	(0.0166)	(0.0167)	(0.0167)	(0.0167)	(0.0171)
User income					
Rolling average spending in prior 6 months	0.0027	0.0027	0.0027	0.0026	0.0028
(thousands CNY)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0031)
Std dev of rolling spending levels in prior 6	-0.0024	-0.0024	-0.0024	-0.0024	-0.0024
months (thousands CNY)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0021)
Current month spending (thousands CNY)	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0011 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Fixed Effects					
Month	TRUE	TRUE	TRUE	TRUE	TRUE
User	TRUE	TRUE	TRUE	TRUE	TRUE
Manager Degree	TRUE	TRUE	TRUE	TRUE	TRUE
Fund Objective	TRUE	TRUE	TRUE	TRUE	TRUE
Standard Error Clustering					
User	TRUE	TRUE	TRUE	TRUE	TRUE
Base Dummy Variables					
Gender	Male	Male	Male	Male	Male
R^2 (Within)	0.0001	0.0002	0.0003	0.0002	-0.0001
N	2,272,010	2,272,010	2,272,010	2,268,451	2,197,949

Panel B. Fund flow sensitivity to performance at the aggregate fund level

	Dependent Variable
	Quarterly Level Fund Flow
	(1)
Fund performance	
Fund previous quarter return ranking	0.1301***
	(0.0303)
Managerial characteristics	
Manager gender (Female)	-0.0680
	(0.0989)
Manager tenure	0.0122
	(0.0117)
Fund characteristics	
Fund risk (Previous month)	0.1951***
	(0.0700)
Log(TNA) (previous quarter)	-0.3369***
	(0.0722)
Aggregate fund flow (previous quarter)	-0.0017
	(0.0575)
Fund sales fee (%)	-1.8038***
	(0.6228)
Fund management fee (%)	-0.0228***
	(0.0077)
Fund transaction fee (%)	-0.0456***
	(0.0173)
Fixed Effects	
Month	TRUE
Fund	TRUE
Manager Degree	TRUE
Standard Error Clustering	
Fund	TRUE
Base Dummy Variables	
Gender	Male
R^2 (Within)	0.1258
N	2,005

Table 3

This table reports coefficients from logistic regressions for first-time fund investors on the fintech platform. The dependent variable is the gender of the fund manager when the investor invests for the first time. Column (1) includes only regressors that describe user characteristics. Column (2) includes only regressors that describe fund characteristics. Column (3) includes regressors that both describe fund and user characteristics. All variables are defined in the Appendix. All models include fund objective fixed effects, whose coefficients are suppressed. Model 2 also includes manger degree fixed effects. Standard errors, which are heteroskedasticity robust, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Fund performance		
Fund prior 1-month NAV return rank	-0.3347 ***	-0.4617 ***
	(0.0290)	(0.0380)
Managerial characteristics		
Manager tenure		-0.7833 ***
		(0.0110)
Fund characteristics		
Fund risk (Previous month)		-0.0722 ***
		(0.0220)
Log(Fund age)		0.4525 ***
		(0.0400)
Log(TNA) (previous quarter)		-0.2684 ***
		(0.0090)
Aggregate fund flow (previous quarter)		-0.2868 ***
		(0.0130)
Fund sales fee (%)		-1.1532 **
		(0.5496)
Fund management fee (%)		0.3031 ***
		(0.0228)
Fund transaction fee (%)		-1.6371 ***
		(0.0505)
User characteristics		
User age	-0.0038 ***	-0.0034 **
	(0.0010)	(0.0010)
User city tier	0.0186 **	0.0300 ***
	(0.0070)	(0.0080)
User risk band	-0.0139	-0.0166
	(0.0090)	(0.0100)
User gender	-0.0342 *	-0.0218
	(0.0200)	(0.0220)
Fintech platform income (High)	-0.0227	-0.031
	(0.0290)	(0.0320)
Fintech platform income (Low)	0.1041	0.1135
	(0.0780)	(0.0830)
Rolling average spending in prior 6 months (thousands CNY)	-0.0023	-0.0018
	(0.0020)	(0.0020)
Std dev of rolling spending levels in prior 6 months (thousands CNY)	0.0014	0.001
	(0.0010)	(0.0020)
Current month spending (thousands CNY)	-0.0017 *	-0.0016 *
	(0.0010)	(0.0010)
Pseudo R^2	0.07929	0.2045
N	142,587	139,565

Table 4

This table reports coefficients from panel-OLS regressions for the period between August 2017 to July 2019. In Panel A, the dependent variable is the user's fund flow, defined as the difference between the user's current month fund amount and the prior month fund amount (adjusting for capital gains or losses), divided by previous month fund amount. The 1-, 3-, 6-, and 12-month return rankings are the fund's NAV return over the respective 1-, 3-, 6- and 12-months ranked into percentiles. Column (1) uses funds' prior month NAV returns ranked within funds with the same fund objective as the measure of fund performance. Columns 2-4 use each fund's past 3-, 6- and 12-month NAV returns ranked within funds with the same fund objective as the measure of fund performance, respectively. Panel B Columns 1-3 report coefficients for the effect of current month's fund performance on the future 3-, 6- and 12-month performance, respectively. In Panel C, the dependent variable is each user's fund flow and we split our sample into two subsamples. The winner subsample in Column (1) consists of funds whose returns have increased in the previous month compared to two months ago, and the loser subsample in Column (2) consists of funds whose returns have decreased in the previous month compared to two months previously. Column (3) includes all funds in the sample and adds a dummy variable that indicates if the fund's performance has increased in the previous month compared to two months previously. In Panel D, the dependent variable is each user's fund flow, and we apply a piecewise regression approach. Column (1) splits funds' previous month NAV returns ranked within funds with the same fund objective into the bottom 20%, middle 60% and top 20% quintiles and apply a piecewise regression approach. Column (2) splits funds' previous month NAV returns ranked within funds with the same fund objective into the bottom 15%, middle 70% and top 15% quintiles and apply a piecewise regression approach. Column (3) splits funds' previous month NAV returns ranked within funds with the same fund objective into the bottom 10%, middle 80% and top 10% quintiles and apply a piecewise regression approach. Column (4) splits funds' previous month NAV returns ranked within funds with the same fund objective into the bottom 5%, middle 90% and top 5% quintiles and apply a piecewise regression approach. Column (5) splits funds' previous month NAV returns ranked within funds with the same fund objective into the bottom 1%, middle 98% and top 1% quintiles and apply a piecewise regression approach. All other variables are defined in the Appendix. The panel-OLS regressions in Panel A and C include user, month, fund objective, and manager degree fixed effects, whose coefficients are suppressed. The panel-OLS regressions in Panel B include fund, month and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, clustered at the user level in Panel A and C and at the fund level in Panel B, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Fund flow-performance sensitivity over different ranking horizons

	Lagged alternative performance measures (Independent Variables) Return ranking over			
	1-month	3-month	6-month	12-month
	(1)	(2)	(3)	(4)
Fund performance				
Fund performance ranking	0.3860 ***	0.4816 ***	0.5178 ***	0.2872 ***
	(0.0263)	(0.0274)	(0.0302)	(0.0317)
Fund performance × Manager gender (Female)	-0.3258 ***	-0.2520 ***	-0.2642 ***	-0.2013 ***
	(0.0781)	(0.0711)	(0.0703)	(0.0724)
Managerial characteristics				
Manager gender (Female)	0.2062 ***	0.1617 ***	0.1626 ***	0.1587 ***
	(0.0472)	(0.0459)	(0.0463)	(0.0520)
Manager tenure	0.0465 ***	0.0441 ***	0.0383 ***	0.0403 ***
	(0.0070)	(0.0070)	(0.0070)	(0.0071)
Fund characteristics				
Fund risk (Previous month)	0.3543 ***	0.3693 ***	0.3560 ***	0.4482 ***
	(0.0313)	(0.0312)	(0.0314)	(0.0329)
Log(Fund age)	0.0173	0.0229	0.0301	0.0234
	(0.0292)	(0.0292)	(0.0294)	(0.0335)
Log(TNA) (previous quarter)	0.0523 ***	0.0533 ***	0.0399 ***	0.0315 ***
	(0.0092)	(0.0092)	(0.0093)	(0.0095)
Aggregate fund flow (previous quarter)	-0.0213 ***	-0.0247 ***	-0.0302 ***	0.0126
	(0.0038)	(0.0037)	(0.0038)	(0.0120)
Fund sales fee (%)	0.7621 ***	0.8627 ***	0.7912 ***	0.8129 ***
	(0.2530)	(0.2521)	(0.2539)	(0.2688)
Fund management fee (%)	-0.1963 ***	-0.1562 ***	-0.1379 ***	-0.1642 ***
	(0.0199)	(0.0201)	(0.0203)	(0.0207)
Fund transaction fee (%)	-0.0258	-0.0294 *	-2.1647	-2.2535
	(0.0167)	(0.0167)	(0.0167)	(0.0171)
User income				
Rolling average spending in prior 6 months (thousands CNY)	0.0027	0.0027	0.0027	0.0028
	(0.0030)	(0.0030)	(0.0030)	(0.0031)
Std dev of rolling spending levels in prior 6 months (thousands CNY)	-0.0024	-0.0024	-0.0024	-0.0024
	(0.0020)	(0.0020)	(0.0020)	(0.0021)
Current month spending (thousands CNY)	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0011 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2 (Within)	0.0002	0.0003	0.0003	-0.0001
N	2,272,010	2,272,010	2,268,451	2,197,949

Panel B. Predictability of future returns based on one month return rankings

	Dependent Variables		
	Future 3-month return rank	Future 6-month return rank	Future 12-month return rank
	(1)	(2)	(3)
Manager gender (Female)	0.0435	0.0256	-0.0184
	(0.0464)	(0.0496)	(0.0625)
Fund current 1-month NAV return rank	-0.0303**	-0.0268**	-0.0496***
	(0.0126)	(0.0111)	(0.0096)
Fund current 1-month NAV return rank × Manager gender (Female)	0.0213	0.0068	0.0055
	(0.0307)	(0.0278)	(0.0209)
Fund Level Flow (Current Quarter)	0.0245*	0.0279*	0.038***
	(0.0142)	(0.0161)	(0.0142)
Manager tenure	-0.0235***	-0.02*	-0.0053
	(0.0078)	(0.0118)	(0.0161)
Fund risk (Current month)	-0.1372***	-0.1141***	-0.1035***
	(0.0232)	(0.0256)	(0.0252)
Log(TNA)	-0.0594***	-0.1066***	-0.1329***
	(0.0196)	(0.0230)	(0.0234)
Fund sales fee (%)	0.0172	-0.3700	-0.2334
	(0.3206)	(0.3185)	(0.2418)
Fund management fee (%)	-0.0146***	-0.0154***	-0.006491
	(0.0050)	(0.0059)	(0.0050)
Fund transaction fee (%)	-0.0294***	-0.0362***	-0.0291**
	(0.0098)	(0.0125)	(0.0117)
R^2 (Within)	0.0061	0.0423	0.0628
N	7,252	7,250	7,029

Panel C. Symmetry in attention bias to increases and decreases in performance

	Subsamples		
	Winners	Losers	All Funds
	(1)	(2)	(3)
Fund performance			
Fund performance ranking	0.8146 ***	0.2798 ***	0.2872 ***
	(0.0783)	(0.0305)	(0.0299)
Fund Performance × Manager gender (Female)	-0.7842 ***	-0.1926 **	-0.2014 **
	(0.1822)	(0.0952)	(0.0937)
Return increase dummy			-0.1406 ***
			(0.0327)
Return increase dummy × Manager gender (Female)			0.2157 **
			(0.0957)
Return increase dummy × Fund performance ranking			0.4819 ***
			(0.0663)
Return increase dummy × Manager gender (Female) ×			-0.5453 ***
Fund performance ranking			(0.1761)
Managerial characteristics			
Manager gender (Female)	0.5110 ***	0.1331 **	0.1560 ***
	(0.1076)	(0.0559)	(0.0543)
Manager tenure	0.0638 ***	0.0365 ***	0.0458 ***
	(0.0169)	(0.0083)	(0.0070)
Fund characteristics			
Fund risk (Previous month)	0.2717 ***	0.4365 ***	0.3609 ***
	(0.0747)	(0.0382)	(0.0314)
Log(Fund age)	-0.1323 *	0.0397	0.0061
	(0.0736)	(0.0337)	(0.0291)
Log(TNA) (previous quarter)	0.0869 ***	0.0516 ***	0.0569 ***
	(0.0232)	(0.0107)	(0.0092)
Aggregate fund flow (previous quarter)	-0.0255 **	-0.0109 **	-0.0181 ***
	(0.0099)	(0.0043)	(0.0037)
Fund sales fee (%)	0.91315	0.8585 ***	0.7888 ***
	(0.5708)	(0.3087)	(0.2525)
Fund management fee (%)	-0.2671 ***	-0.1473 ***	-0.1814 ***
	(0.0528)	(0.0227)	(0.0198)
Fund transaction fee (%)	-0.027151	-0.014163	-0.0362 **
	(0.0402)	(0.0199)	(0.0168)
User income			
Rolling average spending in prior 6 months	0.0072	0.0017	0.0027
(thousands CNY)	(0.0097)	(0.0024)	(0.0030)
Std dev of rolling spending levels in prior 6	-0.0065	-0.0015	-0.0024
months (thousands CNY)	(0.0068)	(0.0015)	(0.0020)
Current month spending (thousands CNY)	-0.0028 **	-0.0008 *	-0.0013 ***
	(0.0012)	(0.0004)	(0.0004)
R^2 (Within)	0.0012	0.0002	0.0003
N	588,136	1,752,974	2,272,010

Panel D. OLS piece-wise regression results, cut on differing levels of fund performance rankings

	Top 20% Middle 60% Bottom 20%	Top 15% Middle 70% Bottom 15%	Top 10% Middle 80% Bottom 10%	Top 5% Middle 90% Bottom 5%	Top 1% Middle 98% Bottom 1%
	1-month	1-month	1-month	1-month	1-month
	(1)	(2)	(3)	(4)	(5)
Fund performance					
Top section fund performance ranking	1.1181 ***	1.7533 ***	3.5568 ***	9.8232 ***	58.571 ***
	(0.1993)	(0.2808)	(0.4539)	(1.0383)	(6.0587)
Top section fund performance × Manager gender (Female)	-0.4203	-0.758	-1.8545	-7.3135 *	-87.979 ***
	(0.5825)	(0.8465)	(1.4706)	(3.8518)	(21.5930)
Mid-section fund performance ranking	0.2727 ***	0.2565 ***	0.2290 ***	0.2323 ***	0.2844 ***
	(0.0497)	(0.0414)	(0.0356)	(0.0305)	(0.0266)
Mid-section fund performance × Manager gender (Female)	-0.2239 *	-0.1826 *	-0.1647 *	-0.1454 *	-0.1516 *
	(0.1182)	(0.1004)	(0.0885)	(0.0813)	(0.0788)
Bottom section fund performance ranking	0.3364 *	0.3857	0.6760 *	1.7871	76.406 *
	(0.1717)	(0.2412)	(0.4085)	(1.1122)	(46.4110)
Bottom section fund performance × Manager gender (Female)	-1.0481 *	-1.8730 **	-3.0886 **	-6.7705 **	-160.36
	(0.5517)	(0.7901)	(1.3219)	(3.1512)	(203.9500)
Managerial characteristics					
Manager gender (Female)	0.3140 ***	0.3818 ***	0.4162 ***	0.4558 ***	1.7391
	(0.0932)	(0.1054)	(0.1234)	(0.1510)	(2.0327)
Manager tenure	0.0452 ***	0.0441 ***	0.0422 ***	0.0413 ***	0.0421 ***
	(0.0069)	(0.0070)	(0.0070)	(0.0070)	(0.0070)
Fund characteristics					
Return standard deviation (Previous month)	0.3287 ***	0.3224 ***	0.3190 ***	0.3133 ***	0.3170 ***
	(0.0313)	(0.0314)	(0.0315)	(0.0315)	(0.0313)
Log(Fund age)	0.0147	0.0143	0.0162	0.0176	0.0074
	(0.0290)	(0.0290)	(0.0291)	(0.0292)	(0.0292)
Log(Total Net Asset) (previous quarter)	0.0550 ***	0.0550 ***	0.0539 ***	0.0525 ***	0.0505 ***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0093)
Aggregate fund flow (previous quarter)	-0.0220 ***	-0.0222 ***	-0.0226 ***	-0.0233 ***	-0.0234 ***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Standardized fund sales fee	78.527 ***	78.794 ***	78.354 ***	80.097 ***	78.454 ***
	(25.2880)	(25.2840)	(25.2750)	(25.2850)	(25.2990)
Standardized fund management fee	-20.409 ***	-20.519 ***	-20.415 ***	-20.890 ***	-21.516 ***
	(2.0020)	(2.0034)	(2.0040)	(2.0003)	(1.9935)
Standardized fund transaction fee	-2.4102	-2.4935	-2.6424	-2.1544	-1.166
	(1.6706)	(1.6725)	(1.6738)	(1.6730)	(1.6661)
User income					
Rolling average spending in prior 6 months (thousands CNY)	0.0027	0.0027	0.0027	0.0027	0.0027
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Std dev of rolling spending levels in prior 6 months (thousands CNY)	-0.0024	-0.0024	-0.0024	-0.0024	-0.0024
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Current month spending (thousands CNY)	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0013 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)

R^2 (Within)	0.0003	0.0003	0.0003	0.0004	0.0004
N	2,272,010	2,272,010	2,272,010	2,272,010	2,272,010

Table 5

This table reports coefficients from panel-OLS regressions for a placebo regression where we randomly assign managerial gender (male and female) to funds in our data in the ratio of 9:1 (approximately the actual ratio of male vs female managers). All other variables are defined in the Appendix. The panel-OLS regressions include user, month, fund objective, and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, clustered at the user level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	1-month performance
Fund performance	
Fund performance ranking	0.3538 ***
	(0.0265)
Fund Performance × Placebo Manager gender (Female)	0.0237
	(0.0809)
Managerial characteristics	
Placebo manager gender (Female)	0.0079
	(0.0425)
Manager tenure	0.0466 ***
	(0.0066)
Fund characteristics	
Fund risk (Previous month)	0.3571 ***
	(0.0314)
Log(Fund age)	0.0088
	(0.0279)
Log(TNA) (previous quarter)	0.0512 ***
	(0.0091)
Aggregate fund flow (previous quarter)	-0.0214 ***
	(0.0038)
Fund sales fee (%)	77.674 ***
	(25.2330)
Fund management fee (%)	-19.662 ***
	(1.9861)
Fund transaction fee (%)	-3.0001 *
	(1.6454)
User income	
Rolling average spending in prior 6 months (thousands CNY)	0.0027
	(0.0030)
Std dev of rolling spending levels in prior 6 months	-0.0024
(thousands CNY)	(0.0020)
Current month spending (thousands CNY)	-0.0013 ***
	(0.0004)
R^2 (Within)	0.0002
N	2,272,010

Table 6

This table reports coefficients from panel-OLS regressions for the effect of funds' prior months' Jensen's alpha ranks or average daily return ranks on users' current month fund flow for the period between August 2017 to July 2019. The dependent variable is each user's fund flow, defined as the difference between the user's current month fund amount and the prior month fund amount, divided by previous month fund amount. Column (1) and (2) use funds' prior month Jensen's alpha ranked within funds with the same fund objective as the measure of fund performance. Column (3) and (4) use funds' previous month daily returns ranked within funds with the same fund objective as the measure of fund performance. The rolling average spending in the past six months is computed as the rolling average of each user's spending on the fintech platform over the past 6 months and the rolling spending deviation over the prior 6 months is the standard deviation of each user's spending on the fintech platform over the past 6 months. Both the rolling average and rolling standard deviations are standardized to avoid extremely large or extremely small coefficients. All other variables are defined in the Appendix. All models include user, month, fund objective, and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male while the base manager degree level is an undergraduate degree. Standard errors, which are clustered at the user level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Lagged alternative performance measures (Independent Variables)			
	Jensen's Alpha ranking		Average return ranking	
	(1)	(2)	(3)	(4)
Fund performance				
Fund performance	0.3717 ***	0.4031 ***	0.3320 ***	0.3626 ***
	(0.0250)	(0.0262)	(0.0244)	(0.0257)
Fund Performance × Manager gender (Female)		-0.3365 ***		-0.3051 ***
		(0.0758)		(0.0714)
Managerial characteristics				
Manager gender (Female)	0.0294	0.2126 ***	0.0329	0.2006 ***
	(0.0284)	(0.0461)	(0.0284)	(0.0438)
Manager tenure	0.0468 ***	0.0468 ***	0.0467 ***	0.0471 ***
	(0.0070)	(0.0070)	(0.0070)	(0.0070)
Fund characteristics				
Fund risk (Previous month)	0.3474 ***	0.3420 ***	0.3299 ***	0.3254 ***
	(0.0314)	(0.0314)	(0.0315)	(0.0314)
Log(Fund age)	0.0168	0.0153	0.0197	0.0169
	(0.0292)	(0.0292)	(0.0293)	(0.0292)
Log(TNA) (previous quarter)	0.0539 ***	0.0542 ***	0.0517 ***	0.0524 ***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)
Aggregate fund flow (previous quarter)	-0.0232 ***	-0.0234 ***	-0.0231 ***	-0.0234 ***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Fund sales fee (%)	0.7483 ***	0.7629 ***	0.7260 ***	0.7407 ***
	(0.2529)	(0.2529)	(0.2529)	(0.2530)
Fund management fee (%)	-0.1908 ***	-0.1925 ***	-0.1932 ***	-0.1948 ***
	(0.0199)	(0.0199)	(0.0199)	(0.0199)
Fund transaction fee (%)	-0.021807	-0.026806	-0.023738	-0.0279 *
	(0.0167)	(0.0167)	(0.0167)	(0.0167)
User income				
Rolling average spending in prior 6 months	0.0027	0.0027	0.0027	0.0027
(thousands CNY)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Std dev of rolling spending levels in prior 6 months	-0.0024	-0.0024	-0.0024	-0.0024
(thousands CNY)	(0.0020)	(0.0020)	(0.0020)	(0.0020)

Current month spending (thousands CNY)	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0013 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2 (Within)	0.0002	0.0002	0.0002	0.0002
N	2,272,010	2,272,010	2,272,010	2,272,010

Table 7

This table reports coefficients for the effect of managerial gender on fund performance for the period between August 2017 to July 2019. The dependent variables are various measures of fund performance. Column (1) uses the funds' current month NAV returns ranked within funds with the same fund objective as the dependent variable. Column 2-4 use the funds' current 3-, 6-, and 12-month NAV returns ranked within funds with the same fund objective as dependent variables, respectively. Column (5) uses funds' current-month daily return standard deviation as the dependent variable. Column (6) uses funds' current-month Sharpe ratio as the dependent variable. Column 7-8 uses funds' current-month CAPM beta and alpha as dependent variables. Column (9) uses funds' Treynor index as the dependent variable. Column 10-11 use funds' TM model market timing ability and stock selection ability as dependent variables. Column 12-15 use funds' CL model market timing and stock selection ability as dependent variables. All other variables are defined in the Appendix. All models include fund, month, and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, which are clustered at the fund level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Fund manager performance regressions

	Dependent Variables							
	1-month return ranking	3-month return ranking	6-month return ranking	12-month return ranking	Return Std. Dev.	Sharpe Ratio	CAPM Beta	CAPM Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manager gender (Female)	0.0424*	0.0767	0.0449	-0.0351	-0.0701	0.0099	-0.0212	-0.0017
	(0.0239)	(0.0493)	(0.0647)	(0.0722)	(0.0812)	(0.0161)	(0.0721)	(0.0158)
Log(TNA) (previous quarter)	-0.0517***	-0.0796***	-0.0476***	0.035	0.0262	-0.0222***	0.0364	-0.0314***
	(0.0143)	(0.0178)	(0.0166)	(0.0260)	(0.0319)	(0.0085)	(0.0288)	(0.0080)
Aggregate fund flow (previous quarter)	-0.0014	0.0255*	0.0913***	0.0618***	0.0187	0.0018	-0.0196	-0.0036
	(0.0118)	(0.0155)	(0.0176)	(0.0174)	(0.0177)	(0.0065)	(0.0160)	(0.0060)
Manager tenure	-0.0182***	-0.0252***	-0.0322***	-0.0384***	0.0081	-0.0115***	-0.0052	-0.0099***
	(0.0051)	(0.0072)	(0.0094)	(0.0114)	(0.0091)	(0.0022)	(0.0081)	(0.0026)
Fund risk (Previous Month)	-0.0653***	0.0314	0.0995***	0.1686***				
	(0.0189)	(0.0247)	(0.0235)	(0.0267)				
Fund sales fee (%)	0.338597	0.010095	-0.422233	0.247107	0.316774	0.158524	0.1126	0.26023
	(0.2839)	(0.3673)	(0.3607)	(0.5159)	(0.6907)	(0.2572)	(0.4702)	(0.2181)
Fund management fee (%)	-0.0083*	-0.0165***	-0.0185***	-0.0758**	-0.003582	0.0069**	-0.0112***	-0.003043
	(0.0050)	(0.0064)	(0.0068)	(0.0325)	(0.0027)	(0.0032)	(0.0029)	(0.0024)
Fund transaction fee (%)	-0.0214***	-0.0388***	-0.0584***	-0.023901	0.01552	-0.0183***	0.0275***	-0.0167***
	(0.0082)	(0.0133)	(0.0146)	(0.0208)	(0.0116)	(0.0031)	(0.0104)	(0.0041)
R^2 (Within)	0.0094	0.0338	0.0472	0.0203	-0.0006	0.0127	0.0174	0.0123
N	6,424	6,424	6,405	5,913	6,424	6,424	6,424	6,424

Fund manager performance regressions (continued)

	Dependent Variables						
	Treynor Index	TM-Model Market Timing	TM-Model Stock Selection	CL-Model Bear Market Timing	CL-Model Bull Market Timing	CL-Model Market Timing	CL-Model Stock Selection
	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Manager gender (Female)	0.6975	0.0449	0.0108	-0.0325	-0.0074	0.0251	0.0124
	(0.6593)	(0.0273)	(0.0147)	(0.0913)	(0.0679)	(0.0755)	(0.0202)
Log(TNA) (previous quarter)	-0.1875	0.0073	-0.0332***	0.0577*	0.032	-0.0257	-0.0279**
	(0.1957)	(0.0164)	(0.0091)	(0.0349)	(0.0275)	(0.0326)	(0.0118)
Aggregate fund flow (previous quarter)	-0.0094	-0.0063	-0.0117*	-0.0261	-0.0023	0.0238	-0.0165*
	(0.0720)	(0.0109)	(0.0070)	(0.0203)	(0.0206)	(0.0250)	(0.0092)
Manager tenure	0.0594	-0.0025	-0.0098***	-0.0006	-0.0049	-0.0043	-0.0101**
	(0.0417)	(0.0059)	(0.0028)	(0.0121)	(0.0087)	(0.0134)	(0.0040)
Standardized fund sales fee (%)	0.940788	0.327851	0.2527*	-0.09152	0.194437	0.285952	0.268855
	(2.7052)	(0.2369)	(0.1515)	(0.3778)	(0.6505)	(0.3991)	(0.1636)
Standardized fund management fee (%)	-0.2279***	-0.006065	-0.002134	-0.007477	-0.0119***	-0.004459	-0.0026*
	(0.0326)	(0.0052)	(0.0016)	(0.0079)	(0.0042)	(0.0115)	(0.0014)
Standardized fund transaction fee (%)	0.04102	0.000956	-0.0167***	0.0430***	0.018296	-0.02473	-0.0134***
	(0.0296)	(0.0108)	(0.0041)	(0.0138)	(0.0139)	(0.0174)	(0.0051)
R^2 (Within)	0.0339	0.0020	0.0060	0.0153	0.0026	0.0044	0.0010
N	6,424	6,424	6,424	6,424	6,424	6,424	6,424

Table 8

This table reports coefficients from Propensity-Score-Matching (PSM) regressions for the effects of funds' prior month performance and manager gender on users' current month fund flow for the period between August 2017 to July 2019. Panel A reports the propensity score matching logistic regression pre-matching, where the dependent variable equals 1 if the fund manager is female and 0 if the fund manager is male. Fund objective fixed effects and an intercept are included. Panel B reports pre- and post-match sample covariate balance tests. Panel C reports the post-match panel-OLS regression results, where each female manager is matched to a male manager. Panel C Columns 1-4 report coefficient results when 1-, 3-, 6-, and 12-month fund return ranks are used as fund performance measures, respectively. Manager degree (Undergraduate) is a dummy variable that equals 1 if the fund manager only has an undergraduate degree (or equivalently, do not have a degree equivalent to a master's degree or higher). All other variables are defined in the Appendix. The base gender dummy variable is male. All models in Panel C include fund, month, and manager degree fixed effects, whose coefficients are suppressed. Standard errors in panel C, which are clustered at the user level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Pre-match propensity score regression

	Manager gender
Fund performance	
Fund prior 1-month NAV return rank	0.0606
	(0.1900)
Fund prior 3-month NAV return rank	0.0578
	(0.2470)
Fund prior 6-month NAV return rank	-0.2484
	(0.2820)
Fund prior 12-month NAV return rank	0.6896 ***
	(0.2280)
Fund characteristics	
Fund risk (Previous month)	-0.4415 ***
	(0.1030)
Log(Fund age)	0.8659 ***
	(0.1420)
Log(TNA) (previous quarter)	-0.1300 ***
	(0.0370)
Aggregate fund flow (previous quarter)	0.0405
	(0.0540)
Fund sales fee (%)	1.272255
	(0.8695)
Fund management fee (%)	-0.034297
	(0.0691)
Fund transaction fee (%)	-0.3559 ***
	(0.0827)
Managerial characteristics	
Manager tenure	-0.2716 ***
	(0.0360)
Manager degree (Undergraduate)	-17.5518 ***
	(0.2220)
N	3,512
Pseudo R^2	0.0724

Panel B: T-tests: Covariate balance

	Pre				Post			
	Male	Female	Difference	Two-sample t-test P-value	Male	Female	Difference	Two-sample t-test P-value
Fund performance								
Fund prior 1-month NAV return rank	0.50	0.53	-0.03	0.02	0.55	0.53	0.02	0.31
Fund prior 3-month NAV return rank	0.50	0.53	-0.03	0.01	0.52	0.53	-0.01	0.48
Fund prior 6-month NAV return rank	0.50	0.54	-0.04	0.01	0.53	0.54	0.00	0.80
Fund prior 12-month NAV return rank	0.49	0.56	-0.06	0.00	0.56	0.56	0.00	0.79
Fund characteristics								
Fund risk (Previous month)	1.43	1.36	0.07	0.00	1.37	1.36	0.02	0.47
Log(Fund age)	3.65	3.62	0.03	0.09	3.58	3.62	-0.04	0.16
Log(TNA) (previous quarter)	19.89	19.60	0.30	0.00	19.48	19.60	-0.12	0.24
Aggregate fund flow (previous quarter)	0.03	0.08	-0.05	0.25	0.06	0.08	-0.02	0.60
Fund sales fee	0.01%	0.02%	0.00	0.00	0.02%	0.02%	0.00	0.92
Fund management fee	1.71%	1.57%	0.00	0.00	1.55%	1.57%	0.00	0.66
Fund transaction fee	1.07%	0.89%	0.00	0.00	0.85%	0.89%	0.00	0.35
Managerial characteristics								
Manager tenure	2.44	1.99	0.45	0.00	2.0199	1.9889	0.03	0.66
Undergraduate degree (Count)	69	0	69.00		590	590	0.00	

Panel C. Regression estimates, post-matching

	Lagged alternative performance measures (Independent Variables)			
	Fund prior 1-month NAV return rank	Fund prior 3-month NAV return rank	Fund prior 6-month NAV return rank	Fund prior 12-month NAV return rank
	(1)	(2)	(3)	(4)
Fund performance				
Fund performance ranking	0.3721 ***	0.6278 ***	0.9451 ***	0.3145 ***
	(0.0749)	(0.0877)	(0.1109)	(0.0979)
Fund Performance × Manager gender (Female)	-0.1952 *	-0.3143 ***	-0.5170 ***	-0.2114 *
	(0.1108)	(0.1164)	(0.1242)	(0.1189)
Managerial characteristics				
Manager gender (Female)	0.0954	0.1622 **	0.2470 ***	0.1275
	(0.0724)	(0.0783)	(0.0806)	(0.0881)
Manager tenure	0.0815 ***	0.0784 ***	0.0621 ***	0.0824 ***
	(0.0171)	(0.0173)	(0.0177)	(0.0172)
Fund characteristics				
Fund risk (Previous month)	0.2197 ***	0.1531 **	0.1454 *	0.2639 ***
	(0.0780)	(0.0771)	(0.0777)	(0.0790)
Log(Fund age)	-0.2046 ***	-0.1972 ***	-0.1765 ***	-0.1575 **
	(0.0643)	(0.0638)	(0.0636)	(0.0638)
Log(TNA) (previous quarter)	0.0698 ***	0.0745 ***	0.0659 ***	0.0544 **
	(0.0226)	(0.0225)	(0.0226)	(0.0227)
Aggregate fund flow (previous quarter)	-0.0469	-0.0431	-0.1032 **	-0.043
	(0.0416)	(0.0407)	(0.0426)	(0.0410)
Fund sales fee (%)	-0.16025	0.001715	-0.12596	-0.22429
	(0.5620)	(0.5637)	(0.5640)	(0.5650)
Fund management fee (%)	-0.1896 ***	-0.1321 **	-0.0861	-0.1767 ***
	(0.0547)	(0.0548)	(0.0554)	(0.0540)
Fund transaction fee (%)	0.01188	-0.012067	-0.000244	0.002672
	(0.0508)	(0.0508)	(0.0499)	(0.0500)
User income				
Rolling average spending in prior 6 months	-0.002	-0.002	-0.002	-0.0019
(thousands CNY)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Std dev of rolling spending levels in prior 6	0.0024	0.0025	0.0025	0.0024
months (thousands CNY)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Current month spending (thousands CNY)	-0.0013	-0.0013 *	-0.0014 *	-0.0013
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
R^2 (Within)	0.0004	0.0008	0.0010	0.0003
N	676,270	676,270	676,270	676,270

Table 9

This table reports coefficients from panel-OLS regressions for the period between August 2017 to July 2019, controlling for the frequency of media mentions of fund managers' names. The dependent variable is the user's fund flow. Media mention frequency rank is the ranking of the number of times each manager's name is mentioned in the news in each month. Positive mention frequency rank is the ranking of the number of times each manager's name is positively mentioned in the news in each month. Negative mention frequency rank is the ranking of the number of times each manager's name is negatively mentioned in the news in each month. Media mention frequency × manager gender (Female) is the interaction term between media mention frequency rank and the gender of the fund manager. Negative (positive) mention frequency rank × manager gender (Female) × Fund Performance is the triple interaction term of negative (positive) mention frequency, the gender of the fund manager and fund performance. All other variables are defined in the Appendix. The panel-OLS regressions include user, month, fund objective, and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, clustered at the user level in Panel A and C and at the fund level in Panel B, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Lagged alternative performance measures (Independent Variables) Return ranking over			
	1-month	1-month	1-month	1-month
	(1)	(2)	(3)	(4)
Media				
Media mention frequency rank	0.2537 ***			
	(0.0269)			
Media mention frequency rank × Manager gender (Female)	-0.3727 ***			
	(0.0721)			
Negative mention frequency rank		-0.1867 ***	-0.0871	-0.0906
		(0.0445)	(0.0608)	(0.0631)
Positive mention frequency rank		0.2366 ***	-0.1292 ***	-0.1431 ***
		(0.0269)	(0.0452)	(0.0466)
Negative mention frequency rank × Fund Performance			0.0279	-0.0133
			(0.1519)	(0.1576)
Positive mention frequency rank × Fund Performance			0.6780 ***	0.7766 ***
			(0.0824)	(0.0868)
Manager gender (Female) × Negative mention frequency rank × Fund Performance				0.539
				(0.3970)
Manager gender (Female) × Positive mention frequency rank × Fund Performance				-1.2285 ***
				(0.3128)
Fund performance				
Fund performance ranking	0.3965 ***	0.3797 ***	0.2384 ***	0.2169 ***
	(0.0265)	(0.0268)	(0.0290)	(0.0292)
Fund Performance × Manager gender (Female)	-0.2920 ***	-0.3206 ***	-0.2700 ***	-0.0367
	(0.0779)	(0.0781)	(0.0779)	(0.0831)
Managerial characteristics				
Manager gender (Female)	0.2525 ***	0.2012 ***	0.1691 ***	0.1112 **
	(0.0480)	(0.0471)	(0.0471)	(0.0494)
Manager tenure	0.0499 ***	0.0505 ***	0.0508 ***	0.0529 ***
	(0.0070)	(0.0070)	(0.0070)	(0.0070)

Fund characteristics				
Fund risk (Previous month)	0.3364 ***	0.3272 ***	0.3162 ***	0.3116 ***
	(0.0312)	(0.0311)	(0.0312)	(0.0314)
Log(Fund age)	0.0287	0.0343	0.0271	0.0234
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Log(TNA) (previous quarter)	0.0389 ***	0.0415 ***	0.0411 ***	0.0408 ***
	(0.0093)	(0.0093)	(0.0093)	(0.0093)
Aggregate fund flow (previous quarter)	-0.0198 ***	-0.0199 ***	-0.0208 ***	-0.0209 ***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Fund sales fee (%)	0.7884 ***	0.7971 ***	0.7277 ***	0.7173 ***
	(0.2529)	(0.2529)	(0.2532)	(0.2530)
Fund management fee (%)	-0.1855 ***	-0.1834 ***	-0.1810 ***	-0.1825 ***
	(0.0200)	(0.0200)	(0.0200)	(0.0201)
Fund transaction fee (%)	-0.022198	-0.02312	-0.016431	-0.019658
	(0.0167)	(0.0167)	(0.0167)	(0.0167)
User income				
Rolling average spending in prior 6 months	0.0027	0.0027	0.0027	0.0027
(thousands CNY)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Std dev of rolling spending levels in prior 6	-0.0024	-0.0024	-0.0024	-0.0024
months (thousands CNY)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Current month spending (thousands CNY)	-0.0013 ***	-0.0013 ***	-0.0013 ***	-0.0013 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2 (Within)	0.0004	0.0004	0.0005	0.0006
N	2,272,010	2,272,010	2,272,010	2,272,010

Table 10

This table reports coefficients from panel-OLS regressions for the effects of funds' prior month performance and manager gender on users' current month fund flow for different subsamples. Column (1) reports coefficients where the triple-interaction term is fund performance × manager gender (female) × investor gender. Column (2) reports coefficients where the triple-interaction term is fund performance × manager gender (female) × investor age. Column (3) reports coefficients where the triple-interaction term is fund performance × manager gender (female) × investor city size. Column (4) reports coefficients where the triple-interaction term is fund performance × manager gender (female) × investor risk aversion. All other variables are defined in the Appendix. All models include user income, month, fund objective and manager degree fixed effects, whose coefficients are suppressed. Standard errors, which are clustered at the user level, are reported in parentheses. The base gender dummy variable is male. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	User Characteristics (Triple Interaction Variables)			
	(1)	(2)	(3)	(4)
User characteristics				
User gender	-0.1966 ***	-0.3200 ***	-0.3200 ***	-0.3222 ***
	(0.0234)	(0.0162)	(0.0162)	(0.0163)
Fund performance × User gender	-0.2495 ***			
	(0.0458)			
Fund performance × User gender × Manager gender (Female)	0.1319 *			
	(0.0696)			
User age	0.0097 ***	0.0044 ***	0.0097 ***	0.0093 ***
	(0.0011)	(0.0015)	(0.0011)	(0.0011)
Fund performance × User age		0.0105 ***		
		(0.0029)		
Fund performance × User age × Manager gender (Female)		-0.0031		
		(0.0043)		
User city tier	0.0371 ***	0.0371 ***	0.0204 *	0.0363 ***
	(0.0070)	(0.0070)	(0.0105)	(0.0070)
Fund performance × User city tier			0.0382 *	
			(0.0199)	
Fund performance × User city tier × Manager gender (Female)			-0.0581 **	
			(0.0285)	
User risk band	0.0075	0.0077	0.0075	-0.0044
	(0.0087)	(0.0087)	(0.0087)	(0.0132)
Fund performance × User risk band				0.0081
				(0.0240)
Fund performance × User risk band × Manager gender (Female)				0.0116
				(0.0354)
Fund performance				
Fund performance	0.4897 ***	0.0603	0.3094 ***	0.3749 ***
	(0.0335)	(0.0952)	(0.0525)	(0.0798)
Fund performance × Manager gender (Female)	-0.4651 ***	-0.3151 **	-0.2764 ***	-0.4555 ***
	(0.0802)	(0.1537)	(0.1009)	(0.1313)
Managerial characteristics				
Manager gender (Female)	0.2861 ***	0.2837 ***	0.2847 ***	0.2861 ***
	(0.0404)	(0.0404)	(0.0404)	(0.0406)

Manager tenure	0.0690 ***	0.0688 ***	0.0689 ***	0.0688 ***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Fund characteristics				
Fund risk (Previous month)	0.4809 ***	0.4811 ***	0.4807 ***	0.4826 ***
	(0.0274)	(0.0274)	(0.0274)	(0.0275)
Log(Fund age)	-0.0996 ***	-0.0997 ***	-0.1004 ***	-0.1009 ***
	(0.0240)	(0.0240)	(0.0240)	(0.0241)
Log(TNA) (previous quarter)	0.1009 ***	0.1012 ***	0.1012 ***	0.1014 ***
	(0.0072)	(0.0072)	(0.0072)	(0.0072)
Aggregate fund flow (previous quarter)	-0.0203 ***	-0.0204 ***	-0.0204 ***	-0.0203 ***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Fund sales fee (%)	1.3562 ***	1.3548 ***	1.3574 ***	1.3660 ***
	(0.2062)	(0.2062)	(0.2062)	(0.2077)
Fund management fee (%)	-0.4018 ***	-0.4012 ***	-0.4019 ***	-0.4034 ***
	(0.0196)	(0.0196)	(0.0196)	(0.0197)
Fund transaction fee (%)	0.004128	0.003945	0.004291	0.003225
	(0.0146)	(0.0146)	(0.0146)	(0.0146)
User income				
Rolling average spending in prior 6 months	0.0038	0.0038	0.0038	0.0039
(thousands CNY)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Std dev of rolling spending levels in prior	-0.0017	-0.0017	-0.0017	-0.0017
6 months (thousands CNY)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Current month spending (thousands	-0.0005	-0.0005	-0.0005	-0.0005
CNY)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2 (Within)	-0.0001	-0.0001	-0.0001	-0.0001
N	2,268,870	2,268,870	2,268,870	2,258,747

Table 11

This table reports coefficients from three-stage instrumental variable regressions for the effects of funds' prior month performance and manager gender on users' current month fund flow. Panel A reports the coefficients of the first-stage Logit regressions, while Panel B reports the coefficients of the third-stage instrumental variable regressions. The female new-born ratio is the proportion of new-born female babies amongst all babies in the year 2010 at the local district level. The female illiteracy ratio is the proportion of females that are illiterate amongst all females that are 15 years or order, in the year 2010 at the local district level. All other variables are defined in the Appendix. The Logit regressions in Panel A include fund objective and manager degree fixed effects, whose coefficients are suppressed. The panel-OLS regressions in Panel B include user, month, fund objective and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, which are heteroskedasticity robust in Panel A and clustered at the user level in Panel B, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. First stage (Logit) regressions

	(1)	(2)
Instrumental Variable		
Female new-born ratio	0.3031 *	
	(0.1580)	
Female illiteracy ratio		-0.4627 ***
		(0.0900)
Fund performance		
Fund prior 1-month NAV return rank	0.2151 ***	0.2150 ***
	(0.0080)	(0.0080)
Managerial characteristics		
Manager tenure	-0.7416 ***	-0.7416 ***
	(0.0020)	(0.0020)
Fund characteristics		
Fund risk (Previous month)	-0.4690 ***	-0.4689 ***
	(0.0060)	(0.0060)
Log(Fund age)	1.5881 ***	1.5879 ***
	(0.0080)	(0.0080)
Log(TNA) (previous quarter)	-0.2790 ***	-0.2790 ***
	(0.0030)	(0.0030)
Aggregate fund flow (previous quarter)	-0.0781 ***	-0.0780 ***
	(0.0010)	(0.0010)
Fund sales fee (%)	-4.3926 ***	-4.3916 ***
	(0.0616)	(0.0616)
Fund management fee (%)	0.5739 ***	0.5739 ***
	(0.0078)	(0.0078)
Fund transaction fee (%)	-0.2937 ***	-0.2938 ***
	(0.0061)	(0.0061)
User characteristics		
User age	0.0011 ***	0.0012 ***
	(0.0000)	(0.0000)
User city tier	0.0080 ***	0.0123 ***
	(0.0020)	(0.0020)
User risk band	0.0282 ***	0.0282 ***
	(0.0030)	(0.0030)

User gender	-0.0166 ***	-0.0174 ***
	(0.0060)	(0.0060)
Fintech platform income (High)	-0.0318 ***	-0.0302 ***
	(0.0090)	(0.0090)
Fintech platform income (Low)	0.0246	0.0249
	(0.0250)	(0.0250)
Rolling average spending in prior 6 months (thousands CNY)	0.0009 **	0.0009 **
	(0.0000)	(0.0000)
Std dev of rolling spending levels in prior 6 months (thousands CNY)	-0.0028 ***	-0.0028 ***
	(0.0000)	(0.0000)
Current month spending (thousands CNY)	0.0001	0.0001
	(0.0000)	(0.0000)
Pseudo R^2	0.2030	0.2030
N	1,928,212	1,928,212

Panel B. Third-stage regressions

	Instruments	
	Female new-born ratio	Female illiteracy ratio
	(1)	(2)
Fund performance		
Fund prior 1-month NAV return rank	0.8013 ***	0.8029 ***
	(0.0387)	(0.0387)
Fund prior 1-month NAV return rank × Manager gender (Female)	-2.5646 ***	-2.5737 ***
	(0.2700)	(0.2697)
Managerial characteristics		
Manager gender (Female)	4.9886 ***	4.9461 ***
	(0.4860)	(0.4831)
Manager tenure	0.3692 ***	0.3651 ***
	(0.0447)	(0.0444)
Fund characteristics		
Fund risk (Previous month)	0.0728 ***	0.0711 ***
	(0.0255)	(0.0254)
Log(Fund age)	-1.2178 ***	-1.2066 ***
	(0.1249)	(0.1242)
Log(TNA) (previous quarter)	0.2336 ***	0.2325 ***
	(0.0143)	(0.0143)
Aggregate fund flow (previous quarter)	0.0024	0.0024
	(0.0034)	(0.0034)
Fund sales fee (%)	2.8238 ***	2.8094 ***
	(0.2859)	(0.2852)
Fund management fee (%)	-0.4931 ***	-0.4910 ***
	(0.0306)	(0.0305)
Fund transaction fee (%)	0.0439 **	0.0427 **
	(0.0212)	(0.0211)
User characteristics		
User age	0.0090 ***	0.0090 ***
	(0.0012)	(0.0012)
User city tier	0.0361 ***	0.0362 ***
	(0.0075)	(0.0075)
User risk band	0.0099	0.0099
	(0.0095)	(0.0095)
User gender	-0.3012 ***	-0.3013 ***
	(0.0179)	(0.0179)
Fintech platform income (High)	0.2207 ***	0.2206 ***
	(0.0253)	(0.0253)
Fintech platform income (Low)	-0.0408	-0.0407
	(0.0769)	(0.0769)
Rolling average spending in prior 6 months (thousands CNY)	0.0044	0.0044
	(0.0027)	(0.0027)
Std dev of rolling spending levels in prior 6 months (thousands CNY)	-0.0018	-0.0018
	(0.0017)	(0.0017)
Current month spending (thousands CNY)	-0.0007	-0.0007
	(0.0005)	(0.0005)
R^2 (Within)	-0.0072	-0.0070
N	1,928,212	1,928,212

Table 12

This table reports coefficients from cross-sectional OLS regressions for the effects of managerial gender on users' fund flow volatilities during our sample period. The dependent variable, fund volatility, is defined as the standard deviation of each user's fund flow for each fund during the sample period. All other variables are defined in the Appendix. The model includes user, fund objective, and manager degree fixed effects, whose coefficients are suppressed. The base gender dummy variable is male. Standard errors, which are clustered at the user level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Fund performance	
Fund (Previous) 1-month NAV Return Rank	2.2510 ***
	(0.2377)
Managerial characteristics	
Manager Gender (Female)	-0.1163 *
	(0.0685)
Fund characteristics	
Fund Risk (Previous Month)	0.4364 ***
	(0.1083)
Log(Fund age)	-0.1671 **
	(0.0829)
Log(TNA) (previous quarter)	0.3735 ***
	(0.0279)
Fund sales fee (%)	4.0561 ***
	(0.8354)
Fund management fee (%)	-0.4638 ***
	(0.0730)
Fund transaction fee (%)	0.030346
	(0.0577)
User income	
Standardized Rolling Average Spending in the Past 6 Months	-0.0031
	(0.0130)
Standardized Rolling Spending Standard Deviation in the Past 6 Months	0.0016
	(0.0083)
Current Month Spending	-0.0068
	(0.0043)
R^2 (Within)	0.0048
N	284,753