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The Effects of Misperceived Managerial Skills: Evidence from Chinese Mutual Funds

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Abstract

Many mutual fund investors rely primarily on past performance and likely do not engage in sophisticated analysis of managers' alpha when making investment decisions. This paper explores how investors' misperception of managerial skill affects mutual funds' market power and investors' welfare, using data from China's mutual fund market. Our findings indicate that investors often confuse the effects of fund exposures to common systematic factors with genuine managerial skill, thereby increasing the market power of funds. Market power of funds are higher when investor demand arises from factor-related returns. Counterfactual experiments suggest that employing more sophisticated asset pricing models to assess fund managerial skills can enhance investor welfare. For instance, basing investment decisions on performance adjusted by a 4-factor model could increase investor welfare by \$203 to \$674 per year for each investor.

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1 Introduction

A persistent and robust phenomenon in mutual fund literature is that investors consistently chase past performance. [1] Another well-documented phenomenon in financial research is the persistent underperformance of the mutual fund industry relative to market benchmarks. [2] Given their poor performance, one might expect that performance-chasing investors would compel mutual funds to reduce their fees. Indeed, according to annual statistics reported by the Investment Company Institute, average equity mutual fund expense ratios in the United States decreased by 60 percent between 1996 and 2023. However, the situation differs in emerging markets. In China, for instance, despite over 5,000 mutual funds competing in the market as of 2017, the average expense ratio remained at 1.75% — significantly higher than the 0.75% observed in the United States (Jiang, 2020). Remarkably, mutual fund profits in these markets appear robust, with their economic rents persisting despite the substantial number of competitors in the industry. How mutual funds are able to sustain market power when investors are chasing past performance?

In this paper, we aim the empirically investigate whether investors' misperceptions of the managerial skill can explain this puzzling contradiction. The seminal work of Berk and Green (2004) posits that investors compete for scarce managerial talent by allocating additional capital to perceived high-performing managers. Skilled managers, in turn, extract this surplus by charging higher fees. Their theory predicts that managerial skill is matched with fund scale and fees. However, recent research challenges this equilibrium. Song (2020) demonstrates that mutual fund investors are not as sophisticated in assessing managerial skill as modeled by Berk and Green (2004) , revealing a significant mismatch between skill and scale among actively managed equity mutual funds.

[1] See, for example, Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998).
[2] See Berk and Green (2004), Glode (2011).

Investors do not ajust for common factors such as size and value factors when making investment decisions. Li and Qiu (2014) present a model showing that if investors incorrectly evaluate managerial skills, certain funds can obtain greater market power due to these misperceptions. Our paper extends the existing literature by providing new empirical evidence on the dual impact of investors' misperceptions: their influence on mutual funds' market powers and the consequent effects on investor welfare.

Our study focuses on China's rapidly growing mutual fund market, the largest emerging financial market in the world, which is characterized by a relatively unsophisticated investor base (Jiang, 2020). The market is predominantly composed of retail investors who, compared to their counterparts in more developed markets, allocate a smaller proportion of their savings to mutual funds. These investors typically exhibit shorter investment horizons and a pronounced tendency to chase past performance. Understanding the effects of investors' misperceptions is crucial, not only for comprehending investor behavior but also for informing policy decisions. If investment choices are primarily driven by misperceived managerial skills, investors may be making suboptimal decisions that diminish their realized welfare. Importantly, these misconceptions could potentially be mitigated through enhanced information disclosure. Our findings have potential implications beyond China, extending to other emerging markets characterized by similarly unsophisticated investor bases.

Our paper is structured in three parts, with the first part investigating two key phenomena in the Chinese equity mutual fund market. First, investors willingly pay higher fees for funds with high FRRs, despite the availability of these returns through less expensive index funds. Second, we find that FRRs does not possess persistence. Our analysis reveals that investors in Chinese equity fund markets demonstrate limited sophistication in evaluating managers' alphagenerating capabilities and fail to differentiate between returns attributable to systematic risk factor exposure and those stemming from managerial skill (alpha). Theoretically, a fund's past performance is attributable to two components: the alpha and FRRs. A rational investor would differentiate between these two sources of returns, pursuing only alpha while remaining indifferent to FRRs. This is because the primary purpose of investing in an actively managed fund is to obtain alpha, which represents the manager's ability to outperform the market.[3]

In the second part of our paper, we employ the standard framework developed by Berry, Levinsohn, and Pakes (1995) to estimate an investor demand model that accounts for competition among mutual funds. Using the results from this model, we examine how misperceived managerial skills influence funds' market power. The estimated model allows us to decompose mutual funds' costs and markups, which are not directly observable in the data.

Our estimation process utilizes data on mutual fund market shares and characteristics. The results indicate that investors prefer funds with lower fees and higher past raw returns. We extend this analysis by separating returns into alpha and factor-related components. We find that while investors chase past raw returns, they also respond to factor-related returns. Using the demand estimation results, we calculate marginal costs and market power (defined as [Fees - marginal cost] / Fees). The average market power is approximately 0.41, indicating that funds charge substantial markups to investors.

To assess the impact of investors' misperceptions on fund-specific market power, we regress market power on the demand elasticity for FRRs. Our findings

[3] Barber, Huang, and Odean (2016) clearly explain why investors should adjust for factor-related returns. Historically, small stocks have shown correlated returns and earned higher averages than large stocks. A rational investor incorporates size effect into manager skill evaluation. If small stocks outperform large stocks in a year, the investor will not conclude that all small-cap fund managers are highly skilled. A rational investor will distinguish skill from factor-related returns (FRRs) that could be earned through passive investments.

reveal that the elasticity for FRRs have a significant positive impact on its market power. On average, higher FRRs chasing allow funds to enjoy greater market power. Specifically, for every 1% increase in elasiticty for FRRs, market power increases by 0.21%. The underlying mechanism is that funds can charge higher markups when investors are less responsive to fees. If managerial skill enhances a fund's perceived quality, funds with superior skills can charge higher markups without losing investors, as investors become less sensitive to fees when they perceive the fund's quality to be high. Our results are consistent with this mechanism. We found that reduced investor fee elasticity correlated with higher elasticity for FRRs. For every 1% increase in FRRs, the own-fee elasticity decreases by 0.15%. This suggests that investors become less price-sensitive as the degree of investor misperception increase. This situation is inefficient for investors, as FRRs do not reflect the true quality of the fund and can be obtained through more cost-effective passive investments without incurring high fees.

In the third part of the paper, we utilize the estimated parameters to quantify the welfare implications of misperceived managerial skill. First, we simulate scenarios where investors employ more advanced asset pricing models to evaluate fund performance. Our findings indicate that when investors concentrate solely on alpha, they pay lower fees. The disparity between actual and counterfactual fees is more pronounced for funds with higher FRRs. This implies that when investors focus exclusively on alpha, their willingness to pay for funds with higher FRRs diminishes. Due to the misperception of managerial skill, funds with higher FRRs charge fees that exceed what their true skill level warrants. Second, if investors base their decisions on the 4-factor alpha, they can improve their annual welfare by $203 to $677 per investor. This suggests that when investors utilize more sophisticated asset pricing models, the equilibrium fees decrease, enhancing their welfare. Our results are policy-relevant as investors are making suboptimal choices that reduce their welfare, and these mistakes can potentially be mitigated through improved information disclosure or financial literacy education initiatives.

Our paper contributes to the literature on mutual fund investor behavior. Mutual fund investors exhibit behavior that is generally considered unsophisticated (Barber, Odean, and Zheng, 2005; Phillips, Pukthuanthong, and Rau, 2016; Choi and Robertson, 2020). Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) find that mutual fund investors appear to attribute returns associated with fund exposures to common factors to managerial skill. Previous literature has focused on explaining this investor behavior. Evans and Sun (2018) and Ben-David, Li, Rossi, and Song (2022) argue that these investor behaviors can be partially explained by investors' reliance on Morningstar ratings as their primary investment signals. Song (2020) highlights the performance implications of mutual fund investor behavior, demonstrating that active mutual funds with positive FRRs accumulate assets to the point of significant underperformance. Building on the observation that mutual fund investors inadequately account for systematic factors, this paper demonstrates that investor demand based on FRRs leads to significantly increased market power for funds and substantial welfare costs for investors. Our research goes further by quantifying and emphasizing the welfare implications of this investor behavior.

Our paper is also related to research on the relationship between mutual fund fees and performance. There is ongoing debate in the literature regarding whether fees charged by fund managers are linked to their skills. Some studies conclude that, net of expenses, investors in high-fee funds earn significantly worse factor-adjusted returns than do investors in low-fee funds (Gruber, 1996; Christoffersen and Musto, 2002; Gil-Bazo and Ruiz-Verdú, 2009; Cooper, Halling, and Yang, 2021). On the other hand, Sheng, Simutin, and Zhang (2023) find that funds with different fees invest in stocks with different investment and profitability characteristics. After controlling for exposures to profitability and investment factors, they find high-fee funds significantly outperform low-fee funds before expenses and achieve similarly poor net-of-fees performance. Our research contributes to this ongoing discussion by demonstrating the importance of investor sophistication in relation to fund fees and fund manager skills. We find that in situations where investor sophistication is lower, the mismatch between fund fees and managerial skills becomes more severe.

Our research draws significant inspiration from Li and Qiu (2014). Their study presents a theoretical argument closely aligned with our paper's motivation: mutual funds become better-performing in various market situations by differentiating themselves from others in terms of FRRs. As investors chase past fund performance, winning funds attract more investors and gain market power. Li and Qiu (2014) provide two key empirical findings using U.S. mutual fund market data: 1) A fund's FRRs have a significantly positive impact on its market share; 2) The deviation of a fund's factor loadings from the industry median is significantly and positively associated with its fee. Our research continues and expands upon the work of Li and Qiu (2014) in two key aspects: First, our analysis similarly posits that when investors chase FRRs, funds can gain greater market power, as investors are willing to bear higher fees from funds they perceive as better performing. However, our research focuses more on the ex-post effects. We find that not only ex-ante differentiation but also ex-post FRRs can enable funds to gain market power. Second, we apply a structural model that can more directly estimate important concepts in Li and Qiu's (2014) study, such as market power and investor price elasticity. This approach allows us to more directly validate their theory and, building on their theoretical foundation, further explore the impact of FRR chasing on investor welfare.

The rest of the study is organized as follows. Section 2 decribes the data we use. Section 3 document primary analysis results in the Chinese equity mutual fund markets. Section 4 describes the demand model of investors. Section 5 discusses the model estimation, estimation results and counterfactual analyses. Section 6 concludes.

2 Data and Variable Description

This study investigates Chinese domestic equity funds, encompassing general stock and equity-oriented hybrid funds, from December 2011 to December 2021. The mutual fund data used in this paper comes from the CSMAR Fund Market Research Database. Notably, index funds, exchange-traded funds (ETFs), and split-share structure funds were deliberately omitted from our analysis. We limit our examination to mutual funds started in 2011, which marks a pivotal point when China's actively managed fund sector began demonstrating stable expansion. Furthermore, we exclude funds lacking available monthly returns data for at least three years. The resultant dataset comprises 708 distinct mutual funds from 83 fund families.

2.1 Measurements of performance

In this paper, we primarily focus on two indicators that assess the past performance of funds: raw returns and risk-adjusted returns. We use the following formula to calculate the percentage change in net asset value (NAV):

$$R_{j,t} = \frac{NAV_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}}$$

$R_{j,t}$ is the raw return in year t. Raw return is the return that investors achieve. In addition, following Song's (2020) approach, using different asset pricing models, such as Carhart (1997) and Fama & French (2015), mutual fund returns can be broken down into two parts: Alpha, which is the portion uncorrelated with risk factors, and FRRs, which represents the risk-compensating component associated with the fund's investment style. Specifically, fund performances relative to the Carhart 4-factor model are estimated and modeled as:

$$R_{j,m} - R_f = \alpha_j^{4F} + m_j MKT_m + s_j SMB_m + h_j HML_m + u_j UMD_m + \varepsilon_{jm} \quad (1)$$

where $R_{j,m}$ is the mutual fund raw return in month m. R_f is the return on the risk-free rate. R_f is calculated based on the Shanghai Interbank Offered Rate (SHIBOR) for a three-month term. SMB_m is the return on a size factor (small minus big stocks), HML_m is the return on a value factor (high minus low book-to-market stocks), UMD_m is the return on a momentum factor (up minus down stocks). α_j^{4F} is the mean return unrelated to the fund's exposure to factors in the 4-factor model. For each fund in yeat t, we estimate the equation (1). We then calculate the alpha for the fund in year t as its realized return less returns related to the fund's market, size, value, momentum exposures.

$$\hat{\alpha}_j^{4F} = (R_{j,m} - R_f) - [\hat{m}_j MKT_m + \hat{s}_j SMB_m + \hat{h}_j HML_m + \hat{u}_j UMD_m] \quad (2)$$

We repeat this procedure for all years and all funds to obtain a fund-year level alphas and FRRs in our sample. For robustness, we also do the same calculation for other factor models. For example, we estimate a fund's Fama-French 5-factor model using the the following equation:

$$R_{j,m} - R_f = \alpha_j^{5F} + m_j MKT_m + s_j SMB_m + r_j RMW_m + c_j CMA_m + \varepsilon_{jm} \quad (3)$$

where RMW_m is the return of the portfolio that goes long on stocks with robust operating profitability and short on stocks with weak operating profitability. CMA_m is the return of the portfolio that goes long on stocks with low investments and short on stocks with high investments.

2.2 Descriptive statistics

Table 1 presents descriptive statistics on fund characteristics across fund-year observations. The average age of the fund is 7.9 years. The average age of funds in China is much lower than that of the United States market. The average annual expense ratio for sample funds is 2.9%. The expense ratio is still very high compared to the United States market. According to Barber, Huang, and Odean (2016), the average expense ratio of actively managed equity funds was 1.28%, much smaller than that in China. The mean yearly raw return is 16.4%. It is worth noting that the mean alpha of funds is consistently positive regardless of which method is used to calculate alpha. The average yearly alpha is 0.2%. This pattern is different from the finding in the United States. Although the causes of the discrepancies above require systematic investigation, the younger average age, higher average fees, and positive average risk-adjusted returns indicate that China's mutual fund market is less mature than that of the United States. This finding suggests that the mutual fund industry in China is not running as efficiently as the United States market.

3 Primary Analyses

In this section, we document two facts about investors in the Chinese equity mutual fund markets: (i) Funds with high FRRs are more expensive, despite the availability of these returns through less expensive index funds. (ii) FRRs does not possess persistence.

3.1 Past returns and fees

In this subsection, we analyze the relationship between the past performance of funds and their expense ratios. We consider the following regression specification:

$$f_{j,t} = \alpha R_{j,t-1} + x_{j,t}^{'}\beta + \gamma_j + \gamma_t + \varepsilon_{j,t} \tag{4}$$

where $f_{j,t}$ is the fees of fund j in year t. Fee ratio is the sum of management fee, custodian fee, and sales fee as a percentage of TNA. $x_{j,t}$ captures characteristics of fund j in year t, and γ_j and γ_t are fund and year fixed effects, respectively.

Column 1 of Table 2 reports the results. The first column shows that past returns is significantly and positively associated with fees. If a fund increases the past return by 1%, the fees will increase by 0.005%. It suggests that funds with higher past returns charge a higher fees. In columns 2 and 3, we report the results of decomposing the funds' past performance based on the 4-factor and 5-factor models, respectively. Results indicate that a one standard deviation increase in the 4-factor FRRs is associated with 0.01% (= 0.97*0.013) higher fees. Following Li and Qiu (2014), we also control for the total deviation of risk factor loadings. However, we do not find that risk-factor loadings significantly affect fees. This finding indicates that investors are more concerned with ex-post outcomes than ex-ante factor exposure differences.

3.2 FRRs persistence

If FRRs were persistent, it would be reasonable for funds with higher FRRs to charge higher fees. We use the dynamic panel data analysis to test performance persistence at an annual horizon:

$$Frrs_{j,t} = \alpha^F Frrs_{j,t-1} + x_{j,t}^{'}\beta + \gamma_j + \gamma_t + \varepsilon_{j,t} \tag{5}$$

where $Frrs_{j,t}$ are the factor-related returns. $x_{j,t}$ captures characteristics of fund j in year t, and γ_j and γ_t are fund and year fixed effects, respectively. If funds with high FRRs consistently maintain high FRRs in subsequent years, we would expect to observe a positive regression coefficient α^F. This positive coefficient would indicate persistence in FRR performance across time periods. We apply the Arellano and Bond (1991) difference GMM estimator.

Table 3 presents the dynamic panel regression results. In the column 1, we can see that the previous year's FRRs did not have a statistically significant impact on current FRRs. Our analysis indicates that FRRs do not demonstrate persistence over time. We also investigate the persistence of 4-factor alpha and 5-factor alpha. In column 2, we can see that a 1% increase in fund 4-factor alpha is associated with 0.07% increase in 4-factor alpha in the following year. Overall, investors should not pay higher fees for the FRRs, as this component is not sustainable.

4 The Empirical Model

In summary, investors focus on the past performance of funds when selecting them, without distinguishing between the portions of alpha and FRRs in past performance. They are willing to pay higher fees for funds with higher past performance. Such high fees can harm investors and erode fund profits. Quantifying investors' losses and fund returns using a reduced-form analysis is challenging because the counterfactual expense ratios that funds can charge if investors do not solely judge based on past performance are unobservable. Therefore, we proceed to address these questions through a structural model.

The model works as follows. In each period t, investors, indexed by i, choose among a discrete number of differentiated mutual funds, indexed by $j = 0, 1, 2, \ldots, J_t$, including an outside good ($j = 0$). Within each period t, each mutual fund j sets fees f_j and investors choose the mutual funds in which to invest their money. Our model is static for each period t. For simplicity we omit the subscript t, which indexes time.

4.1 Investor demand

There are J mutual funds available, and each investor i seeks to invest a mutual fund from the list. We apply the characteristics-space approach (Berry, Levinsohn and Pakes 1995). This approach has begun to be widely employed in finance research. [4] We follow this approach and assume that each mutual fund can be represented as a bundle of characteristics and investor have preferences over these characteristics. Investor i's untility from investing fund j is given by

$$u_{i,j} = -\theta_{1,i} f_j + \theta_{2,i} R_j + \beta X_j + \xi_j + \varepsilon_{i,j} \tag{6}$$

where f_j is the fee of fund j, R_j is the raw past returns of fund j, X_j is the observed characteristics of fund j, ξ_j represents untility from the unobserved characteristics of fund j, and $\varepsilon_{i,j}$ denotes the idiosyncratic utility shocks. A investor that selects the outside fund receives $u_{i,0} = \varepsilon_{i,0}$. In this framework,

[4]Massa (2003), Minamihashi and Wakamori (2014), and Baker, Egan, and Sarkar (2022) apply this framework to study mutual funds and mutual fund choice. An, Benetton, and Song (2023) use it to show that index providers charge large markups to ETFs that are passed on to investors.

a fund is decomposed into the bundle of characteristics (f_j, R_j, X_j, ξ_j) where (f_j, R_j, X_j) is observed but ξ_j is unobserved to econometrician.

Different investors have different sensitivities to fund performance and fees (Christoffersen and Musto, 2002). We allowed the coefficients (β_1, β_2) to vary over investor i. The investor-specific coefficients allows us to incorporate investors' heterogeneity. We assume that the consumer-specific coefficients depand on a set of unobserved demographic variables according to

$$\beta_{m,i} = \beta_m^o + \beta_m^u \nu_{m,i}$$

where $\nu_{m,i} \sim N(0,1)$, β_m^o is the average valuation for tha characteristic m, β_m^u is the standard deviation for the valuation. We can obtain the following expression of the individual choice probability by assuming $\varepsilon_{i,j}$ follows the mean-zero i.i.d. Type 1 extreme value distribution:

$$Pr(iChoosesj) = \frac{exp(-\beta_{1,i} f_j + \beta_{2,i} R_j + \beta X_j + \xi_j)}{\sum_{k \in J} exp(-\beta_{1,i} f_k + \beta_{2,i} R_k + \beta X_k + \xi_k)} \tag{7}$$

If infinitely many investors are in a market, the predicted market share s_j^m can be written as

$$s_j^m = \int_i \frac{exp(-\beta_{1,i} f_j + \beta_{2,i} R_j + \beta X_j + \xi_j)}{\sum_{k \in J} exp(-\beta_{1,i} f_k + \beta_{2,i} R_k + \beta X_k + \xi_k)} dF(\nu_i) \tag{8}$$

4.2 Mutual funds

Consider the profits of family F controls several funds J_F and sets fees f_j.

$$max_{f_j : j \in J_F} \sum_{j \in J_F} s_j M(f_j - c_j)$$

where M is the size of market. Each family chooses the fees that maximiaze its profit. The first-order conditions for optimality are

$$s_j + \sum_{k \in J_F} (f_k - c_k) \frac{\partial s_k}{\partial f_j} = 0 \tag{9}$$

5 Estimation, results, and counterfactual analysis

5.1 Model estimation

Since the empirical model includes heterogeneity, as in equation (8). We need to use simulation method to obatin the predicted market share:

$$s_j^m = \frac{1}{n^s} \sum_{i=1}^{n_s} \frac{exp(-\beta_{1,i} f_j + \beta_{2,i} R_j + \beta X_j + \xi_j)}{\sum_{k \in J} exp(-\beta_{1,i} f_k + \beta_{2,i} R_k + \beta X_k + \xi_k)} \tag{10}$$

Since we can observe the market share of each fund, we can estimate the parameter by minimizing the distance between the observed and the predicted market shares. Specifically, the ξ_j represents untility from the unobserved characteristics of fund j. Because ξ_j represents the fund characteristics that are unobservable to the econometrician, it might be correlated with other observed fund characteristics. In our context, ξ_j can be seen as the unobserved fund manager skill, then, we expect that fund manager with good unobserved skill can charge higher fees, implying that ξ_j will be correlated with the fees. With a suitable set of instruments $\mathbf{z}_j$ to correct for the endogeneity of ξ_j, we can estimate the model parameters by using GMM with moment condition $\mathbb{E}[\xi_j | \mathbf{z}_j, \mathbf{x}_j] = 0$. We use the estimation algorithm developed by Berry, Levinsohn and Pakes (1995).

We follow the literature to use a set of differentiation IVs developed by Gandhi and Houde (2019). The differentiation IVs uses the Euclidian distance between mutual fund j and its rivals along mutual fund characteristic k:

$$z_{j,k} = \sqrt{\sum_{l}(x_{l,k} - x_{j,k})^2}$$

We use the fee, fund age, and return volatility to calculate the differentiation IVs. These IVs capture the relative position of each fund in the characteristic space. The idea is that a fund's fees in a market depends on the market structure. If similar funds are in the market, the fees will tend to be lower. Then, the relative position of each fund in the characteristics will be a vaild instrument for the fees in a given market. With the demand estimates in hand, we can recover estimates of markups. We can rewrite the first-order conditions (9) in matrix form:

$$\mathbf{f} - \mathbf{c} = \Omega^{-1}\mathbf{S} \tag{11}$$

Here the markup $\mathbf{f} - \mathbf{c}$ depends on Ω, a $J \times J$ matrix of demand derivatives given by:

$$\Omega \equiv -H \odot \frac{\partial \mathbf{s}}{\partial \mathbf{p}} \tag{12}$$

which is the element-wise hadamard prodcut of two $J \times J$ matrices: the matrix of demand derivatives with each (j, l) entry given by $\frac{\partial \mathbf{s}}{\partial \mathbf{p}}$ and the ownership matrix H with each (j, l) entry indicating whether the same mutual fund family controls j and l. We can obatian the derivatives of the demand function $\frac{\partial \mathbf{s}}{\partial \mathbf{p}}$ from the demand system and calculate the full set of Ω. Hence, from these J equations, we solve for the J margins $\mathbf{f} - \mathbf{c}$. The markups can then be obtained as:

$$Markups = \frac{f_j - c_j}{f_j} \tag{13}$$

5.2 Demand estimation results

Table 4 reports estimates for demand parameters. In column 1, the first and fifth rows suggest that for the average investor, higher past raw returns and lower fees increase the utility derived from the fund. To further examine whether investors consider factors that explain variations in fund performance, we decomposed the past performance of funds using both 4-factor and 5-factor models. The second column presents estimates for the 4-factor model, while the third column shows estimates for the 5-factor model. Our analysis reveals that both alpha and FRRs positively affect investors' utility.

To demonstrate the importance of fund characteristics on investor choices, we compare their impacts on utility by increasing each characteristic above its mean by one standard deviation. The increase in utility for 4-factor FRRs is 0.04 (= 3.203 * 0.013). This indicates that an investor is willing to pay 2.36% (= 0.04 / 1.695) of their investment to enjoy an increase in past return by one standard deviation. On the other hand, the increase in utility for 4-factor alpha is 0.02 (= 1.211 * 0.013). Investors are willing to pay 1.18% of their investment for one standard deviation higher 4-factor alpha. All else equal, investors demonstrate a higher willingness to pay for FRRs. This willingness to pay can be interpreted as either capturing investors' beliefs about returns or the non-pecuniary utility investors derive from investing in a fund with higher FRRs. Given that the primary objective of active fund investors is to achieve higher returns, we posit that willingness to pay primarily captures the former in this context. We observe that investors are willing to pay more for FRRs due to higher expected returns. This observation could stem from two possibilities: either investors lack the sophistication to utilize risk-adjusted returns when evaluating managerial skills, or they understand how to use risk-adjusted returns but prefer to evaluate managerial skill based on total returns. Regardless of the underlying reason, investor responsiveness to FRRs suggests a potential for investor misperception.

Estimates of heterogeneity around these means are presented in the third and seventh rows. The rows labeled "S.D." capture the effects of unobserved demographic characteristics. The unobserved demographic characteristics were drawn from a standard normal distribution. For each year, I drew 10,000 investors (n^s= 10000 in equation (10)). Investors value fees negatively, on average, but standard deviations for the valuation are positive and significantly different from zero. However, we did not find similar heterogeneity in the past raw returns. This finding suggests that investors exhibit heterogeneity in their responses to fees.

5.3 The effect of investor misperception on market powers

Our research indicates that investors respond significantly to FRRs and are willing to pay a premium for higher FRRs. This tendency to chase FRRs allow mutual funds to exert greater market power. The first-order condition for each fund j can be written as:

$$f_j = \frac{1}{1+\frac{1}{\epsilon_{jj}}}[c_j + \sum_{k \in J_F \setminus j} (f_k - c_k)\frac{\partial s_k}{\partial f_j}[-\frac{\partial s_j}{\partial f_j}]^{-1}] \tag{14}$$

Equation (14) shows the inverse elasticity markup applied to the marginal cost of j. The demand elasticity of fund j to the fee can be calculated by:

$$\epsilon_{jj} = -\frac{f_j}{s_j}\int_i \beta_{1,i} s_j(1-s_j)dF(\nu_i) \tag{15}$$

Where ϵ_{jj} is the fee elasticity on fees and $\beta_{1,i}$ is the fee sensitivity. The demand elasticity to the fee varies over time through changing fund characteristics, interacting with the distribution of random coefficients on the fee. When the fee increases, the more fees elastic investors substitute into competing funds with lower fees. However, FRRs chasing makes demand for funds with higher FRRs become relatively inelastic to fees because investors can tolerate the higher fees charged by the funds. Thus, the elasticity to the fee decreases because remaining investors are less price elastic on average. As a result, funds with higher FRRs possesses market power because investors can tolerate the higher fees charged by the funds.

To test this mechnism, we first examined the relationship between demand elasticity and FRRs.[5] Table 5 presents the results of our analysis. Column (1) reports the estimates using the demand elasticity for 4-factor FRRs, while column (2) displays the estimates based on the 5-factor FRRs model. We find that both the coefficients of 4-factor alpha and FRRs are negative and statistically significant. For every 1% increase in 4-factor alpha, investors' own-fees elasticity decreases by 1.02%. Similarly to alpha, FRRs also have negative effect, for every 1% increases in FRRs, own-fees elasticity decreases by 0.9%. Investors' own-fees elasticity declines not only due to the alpha component of past returns but also due to the FRRs component.

Then we examined the relationship between market powers and FRRs. We report the estimates in column (1) of Table 6. The coefficient on the 4-factor FRRs is 0.972, indicating that market power increases by 0.013% (= 0.987 * 0.013) per one standard deviation increase in the FRRs. The magnitude of the effect is similar for the 5-factor FRRs. A one standard deviation increase in elasticity for 5-factor FRRs is associated with a 0.012% (= 0.971 * 0.013) increase in market power. Regarding control variables, funds with higher total deviation of risk factor loadings also exhibit higher market power. By differentiating them-

[5]The demand elasticity of the demand system is

$$\frac{\partial s_{j,t}}{\partial f_{j,t}} \frac{f_{j,t}}{s_{j,t}} = -\frac{f_{j,t}}{s_{j,t}} \int_i \theta_{1,i} s_{i,j} (1 - s_{i,j}) dF(\nu_i)$$

$s_{i,j}$ is the individual predicted quantity shares in year t.

selves from other risk factor loadings, funds can obtain greater market power. Notably, even after accounting for the effects of factor exposure as proposed by Li and Qiu (2014), the impact of investors' FRRs chasing remains significant.

5.4 Counterfactual analysis

In the previous subsection, we show that the misperceived managerial skills increases the markups of funds. In this section, we examine various counterfactual scenarios in order to analyze the impact of misperceived managerial skills on fees and investor welfare. We examine how fees and investor welfare would change in a hypothetical scenario where they distinguish between alpha and FRRs and only react to alpha.

We assume that funds have market power, which enables them to modify their pricing strategies in response to changes in the performance benchmarks used by investors to assess fund performance. This assumption is based on the findings we presented in the previous section. We simulate the equilibrium vector of expense ratios under alternative scenarios, assuming that investor only focus on the alpha. The counterfactual equilibrium fees are obtained by solving for the fees $\mathbf{f}^*$that satisfy the fixed point:

$$\mathbf{f}^* - \mathbf{c} = \Omega^{-1}\mathbf{S}(\mathbf{f}^*, frr_{No}) \tag{16}$$

5.4.1 Counterfactual analysis: fees

Using the simulated counterfactual equilibrium fees $\mathbf{f}^*$and baseline fess $\mathbf{f}$, we can compute the change in fees in a hypothetical scenario. The change in fees is given by:

$$\triangle\mathbf{f} = \mathbf{f}^* - \mathbf{f}$$

$\triangle \mathbf{f}$ shows the change rate between the simulated counterfactual equilibrium fees that investors would pay if they only used alpha to evaluate fund performance and the actual fees they pay. The average price difference is approximately -0.015. This means that on average, when investors only focus on alpha, fees will decrease by 1.5%. This results is consistent with the findings we presented in the previous section. If investors could use more sophisticated metrics to assess fund managerial skills, they would not need to pay fees for the FRRs component, leading to lower counterfactual equilibrium fees.

To better understand the factors influencing the change rate, we regressed the change rate on the same set of fixed effects and controls used in our previous analysis. We present the results in Table 7. Our findings indicate that funds with higher FRRs experience greater decreases in counterfactual equilibrium fees (fees that would prevail if investors did not respond to FRRs). Conversely, funds with higher alpha experience smaller decreases in these counterfactual equilibrium fees. These results suggest that when investors focus solely on alpha and do not respond to FRRs, high-quality funds can still exert market power. However, this scenario leaves less room for fund managers to obtain market power by loading on factor returns.

5.4.2 Counterfactual analysis: welfare

In the random coefficient model, the investor surplus generated by a set of funds can be written as

$$CS_{i,t} = \frac{ln(\sum_{j=1}^{J} exp(\delta_{j,t} + \mu_{i,j,t}))}{\theta_{1,i}} \tag{17}$$

Following Nevo (2001), we apply the compensating variation to measure the change in investor welfare. Using these simulated counterfactual equilibrium expense ratios $\mathbf{f}^*$, we can calculate the change in investor welfare by comparing the investor surplus in the scenario where investors only focus on alpha with the investor in the baseline. The investor surplus under the counterfactual equilibrium can be written as

$$CS_{i,t}^{Counterfactual} = \frac{ln(\sum_{j=1}^{J} exp(\delta_{j,t}^{Counterfactual} + \mu_{i,j,t}^{Counterfactual}))}{\theta_{1,i}} \tag{18}$$

Following Nevo (2000), we use the compensating variation to measure the change in investor welfare. The compensating variation in year t is given by

$$CV_t = \int_i [CS_{i,t}^{Counterfactual} - CS_{i,t}]dF(\nu_i) \tag{19}$$

CV_t represents the percentage gain in investor welfare for each yuan invested in year t. This quantifies the amount of money that must be taken from consumers to leave them as well off as they were before the change. If the compensating variation is positive (negative), it indicates that the investor is better off (worse off). Column 1 of table 8 shows that investor welfare increases by 7.6% to 18% when investors select funds based on alpha decomposed by the four-factor model. This suggests that using more sophisticated factor models to evaluate fund performance can improve investor welfare. To compute the welfare impact per capita in the year t, we multiply the CV_t with invest amounts per capita in year t. We utilize the per capital investment amount mentioned in the "Insights into Profitability of Publicly Offered Equity Funds Investors Report, " jointly published by ICBC Credit Suisse Asset Management, China Universal Asset Management, and China Southern Asset Management.[6] Female fund investors held an average investment of 26,595 yuan by 2020 (past 15 years). Table 8 (second column) shows the monetary value of the welfare change, ranging from 1445 yuan to 4800 yuan (US$203 to US$674). According to the China Securities Investment Fund Association's "National Public

[6]https://www.fund001.com/webimages/upload2012/2023/03/17/135329367_0_890b51b6-b112-3c1e-b39c-a9a3a7865ec5.pdf

Fund Investor Status Survey Report (2019)" (March 9, 2019), there were 606.75 million non-institutional investor accounts in China's public mutual funds by December 2019. Extrapolating the maximum per capita welfare increase (4800 yuan) to this investor base suggests a potential market-wide welfare gain of 2.9124 trillion yuan (US$20,535 million). We also report the results using the five-factor model alpha in the third and fourth columns. We find similar welfare improvement effects.

6 Conclusion

This study provides empirical evidence on the impact of investors' misperceptions of managerial skill in the Chinese mutual fund market. Our findings reveal that investors often conflate FRRs with managerial skill, leading to increased market power for funds and welfare costs for investors.

Our analysis demonstrates that investors are willing to pay higher fees for funds with higher FRRs, despite the lack of persistence in these returns. This behavior allows funds to exert greater market power, as evidenced by the positive relationship between FRRs and fund markups. Using a structural demand model, we quantify the welfare implications of this investor behavior. Our counterfactual analyses suggest that if investors were to focus solely on alpha when making investment decisions, fund fees would decrease by an average of 5.42%. Moreover, we estimate that employing more sophisticated asset pricing models to assess fund performance could significantly enhance investor welfare. For instance, basing investment decisions on performance adjusted by a 4-factor model could increase investor welfare by 7.6% to 18% per year, translating to a monetary value of 1445 yuan to 4800 yuan (US$203 to US$674) per investor annually.

These findings have important implications for both investors and policymakers in China and potentially other emerging markets with similarly unsophisticated investor bases. They highlight the need for improved financial literacy and more comprehensive disclosure practices to help investors better distinguish between alpha and FRRs.

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Table 1: Summary Statistics

	Obs	Mean	SD	25th	75th
Fund market shares	3,515	0.001	0.002	0.000	0.002
Fund age (years)	3,515	7.940	3.299	5.000	10.000
Fees (expense ratio)	3,515	0.029	0.018	0.021	0.034
Turnover ratio	3,515	4.089	3.291	2.015	5.042
Volatility of return	3,515	0.062	0.028	0.043	0.075
Past return	3,515	0.164	0.295	-0.053	0.351
Institution ratio	3,515	0.194	0.241	0.001	0.305
Size	3,515	20.670	1.457	19.747	21.725
4-factor alpha	3,515	0.002	0.013	-0.005	0.009
4-factor FFRs	3,515	0.005	0.013	-0.003	0.013
5-factor alpha	3,515	0.001	0.013	-0.007	0.009
5-factor FFRs	3,515	0.006	0.014	-0.002	0.014

Note: This table reports summary statistics for our sample at the mutual fund levels. Our sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds.

Table 2: Mutual Fund Fees and Past Returns

	Fees (expense ratios)		
	(1)	(2)	(3)
Past return	0.005***	-	-
	(0.001)	-	-
4-factor alpha	-	0.117***	-
	-	(0.021)	-
4-factor FRRs	-	0.097**	-
	-	(0.026)	-
5-factor alpha	-	-	0.116***
	-	-	(0.022)
5-factor FRRs	-	-	0.097***
	-	-	(0.026)
Volatility of return	-0.068***	-0.075***	-0.077***
	(0.015)	(0.016)	(0.015)
Fund age	-0.011***	-0.010**	-0.010**
	(0.003)	(0.003)	(0.003)
Turnover ratio	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
Institution ratio	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Size	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
TDRFL	-	-0.000	-0.000
	-	(0.000)	(0.000)
Mutual Fund FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-sq.	0.329	0.331	0.331
Observations	3,384	3,375	3,375

Note: This table reports the estimates of equation (4). The dependent variable is the Fee ratios (expense ratio). Fee ratio is the sum of management fee, custodian fee, and sales fee as a percentage of TNA. TDRFL (total deviation of risk factor loadings) is the deviation by substracting the industry median risk factor loading from a fund's risk factor loading. The sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Standard errors clustered at the fund level are shown in the parentheses.*** P<0.01, ** p<0.05, * p<0.10 denotes statistical significant at the 1%, 5% and 10% levels.

Table 3: Performance Persistence of Funds

	$FRRs_{j,t}$		$Alpha_{j,t}$	
	(1)	(2)	(3)	(4)
$FRRs_{j,t-1}$	-0.003	0.046	0.058	-0.072**
	(0.152)	(0.104)	(0.043)	(0.028)
$Alpha_{j,t-1}$	0.057	0.070	0.073**	0.055**
	(0.091)	(0.078)	(0.035)	(0.026)
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Serial Correlation (P-value)	0.002	0.006	0.000	0.000
Hansen Test (P-value)	0.341	0.091	0.203	0.074
Observations	2,322	2,322	2,322	2,322

Note: This table reports the estimates of equation (5). The dependent variable in Column (1) is 4-factor FRRs. The dependent variable in Column (2) is 5-factor FRRs. The dependent variable in Column (3) is 4-factor alpha. The dependent variable in Column (4) is 5-factor alpha. We apply one-step GMM method for dynamic panel-data estimation. The sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Serial correlation shows the p-value of the test of serial correlation in the error terms under the null of no serial correlation. The Hansen test presents p-values of the test of overidentifying restrictions of the instruments under the null of instrument validity. *** P<0.01, ** p<0.05, * p<0.10 denotes statistical significant at the 1%, 5% and 10% levels.

Table 4: Demand Estimation Results

	(1)	(2)	(3)
Fees - Mean	-4.406***	-1.695**	-1.824**
	(1.020)	(0.887)	(0.623)
Fees - S.D.	1.420***	2.940***	2.267***
	(0.396)	(0.549)	(0.475)
Past return - Mean	0.944***	-	-
	(0.072)	-	-
Past return - S.D.	0.143	-	-
	(0.612)	-	-
Alpha - Mean	-	1.211***	1.022***
	-	(0.409)	(0.433)
Alpha - S.D.	-	0.393	0.768**
	-	(0.241)	(0.274)
FRRs - Mean	-	3.203**	3.181**
	-	(1.447)	(1.319)
FRRs - S.D.	-	0.344	0.833**
	-	(0.408)	(0.229)
Volatility of return	-5.121***	-5.468***	-6.067***
	(0.098)	(0.795)	(1.046)
Fund age	0.671***	1.841***	1.059***
	(0.198)	(0.274)	(0.242)
Turnover ratio	-0.050***	-0.065	-0.006
	(0.019)	(0.190)	(0.033)
Mutual Fund FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,515	3,515	3,515

Note: The random coefficients logit model for demand (8) is estimated by genralized method of moments. Our sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Heteroskedasticity-robust standard errors are reported in parentheses. *** P<0.01, ** p<0.05, * p<0.10 denotes statistical significant at the 1%, 5% and 10% levels.

Table 5: Demand elasticity to fees and FRRs Chasing

	Demand elasticity to fees	
	(1)	(2)
Alpha	-1.021***	-1.014***
	(0.050)	(0.048)
FRRs	-0.902***	-0.912***
	(0.052)	(0.053)
Institution ratio	0.004***	0.004**
	(0.000)	(0.000)
Fund age	-0.186***	-0.185***
	(0.079)	(0.079)
Volatility of return	-0.733*	-0.691
	(0.416)	(0.425)
Turnover ratio	0.067***	0.066***
	(0.003)	(0.003)
Size	-0.111***	-0.1115***
	(0.010)	(0.010)
TDRFL	-0.018**	-0.008**
	(0.007)	(0.004)
Mutual Fund FE	Yes	Yes
Year FE	Yes	Yes
Within R-sq.	0.500	0.027
Observations	3,382	3,382

Note: The dependent variable is the estimated demand elasticity to fees. Our sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Standard errors clustered at the fund level are shown in the parentheses.*** P<0.01, ** p<0.05, * p<0.10. The Demand elasticity to fees is

$$\frac{\partial s_{j,t}}{\partial f_{j,t}} \frac{f_{j,t}}{s_{j,t}} = -\frac{f_{j,t}}{s_{j,t}} \int_i \theta_{1,i} s_{i,j} (1 - s_{i,j}) dF(\nu_i)$$

$s_{i,j}$ is the individual predicted quantity shares in year t.

Table 6: Market Power and FRRs

	$\frac{f_{j,t}-c_{j,t}}{f_{j,t}}$	
	(1)	(2)
Alpha	0.972***	1.008***
	(0.072)	(0.071)
FRRs	0.987***	0.971***
	(0.090)	(0.010)
Institution ratio	-0.005**	-0.005**
	(0.002)	(0.002)
Fund age	0.378	0.375
	(0.232)	(0.232)
Volatility of return	2.172**	2.728**
	(0.796)	(0.938)
Turnover ratio	-0.052***	-0.051***
	(0.006)	(0.005)
Size	0.176***	0.184***
	(0.023)	(0.023)
TDRFL	0.058***	0.010
	(0.015)	(0.007)
Mutual Fund FE	Yes	Yes
Year FE	Yes	Yes
Within R-sq.	0.029	0.027
Observations	3,382	3,382

Note: The dependent variable is the estimated market power. Our sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Standard errors clustered at the fund level are shown in the parentheses.*** P<0.01, ** p<0.05, * p<0.10.

Table 7: Counterfactual analysis: Fees

	$f^*_{j,t} - f_{j,t}$	
	(1)	(2)
Alpha	-0.139***	-0.101***
	(0.033)	(0.031)
FRRs	0.380***	0.365***
	(0.042)	(0.041)
Institution ratio	0.000	0.000
	(0.000)	(0.000)
Fund age	0.003	0.003
	(0.009)	(0.009)
Volatility of return	0.064*	0.064
	(0.035)	(0.042)
Turnover ratio	-0.002***	-0.002***
	(0.000)	(0.000)
Size	0.003**	0.003**
	(0.001)	(0.001)
TDRFL	0.001*	0.000
	(0.001)	(0.000)
Mutual Fund FE	Yes	Yes
Year FE	Yes	Yes
Within R-sq.	0.018	0.017
Observations	3,381	3,381

Note: The dependent variable is the change in fees in a counterfactual analysis. $f^*_{j,t}$ is the simulated counterfactual equailibrium fees. Our sample consists of equity funds and equity-oriented balanced funds in the Chinese market from December 2011 to December 2021, excluding index funds, ETFs, and leveraged funds. Standard errors clustered at the fund level are shown in the parentheses.*** P<0.01, ** p<0.05, * p<0.10.

Table 8: Counterfactual analysis: Changes in Consumer Welfare

	CV (%)	CV (Yuan)	CV (%)	CV (Yuan)
	4-factor	4-fator	5-factor	5-factor
	(1)	(2)	(3)	(4)
2011	7.69	2045.16	8.08	2148.88
2012	6.16	1639.52	6.50	1727.80
2013	5.43	1445.28	5.75	1528.81
2014	7.93	2109.31	8.31	2210.88
2015	9.97	2651.11	10.49	2791.07
2016	11.49	3056.80	12.08	3212.32
2017	8.95	2381.10	9.42	2505.09
2018	12.95	3443.65	13.58	3611.08
2019	18.05	4800.39	18.94	5036.12
2020	14.26	3791.66	14.98	3982.61
2021	16.39	4359.45	17.19	4571.15

Note: This table reports the compensating variation across simulated investors.