ENDOGENOUS DYNAMIC CONCENTRATION OF THE ACTIVE FUND MANAGEMENT INDUSTRY, HETEROGENEOUS MANAGER ABILITIES, AND STOCK MARKET VOLATILITY

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Abstract. We introduce continuous-time models of concentration in the active fund management industry, where managers with heterogeneous dynamic unobservable abilities compete for investments of risk-neutral or risk-averse investors. Dynamics of managers' inferred abilities determine dynamics of equilibrium fund sizes thus concentration, measured by the Herfindahl-Hirschman Index (HHI). Positive performance shocks of managers, whose inferred abilities are sufficiently large (small) relative to those of other managers, exert positive (negative) impacts on HHI, but managers' higher performance variations mitigate these impacts. Higher stock market volatility decreases HHI when the fund size distribution is skewed to the right. Our empirical results support our theory.

Keywords: Active fund management, Market concentration, Dynamic unobservable manager ability, Fund performance, Performance variation, Learning, Volatility

JEL Codes: G11, G14, G23, J24, L11

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1 Introduction

Active fund management industry (AFMI) investors seek excess returns over passive indices by allocating wealth, based on preference, to AFMI managers, who implement costly portfolio strategies and charge fees [e.g., Berk and Green (2004) and Berk (2005)]. This implies that in AFMI buyers (investors) determine the quantity of production (investment amount). The producers (fund managers), with fixed prices (management fees), stimulate production quantities to increase profits. These features make AFMI different from classical production industries, in which producers determine product prices and production quantities, and buyers decide the quantities they buy. These special features also make the analysis of AFMI concentration different from those of classical production industries. Current literature has shown that AFMI concentration has significant impact on AFMI size and performance [Feldman, Saxena, and Xu (2020, 2023)], implying that AFMI concentration dynamics exert significant effects on AFMI over time. As AFMI manages a huge amount of wealth,[1] studying AFMI industrial organization, in particular its dynamic concentration, offers significant economic insights. However, there have been few studies of AFMI concentration dynamics. Our goal is to fill this gap.

We develop a continuous-time framework to model AFMI with multiple heterogeneous active equity funds. Fund managers' abilities to create excess returns over a passive benchmark return (gross alpha) are dynamic and unobservable for both investors and managers. Both infer these abilities by observing fund returns (hereafter, we call the estimates of these abilities as inferred abilities).[2] AFMI has decreasing returns to scale in the sense that funds' total costs are increasing and convex in the size of assets under active management. Managers set constant management fees and, over time, maximize fund profits by dynamically choosing the size of wealth they actively manage to determine fund net alphas.[3] Risk-neutral investors supply

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[1] According to the Investment Company Institute (ICI), the total net assets of worldwide regulated open-end funds (including mutual funds, exchange-traded funds, and institutional funds) were $63.1 trillion in 2020. See the 2021 Investment Company Fact Book at the ICI website, https://www.ici.org/system/files/2021-05/2021_factbook.pdf, accessed on October 12th, 2021.

[2] The active funds' observable gross alphas follow Itô processes in which the drift terms depend on the dynamic unobservable manager ability levels. These ability levels also follow Itô processes. Their diffusions are (locally, imperfectly) correlated with those of funds' gross alpha processes.

[3] Berk and Green (2004) shows that the case in which the fund manager actively manages the whole fund and

capital with infinite elasticity to funds that offer positive expected net alphas; due to decreasing returns to scale, investments drive expected net alphas to zero.

Fund managers differentiate themselves by their inferred abilities. In equilibrium, a fund's size and, thus, profit is increasing and convex in its manager's inferred ability.[4] This implies that in equilibrium, better managers manage larger funds and receive larger rewards.

In our model and AFMI models in current literature, such as Berk and Green (2004), Choi, Kahraman, and Mukherjee (2016), Brown and Wu (2016), and Feldman and Xu (2022), many common measures of AFMI's industrial organization are less informative than the concentration measure that we use. For example, as fund costs are transferred to investors as deductions in fund returns, a fund's profit margin (the difference of revenue and costs, divided by the revenue) and Lerner Index (the difference of fee and marginal cost, divided by fee) are always equal to one. These results imply that profit margin and Lerner Index cannot effectively measure funds' profitability and market power, respectively. This makes AFMI's concentration dynamics a main attribute in studying the AFMI's industrial organization dynamics.

We use the Herfindahl-Hirschman index (HHI) to measure AFMI concentration, which is the sum of funds' market shares squared,[5] for several reasons. First, HHI reflects the combined influence of both unequal fund sizes and the concentration of activity in a few large funds, so it has advantage over other concentration measures, such as a concentration ratio, which only sums up the market shares of a few largest funds and ignores the information of other funds. Second, some regulatory agencies use HHI to measure concentration.[6] Third, HHI

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chooses the management fee at each time is equivalent to the case in which the fund manager chooses the amount of the fund to actively manage at each time under a fixed management fee. As the latter case is more realistic, we focus on it to conduct our analyses.

[4] The intuition is that to maximize fund profit with a fixed fee, a fund manager tries to attract as much investment as possible by offering positive expected net alpha to investors. Under decreasing returns to scale, the manager's inferred ability determines the expected net alphas that he/she can produce and then determines the equilibrium fund size. A manager with higher inferred ability puts a larger amount of the fund under active management to offer higher expected net alpha, and investors respond to this higher inferred ability more intensively when investing in this fund.

[5] A higher (lower) HHI implies a more (less) concentrated AFMI. The highest value of HHI is one, which implies a monopolistic AFMI. The lowest value of HHI is the inverse of the number of funds, which implies homogeneous funds in the AFMI.

[6] For example, the U.S. Census calculates industry concentration as HHI, used by regulatory agencies such as the Federal Trade Commission and Department of Justice [e.g., Ali, Klasa, and Yeung (2009) and Azar, Schmalz, and Tecu (2018)].

is a common measure of concentration in current theoretical and empirical studies.[7] Fourth, new concentration measures are calculated based on HHI. For example, the normalized Herfindahl-Hirschman index adjusts the effects of the number of rivals [Cremers, Nair, and Peyer (2008)], and the modified Herfindahl-Hirschman index captures the concentrations of producers and of shareholders' ownership [O'Brien and Salop (2000), Azar, Schmalz, and Tecu (2018), and Koch, Panayides, and Thomas (2021)].

We show that managers' relative inferred abilities, sensitivities of gross alphas to abilities, and fund size factors (each of which equals the inverse of the product of a fund's management fee and decreasing returns to scale parameter), together determine the equilibrium AFMI HHI (hereafter, briefly, HHI). The heterogeneity in these parameters and their values relative to each other are relevant in studying HHI. More importantly, fund managers' inferred abilities are dynamic, which drive the dynamics of HHI over time.

Our first prediction on HHI dynamics is that if a manager's inferred ability is sufficiently large (small) relative to those of other managers,[8] then an increase in this manager's inferred ability due to positive performance shock and/or positive ability drift, has a positive (negative) impact on the dynamics of HHI. The reason is that if a manager's inferred ability is sufficiently large, then the fund's equilibrium size is sufficiently large compared to other funds. Even higher inferred ability attracts more investments to this fund, making AFMI more concentrated. On the other hand, if a manager's inferred ability is sufficiently small, then the fund's equilibrium size is sufficiently small relative to other funds. A higher inferred ability attracts more investment to this fund, making its size closer to that of other funds and making AFMI less concentrated.

Our second prediction is that, if a manager's inferred ability is sufficiently large (small) relative to the inferred abilities of other managers, then a higher performance variation of this manager mitigates the positive (negative) impact induced by a positive shock in this manager's

[7] See, for example, theoretical models, such as Bustamante and Donangelo (2017) and Corhay, Kung, and Schmid (2020), that study firm concentration, and Feldman, Saxena, and Xu (2020, 2023) that study AFMI concentration; and see empirical models, such as Cornaggia, Mao, Tian, and Wolfe (2015), that study labor concentration and industry concentration, Spiegel and Tookes (2013) and Gu (2016) that study product market concentration, and Giannetti and Saidi (2019) that study credit concentration.

[8] The inferred ability level that is sufficiently large (small) is determined by an interesting relation involving the fund size, AFMI size, and the sum of squares of AFMI fund sizes. Please see Corollary RN2.1 below.

performance on the dynamics of HHI. The reason is that if a manager's performance variation is higher, then investors allocate smaller weights to this manager's performance shocks when learning about his or her ability. Consequently, investment flows react less intensively to a positive shock in this manager's performance, which mitigates the positive (negative) impact of this positive shock on the dynamics of HHI.

We further extend our model to allow sensitivities of gross alphas to manager abilities to be decreasing functions of stock market volatility. We make this assumption because higher stock market volatility increases market stress and redemption risk, which induces managers to prepare a larger cash buffer and impedes managers in implementing strategies to create abnormal returns [Jin, Kacperczyk, Kahraman, and Suntheim (2022)]. This setting makes our framework a nonlinear one and enables us to study the effect of stock market volatility on HHI.[9] Under this setting, given the same inferred manager abilities, higher stock market volatility decreases fund expected gross alphas, thus equilibrium fund sizes. As changes in large funds' sizes exert a large impact on the dynamics of HHI, the aggregate effect of higher stock market volatility on the dynamics of HHI is negative when extremely large funds exist. In other words, we predict that if the distribution of fund sizes is skewed to the right, then HHI decreases with stock market volatility. This is our third prediction.

Moreover, we examine a special case in which managers' unobservable abilities are constant and associate with gross alphas within a linear framework. In this case, as time goes to infinity, AFMI reaches a steady state in which investors know managers' abilities (managers' inferred abilities stay unchanged).[10] Consequently, investments in funds stay unchanged, making HHI constant. As this result are incompatible with empirical findings that HHI is dynamic in the long term, as shown by Feldman, Saxena, and Xu (2020, 2023) and the empirical section of this paper, linear frameworks with constant manager abilities, such as those of Berk and Green (2004), Choi, Kahraman, and Mukherjee (2016), and Brown and Wu (2016),

[9] In our baseline model, the coefficients of the Itô processes of observable gross alphas and unobservable manager abilities are constant, so it is a linear framework requiring linear filtering techniques to solve it. Linear frameworks in the current literature, such as Berk and Green (2004) and their followers, cannot directly model the effects of economic factors on gross alphas/manager abilities as we do in our nonlinear framework. Our nonlinear framework requires nonlinear filtering techniques to solve it.

[10] The reason is that, over time, the estimation precisions of inferred abilities monotonically increase and the sensitivities of inferred abilities to performance shocks monotonically decrease to zero.

do not explain the empirical dynamics of HHI. Thus, it is important to study HHI with dynamic manager abilities, especially under a nonlinear framework.

We show that our results hold for the case where investors are mean-variance risk averse who maximize portfolio instantaneous Sharpe ratios. In equilibrium, investors' risk considerations decrease fund sizes. However, the way to compare fund sizes relative to those of others does not depend on investors' risk considerations, so the dynamics of HHI relates to managers' relative inferred abilities in a way similar to that in the case of risk-neutral investors.

We also demonstrate that our model is compatible with effects of fund entrances and exits on HHI. We allow the total number of funds to change over time and funds exit (enter) the market if their managers' inferred abilities decrease (increase) to zero.[11] We show that under this setting, fund entrances and exits do not immediately affect the dynamics of HHI, but they change the set of funds in AFMI, a change that exerts impacts on the dynamics of HHI as captured by our model.

Further, we show that when we measure HHI at the fund family level (such that HHI is the sum of fund families' market shares squared), the earlier three predictions on fund-level HHI dynamics still hold if similar requirements on the fund families' aggregate inferred abilities/family sizes are satisfied.[12]

In addition, we show that if HHI changes proportionally gross alpha sensitivities to abilities and fund size factors, then the effects of HHI on these parameters do not affect funds' relative sizes, such that our earlier results of HHI still hold. Thus, our equilibrium is compatible with those in the current literature where AFMI concentration affects equilibrium fund alphas and sizes [e.g., Pastor and Stambaugh (2012), and Feldman, Saxena, and Xu (2020, 2023)].

To empirically test our theoretical predictions, we use the active equity mutual fund data from the Center for Research in Security Prices (CRSP). Our sample period is January 1990 to December 2020, and we use monthly data. First, we define the large-fund group as the

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[11] In other words, funds' survival levels of their managers' inferred abilities are zero. These survival levels can be regarded as those endogenously chosen by profit-maximizing managers. The reason is that funds with positive inferred abilities earn positive equilibrium profits and optimally choose to stay in the market to earn the profits, whereas without short selling of assets, funds with negative inferred abilities optimally choose to put zero assets under active management to avoid losses and exit AFMI.

[12] In particular, in the first two predictions, we require that the manager is in a fund family with sufficiently large (small) aggregate inferred ability relative to that of other fund families. In the third prediction, we require the distribution of fund family sizes to be skewed to the right. See the detailed analysis in Section 2.9.

five funds that have the largest sizes, and the small-fund group as the funds with fund size values from the fifth percentile to the tenth percentile. These funds are likely to be sufficiently large and sufficiently small, respectively, relative to other funds, and can be used to test our theoretical predictions. Second, we define the shocks in these two groups' performances relative to those of other funds as the changes of these groups' market shares, because funds' market shares indicate their managers' inferred abilities relative to those of other funds, as shown in our model.

Third, to measure fund performance, we use 24-month rolling windows to estimate one-month-ahead fund net alphas, using the five-factor model developed by Fama and French (2015) and the four-factor model developed by Fama and French (1993) and Carhart (1997). Then, we develop three measures of performance variation. Following Amihud and Goyenko (2013), our first measure is the $1 - R^2$ in each rolling-window regression, which is equal to the residual sum of squares divided by the total sum of squares.[13] As the residuals in each factor model regression can be regarded as the in-sample estimates of abnormal returns, $1 - R^2$ can be regarded as the in-sample estimate of fund performance variation (normalized by total variation of the dependent variable). Our second and third measures of performance variation are the standard deviation of fund net alpha and of fund gross alpha, respectively, where fund gross alpha is fund net alpha plus annual expense ratio divided by 12. These two measures are the performance volatility measures used by Huang, Wei, and Yan (2021). Forth, similar to the current literature, such as Jin, Kacperczyk, Kahraman, and Suntheim (2022), we choose the option-implied volatility index (VIX) as our measure of stock market volatility.

We first show that the flow–net alpha sensitivity significantly decreases with the VIX level and significantly decreases with our measures of performance variation. This empirical evidence supports our assumptions that sensitivities of gross alphas to manager abilities decrease with stock market volatility and that investors, when learning about the manager's ability, rely less on fund performance if the fund's performance is more volatile. We also show that in our sample some extremely large funds and fund families exist in the market, and funds in a large-fund (small-fund) group are in fund families that are very large (small) relative to

[13] Amihud and Goyenko (2013) demonstrate that this $1 - R^2$ measure is highly related to fund performance.

other fund families. Then, by our theory, our three predictions should hold whether we measure HHI at the fund level or fund family level.

In testing our predictions, we first measure HHI at the fund level, and regress the change in HHI on the lagged changes in the VIX level and in the market shares of the large-fund group and small-fund group. We find that an increase in VIX significantly decreases HHI, showing that higher stock market volatility exerts a negative aggregate impact on HHI. Also, an increase in the large-fund group's market share significantly increases HHI, showing that a positive shock in this group's relative performance induces positive impact on the change of HHI. This positive impact is smaller when this group's performance variation is higher, as the interaction term of the large-fund group's change of market share and performance variation is significantly negative. Also, the coefficient of the change in the market share of the small-fund group is negative but insignificant; however, the interaction term of the small-fund group's change of market share and performance variation is significantly positive. This implies that this group's performance variation is likely to mitigate the impact of the shocks in this group's relative performance on the dynamics of HHI. In addition, we find consistent results when we measure HHI at the fund family level. Our results are robust to different measures of change in stock market volatility, different classifications of the large-fund group and small-fund group, and different estimation methods of the regression models. In general, our empirical results are consistent with our theoretical predictions.

The above findings have relevant implications. As shown above, AFMI concentration is higher if stock market volatility is lower and/or if large funds perform better with lower performance variation. This higher concentration would increase fund net alphas and AFMI size, on average, as shown by Feldman, Saxena, and Xu (2020). Thus, investors should incorporate stock market volatility and the performance and performance variation of large funds into their decision of fund investments.

We offer additional empirical evidence of HHI that support our theory and that are consistent with those in the literature. For example, we show the aggregate size of funds that enter (exit) the market is negligible compared to the AFMI size, which supports our framework that fund entrance (exit) does not exert immediate impact on HHI dynamics. Also, we show that HHI of the U.S. active equity mutual fund market, whether measured at the fund or fund family level, fluctuates over the last few decades and does not converge, consistent with a framework with dynamic unobservable manager abilities and inconsistent with a framework with constant such abilities where HHI converges. Moreover, we find that from the early 1990s to the early 2000s, the number of funds and fund families keep increasing whereas HHIs at the fund and fund family levels keep decreasing. This is consistent with the fact that in this period, AFMI incumbents that have a high overlap in their portfolio holdings with those of new entrants experience lower fund flows and lower alphas [Wahal and Wand (2011)], and with the fact that there is a decrease in fund manager performance in similar periods [Kosowski, Timmermann, Wermers, and White (2006) and Fama and French (2010)]. The reason is that as new funds hold portfolios similar to those of the incumbents, it is more difficult for funds to outperform each other, so managers' inferred abilities become close to each other, inducing close fund and fund family sizes and lower HHIs.

Contribution to the Literature

This paper makes multiple contributions to the literature. First, to our best knowledge, we develop the first model of equilibrium dynamic AFMI concentration under a framework of multiple heterogeneous managers with dynamic unobservable abilities. We theoretically show how AFMI concentration (competitiveness) evolves with different factors over time and show that our results hold 1) whether investors are risk neutral or mean-variance risk averse, 2) under funds' entrances and exits, and 3) when AFMI concentration exerts impacts on alpha production and fund size factors. Our paper offers new insights compared to the current literature on AFMI competitiveness [e.g., Pastor and Stambaugh (2012), and Feldman, Saxena, and Xu (2020, 2023)], which studies one-period fixed-point equilibrium AFMI concentration.

Second, novel to the literature, we provide empirical evidence of how relative fund performances, performance variations, and stock market volatility drive AFMI HHI dynamics. This evidence supports our theory. Our empirical findings relate to current literature on AFMI performance, volatility, and market stress [e.g., Amihud and Goyenko (2013), Huang, Wei, and Yan (2021), Jin, Kacperczyk, Kahraman, and Suntheim (2022)].

Third, we theoretically and empirically study AFMI HHIs at the fund and fund family levels to offer more insights than those implied by the current literature [e.g., Pastor and Stambaugh (2012), and Feldman, Saxena, and Xu (2020, 2023)], which studies only the fund-level competitiveness. Our HHI at the fund family level is consistent with the current findings that member funds in a fund family can cooperate to compete in the market [e.g., Evans, Prado, and Zambrana (2020), Eisele, Nefedova, Parise, and Peijnenburg (2020), and Xu (2023)].

Forth, our model explains stylized findings in AFMI concentration, size, and performance in a compatible way, such as those by Kosowski, Timmermann, Wermers, and White (2006), Fama and French (2010), and Wahal and Wand (2011).

Finally, we further demonstrate that a nonlinear framework of manager abilities and gross alphas explain and predict AFMI HHI dynamics better than a linear framework. We show that using our nonlinear framework, we can easily model effects of economic factors, such as stock market volatility, on the dynamics of HHI; linear frameworks that are commonly used in the current literature, such as those of Berk and Green (2004), Dangl, Wu, and Zechner (2008), Choi, Kahraman, and Mukherjee (2016), and Brown and Wu (2016), cannot do this. This result provides guidelines for future research on the dynamics of AFMI concentration and supports the spirit of Feldman and Xu (2022), which introduces this type of nonlinear framework in studying AFMI phenomena.

The rest of this paper is organized as follows. Section 2 introduces our model. Section 3 provides our empirical study. Section 4 concludes and discusses future research on this area.

2 A Model of AFMI Concentration

We introduce a rational equilibrium model to study the dynamics of AFMI concentration. In our model, investors can invest in multiple independent heterogeneous active funds, each with one manager, and in a passive benchmark portfolio. This multiple-fund setting is similar to the one in Brown and Wu (2016). Within a continuous-time framework, we study the active fund managers and investors over a time interval, at times t, $t \in [0, T]$, where T, $T > 0$ is a constant, allowed to be sufficiently large (i.e., $T \to \infty$) when we study the steady state in some special cases. Our baseline model uses a linear framework as shown in Section 2.1 to study the dynamics of AFMI concentration. Then, we extend our framework to a nonlinear one as shown in Section 2.5 to study how the dynamics of stock market volatility affects that of AFMI concentration. Sections 2.4 to 2.8 study AFMI concentration at the fund level, whereas Section 2.9 studies AFMI concentration at the fund family level. Other settings of our model are similar to those in the current literature.[14]

2.1 Observable Fund Returns and Unobservable Manager Abilities: Filtering

There are n, $n \geq 2$, active funds in the market, which create returns for investors by investing their wealth in the stock market. Let $\boldsymbol{\xi}_\mathbf{t}$, $0 \leq t \leq T$ be an $n \times 1$ vector of active funds' gross share prices, i.e., share price before fund costs and fees, where the ith element is $\xi_{i,t}$, $i = 1, \dots, n$. Then, $\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t}$ is the $n \times 1$ vector of the instantaneous fund gross returns, where $\mathbf{I}(\boldsymbol{\xi}_\mathbf{t})$ is an $n \times n$ diagonal matrix with $\xi_{i,t}$ as the ith diagonal element. The $n \times 1$ vector $\mathbf{d}\boldsymbol{\xi}_\mathbf{t}$ has its ith element as $d\xi_{i,t}$, which is the differential of $\xi_{i,t}$, $i = 1, \dots, n$. Hereafter, a vector with $\mathbf{d}$ on the left has a similar definition. For simplification, we assume that active funds have beta loads of one on the passive benchmark portfolio. To focus on the active funds' returns, similar to Feldman and Xu (2022), we normalize the passive benchmark portfolio's return to zero so that the vector of instantaneous fund gross returns in excess of the passive benchmark is also $\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t}$. Hereafter, we call $\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t}$ the funds' instantaneous gross alphas, or briefly, gross alphas.

Fund gross alphas depend on the $n \times 1$ vector of fund managers' instantaneous abilities, $\boldsymbol{\theta}_\mathbf{t}$, $0 \leq t \leq T$, to beat the benchmark, where the ith element is $\theta_{i,t}$, $i = 1, \dots, n$. We call them, briefly, abilities. These abilities are unobservable to both fund managers and investors. Fund managers and investors learn about $\boldsymbol{\theta}_\mathbf{t}$ by observing the history of fund gross alphas $\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t}$, $0 \leq s \leq t$ (or equivalently by observing $\boldsymbol{\xi}_\mathbf{s}$, $0 \leq s \leq t$). We assume a complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$ with filtration $\{\mathcal{F}_t\}_{0 \leq t \leq T}$. The $n \times 1$ vectors of independent Wiener processes, $\mathbf{W}_{\mathbf{1},\mathbf{t}}$ and $\mathbf{W}_{\mathbf{2},\mathbf{t}}$, $0 \leq t \leq T$, are adapted to this filtration, where their ith elements are $W_{1i,t}$ and $W_{2i,t}$, $i = 1, \dots, n$, respectively.[15] The unobservable $\boldsymbol{\theta}_\mathbf{t}$ and the observable $\boldsymbol{\xi}_\mathbf{t}$ evolve as follows:

$$\mathbf{d}\boldsymbol{\theta}_\mathbf{t} = (\mathbf{a_0} + \mathbf{a_1}\boldsymbol{\theta}_\mathbf{t})dt + \mathbf{b_1}\mathbf{dW}_{\mathbf{1},\mathbf{t}} + \mathbf{b_2}\mathbf{dW}_{\mathbf{2},\mathbf{t}}, \tag{1}$$

$$\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t} = \mathbf{A}\boldsymbol{\theta}_\mathbf{t}dt + \mathbf{B}\mathbf{dW}_{\mathbf{2},\mathbf{t}}, \tag{2}$$

with initial conditions $\boldsymbol{\theta}_\mathbf{0}$ and $\boldsymbol{\xi}_\mathbf{0}$, respectively. The $n \times 1$ constant vector $\mathbf{a_0}$ has its ith

[14] Similar to Berk and Green (2004), Brown and Wu (2016), and Feldman and Xu (2022), managers and investors are symmetrically informed; the model is in partial equilibrium; managers' actions do not affect the passive benchmark returns; and we do not model sources of managers' abilities to outperform the passive benchmarks portfolios.
[15] For any i and j, $dW_{1i,t}dW_{2j,t} = 0$; and for any $i \neq j$, $dW_{1i,t}dW_{1j,t} = 0$ and $dW_{2i,t}dW_{2j,t} = 0$.

element $a_{i,0}$, $i = 1, \dots, n$, whereas the $n \times n$ constant diagonal matrices $\mathbf{a_1}$, $\mathbf{b_1}$, $\mathbf{b_2}$, $\mathbf{A}$, and $\mathbf{B}$ have their ith diagonal elements $a_{i,1}$, $b_{i,1}$, $b_{i,2}$, A_i, and B_i, $i = 1, \dots, n$, respectively. We assume that $A_i > 0$, $i = 1, \dots, n$ and, without loss of generality, we assume $B_i > 0$, $i = 1, \dots, n$. While abilities are unobservable to managers and investors, the evolution processes ("laws of motion") and all parameter values are common knowledge.

The above setting implies the following. First, manager abilities, $\boldsymbol{\theta_t}$, follow dynamic processes. Second, the fund gross alphas, $\mathbf{I^{-1}(\boldsymbol{\xi}_t)d\boldsymbol{\xi}_t}$, depend on the managers' abilities and on random shocks. As $A_i > 0$, $i = 1, \dots, n$, a manager with positive (negative) ability tends to create positive (negative) fund gross alpha, and the larger A_i is, the higher is the sensitivity of gross alpha to ability. As B_i, $i = 1, \dots, n$ is the diffusion coefficient of fund i's gross alpha, the larger B_i is, the larger is the variation of fund i's gross alpha.[16] Third, as $\mathbf{a_1}$, $\mathbf{b_1}$, $\mathbf{b_2}$, $\mathbf{A}$, and $\mathbf{B}$ are diagonal matrices, over time a manager's ability and gross alpha are independent of those of other managers.[17,18] Fourth, where $b_{i,2} > 0$ ($b_{i,2} < 0$), manager i's ability and fund gross alpha are instantaneously positively (negatively) correlated, as $b_{i,2}B_i > 0$ ($b_{i,2}B_i < 0$). Where $b_{i,2} = 0$, and $b_{i,1} > 0$, manager i's ability and gross alpha are instantaneously uncorrelated. A larger $b_{i,2}$ relative to $b_{i,1}$ implies a higher instantaneous correlation between manager i's gross alpha and ability. Finally, as gross alphas are returns over the passive benchmark return, our setting incorporates any effects of innovations in the passive benchmark, such as those in the exchange traded fund (ETF) market, on funds' performances.[19]

To facilitate our analysis, we define the following terms:

- $\mathcal{F}_t^{\boldsymbol{\xi}} \triangleq$ the σ-algebras generated by $\{\boldsymbol{\xi}_s, 0 \le s \le t\}$, with $\left\{\mathcal{F}_t^{\boldsymbol{\xi}}\right\}_{0 \le t \le T}$ as the corresponding filtration over $0 \le t \le T$;

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[16] Notice that for fund i, $i = 1, \dots, n$, the parameter B_i determines the instantaneous variance of $d\xi_{i,t}/\xi_{i,t}$ at time t, as $\mathrm{Var}\left(d\xi_{i,t}/\xi_{i,t} | \mathcal{F}_t\right) = B_i^2 dt$, and determines the instantaneous quadratic variation of $d\xi_{i,t}/\xi_{i,t}$ at time t, as $\left(d\xi_{i,t}/\xi_{i,t}\right)^2 = B_i^2 dt$. Thus, we can regard B_i as a parameter indicating fund i's performance variation.

[17] For any $i \ne j$, $d\theta_{i,t} d\theta_{j,t} = 0$, $d\theta_{i,t}\left(d\xi_{j,t}/\xi_{j,t}\right) = 0$, and $\left(d\xi_{i,t}/\xi_{i,t}\right)\left(d\xi_{j,t}/\xi_{j,t}\right) = 0$.

[18] Existing literature shows that in some fund families, as funds are managed by the same team of managers, their abilities and alphas are correlated such that we can learn about the ability of a fund from another fund's performance [e.g., Brown and Wu (2016) and Choi, Kahraman, and Mukherjee (2016)]. This correlation does not affect our model's insight, so for simplicity, we assume independence in managers' abilities and gross alphas.

[19] Existing literature, such as Cremers, Ferreira, Matos, and Starks (2016), shows that the innovation of the index fund/ETF market affects the performances of active funds. As index funds and ETFs serve as passive benchmarks of active funds in practice, our active funds' gross alphas, $\mathbf{I^{-1}(\boldsymbol{\xi}_t)d\boldsymbol{\xi}_t}$, capture any effects of index funds/ETFs on active funds' performances.

- $\mathbf{m_t} \triangleq$ the $n \times 1$ vector of mean of $\boldsymbol{\theta}_\mathbf{t}$ conditional on the observations $\boldsymbol{\xi}_\mathbf{s}$, $0 \le s \le t$, i.e., $\mathbf{m_t} \triangleq \mathrm{E}(\boldsymbol{\theta}_\mathbf{t}|\mathcal{F}_t^{\boldsymbol{\xi}})$;
- $\boldsymbol{\gamma}_\mathbf{t} \triangleq$ the $n \times n$ covariance matrix of $\boldsymbol{\theta}_\mathbf{t}$ conditional on the observations $\boldsymbol{\xi}_\mathbf{s}$, $0 \le s \le t$, i.e., $\boldsymbol{\gamma}_\mathbf{t} \triangleq \mathrm{E}[(\boldsymbol{\theta}_\mathbf{t} - \mathbf{m_t})(\boldsymbol{\theta}_\mathbf{t} - \mathbf{m_t})'|\mathcal{F}_t^{\boldsymbol{\xi}}]$.

As $\mathbf{m_t}$ is the expected abilities inferred from observable fund returns, hereafter, we briefly call $\mathbf{m_t}$ as inferred abilities. We assume that the conditional distribution of $\boldsymbol{\theta}_\mathbf{0}$ given $\boldsymbol{\xi}_\mathbf{0}$ (the prior distribution) is Gaussian, $N(\mathbf{m_0}, \boldsymbol{\gamma}_\mathbf{0})$, where $\boldsymbol{\gamma}_\mathbf{0}$ is a $n \times n$ diagonal matrix, and elements of $\boldsymbol{\xi}_\mathbf{0}$, $\mathbf{m_0}$, and $\boldsymbol{\gamma}_\mathbf{0}$ have finite values.

Managers and investors update their estimates of $\boldsymbol{\theta}_\mathbf{t}$ using their observations of $\boldsymbol{\xi}_\mathbf{t}$ in a Bayesian fashion (i.e., "optimal filtering").[20] These techniques used in numerous previous studies, such as Dothan and Feldman (1986), Feldman (1989, 2007), Berk and Stanton (2007), Dangl, Wu, and Zechner (2008), Brown and Wu (2013, 2016), and Feldman and Xu (2022). In our case, let $\mathcal{F}_t^{\boldsymbol{\xi}_0, \overline{\mathbf{W}}}$, $0 \le t \le T$ be the σ-algebras generated by $\{\boldsymbol{\xi}_\mathbf{0}, \overline{\mathbf{W}}_\mathbf{s}, 0 \le s \le t\}$. Then,

$$\overline{\mathbf{W}}_\mathbf{t} = \int_0^t \mathbf{B}^{-1}[\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t} - \mathbf{A}\mathbf{m}_\mathbf{s} ds] \tag{3}$$

is an $n \times 1$ vector of independent Wiener process with respect to the filtration $\left\{\mathcal{F}_t^{\boldsymbol{\xi}}\right\}_{0 \le t \le T}$, with the ith element as $\overline{W}_{i,t}$ and with its initial value $\overline{\mathbf{W}}_\mathbf{0}$ being a zero $n \times 1$ vector. The σ-algebras $\mathcal{F}_t^{\boldsymbol{\xi}}$ and $\mathcal{F}_t^{\boldsymbol{\xi}_0, \overline{\mathbf{W}}}$ are equivalent. $\overline{\mathbf{W}}_\mathbf{t}$ innovates the inferred abilities $\mathbf{m_t}$. The variables $\mathbf{m_t}$, $\boldsymbol{\xi}_\mathbf{t}$, and $\boldsymbol{\gamma}_\mathbf{t}$ are the unique, continuous, $\mathcal{F}_t^{\boldsymbol{\xi}}$-measurable solutions of the system of equations

$$\mathbf{dm_t} = (\mathbf{a_0} + \mathbf{a_1}\mathbf{m_t})dt + \boldsymbol{\sigma}_\mathbf{m}(\boldsymbol{\gamma}_\mathbf{t})\mathbf{d}\overline{\mathbf{W}}_\mathbf{t}, \tag{4}$$

$$\mathbf{I}^{-1}(\boldsymbol{\xi}_\mathbf{t})\mathbf{d}\boldsymbol{\xi}_\mathbf{t} = \mathbf{A}\mathbf{m_t}dt + \mathbf{B}\mathbf{d}\overline{\mathbf{W}}_\mathbf{t}, \tag{5}$$

$$\mathbf{d}\boldsymbol{\gamma}_\mathbf{t} = [\mathbf{b_1}\mathbf{b_1} + \mathbf{b_2}\mathbf{b_2} + 2\mathbf{a_1}\boldsymbol{\gamma}_\mathbf{t} - \boldsymbol{\sigma}_\mathbf{m}(\boldsymbol{\gamma}_\mathbf{t})\sigma_m'(\boldsymbol{\gamma}_\mathbf{t})]dt, \tag{6}$$

where

$$\boldsymbol{\sigma}_\mathbf{m}(\boldsymbol{\gamma}_\mathbf{t}) \triangleq (\mathbf{b_2}\mathbf{B} + \mathbf{A}\boldsymbol{\gamma}_\mathbf{t})'\mathbf{B}^{-1}, \tag{7}$$

[20] This type of model is solved in Liptser and Shiryaev (2001a, Ch. 8; 2001b, Ch. 12). More general models with settings similar to those presented by Liptser and Shiryaev (2001a,b) allow model parameters to be functions of the stochastic gross alphas.

with initial conditions $\boldsymbol{\xi_0}$, $\mathbf{m_0}$, and $\boldsymbol{\gamma_0}$. The random process $(\boldsymbol{\theta_t}, \boldsymbol{\xi_t})$, $0 \le t \le T$ is conditionally Gaussian given $\mathcal{F}_t^{\boldsymbol{\xi}}$.[21]

Taking a closer look at $\mathbf{d}\boldsymbol{\gamma_t}$, we find that as $\boldsymbol{\gamma_0}$ and the parameter matrices in Equations (6) and (7) are diagonal, $\boldsymbol{\gamma_t}$ and $\boldsymbol{\sigma_m}(\boldsymbol{\gamma_t})$ are diagonal. Then, we can define the ith diagonal element of $\boldsymbol{\gamma_t}$ as $\gamma_{i,t}$, $i = 1, \dots, n$, which is the variance of $\theta_{i,t}$ conditional on the observations of fund share prices, representing the imprecision of the estimate $m_{i,t}$. We have

$$d\gamma_{i,t} = \left[b_{i,1}^2 + b_{i,2}^2 + 2a_{i,1}\gamma_{i,t} - \sigma_{i,m}^2(\gamma_{i,t})\right]dt, \tag{8}$$

where $\sigma_{i,m}(\gamma_{i,t})$, $i = 1, \dots, n$, is the ith diagonal element of $\boldsymbol{\sigma_m}(\boldsymbol{\gamma_t})$ that

$$\sigma_{i,m}(\gamma_{i,t}) \triangleq (b_{i,2}B_i + A_i\gamma_{i,t})/B_i. \tag{9}$$

As $\boldsymbol{\gamma_t}$ and $\boldsymbol{\sigma_m}(\boldsymbol{\gamma_t})$ are diagonal, by Equation (4), $m_{i,t}$ is unaffected by $\bar{W}_{j,t}$ or $\gamma_{j,t}$ for any $i \neq j$. Thus, a manager's inferred ability and its precision are independent of those of other managers, which simplifies our analyses in the following sections.[22]

To make economic sense, we assume a nonnegative $b_{i,2}$, $i = 1, \dots, n$, which induces a positive $\sigma_{i,m}(\gamma_{i,t})$ as shown in Equation (9) (because B_i and A_i are positive).[23] In other words, under this setting, for each fund a positive (negative) shock in fund gross alpha induces an increase (a decrease) in the manager's inferred ability.[24]

---

[21] The technical requirements to prove the theorems are regular conditions over the period $0 \le t \le T$, such as boundedness of parameter values, integrality of variables, and finite moments of variables. See the requirements of the corresponding theorems in Liptser and Shiryaev (2001a, 2001b). The intuition of these requirements is that, over a finite time period, almost surely manager abilities, fund gross alphas, and their variations should be finite so that the learning processes are well defined. These requirements are satisfied, due to our finite parameter values, finite initial values, and the finite horizon within which we study our model. In the real world, abilities that keep improving or deteriorating over a short period, or abilities that revert to a finite mean over a long period, would satisfy the technical requirements and follow our learning processes.

[22] If the parameter matrices in Equations (6) and (7) and/or the initial values are not diagonal, then a manager's inferred ability could depend on innovation shocks to other funds and the precision of the inferred ability could depend on the correlations of this manager's ability and gross alpha with those of other managers. Consequently, a fund's equilibrium size, shown in the next sections, could depend on other fund managers' inferred abilities. This complicates our discussions and does not affect our main insights, so we do not introduce this complexity.

[23] This is because a negative $b_{i,2}$ induces a negative instantaneous/idiosyncratic correlation, which can give rise to negative total correlation. If $\gamma_{i,t}$ weighs the positive systematic source of correlation, A_i, insufficiently high, then the negative instantaneous/idiosyncratic source of correlation $b_{i,2}B_i$ dominates. Thus, under these special parameter values, which we do not allow here, the dynamics $\gamma_{i,t}$ may induce correlation between inferred ability and performance shocks, which changes sign over time, resulting in a transient nonmonotonic relation between performance shocks and inferred ability even under the linear structure that we analyze in this section. For detailed analysis of this nonmonotonicity, see Feldman (1989, Proposition 4).

[24] In this linear structure, depending on parameter values, the dynamics of $d\gamma_{i,t}$, induces a $\gamma_{i,t}$ that

The above results imply that investors make their optimal decisions in two steps. First, they observe the history of the funds' share prices, $\boldsymbol{\xi}_{\mathbf{t}}$, restructure the state space to consist of only observable processes while maintaining informational equivalence,[25] and generate a posterior distribution of the fund manager abilities. In this way, they convert the problem from a non-Markovian one to an equivalent tractable Markovian one.[26,27] Second, they use their posterior estimate, $\mathbf{m}_{\mathbf{t}}$, to predict the fund gross alphas in the forthcoming future, as shown by Equation (5). They use this prediction in solving their optimization problems.

2.2 Investors' Optimizations and Fund Managers' Optimizations

Using the above filter to re-represent the state space $\{\boldsymbol{\theta}_{\mathbf{t}}, \boldsymbol{\xi}_{\mathbf{t}}\}$ in terms of observable variables $\{\boldsymbol{\xi}_{\mathbf{t}}, \mathbf{m}_{\mathbf{t}}, \boldsymbol{\gamma}_{\mathbf{t}}\}$, we solve investors' and fund managers' optimization problems.

We assume that there are infinitely many small risk-neutral investors in the market and that each investor's investment decision does not affect the funds' returns and sizes, although all investors together do affect these variables. An investor's portfolio return depends on three components: fund gross alphas, management fees, and fund costs. Similar to Berk and Green (2004), Feldman, Saxena, and Xu (2020, 2023), Feldman and Xu (2022), and other related models, we assume the following. Each fund manager chooses the amount of the fund to actively manage at each time t under fixed management fees f_i, $i = 1, \dots, n$. There are decreasing returns to scale at the fund level. For fund i, $i = 1, \dots, n$, at time t, fund costs variable $C_i\left(q_{i,t}^a\right)$ is an increasing and convex function of the fund amount that is under active management $q_{i,t}^a$, such that

$$C_i\left(q_{i,t}^a\right) = c_i {q_{i,t}^a}^2. \tag{10}$$

Of $q_{i,t}$, the total asset managed by fund i (i.e., fund i's size), the amount $q_{i,t} - q_{i,t}^a$ $(q_{i,t} -$

monotonically increases, decreases, or stays unchanged over time. Consequently, $\sigma_{i,m}(\gamma_{i,t})$, monotonically increases, decreases, or stays unchanged, respectively, over time. Also, $\gamma_{i,t}$ monotonically converges to its steady state, where $d\gamma_{i,t} = 0$. Consequently, $\sigma_{i,m}(\gamma_{i,t})$ also has a steady state at which it converges monotonically.

[25] See Feldman (1992) for demonstration of this type of informational equivalence.

[26] Notice that in these optimization processes, the unobservable manager abilities $\boldsymbol{\theta}_{\mathbf{t}}$ is replaced by its observable conditional mean, $\mathbf{m}_{\mathbf{t}}$, updated by a new Wiener process $\overline{\mathbf{W}}_{\mathbf{t}}$, and that $\mathbf{m}_{\mathbf{t}}$ is continuously updated as a function of the dynamic conditional covariance matrix $\boldsymbol{\gamma}_{\mathbf{t}}$. Hence, investors' problems become Markovian, which makes the problems tractable (allowing a state vector solution).

[27] The elliptical nature our conditionally Gaussian structure allows closure of the filter after two conditional moments. Otherwise, all the conditional higher moments would be part of the filter, and the choice of which higher moments to ignore would be a function of the desired precision.

$q_{i,t}^a \geq 0$) is invested in the passive benchmark, earning the passive benchmark portfolio return and inducing no fund costs. The amount $q_{i,t}^a$ generates fund gross alphas.

At time t, let the price of fund i's asset under management net of fund costs and fees be $S_{i,t}$, $0 \leq t \leq T$. Then, the active fund's net return is $dS_{i,t}/S_{i,t}$. As we normalize the passive benchmark portfolio's return to zero, the active fund's net return in excess of the passive benchmark is $dS_{i,t}/S_{i,t} - 0 = dS_{i,t}/S_{i,t}$. Hereafter, we call $dS_{i,t}/S_{i,t}$ fund i's instantaneous net alpha, or briefly net alpha. Based on the above discussion, we have,

$$\frac{dS_{i,t}}{S_{i,t}} = \frac{q_{i,t}^a}{q_{i,t}} \frac{d\xi_{i,t}}{\xi_{i,t}} - \frac{C_i\left(q_{i,t}^a\right)}{q_{i,t}} dt - f_i dt. \tag{11}$$

Similar to Berk and Green (2004) and Feldman and Xu (2022), we assume that risk-neutral investors supply capital with infinite elasticity to funds that have positive expected fund net alphas, driving the conditional expectation of fund net alphas to zero at each time t. Thus, we have the following condition in equilibrium:

$$\mathrm{E}\left[\frac{dS_{i,t}}{S_{i,t}} \middle| \mathcal{F}_t^{\xi}\right] = 0,\ \forall t, i = 1, \dots, n. \tag{12}$$

Taking conditional expectation on Equation (11) and setting it to zero, we have

$$\frac{q_{i,t}^a}{q_{i,t}} A_i m_{i,t} - \frac{c_i {q_{i,t}^a}^2}{q_{i,t}} - f_i = 0. \tag{13}$$

Rearranging,

$$f_i q_{i,t} = A_i m_{i,t} q_{i,t}^a - c_i {q_{i,t}^a}^2. \tag{14}$$

As any fund costs are deducted from investment returns before the returns are transferred to investors [as shown by the fund net alpha Equation (11)], the term $f_i q_{i,t}$ is manager i's profit. Manager i wants to maximize profit $f_i q_{i,t}$ by choosing $q_{i,t}^a$. Then, manager i's problem is

$$\max_{q_{i,t}^a} f_i q_{i,t} = \max_{q_{i,t}^a} A_i m_{i,t} q_{i,t}^a - c_i {q_{i,t}^a}^2 \tag{15}$$

subject to the constraint

$$0 \leq q_{i,t}^a \leq q_{i,t},\ \forall\, i = 1, \dots, n. \tag{16}$$

As in Berk and Green (2004) and Feldman and Xu (2022), we define $\underline{m}_{i,t}$, $i = 1, \dots, n$, such that if $m_{i,t} < \underline{m}_{i,t}$, fund i receives no investments from investors and exits the market.

Hereafter, we briefly call $\underline{m}_{i,t}$, $i = 1, \dots, n$ the survival levels. Here we assume $\underline{m}_{i,t} \geq 0$.[28] The optimal amount under active management and the optimal total assets under management, $q_{i,t}^{a^*}$ and $q_{i,t}^*$, are not trivial where $m_{i,t} \geq \underline{m}_{i,t}$; otherwise, they are both zero.

Solving investors' and managers' problems, we obtain the equilibrium optimal solutions for funds surviving in the market

$$q_{i,t}^{a^*} = \frac{A_i m_{i,t}}{2c_i}, \tag{17}$$

$$q_{i,t}^* = \frac{\left(A_i m_{i,t}\right)^2}{4c_i f_i}. \tag{18}$$

To simplify the notations, we define fund i's size factor as X_i such that

$$X_i \triangleq \frac{1}{4c_i f_i}. \tag{19}$$

The higher the decreasing returns to scale parameter c_i and the higher the management fee f_i are, the lower is fund i's size factor and, then, the lower is the equilibrium fund size $q_{i,t}^*$. Then,

$$q_{i,t}^* = X_i\left(A_i m_{i,t}\right)^2. \tag{20}$$

Proof. See the Internet Appendix. □

2.3 Equilibrium Market Power and Market Structure

We demonstrate that AFMI concentration is the key measure to study AFMI's industrial organization, while other common measures are less informative in equilibrium.

As investors receive net alphas from funds, any fund costs are transferred to investors as reductions in fund net alphas so that fund managers bear no costs in operation. Then, in equilibrium, for $i = 1, \dots, n$, manager i's profit is the revenue $f_i q_{i,t}^*$, and the profit rate on each dollar under management is f_i, a constant. A manager's profit margin, i.e., the difference between revenue and costs, divided by the revenue, is always one $\left[\left(f_i q_{i,t}^* - 0\right)/f_i q_{i,t}^* = 1\right]$. Also, if we calculate a manager's profit markup, i.e., revenue divided by costs, we find that the

[28] The reason is that given updated information, for fund i, the expected instantaneous gross alpha accumulated in dt is $\mathrm{E}\left(d\xi_{i,t}/\xi_{i,t}|\mathcal{F}_t^{\xi}\right) = A_i m_{i,t} dt$, with $A_i > 0$. If $m_{i,t} < 0$, the expected instantaneous gross alpha is negative. With positive fund costs and fees, the expected instantaneous net alpha earned by investors in dt would be substantially smaller than zero, so they would switch their investments to the passive benchmark portfolio. Thus, we do not allow $m_{i,t} < 0$ for a surviving fund.

profit markup $[= f_i q^*_{i,t}/0]$ is positive infinity. This does not imply that the manager has infinite profitability. Notice again that it is the investors who determine the quantity of production (fund sizes), and investors choose the quantity to capture any positive expected net alpha. As a manager's profit rate is fixed at its constant management fee, he or she needs to attract investments as much as possible by maximizing the expected fund net alpha; as the manager's ability to create the fund net alpha is limited, the equilibrium profit is limited.

A fund's market power can be measured by its Lerner Index, which is the difference between fee and marginal cost, divided by fee. From the above discussion, we can see that a fund's Lerner Index is always one $[= (f_i - 0)/f_i]$.

The above results show that in this framework and those with similar settings commonly used by the current literature, there are no dynamics in the common measures of a manager's profitability and market power. The values of these measures do not offer information on the dynamics of AFMI. In contrast, the market structure of AFMI is dynamic, as funds' relative sizes change over time. Thus, to understand the dynamics of AFMI industrial organization, we need to focus on the dynamics of its market structure, in particular, the dynamics of AFMI concentration.

2.4 Equilibrium AFMI Concentration

We use the Herfindahl-Hirschman Index (HHI) to measure AFMI concentration for the reasons discussed in our Introduction section. Let $\mathbf{q}^*_\mathbf{t}$ be the $n \times 1$ vector of the equilibrium fund sizes with the ith element as $q^*_{i,t}$. Based on Equation (20), we have,

$$\mathbf{q}^*_\mathbf{t} = \mathbf{A}^2\mathbf{I}^2(\mathbf{m}_\mathbf{t})\mathbf{X}, \tag{21}$$

where $\mathbf{I}(\mathbf{m}_\mathbf{t})$ is a $n \times n$ diagonal matrix with the ith element as the ith element of $\mathbf{m}_\mathbf{t}$, and $\mathbf{X}$ is a $n \times 1$ vector with the ith element as X_i. Then, the $n \times 1$ vector of the equilibrium fund market shares, $\mathbf{w}^*_\mathbf{t}$, is

$$\mathbf{w}^*_\mathbf{t} = \frac{\mathbf{q}^*_\mathbf{t}}{\mathbf{q}^{*\prime}_\mathbf{t}\mathbf{1}}, \tag{22}$$

where $\mathbf{1}$ is an $n \times 1$ vector of ones. By definition, the equilibrium AFMI HHI (henceforth we briefly call it HHI) is

$$HHI^*_t \triangleq \mathbf{w}^{*\prime}_\mathbf{t}\mathbf{w}^*_\mathbf{t} = \frac{\mathbf{q}^{*\prime}_\mathbf{t}\mathbf{q}^*_\mathbf{t}}{(\mathbf{q}^{*\prime}_\mathbf{t}\mathbf{1})^2}. \tag{23}$$

We measure HHI at the fund level in Sections 2.4 to 2.8, and then we study HHI measured at the fund family level in Section 2.9. Substituting Equations (21) into Equation (23), we have the following result.

Proposition RN1. HHI and Relative Inferred Abilities

In equilibrium, HHI relates to managers' inferred abilities as follows

$$HHI_t^* = \frac{\mathbf{X}'\mathbf{A}^4\mathbf{I}^4(\mathbf{m_t})\mathbf{X}}{[\mathbf{X}'\mathbf{A}^2\mathbf{I}^2(\mathbf{m_t})\mathbf{1}]^2} = \frac{\sum_{i=1}^n X_i^2\left(A_i m_{i,t}\right)^4}{\left[\sum_{i=1}^n X_i\left(A_i m_{i,t}\right)^2\right]^2} \tag{24}$$

and we can denote $HHI_t^* \triangleq HHI_t^*(\mathbf{m_t})$. □

Proposition RN1 shows that funds' size factors, sensitivities of gross alphas to abilities, and managers' relative inferred abilities together determine HHI. If managers are homogeneous such that these factors are the same for all managers, then funds' sizes are the same and HHI_t^* is constant at its minimum value $1/n$. If managers are heterogeneous such that these parameters are different for different managers, then HHI_t^* can take any value between $1/n$ and its maximum value 1, where AFMI is monopolistic. To offer more insights to the market equilibrium, we focus on the case of heterogeneous managers in this paper. As $\mathbf{m_t}$ is the only variable in Equation (24), HHI_t^* can be regarded as a function driven by $\mathbf{m_t}$.

Notice that Feldman, Saxena, and Xu (2020) (hereafter, FSX), in a one-period model, also derive the endogenous HHI, which is a function of the constant decreasing returns to scale parameters in the fixed-point equilibrium, as shown in their Equation (33). Our continuous-time model not only derives this result because the constant decreasing returns to scale parameters are captured by the fund size factors in our model, but also suggests that investors' expectations of managers' (relative) abilities are relevant in determining fund sizes, thus HHI. As these expectations are dynamic over time, HHI is also dynamic over time; factors affecting the dynamics of these expectations also affect that of HHI. Thus, our model offers new and important insights into HHI over the FSX model. The following proposition shows how the changes of investors' inferences of manager abilities influence the dynamics of HHI.

Proposition RN2. Dynamics of HHI and Changes in Relative Inferred Abilities

HHI evolves as follows

$$
\begin{aligned}
dHHI_t^* &= \frac{\partial HHI_t^*}{\partial \mathbf{m_t}'}\mathbf{dm_t} + \frac{1}{2}\mathbf{dm_t'}\frac{\partial^2 HHI_t^*}{\partial \mathbf{m_t}'\partial \mathbf{m_t}}\mathbf{dm_t} \\
&= \frac{\partial HHI_t^*}{\partial \mathbf{m_t}'}\boldsymbol{\sigma}_{\mathbf{m}}(\boldsymbol{\gamma}_{\mathbf{t}})\mathbf{d\overline{W}_t} + \frac{\partial HHI_t^*}{\partial \mathbf{m_t}'}(\mathbf{a_0} + \mathbf{a_1 m_t})dt \\
&\quad + \frac{1}{2}\mathbf{trace}\left[\boldsymbol{\sigma}_{\boldsymbol{m}}'(\boldsymbol{\gamma}_{\mathbf{t}})\frac{\partial^2 HHI_t^*}{\partial \mathbf{m_t}'\partial \mathbf{m_t}}\boldsymbol{\sigma}_{\mathbf{m}}(\boldsymbol{\gamma}_{\mathbf{t}})\right]dt.
\end{aligned} \tag{25}
$$

To facilitate our discussion, we rewrite $dHHI_t^*$ in scalar form:

$$
\begin{aligned}
dHHI_t^* &= \sum_{i=1}^{n}\left[\frac{\partial HHI_t^*}{\partial m_{i,t}}dm_{i,t} + \frac{1}{2}\frac{\partial^2 HHI_t^*}{\partial {m_{i,t}}^2}\left(dm_{i,t}\right)^2\right] \\
&= \sum_{i=1}^{n}\left[\frac{\partial HHI_t^*}{\partial m_{i,t}}\sigma_{i,m}\left(\gamma_{i,t}\right)d\overline{W}_{i,t} + \frac{\partial HHI_t^*}{\partial m_{i,t}}\left(a_{i,0} + a_{i,1}m_{i,t}\right)dt \right. \\
&\quad \left. + \frac{1}{2}\frac{\partial^2 HHI_t^*}{\partial {m_{i,t}}^2}\sigma_{i,m}^2 dt\right],
\end{aligned} \tag{26}
$$

where

$$
\frac{\partial HHI_t^*}{\partial m_{i,t}} = 4X_i A_i^2 m_{i,t} \times \frac{q_{i,t}^* \sum_{j=1}^{n} q_{j,t}^* - \sum_{j=1}^{n} q_{j,t}^{*2}}{\left(\sum_{j=1}^{n} q_{j,t}^*\right)^3}, \tag{27}
$$

and

$$
\frac{\partial^2 HHI_t^*}{\partial {m_{i,t}}^2} = 4X_i A_i^2 \times \left[\frac{3q_{i,t}^* \sum_{j=1}^{n} q_{j,t}^* + \dfrac{6q_{i,t}^*\left(\sum_{j=1}^{n} q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^{n} q_{j,t}^*\right)} - 8q_{i,t}^{*2} - \sum_{j=1}^{n} q_{j,t}^{*2}}{\left(\sum_{j=1}^{n} q_{j,t}^*\right)^3}\right]. \tag{28}
$$

Proof. Apply Itô's Lemma on $HHI_t^*(\mathbf{m_t})$ and substitute Equation (4) into the expression, using the property of independence of $\overline{W}_{i,t}$, $i = 1, \ldots, n$. □

Proposition RN2 shows how HHI changes with inferred abilities over time. We summarize the key insights directly from Proposition RN2 in the following two corollaries, followed by explanations and intuitions.

Corollary RN2.1. Size of Inferred Ability and Impact on Dynamics of HHI

If $m_{i,t} > \underline{m}_{i,t}$, then we have the following.

a. If $m_{i,t}$ is sufficiently large (small) such that $q^*_{i,t} > \frac{\sum_{j=1}^{n} q^{*2}_{j,t}}{\sum_{j=1}^{n} q^*_{j,t}}$ ($q^*_{i,t} < \frac{\sum_{j=1}^{n} q^{*2}_{j,t}}{\sum_{j=1}^{n} q^*_{j,t}}$), then an increase in $m_{i,t}$ has a positive (negative) impact on $dHHI^*_t$.

b. If $m_{i,t}$ is sufficiently large or sufficiently small such that $3q^*_{i,t} \sum_{j=1}^{n} q^*_{j,t} + \frac{6q^*_{i,t}\left(\sum_{j=1}^{n} q^{*2}_{j,t}\right)}{\left(\sum_{j=1}^{n} q^*_{j,t}\right)} - 8q^{*2}_{i,t} - \sum_{j=1}^{n} q^{*2}_{j,t} < 0$, then HHI^*_t is concave in $m_{i,t}$. Over the next infinitesimal period dt, this concavity has a negative impact on $dHHI^*_t$. If all $m_{i,t}$ for $i = 1, \dots, n$ are sufficiently close to each other, making $q^*_{i,t}$ for $i = 1, \dots, n$ sufficiently close such that $3q^*_{i,t} \sum_{j=1}^{n} q^*_{j,t} + \frac{6q^*_{i,t}\left(\sum_{j=1}^{n} q^{*2}_{j,t}\right)}{\left(\sum_{j=1}^{n} q^*_{j,t}\right)} - 8q^{*2}_{i,t} - \sum_{j=1}^{n} q^{*2}_{j,t} > 0$, then the HHI^*_t is convex in $m_{i,t}$. Over dt, this convexity has a positive impact on $dHHI^*_t$.

Proof. See the Internet Appendix. □

To understand Corollary RN2.1a, we observe from Equation (27) that if fund i's inferred ability $m_{i,t}$ is sufficiently large (small) relative to those of other funds, such that $q^*_{i,t} > \frac{\sum_{j=1}^{n} q^{*2}_{j,t}}{\sum_{j=1}^{n} q^*_{j,t}}$ ($q^*_{i,t} < \frac{\sum_{j=1}^{n} q^{*2}_{j,t}}{\sum_{j=1}^{n} q^*_{j,t}}$), then $\frac{\partial HHI^*_t}{\partial m_{i,t}}$ is positive (negative). Then, as shown in Equation (26), an increase in manager i's inferred ability, due to a sufficiently large drift term in inferred ability, $a_{i,0} + a_{i,1} m_{i,t}$, or a sufficiently large innovation shock in performance, $d\bar{W}_{i,t}$, has a positive (negative) impact on the change in HHI, $dHHI^*_t$.

The intuition is that, if manager i's inferred ability is sufficiently large relative to other managers' inferred abilities, then fund i's size is sufficiently large relative to other funds' sizes, and fund i dominates in the market. A higher inferred ability attracts more investment to fund i, making it larger and making AFMI more concentrated at fund i. On the other hand, if manager i's inferred ability is sufficiently small relative to other managers' inferred abilities, then fund i's size is sufficiently small relative to other funds' sizes. A higher inferred ability attracts more investment to fund i, making its size closer to those of other funds and then making AFMI less concentrated.

To understand Corollary RN2.1b, consider the second-order partial derivative shown in Equation (28). If manager i's inferred ability $m_{i,t}$ is sufficiently large (small) relative to those of other managers, such that $q^*_{i,t}$ is sufficiently large (small) relative to $q^*_{j,t}$'s for $j \neq i$, then

$\frac{\partial^2 HHI_t^*}{\partial m_{i,t}{}^2} < 0$ and HHI_t^* is concave in $m_{i,t}$. Then, over the next infinitesimal period dt, this concavity has a negative impact on $dHHI_t^*$. If all managers' inferred abilities are sufficiently close to each other's such that funds' sizes are sufficiently close, making HHI_t^* close to its minimum value $1/n$, then $\frac{\partial^2 HHI_t^*}{\partial m_{i,t}{}^2} > 0$ and HHI_t^* is convex in $m_{i,t}$. Then, over the next infinitesimal period dt, this convexity has a positive impact on $dHHI_t^*$.

The intuition is that if fund i's market share is sufficiently large (small) due to manager i's sufficiently large (small) inferred ability, then AFMI is concentrated at fund i (at other funds). Although a higher (lower) inferred ability of manager i can make AFMI more concentrated at fund i (at other funds), it becomes more and more difficult to increase the concentration in this way. On the other hand, if all managers' inferred abilities are close, such that funds' sizes are close, then a larger and a smaller inferred ability of manager i both can make fund i's size deviate from other funds' sizes, making AFMI more concentrated. It is easier to make fund i's size deviate from other funds' sizes and to increase HHI if the absolute change in manager i's inferred ability is larger in this case.

For illustration, we simulate HHI over different levels of inferred abilities in the Internet Appendix.

Corollary RN2.2. Interaction Effect of Performance Shock and Performance Variation

If $m_{i,t} > \underline{m}_{i,t}$, then we have the following result. If $m_{i,t}$ is sufficiently large (small) such that $q_{i,t}^* > \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}$ ($q_{i,t}^* < \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}$), then a positive $d\overline{W}_{i,t}$ exerts a positive (negative) impact on $dHHI_t^*$, and a higher B_i mitigates this positive (negative) impact. □

Corollary RN2.2 shows that the interaction effect of $d\overline{W}_{i,t}$ and B_i on $dHHI_t^*$ is negative (positive) if $m_{i,t}$ is sufficiently large (small) relative to $m_{j,t}$'s for $j \neq i$. This is because $\sigma_{i,m}(\gamma_{i,t}) > 0$, and a higher B_i decreases $\sigma_{i,m}(\gamma_{i,t})$, as shown in Equation (9). Also, a higher B_i does not affect $\frac{\partial HHI_t^*}{\partial m_{i,t}}$, as implied by Equation (27). Thus, a higher B_i decreases the absolute value of $\frac{\partial HHI_t^*}{\partial m_{i,t}}\sigma_{i,m}(\gamma_{i,t})$, which is the coefficient of $d\overline{W}_{i,t}$ in the expression of $dHHI_t^*$, as shown in Equation (26). If $m_{i,t}$ is sufficiently large (small) relative to $m_{j,t}$'s for

$j \neq i$, then $\frac{\partial HHI_t^*}{\partial m_{i,t}}$ and thus $\frac{\partial HHI_t^*}{\partial m_{i,t}} \sigma_{i,m}(\gamma_{i,t})$ are positive (negative). Then, a smaller absolute value of $\frac{\partial HHI_t^*}{\partial m_{i,t}} \sigma_{i,m}(\gamma_{i,t})$ induced by a higher B_i makes $\frac{\partial HHI_t^*}{\partial m_{i,t}} \sigma_{i,m}(\gamma_{i,t})$ smaller (larger).

The intuition of the above result is as follows. A positive shock in manager i's performance induces higher manager i's inferred ability thus higher fund i's size. If this manager's inferred ability is sufficiently large (small) relative to those of other managers, a higher manager i's inferred ability increases (decreases) HHI, as mentioned in the earlier discussion. In this case, this positive performance shock increases (decreases) HHI. Moreover, if manager i's performance variation is higher, then investors allocate smaller weights on manager i's performance shocks when learning about her ability. Consequently, a positive shock in manager i's performance induces smaller impact on her inferred ability, and thus induces a positive (negative) impact with a smaller absolute value on HHI.

2.5 Equilibrium AFMI Concentration and Stock Market Volatility: Extension to a Nonlinear Framework

We analyze how stock market volatility affects manager abilities and then AFMI concentration by extending our linear framework shown in Equations (1) and (2) to a nonlinear one. Higher stock market volatility increases market stress and redemption risk. The consequential higher redemption from investors and the need of larger cash buffers to manage the higher redemption risk impede managers when implementing investment strategies to produce abnormal returns, making fund gross alphas less related to manager abilities and more related to luck [see, for example, Jin, Kacperczyk, Kahraman, and Suntheim (2022)]. Thus, we assume that sensitivities of gross alphas to manager abilities is a decreasing function of stock market volatility. Let λ_t be a variable that captures the impact of stock market volatility on the sensitivities of gross alphas to manager abilities, i.e., $A_i \triangleq A_i(\lambda_t)$ and $\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$, $i = 1, \ldots, n$, following

$$d\lambda_t = \mu_\lambda dt + \sigma_\lambda dz_t. \tag{29}$$

While, in general, μ_λ and σ_λ could be functions of λ_t and other market variables,[29] for

[29] For example, λ_t could follow an autoregressive process. As long as μ_λ and σ_λ are adapted to $\{\mathcal{F}_t\}_{0 \leq t \leq T}$, the specific forms of μ_λ and σ_λ do not affect our model's main insight.

brevity and simplicity, we assume that μ_λ and σ_λ are constant, and that z_t is a Brownian motion adapted to $\{\mathcal{F}_t\}_{0\le t\le T}$ and independent of $\mathbf{W_{1,t}}$ and $\mathbf{W_{2,t}}$. The learning about manager abilities is unaffected by λ_t because λ_t is unaffected by unobservable manager abilities, $\boldsymbol{\theta}_\mathbf{t}$, and z_t is independent of $\mathbf{W_{1,t}}$ and $\mathbf{W_{2,t}}$. Thus, λ_t is independent of $m_{i,t}$, $i = 1, \dots, n$. Using the analysis in Section 2.4, we derive the dynamics of HHI below.

Proposition RNV. Dynamics of HHI and Changes in Stock Market Volatility

HHI evolves as follows (in scalar form):

$$\begin{aligned} dHHI_t^* &= dX_t + \left(\sum_{i=1}^{n} \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t}\right) d\lambda_t \\ &\quad + \frac{1}{2}\sum_{i=1}^{n}\left[\frac{\partial^2 HHI_t^*}{\partial A_i(\lambda_t)^2}\left(\frac{\partial A_i(\lambda_t)}{\partial \lambda_t}\right)^2 + \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial^2 A_i(\lambda_t)}{\partial {\lambda_t}^2}\right]\sigma_\lambda^2 dt, \end{aligned} \tag{30}$$

where dX_t equals the $dHHI_t^*$ in Equation (26) with A_i replaced by $A_i(\lambda_t)$,

$$\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} = 4X_i m_{i,t}^2 A_i(\lambda_t) \times \frac{q_{i,t}^* \sum_{j=1}^n q_{j,t}^* - \sum_{j=1}^n q_{j,t}^{*2}}{\left(\sum_{j=1}^n q_{j,t}^*\right)^3}, \tag{31}$$

and

$$\begin{aligned} &\frac{\partial^2 HHI_t^*}{\partial A_i(\lambda_t)^2} = 4X_i m_{i,t}^2 \times \\ &\left[\frac{3q_{i,t}^* \sum_{j=1}^n q_{j,t}^* + \frac{6q_{i,t}^*\left(\sum_{j=1}^n q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^n q_{j,t}^*\right)} - 8q_{i,t}^{*2} - \sum_{j=1}^n q_{j,t}^{*2}}{\left(\sum_{j=1}^n q_{j,t}^*\right)^3}\right]. \end{aligned} \tag{32}$$

Proof. Apply Itô's Lemma on $HHI_t^*(\mathbf{m_t}, \lambda_t)$, using the property that λ_t is independent of $m_{i,t}$, $i = 1, \dots, n$. □

Proposition RNV shows how the dynamics of stock market volatility affects that of HHI. We summarize the key insights directly from Proposition RNV in the following corollary.

Corollary RNV. Dynamics of HHI, Changes in Stock Market Volatility, and Fund Sizes

If $m_{i,t} > \underline{m}_{i,t}$ and $m_{i,t}$ is sufficiently large (small) such that $q_{i,t}^* > \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}$ ($q_{i,t}^* < \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}$), then we have $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$ ($\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} > 0$). When $\sum_{i=1}^n \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$

$(\sum_{i=1}^{n} \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t} > 0)$, an increase in λ_t exerts a negative (positive) impact on $dHHI_t^*$. □

To understand Corollary RNV, notice that $\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$, $i = 1, \dots n$, so given the same inferred manager abilities, a higher λ_t decreases fund expected gross alphas and consequently decreases all funds' equilibrium sizes. If fund i's inferred ability $m_{i,t}$ is sufficiently large (small) relative to those of other funds, such that $q_{i,t}^* > \frac{\sum_{j=1}^{n} q_{j,t}^{*2}}{\sum_{j=1}^{n} q_{j,t}^*}$ $(q_{i,t}^* < \frac{\sum_{j=1}^{n} q_{j,t}^{*2}}{\sum_{j=1}^{n} q_{j,t}^*})$, then the decrease in fund i's size exerts a negative (positive) impact on HHI, as shown in the earlier discussions. In other words, when $m_{i,t}$ is sufficiently large (small), we have $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} > 0$ $(\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} < 0)$, so $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$ $(\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t} > 0)$. Then, whether HHI increases with λ_t depends on whether the aggregate effect, $\sum_{i=1}^{n} \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t}$, is positive. From Equation (31), we can see that if fund i is extremely large relative to other funds, due to its large X_i, $A_i(\lambda_t)$, and/or $m_{i,t}$, then $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}$ is positive with a large absolute value, which drives the value of $\sum_{i=1}^{n} \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t}$ when the magnitude of $\frac{\partial A_i(\lambda_t)}{\partial \lambda_t}$ is similar to those of other funds.[30] As $\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$, we would have a negative $\sum_{i=1}^{n} \frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} \frac{\partial A_i(\lambda_t)}{\partial \lambda_t}$ when some extremely large funds exist. In other words, when the distribution of funds' sizes is highly skewed to the right (which is the case in reality[31]), the effect of the decrease in extremely large funds' sizes due to an increase in stock market volatility dominates those of small funds, inducing a lower HHI.

The analysis in this section stresses that a nonlinear frame allowing coefficients of processes of manager abilities and gross alphas to be functions of observable economic factors can model how the dynamics of these factors affect that of HHI. Linear frameworks of manager abilities and gross alphas that are used in the existing literature, such as Berk and Green (2004) and their followers, cannot directly incorporate the effects of economic factors on manager abilities and gross alphas and, consequently, cannot easily model these effects on the dynamics of HHI as we do here. We study only the effect of the stock market volatility on HHI in this section; the effects of other economic factors that might affect HHI, such as technological and

[30] As the change in stock market volatility affects active equity funds in a similar way, it is likely that the magnitudes of $\frac{\partial A_i(\lambda_t)}{\partial \lambda_t}$, $i = 1, \dots, n$ are close to each other.

[31] We also show that the distribution of funds' sizes is highly skewed to the right in our sample in Section 3.

regulatory changes, are left for future research.

2.6 Constant Manager Abilities and HHI

We illustrate a special case of HHI in which manager abilities are constant under the linear framework shown in Section 2.1. In this case, $\mathbf{a_0}$ is an $n \times 1$ zero vector and $\mathbf{a_1}$, $\mathbf{b_1}$, and $\mathbf{b_2}$ are $n \times n$ zero matrices, making $\mathbf{d\theta_t}$ a zero vector. We have

$$\mathbf{dm_t} = \boldsymbol{\sigma}_\mathbf{m}(\boldsymbol{\gamma}_\mathbf{t})\mathbf{d\overline{W}_t}, \tag{33}$$

$$\boldsymbol{\sigma}_\mathbf{m}(\boldsymbol{\gamma}_\mathbf{t}) \triangleq (\mathbf{A}\boldsymbol{\gamma}_\mathbf{t})'\mathbf{B^{-1}}, \tag{34}$$

$$\boldsymbol{\gamma}_\mathbf{t} = [\mathbf{I} + \boldsymbol{\gamma}_\mathbf{0}\mathbf{A}\mathbf{B}^{-2}\mathbf{A}t]^{-1}\boldsymbol{\gamma}_\mathbf{0}, \tag{35}$$

where $\mathbf{I}$ is an $n \times n$ identity matrix. Theorem 12.8 of Liptser and Shiryaev (2001b) provides the proof of the above results. These results show that for fund i, $i = 1, \dots, n$, we have that the imprecision of the estimate $m_{i,t}$, $\gamma_{i,t} = \frac{\gamma_{i,0}B_i^2}{B_i^2 + A_i^2\gamma_{i,0}t}$ decreases to zero over time monotonically, so the sensitivity of inferred ability to performance shocks, $\sigma_{i,m}(\gamma_{i,t}) \triangleq (A_i\gamma_{i,t})/B_i$, also decreases to zero monotonically. Thus, we have the following proposition.

Proposition CA. Constant Manager Abilities and Steady State of HHI

If $\boldsymbol{\theta}_\mathbf{t}$ is a constant vector and $m_{i,t} > \underline{m}_{i,t}$ for $i = 1, \dots, n$, then over time, $\gamma_{i,t}$ and $\sigma_{i,m}(\gamma_{i,t})$ decrease monotonically to zero. As $t \to \infty$, for $i = 1, \dots, n$, $dm_{i,t} = \sigma_{i,m}(\gamma_{i,t})d\overline{W}_{i,t} \to 0$ and $m_{i,t}$, becomes constant, making HHI_t^* a constant. □

Proposition CA shows the steady state of this constant-ability framework. The intuition is that as managers' abilities are unobservable constants, estimation precisions improve monotonically over time, inducing inferred abilities to be increasingly less sensitive to funds' gross alpha realizations. As time goes to infinity, people know managers' abilities, thus do not change their estimates. Then, investors stop changing their investments flows to funds (i.e., fund sizes stay unchanged), making HHI stay unchanged. As empirical HHI does not converge to a constant in the long term, as shown in Feldman, Saxena, and Xu (2020, 2023) and our following empirical section, theoretical models with this framework, such as Berk and Green (2004), Choi, Kahraman, and Mukherjee (2016), and Brown and Wu (2016), lack the explanatory and predictive power of HHI dynamics. For illustration, we simulate HHI in the cases of constant ability and of dynamic ability in the Internet Appendix.

2.7 Mean-Variance Risk-Averse Investors and HHI

To study the effect of investors' risk aversion on HHI, we start with the linear framework in Section 2.1 and assume that investors are mean-variance risk averse and maximize their portfolios' instantaneous Sharpe ratios.[32] This setting is also similar to the one in Pastor and Stambaugh (2012), Feldman, Saxena, and Xu (2020, 2023), and Feldman and Xu (2022).

As risk-averse investors trade off risk and return, we need to redefine our model. First, we cannot normalize the passive benchmark portfolio return to zero as the level of this return is relevant.[33] Here, we define the share price of the passive benchmark portfolio at time t as η_t, and assume that the passive benchmark portfolio return $d\eta_t/\eta_t$ follows

$$\frac{d\eta_t}{\eta_t} = \mu_p dt + \sigma_p dW_{p,t}, \tag{36}$$

where μ_p and σ_p are positive known constants and $W_{p,t}$ is a Wiener Process.

Next, for $i = 1, \dots, n$, we still define $d\xi_{i,t}/\xi_{i,t}$, as the fund gross alphas, which follow the process defined in Equations (1) and (2), and define $dS_{i,t}/S_{i,t}$ as the fund net alphas. As the active funds have beta loading of one on the passive benchmark portfolio, the fund gross return is $d\xi_{i,t}/\xi_{i,t} + d\eta_t/\eta_t$ and the fund net return is $dS_{i,t}/S_{i,t} + d\eta_t/\eta_t$.

For simplification, we assume that the risk source of the benchmark return is independent of that of gross alphas, so

$$dW_{p,t} d\bar{W}_{i,t} = 0,\ \forall t, i = 1, \dots, n. \tag{37}$$

Also, we normalize the risk-free return to zero.[34] All other settings are the same as before.

An investor invests in n active funds and the passive benchmark to maximize the portfolio's instantaneous Sharpe ratio:

[32] These investors' optimal portfolios are growth optimal and are the same as those of investors with Bernoulli logarithmic preferences, who maximize expected utility. See the discussions of mean-variance risk-averse investors in Feldman and Xu (2022).

[33] As mean-variance risk-averse investors' preferences are defined over their whole portfolios, they do not form their decision based on a marginal analysis of the active funds' risk alone. [See, for example, Equation (46), which collapses if the passive benchmark return is normalized to zero.]

[34] Alternatively, we can regard $d\eta_t/\eta_t$ as the passive benchmark portfolio return in excess of the risk-free return.

$$\max_{w_t} \frac{\mathrm{E}\left[\frac{dp_t}{p_t}\middle|\mathcal{F}_t^{\xi}\right]}{\sqrt{\mathrm{Var}\left[\frac{dp_t}{p_t}\middle|\mathcal{F}_t^{\xi}\right]}} \tag{38}$$

subject to

$$\mathbf{v_t}'\mathbf{1} = 1, \tag{39}$$

$$0 \le v_{i,t} \le 1,\ \forall\ i = 1, \dots, n+1, \tag{40}$$

where $\mathbf{v_t}$ is the $(n+1) \times 1$ portfolio weight vector, with the ith element $v_{i,t}$, $i = 1, \dots, n$ as the weight allocated to the ith active fund, and the last element $v_{n+1,t}$ as the weight allocated to the passive benchmark portfolio. Condition (40) is to prevent short selling of active funds or the passive benchmark portfolio. Also, p_t is the portfolio's value, and dp_t/p_t is the investor's instantaneous portfolio return. We define $\mathbf{R_t}$ as the $(n+1) \times 1$ net return vector of these $n+1$ assets, which has elements

$$R_{i,t} = \frac{dS_{i,t}}{S_{i,t}} + \frac{d\eta_t}{\eta_t}, i = 1, \dots, n, \tag{41}$$

$$R_{n+1,t} = \frac{d\eta_t}{\eta_t}. \tag{42}$$

Then, the investor's portfolio net return is

$$\frac{dp_t}{p_t} = \mathbf{v_t}'\mathbf{R_t}. \tag{43}$$

Let the optimal weight allocations be $\mathbf{v_t^*}$. As investors face the same risk-return tradeoff and have the same objective function, they all make the same optimal decision of $\mathbf{v_t^*}$. We define the part of the total wealth of all investors allocated to financial assets (i.e., allocated to the active fund and the passive benchmark portfolio) as V, $V \in (0, +\infty)$, $0 \le t \le T$. To simplify our analyses and focus on how managers' heterogeneity affects the dynamics of HHI, we assume that V is constant and exogenous to both investors and managers.[35] Then, the amount of wealth allocated to fund i, i.e., fund i's size, is $q_{i,t}^* = v_{i,t}^* V$, $i = 1, \dots, n$.

As in the risk-neutral case, we can write the fund manager's profit as a function of $q_{i,t}^a$, i.e., $g_i\left(q_{i,t}^a\right)$, where g_i is a (smooth, increasing, concave) function, shown in the Internet Appendix. Then, manager i's problem is

[35] In reality, this wealth not only depends on the returns from financial assets, but also depends on production activities, research and development expenditures, consumptions, taxes, and many other aspects of the economy that we do not model here. Also, it can change over time and its dynamics can affect the dynamics of HHI. To simplify our model, we do not introduce these complexities of this wealth value.

$$\max_{q_{i,t}^a} f_i q_{i,t} = \max_{q_{i,t}^a} g_i\left(q_{i,t}^a\right) \tag{44}$$

subject to

$$0 \leq q_{i,t}^a \leq q_{i,t},\ \forall\, i = 1, \dots, n. \tag{45}$$

By solving the investors' and managers' problems, we obtain the equilibrium fund size:

$$q_{i,t}^* = \frac{\left(A_i m_{i,t}\right)^2 V \sigma_p^2}{4 f_i\left(B_i^2 \mu_p + c_i V \sigma_p^2\right)}. \tag{46}$$

We define the size factor of fund i when investors are mean-variance risk-averse as

$$X_i^{RA} \triangleq \frac{V\sigma_p^2}{4 f_i\left(B_i^2 \mu_p + c_i V \sigma_p^2\right)} = \frac{1}{4 f_i c_i + \frac{4 f_i B_i^2 \mu_p}{V \sigma_p^2}}. \tag{47}$$

Similar to the results of X_i, a larger decreasing returns to scale parameter, c_i, and a higher management fee, f_i, both decrease the size factor X_i^{RA}. Additionally, higher B_i^2 and μ_p both decrease X_i^{RA}, and higher V and σ_p^2 both increase X_i^{RA}. The intuition is that, holding other parameters unchanged, mean-variance risk-averse investors invest more (less) in fund i if the risk of the passive benchmark's return σ_p^2 (the risk of fund i's gross alpha B_i^2) is higher. Also, investors invest more in fund i if they have more wealth V to invest, and switch from fund i to the passive benchmark if the benchmark's mean return μ_p is higher. Further, we can see that, holding other parameters unchanged, X_i^{RA} is smaller than X_i. In other words, compared to AFMI with risk-neutral investors, AFMI with mean-variance risk-averse investors has smaller equilibrium fund sizes. This is because investors' risk considerations reduce their investment to risky active funds. Using this new definition of fund i's size factor, we have

$$q_{i,t}^* = \left(A_i m_{i,t}\right)^2 X_i^{RA}. \tag{48}$$

Proof. See the Internet Appendix. □

We substitute $q_{i,t}^*$ shown above into the formula of HHI_t^* and derive the following results,

$$HHI_t^* = \frac{\mathbf{X^{RA\prime} A^4 I^4 (m_t) X^{RA}}}{\mathbf{[X^{RA\prime} A^2 I^2 (m_t) 1]^2}} = \frac{\sum_{i=1}^n {X_i^{RA}}^2 \left(A_i m_{i,t}\right)^4}{\left[\sum_{i=1}^n X_i^{RA}\left(A_i m_{i,t}\right)^2\right]^2}, \tag{49}$$

where $\mathbf{X^{RA}}$ is an $n \times 1$ vector with the ith element as X_i^{RA}.

We can see that the form of HHI_t^* in (49) is the same as the one in (24) in the case of risk-neutral investors. The only difference is that here we use $\mathbf{X^{RA}}$ instead of $\mathbf{X}$ as the size factors. Thus, the relation of the dynamics of HHI_t^* and managers' inferred abilities in Proposition RN1 still holds; consequently, the results of Proposition RN2 and Corollaries RN2.1 and RN2.2 hold. Also, if we allow A_i to be a decreasing function of stock market volatility as we do in Section 2.5, then the results of Proposition RNV and Corollary RNV still hold. The intuition is that investors' risk considerations decrease the equilibrium fund sizes, but HHI_t^* depends on relative fund sizes, and the way to compare these sizes does not depend on investors' risk considerations. Thus, the dynamics of HHI_t^* relates to managers' relative inferred abilities in a way similar to that of the risk-neutral case.

The following proposition summarizes the results in this section.

Proposition RA. HHI and Mean-Variance Risk-Averse Investors

When investors are mean-variance risk averse, $q_{i,t}^*$, $i = 1, \dots, n$, are smaller than those when investors are risk neutral, and funds' size factors X_i^{RA}, $i = 1, \dots, n$, not only decrease with c_i and f_i, but also increase with V and σ_p^2 and decrease with B_i^2 and μ_p. Besides the size factors, the other results of Propositions RN1, RN2, and RNV and Corollaries RN2.1, RN2.2, and RNV still hold. □

2.8 Fund Entrances and Exits and HHI

Besides the dynamics of fund managers' relative abilities, a fund's entrance and exit could affect the dynamics of AFMI concentration. Although we do not analyze funds' entrances and exits explicitly, we show that our framework is compatible with the effects of them, if we allow the total number of funds to change over time, i.e., $n = n_t$, and require funds to exit the market if their managers' inferred abilities reduce to zero, i.e., the survival ability level $\underline{m}_{i,t} = 0$, $i = 1, \dots, n_t$.

Notice that in equilibrium, funds with positive (zero) inferred abilities earn positive (zero) profits, as implied by the equilibrium fund sizes in Equation (18) in the risk-neutral case and those in Equation (46) in the mean-variance risk-averse case. When $\underline{m}_{i,t} = 0$, $i = 1, \dots, n_t$, managers with positive inferred abilities optimally stay in the market to earn positive profits. On the other hand, as managers cannot short sell investors' wealth,[36] managers with negative inferred abilities optimally choose to put zero assets under active management to avoid losses, thus exit the market. Therefore, the setting of $\underline{m}_{i,t} = 0$, $i = 1, \dots, n_t$ is consistent with profit-maximizing managers, and these survival ability levels can be regarded as those endogenously chosen by fund managers.

To see how our framework is compatible with the effects of funds' entrances and exits, notice again that equilibrium fund sizes, $q^*_{i,t}$, are functions of managers' inferred abilities, $m_{i,t}$. As the value of $m_{i,t}$ changes continuously, the value of $q^*_{i,t}$ also changes continuously. When $m_{i,t}$ decreases to zero, $q^*_{i,t}$ and fund i's market share decreases to zero, such that when the fund exits the market, the exit does not cause a jump in HHI^*_t. On the other hand, a potential entrant can be regarded as a fund with negative inferred ability. When its inferred ability $m_{i,t}$ increases to zero, it enters the market with an equilibrium fund size $q^*_{i,t}$ equal to zero. After that, if $m_{i,t}$ increases, then $q^*_{i,t}$ increases. As the changes in $m_{i,t}$ and $q^*_{i,t}$ are continuous, the entrance does not cause a jump in HHI^*_t. Then, in these two cases, $dHHI^*_t$ can still be expressed by Equation (25), and the results from Section 2.3 to Section 2.7 are still valid. In other words, funds' entrances (exits) do not affect $dHHI^*_t$ instantaneously, but these funds affect $dHHI^*_t$ after (before) that. This does not mean that fund entrances and exits are irrelevant to AFMI concentration in our model because they change the set of funds in AFMI, a change that exerts impacts on AFMI concentration that are captured by our result in Equation (25).

However, if $\underline{m}_{i,t} > 0$ for any $i = 1, \dots, n_t$, then fund i's exit or entrance creates a jump in HHI^*_t, and we need to incorporate this jump effect when analyzing $dHHI^*_t$. The reason is that when fund i exits the market with $m_{i,t}$ decreasing to $\underline{m}_{i,t}$, its equilibrium fund size $q^*_{i,t}$ jumps from a value larger than (but not close to) zero to zero value, creating a jump in HHI^*_t. On the other hand, when fund i enters the market with $m_{i,t}$ increasing to $\underline{m}_{i,t}$, its equilibrium fund size $q^*_{i,t}$ jumps from zero to a value larger than (but not close to) zero, also creating a jump in HHI^*_t. In these two cases, $dHHI^*_t$ cannot be expressed by Equation (25) because the jump effects should be added.

[36] Managers can short sell some stocks when constructing a portfolio to pursue alphas, but they cannot short the whole portfolio or short the "active management amount", as shown by the constraint $q^a_{i,t} \geq 0$ for any i.

Section 3.3 of this paper offers evidence that the aggregate sizes of funds that enter and that exit the market are trivial compared to the total AFMI size. Thus, when these exits and entrances happen, they do not create jumps in AFMI concentration levels. Therefore, our model can sufficiently explain the dynamics of AFMI concentration when funds exit and enter.

2.9 AFMI Concentration Measured at the Fund Family Level

Current literature shows that affiliated funds in a fund family could cooperate with each other when competing in the market. For example, they can strategically transfer performances among each other to manipulate investment flows and then optimize fund family values [see, for example, Evans, Prado, and Zambrana (2020), Eisele, Nefedova, Parise, and Peijnenburg (2020), and Xu (2023)]. Thus, it is also natural to measure AFMI concentration at the fund family level. Suppose the market has l fund families and family k, $k = 1, \ldots, l$ manages n_k funds, such that the total number of funds in the market, $n = \sum_{k=1}^{l} n_k$. Define

$$HHI_t^* \triangleq \frac{\boldsymbol{Q}_{\mathbf{t}}^{*\prime}\boldsymbol{Q}_{\mathbf{t}}^{*}}{(\boldsymbol{Q}_{\mathbf{t}}^{*\prime}\mathbf{1})^2} = \frac{\sum_{k=1}^{l} Q_{k,t}^{*2}}{\left(\sum_{k=1}^{l} Q_{k,t}^{*}\right)^2}, \tag{50}$$

where $\boldsymbol{Q}_{\mathbf{t}}^{*}$ is the $n \times 1$ vector of the equilibrium fund family sizes with the kth element as $Q_{k,t}^{*} = \sum_{i=1}^{n_k} q_{i,t}^{*}$. Hereafter, we briefly call the HHI defined in Equation (50) as family-level HHI and the one in Equation (23) as fund-level HHI. As $q_{i,t}^{*}$ indicates manager i's inferred ability, $Q_{k,t}^{*}$ indicates family k's aggregate inferred ability. Following an analysis similar to those in the previous sections, we have results of the dynamics of family-level HHI as shown in the following proposition.

Proposition FA. Dynamics of Family-Level HHI

Suppose we define HHI as the one in Equation (50). Whether investors are risk-neutral or mean-variance risk-averse, if $m_{i,t} > \underline{m}_{i,t}$ and fund i belongs to family k whose aggregate inferred ability is sufficiently large (small) such that $Q_{k,t}^{*} > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^{*}}$ $\left(Q_{k,t}^{*} < \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^{*}}\right)$, then we have the following.

a. An increase in $m_{i,t}$ has a positive (negative) impact on $dHHI_t^*$.

b. A positive $d\overline{W}_{i,t}$ exerts a positive (negative) impact on $dHHI_t^*$, and a higher B_i mitigates this positive (negative) impact.

c. We have $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$ ($\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} > 0$). When $\sum_{i=1}^{n}\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} < 0$ ($\sum_{i=1}^{n}\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)}\frac{\partial A_i(\lambda_t)}{\partial \lambda_t} > 0$), an increase in λ_t exerts a negative (positive) impact on $dHHI_t^*$.

Proof. See the Internet Appendix. □

Proposition FA shows that the factors, such as $m_{i,t}$, $\overline{W}_{i,t}$, and λ_t, affect the dynamics of family-level HHI in a way similar to the one when they affect the dynamics of fund-level HHI as shown in Sections 2.4 to 2.7, except in this case, fund families' relative aggregate inferred abilities, captured by family sizes are relevant, instead of fund managers' relative inferred abilities, captured by fund sizes. The reason is that when we measure AFMI concentration by family-level HHI, if a fund belongs to a family k that is sufficiently large (small) such that $Q_{k,t}^* > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^{*}}$ ($Q_{k,t}^* < \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^{*}}$), then an increase in this fund's size, due to the changes in these factors, would increase family k's size, making AFMI more (less) concentrated. Also, the way to compare fund family sizes does not depend on investors' risk considerations, so the above results hold whether investors are risk neutral or mean-variance risk averse.

2.10 Impact of AFMI Concentration on Alpha Productions and Fund Sizes

Current literature, such as Pastor and Stambaugh (2012), and Feldman, Saxena, and Xu (2020, 2023), shows that the AFMI concentration level can affect fund alpha production. Suppose we incorporate this effect in our framework and assume that $A_i = A^i HHI_t,\ i = 1, \ldots, n$ in Equation (2). This setting implies that given the same manager ability, a more concentrated AFMI allows managers to produce higher gross alphas, as they can find more investment opportunities. This setting is consistent with the spirit of the model setting in Feldman, Saxena, and Xu (2020, 2023). Under this setting, we can see that the equilibrium HHIs in Equations (24) and (49) have the same forms as those without this setting (HHI_t in the numerator and denominator cancel out each other in each equation), and all our earlier results hold. Thus, when gross alpha sensitivities to manager abilities are proportional to HHI, then the effect of HHI on alpha production does not affect the dynamics of HHI. The intuition is that when a higher level of HHI increases each fund's gross alpha proportionally, it increases each fund's equilibrium size but does not affect funds' sizes relative to others.

Similarly, if we assume that $X_i = X^i HHI_t$ and $X_i^{RA} = X^{RA,i} HHI_t$, $i = 1, \dots, n$ in Equations (19) and (47), respectively, then the equilibrium HHIs in Equations (24) and (49) have the same forms as those without this setting, and all our earlier results hold. This setting implies that higher concentration affects managerial fees and the decreasing returns to scale, which consequently affect equilibrium fund sizes. This setting is also consistent with the spirit of the model setting in Feldman, Saxena, and Xu (2020, 2023). As a higher level of HHI affects each fund's size proportionally, it does not affect funds' sizes relative to others.

In short, if HHI changes A_i, X_i, and X_i^{RA}, $i = 1, \dots, n$ proportionally, then all our earlier results hold, and our equilibrium is compatible with those in Feldman, Saxena, and Xu (2020, 2023), where AFMI concentration affects equilibrium fund alphas and sizes. However, if HHI affects these parameters disproportionally, then the equilibrium HHI dynamics is more complex, and we leave this issue for future study.

3 Empirical Study

Based on Corollaries RN2.1 and RN2.2, we have the following two predictions, respectively. For funds that are sufficiently large (small) relative to others,

i. increase in these funds' performances relative to those of other funds exerts positive (negative) impacts on fund-level HHI;
ii. higher performance variations in these funds mitigate these positive (negative) impacts on fund-level HHI such that the interaction effects of shocks in relative performance and performance variations are negative (positive) in these funds.

Also, based on Corollary RNV, we have the following prediction.

iii. When the distribution of funds' sizes is highly skewed to the right, an increase in stock market volatility decreases fund-level HHI.

In addition, based on Proposition FA, when family-level HHI measures AFMI concentration, if the funds are in sufficiently large (small) fund families, then we have predictions similar to those shown above for these funds. We test these predictions empirically.

3.1 Methodology

We first develop the measures of fund performance and performance variation. We estimate fund performance using empirical asset pricing models in the current literature, such as the five-factor model developed by Fama and French (2015) (hereafter, FF5) and the four-factor model developed by Fama and French (1993) and Carhart (1997) (hereafter, FFC4). For each fund i, we estimate the following:

$$r_{i,t} = \sum_{j=1}^{M} \beta_{i,j} F_{j,t} + \varepsilon_{i,t}, \tag{51}$$

where $r_{i,t}$ is fund i's net return in excess of risk-free return, $F_{j,t}$ is the return of factor j, $\beta_{i,j}$ is the factor loading of fund i to factor j, M is the number of factors, and $\varepsilon_{i,t}$ is the residual. This model is estimated on a rolling-window basis.

Our first measure of fund performance variation is the $1 - R^2$ of the regression model calculated as $\frac{\sum_t (\hat{\varepsilon}_{i,t})^2}{\sum_t (r_{i,t} - \bar{r}_i)^2}$, where $\hat{\varepsilon}_{i,t}$ is the estimated residual and $\bar{r}_i$ is the average excess return of fund i over the rolling window period. Notice that $\hat{\varepsilon}_{i,t} = r_{i,t} - \sum_{j=1}^{M} \hat{\beta}_{i,j} F_{j,t}$, where $\hat{\beta}_{i,j}$ is the estimate of factor loading to factor j and $\hat{\varepsilon}_{i,t}$ can be regarded as the in-sample estimate of abnormal net return, or net alpha. Consequently, $1 - R^2$ can be regarded as the in-sample estimate of fund performance variation (normalized by total variation of the excess return). Amihud and Goyenko (2013) also find that the measure $1 - R^2$ in such regression models is highly related to fund performance. Similar to Amihud and Goyenko (2013), we use a 24-month rolling window to estimate the models for each fund i, and we denote the $1 - R^2$ estimated by the previous 24-month period (from $t - 1$ to $t - 24$) as $OMR2_{i,t-1}$.

We estimate the (out-of-sample) fund net alpha at time t as the $NetAlpha_{i,t} = r_{i,t} - \sum_{j=1}^{M} \hat{\beta}_{i,j} F_{j,t}$, where $\hat{\beta}_{i,j}$ is estimated using the observations in the previous 24 months. Our second measure of fund performance variation is the standard deviation of the net alphas in the previous 12 months, denoted as $NetAlpha\_Std_{i,t-1}$. For robustness, we also calculate the fund gross alpha as the fund net alpha plus the fund annual expense ratio divided by 12, and then calculate the standard deviation of this gross alpha in the previous 12 months as a measure of fund performance variation, denoted as $GrossAlpha\_Std_{i,t-1}$. These two measures of fund performance variation are the performance volatility measures by Huang, Wei, and Yan (2021).

We next choose the option-implied volatility index (VIX) as our measure of stock market volatility. VIX not only measures stock market volatility but also captures investors' expectation of such volatility, so current literature [e.g., Jin, Kacperczyk, Kahraman, and Suntheim (2022)], uses VIX to measure market stress and panic. Thus, we expect that at a higher VIX level, the stock market is more volatile and stressful, impeding fund managers to implement their investment strategies and consequently reducing the sensitivities of gross alphas to manager abilities.

Fund-Level Analysis: Flow-Performance Sensitivity, Stock Market Volatility, and Performance Variation

As we assume that higher stock market volatility decreases the sensitivity of gross alpha to manager ability, we should find that the equilibrium fund flow–net alpha sensitivity decreases with stock market volatility. Also, as we assume Bayesian learning of manager abilities in our model, then higher performance variation should make investors rely less on fund performance when learning about manager abilities, consequently decreasing the equilibrium fund flow–net alpha sensitivity.[37] Before we test our theoretical predictions, we provide evidence to support these model settings by empirically studying the flow–net alpha sensitivity. We test the following model:

$$\begin{aligned} Flow_{i,t} = \delta_0 &+ \delta_1 NetAlpha_{i,t-1} + \delta_2 NetAlpha_{i,t-1} \times VIX_{t-1} \\ &+ \delta_3 VIX_{t-1} + \delta_4 NetAlpha_{i,t-1} \times Perf\_Var_{i,t-1} \\ &+ \delta_5 Perf\_Var_{i,t-1} + \delta Controls_{i,t-1} + \phi_t + \upsilon_i \\ &+ \varepsilon_{i,t}, \end{aligned} \tag{52}$$

where $Flow_{i,t}$ is the fund percentage flow calculated as the difference between the monthly growth rate of the fund's total net asset under management (TNA) and the fund's monthly net return, VIX_t is the VIX value, and $Perf\_Var_{i,t}$ is a measure of fund performance variation, which is $OMR2_{i,t}$, $NetAlpha\_Std_{i,t}$, or $GrossAlpha\_Std_{i,t}$. We follow the literature [such as Brown and Wu (2016), Franzoni and Schmalz (2017), Harvey and Liu (2019), Jiang, Starks,

[37] In our model, we can easily show that the equilibrium fund flow–net alpha is $\frac{dq_{i,t}^*}{q_{i,t}^*} = \frac{A_i(\lambda_t)\sigma_{i,m}(\gamma_{i,t})}{f_i B_i}\left(\frac{dS_{i,t}}{S_{i,t}}\right) + \frac{A_i^2(\lambda_t)\sigma_{i,m}^2(\gamma_{i,t})}{4f_i^2 B_i^2}\left(\frac{dS_{i,t}}{S_{i,t}}\right)^2 + 2\left[\frac{a_{i,0}}{m_{i,t}} + a_{i,1}\right]dt$, $i = 1, \dots, n$, by applying Itô's Lemma on $q_{i,t}^*$ to calculate $dq_{i,t}^*$ and then divide it by $q_{i,t}^*$. Then, the flow–net alpha sensitivity decreases with B_i and increases with $A_i(\lambda_t)$. This theoretical result is consistent with results in the literature, such as Feldman and Xu (2022).

and Sun (2021), Huang, Wei, and Yan (2021), and Feldman and Xu (2022)] to choose control variables. The vector $Controls_{i,t-1}$ includes the lagged values of the natural logarithm of the fund size ($\ln Size_{i,t-1}$); the natural logarithm of fund age ($lnAge_{i,t-1}$); fund expense ratio ($Expense_{i,t-1}$); fund turnover ratio ($Turnover_{i,t-1}$); the weighted average flow of the fund class based on the Lipper fund classification; i.e., the style flow, ($StyleFlow_{i,t-1}$); fund flow ($Flow_{i,t-1}$); fund family net alpha ($FamAlpha_{i,t-1}$); and the natural logarithm of the number of active equity funds in the fund family ($\ln FamNo_{i,t-1}$). Variables ϕ_t and v_i represent year effects and fund effects, respectively. Detailed definitions and constructions of these variables are shown in the Data Appendix. When analyzing the flow–net alpha relations, we also include the interaction terms of $\ln Size_{i,t-1}$ and $lnAge_{i,t-1}$ with $NetAlpha_{i,t-1}$ because existing literature shows that the flow–net alpha sensitivity is affected by fund size [Brown and Wu (2016)] and fund age [Feldman and Xu (2022)]. To account for potential time-series and cross-sectional correlations in residuals, we cluster standard errors by year and by fund.

If our assumptions are consistent with reality, we should find that δ_2 is significantly negative and δ_4 is significantly negative.

Market-Level Analysis: Dynamics of HHI and Changes in Stock Market Volatility, Fund Performances, and Performance Variations

We test our theoretical predictions using our measures of stock market volatility and fund performance variation. Because it is impractical to include all funds' performances as explanatory variables in one regression model when empirically analyzing the dynamics of HHI,[38] we test our model's predictions based on a group of funds that have sufficiently large sizes and a group of funds that have sufficiently small sizes. We want to test how the changes of these funds' performances affect the dynamics of HHI, holding other funds' performances unchanged, so we need a measure of "relative change" in performance. Here we measure the changes in these funds' performances relative to those in other funds by the changes in these funds' market shares. The reason is that a fund's equilibrium size is a positive function of the fund manager's inferred ability shown in our theoretical model, and then market share, which

[38] In our data section, we show that we have more than three thousand funds in our sample but only 336 monthly observations of HHI. Thus, we cannot directly run a regression based on our theoretical result in Equation (30).

is a fund's size relative to the sum of all fund sizes, indicates a fund manager's inferred ability relative to the abilities of other managers. Consequently, change in a fund's market share indicates change in relative inferred ability due to the change in the fund's performance relative to that of other funds. Then, we test the following model:

$$\begin{aligned} dif\_HHI_t = {} & \delta_0 + \delta_1 dif\_VIX_{t-1} + \delta_2 dif\_MarketShare^L_{t-1} \\ & + \delta_3 dif\_MarketShare^S_{t-1} \\ & + \delta_4 dif\_MarketShare^L_{t-1} \times Perf\_Var^L_{t-1} \\ & + \delta_5 dif\_MarketShare^S_{t-1} \times Perf\_Var^S_{t-1} \\ & + \delta_6 Perf\_Var^L_{t-1} + \delta_7 Perf\_Var^S_{t-1} \\ & + \delta_8 NumGrowth_{t-1} + \phi_t + \varepsilon_t, \end{aligned} \tag{53}$$

where dif_HHI_t is the change in HHI from time $t-1$ to t and dif_VIX_{t-1} is the change in VIX from time $t-2$ to $t-1$. The superscripts B and S denote the large-fund group and small-fund group, respectively. We define the large-fund group as the largest five funds (based on fund TNA values) and the small-fund group as the funds with fund TNA values from the fifth percentile to the tenth percentile because these funds are likely to be sufficiently large and sufficiently small, respectively, relative to other funds.[39] We redefine the large-fund group and small-fund group in each month. The explanatory variable $dif\_MarketShare^L_{t-1}$ ($dif\_MarketShare^S_{t-1}$) is the change in market share of the large-fund group (small-fund group) from time $t-2$ to $t-1$. Also, $Perf\_Var^L_{t-1}$ ($Perf\_Var^S_{t-1}$) is the weighted average of the measure of performance variation within the large-fund group (small-fund group) at time $t-1$, using funds' TNAs at this time as weights. We include $NumGrowth_{t-1}$ as a control variable, which is the change in the number of funds in the market from time $t-2$ to $t-1$, divided by the number of funds at $t-2$. This variable controls the effects of fund exit and entrance on the dynamics of HHI. Also notice that in the model as shown in Equation (53), the dependent variable dif_HHI_t and independent variables dif_VIX_{t-1}, $dif\_MarketShare^L_{t-1}$, $dif\_MarketShare^S_{t-1}$, and $NumGrowth_{t-1}$ are the differences of the time-series variables HHI_t, VIX_{t-1}, $MarketShare^L_{t-1}$, $MarketShare^S_{t-1}$, and number

[39] Because the performances and sizes of funds with fund size values from the lowest five percentiles are very volatile and contain much noise, we choose the funds with fund size values from the fifth percentile to the tenth percentile to construct the small-fund group. We do robustness checks with different classifications of the large-fund group and small-fund group, as shown in the following discussion of the empirical study.

of funds, respectively. By taking the differences in these time-series variables, we address the serial correlation issue in these variables.[40] We also use Newey-West estimates of standard error with the maximum lag of 12 to be considered in the autocorrelation structure to further address the serial correlation issue. We include year dummies, whose effects are denoted by ϕ_t in the model, to control time-related effects of macroeconomic events, such as technological and regulatory changes.

When we use fund-level HHI in the above model, without including explanatory variables $Perf\_Var_{t-1}^{L}$, $Perf\_Var_{t-1}^{S}$, $dif\_MarketShare_{t-1}^{L} \times Perf\_Var_{t-1}^{L}$, and $dif\_MarketShare_{t-1}^{S} \times Perf\_Var_{t-1}^{S}$, we expect δ_1 to be negative when the distribution of funds' sizes is highly skewed to the right because, in this case, higher stock market volatility should induce negative impact on HHI; we expect δ_2 (δ_3) to be positive (negative) because shocks in the relative performance of the large-fund group (small-fund group), measured by the changes in the market share, should induce a positive (negative) impact on HHI. When including these four explanatory variables in this model, we expect δ_4 (δ_5) to be negative (positive) because performance variation of the large-fund group (small-fund group) should mitigate the positive (negative) impact of shocks in the relative performance of this group on HHI. When we use family-level HHI in the above model, if funds in the large-fund group (small-fund group) also belong to fund families that are sufficiently large (small) relative to others, then we have the same predictions on these coefficients.

3.2 Data

We collect our active fund data from the survivor-bias-free mutual fund database of the Center for Research in Security Prices (CRSP). Our sample period is January 1990 to December 2020, and we use monthly data.[41] We exclude index funds, variable annuity funds, and ETFs, and then choose U.S. domestic equity-only mutual funds by using the Lipper fund

[40] The results of this analysis are in Table 4 and Table 5. Dickey–Fuller tests on the residuals of the regressions shown in these tables suggest that there is no unit root in the residuals, so our method sufficiently addresses the serial correlation issue in the time-series variables.

[41] Information on the Lipper fund classification and most of the information on the management company code to identify fund families begins in December of 1999. As we use a 24-month rolling window to estimate fund net alpha, and we need 12 months to estimate alpha standard deviation, our test period starts from January 1993.

classification.[42] This equity fund filter is similar to many of the current empirical studies such as those of Amihud and Goyenko (2013), Brown and Wu (2016), Choi, Kahraman, and Mukherjee (2016), Huang, Wei, and Yan (2021), and Feldman and Xu (2022).

We use the MFLINKS database to aggregate fund share class-level information to fund-level information. In particular, we calculate a fund's TNA by summing up its share classes' TNA and calculate fund size as fund TNA normalized to the December 2020 dollar value[43]. We calculate a fund-level variable's value as the weighted average of share class-level values using share classes' TNAs as weights. Fund family is identified by the management company code,[44] and we use funds' TNAs as weights in calculating fund family performance.

To estimate the FFC4 model, we collect the risk-free rate and the corresponding factors from the Fama-French database in Wharton Research Data Services (WRDS). To estimate the FF5 model, we collect the factors from the Fama-French website.[45] We collect daily observations of VIX from WRDS and calculate the average value of VIX in each month to develop the monthly VIX values. To facilitate interpretation, we divide the VIX value by 100.[46]

When conducting our market-level analysis on the dynamics of HHI, we include the observations of fund net alpha and $1 - R^2$ of the empirical asset pricing model in our sample only if observations of fund net returns are available and fund TNA is positive in all of the previous 24 months (i.e., the estimation window). We include the observations of fund net alpha (gross alpha) standard deviation only if observations of fund net alphas (gross alphas) are available in all the previous 12 months. We also exclude fund observations if the fund's size (in the December 2020 dollar value) is below 15 million.

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[42] We use funds in the following Lipper classes: Large-Cap Core, Large-Cap Growth, Large-Cap Value, Mid-Cap Core, Mid-Cap Growth, Mid-Cap Value, Small-Cap Core, Small-Cap Growth, Small-Cap Value, Multi-Cap Core, Multi-Cap Growth, and Multi-Cap Value. If a fund has a missing Lipper class in some months, we use its Lipper class in the previous months; if there is no information on a Lipper class in the previous months, we use its Lipper class in the later months.

[43] We divide a fund's TNA by the total market capitalization of the U.S. equity market in that month, and then multiply it by the total market capitalization of the U.S. equity market in December 2020. The U.S. equity market information is offered by the CRSP US stock database, and we calculate the total market capitalization using only ordinary common shares, with the share type code in CRSP equal to 10 and 11.

[44] If a fund has a missing management company code in some months, we use the fund's management company code in the previous months; if there is no information of management company code in the previous months, we use the fund's management company code in the later months.

[45] The website address is https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, accessed on July 19, 2022.

[46] In the database, a VIX value of 15, for example, means that the S&P500 index has an annualized volatility of 15% implied by the option prices. We use 15%, or equivalently 0.15, as the VIX value instead of 15.

In doing the fund-level analysis on the effects of stock market volatility and performance variation on the flow–net alpha sensitivity, we further require a fund to have at least 24 months' observations of all the variables in Equation (52). We require a fund family to have at least two funds so that the fund family-level variables are meaningful. We also winsorize all the fund-level variables at the 1% and 99% levels when doing this analysis. The above criteria and process are similar to those in the fund management literature, such as Amihud and Goyenko (2013).

We have 3,158 funds in our sample for our market-level analysis and have 2,437 funds for the fund-level analysis. The Data Appendix details the constructions of all the variables.

3.3 Empirical Results

Table 1 reports the summary statistics of the variables for our fund-level analysis on the flow–net alpha sensitivity. It shows that distributions of fund flow and style flow are slightly skewed to the right, whereas those of fund size and fund family size are highly skewed to the right with a large standard deviation, implying that some extremely large funds and fund families exist in the market. Also, on average, fund net returns are slightly positive, whereas fund net alphas are slightly negative whether estimated by FF5 or FFC4. On average, the values of $1-R^2$ of FF5 and FFC4 are close to 0.08, implying that on average, around 8% of the total variation of fund net returns in excess of risk-free return is due to active management and cannot be explained by these models. The standard deviation of net alpha and that of gross alpha are very close to each other (the differences in the values of these two variables' statistics exist in the sixth or seventh digit after the decimal), as the fund expense ratio is very stable. The VIX value is close to symmetric with a large variation, and it implies that on average, the S&P500 index has an annualized volatility of 20% in our sample period.

Table 2 illustrates the results of the regression model in Equation (52). It shows that in all model specifications, the interaction term of fund net alpha and VIX is significantly negative, suggesting that a higher VIX level significantly decreases the flow–net alpha sensitivity. In all these model specifications, a one-percentage increase in VIX (i.e., the annualized volatility of the S&P500 index increases by 1%), decreases the flow–net alpha sensitivity by around 0.002, holding other variables unchanged. Also, all the interaction terms of fund net alpha and performance variation measure are negative and highly significant, suggesting that higher performance variation significantly reduces the flow–net alpha sensitivity. Particularly, the first three columns report the results for which fund performance and performance variation are estimated by the FF5 model. We find that, holding other variables unchanged, if $OMR2_{i,t-1}$ increases by 0.01, the flow–net alpha sensitivity decreases by 0.0016 on average [model specification (1)]; if $NetAlpha\_Std_{i,t-1}$ or $GrossAlpha\_Std_{i,t-1}$ increases by 0.01, the flow–net alpha sensitivity decreases by 0.0004 on average [model specifications (2) and (3)].[47] The last three columns report the results for which fund performance and performance variation are estimated by the FFC4 model, and the results are highly consistently with those reported in the first three columns.

The above results imply that higher stock market volatility decreases the sensitivity of gross alpha to manager ability, so we observe that it decreases the flow–net alpha sensitivity. The finding that a higher VIX level decreases the flow–net alpha sensitivity is consistent with that in Jin, Kacperczyk, Kahraman, and Suntheim (2022), and consistent with empirical findings that the flow–net alpha sensitivity decreases when the market is in extreme condition, more volatile, and accompanies with more economic uncertainty [Franzoni and Schmalz (2017), Harvey and Liu (2019), and Jiang, Starks, and Sun (2021)]. Also, these results imply that higher performance variation makes investors rely less on fund performance to infer manager abilities and react less intensively to fund performance. This finding is consistent with that in Huang, Wei, and Yan (2021). In short, our empirical results support the assumptions of our theory. Then, based on our theory, our measures of stock market volatility and performance variation should affect the dynamics of HHIs as stated in our empirical predictions.

Table 3 reports the summary statistics of the variables for our market-level analysis on the dynamics of HHIs. It shows that on average, fund-level (family-level) HHI is around 0.01 (0.06) in the U.S. active equity mutual fund market, showing that this market is competitive. The large-fund group, which contains only five funds, on average occupies 17% of the market share, whereas the small-fund group, which contains around seventy funds on average over

[47] The results of model specifications (2) and (3), and model specifications (5) and (6) are very close because the standard deviation of net alpha and that of gross alpha are very close to each other. The difference exists in the sixth digit after the decimal in the coefficients and standard errors.

time, occupies only 0.07% of the market share on average. Also, the small-fund group tends to have a larger performance variation than the large-fund group, as implied by its larger mean values of $1 - R^2$, standard deviation of net alpha, and standard deviation of gross alpha. The change in VIX is small on average but variates a lot, implying that stock market volatility changes substantially over time.

We also find that in our sample, in each month, the aggregate size of funds that enter (exit) the market is only 0.021% (0.067%) of the size of the active equity mutual fund market.[48] This shows that when funds enter (exit) the market, their sizes are trivial and they have little instantaneous impact on the market concentration, although they affect the market concentration after (before) their entrance (exit). This also confirms that our continuous-time framework is compatible with the effects of fund enter and exit, as discussed in Section 2.8.

To offer more insights before we report the test results, we plot fund-level and family-level HHIs, the number of funds and fund families in the market, and market shares of the large-fund and small-fund groups in Figure 1.

First, we can see that both fund-level and family-level HHIs fluctuate a great deal over the last few decades, and neither of them converges to a particular level. This finding is consistent with the framework with dynamic manager abilities but inconsistent with a linear framework with constant manager abilities, where HHI, whether at the fund level or family level, converges to a constant level. Therefore, the finding here is consistent with those of Feldman and Xu (2022).[49] Second, fund-level HHI moves more closely with the market share of the large-fund group than with the inverse of the number of funds. As the market share value indicates the relative inferred ability of this group, this finding is consistent with our theoretical framework that the managers' relative inferred abilities are more relevant than the number of funds when analyzing fund-level HHI. Also, the correlation of family-level HHI and the inverse of the number of fund families is only around 0.4. These results suggest that it is important to study heterogeneous managers for whom HHI (whether at the fund level or family level)

[48] We use the inception date of the first share class of a fund to define its time to enter the market and use the date of a fund's last reported return to define its time to exit the market.

[49] Feldman and Xu (2022) shows that fund flows sensitivities to fund performance are nonmonotonic over time, which is consistent with a nonlinear filtering framework of dynamic unobservable managing abilities and inconsistent with a framework of constant unobservable managing abilities.

captures managers' relative inferred abilities, instead of homogeneous managers because for them, HHI is simply the inverse of the number of competitors.

Further, our theory can explain some of the results in this figure in a way that is compatible with the stylized facts shown in the literature. For example, Wahal and Wand (2011) show that from the late 1990s to 2005, incumbents in the mutual fund market that have a high overlap in their portfolio holdings with those of new entrants experience lower fund flows and lower alphas. Kosowski, Timmermann, Wermers, and White (2006) show that outperforming managers become scarce after 1990 and speculates that this might be due to the competition among the large number of new funds, which reduces the gains from trading. Fama and French (2010) also report a decline in the persistence of alphas after 1992 and speculates that the cause is either diseconomies of scale or the entry of hordes of mediocre funds that make it difficult to uncover truly informed managers. In Figure 1, we observe that the number of funds and fund families keep increasing from the early 1990s to the early 2000s, whereas fund-level and family-level HHIs keep decreasing in this period. If the new entrants in this period hold portfolios similar to those of the incumbents and/or outperformance become scarce in this period, then fund managers' inferred abilities become more similar. By our theoretical results, similarities in managers' inferred abilities and fund family's aggregate inferred abilities lead to similarities in fund sizes and fund family sizes, so fund-level and family-level HHIs decrease.

Table 4 reports the results of our analysis of the dynamics of fund-level HHI, results of the regression model in Equation (53). It shows that the coefficient of dif_VIX_{t-1} is significantly negative in all model specifications. In particular, results in column (1) (other columns) indicate that holding other variables unchanged, a one-percentage increase in VIX decreases fund-level HHI in the next month by around 0.0002 (0.0001). This finding is consistent with our prediction iii that when the distribution of funds' sizes is highly skewed to the right (as shown in Table 1), an increase in stock market volatility decreases fund-level HHI.

Also, in column (1) the coefficient of $dif\_MarketShare_{t-1}^{L}$ is significantly positive, implying that a positive shock in the large-fund group's market share induces an increase in fund-level HHI in the next month. In particular, holding other variables unchanged, if the large-fund group's market share increases by 0.01, then fund-level HHI in the next month would increase by around 0.012. Also, the coefficient of $dif\_MarketShare_{t-1}^{S}$ is negative but is insignificant. The insignificance is probably due to the noise in the small funds' market shares. As change in market share indicates change in relative performance in AFMI in general, the results in column (1) are consistent with our prediction i that, for sufficiently large (small) funds, increase in their performances relative to those of other funds exerts positive (negative) impacts on fund-level HHI.

Columns (2) to (4) offer the results when fund performance and performance variation measures are estimated by the FF5 model. The coefficients of the interaction terms of $dif\_MarketShare^{L}_{t-1}$ and the measures of the large-fund group's performance variation are significantly negative. In particular, holding other variables unchanged, if $OMR2^{L}_{i,t-1}$ increases by one basis point, then the impact of $dif\_MarketShare^{L}_{t-1}$ on dif_HHI_{t} decreases by around 0.0014; if $NetAlpha\_Std^{L}_{i,t-1}$ or $GrossAlpha\_Std^{L}_{i,t-1}$ increases by one basis point, then the impact of $dif\_MarketShare^{L}_{t-1}$ on dif_HHI_{t} decreases by around 0.015. Also, the coefficients of the interaction terms of $dif\_MarketShare^{S}_{t-1}$ and the measures of the small-fund's performance variation are positive and marginally significant. The results in columns (5) to (7) when measures of fund performance and performance variation are estimated by the FFC4 model are consistent with those in columns (2) to (4). We also find that the coefficients of the interaction term of $dif\_MarketShare^{S}_{t-1}$ and $NetAlpha\_Std^{S}_{i,t-1}$, and that of $dif\_MarketShare^{S}_{t-1}$ and $GrossAlpha\_Std^{S}_{i,t-1}$ become more significant in these model specifications. In general, these results are consistent with our prediction ii that higher performance variations in sufficiently large (small) funds mitigate the positive (negative) impacts of the increase in their relative performance on fund-level HHI.

In addition, $NumGrowth_{t-1}$ is significantly positive in all model specifications, implying that a larger growth rate in the fund number is associated with higher fund-level HHI in the following month. This is more evidence against a framework of homogeneous managers, where fund-level HHI is the inverse of the number of funds, and dif_HHI_{t} should decrease with $NumGrowth_{t-1}$. When managers are heterogeneous, a larger number of funds can be associated with a higher HHI, as we show here. Thus, it is important to model heterogeneous managers, as we do in this paper.

Table 5 reports the results of our analysis on the dynamics of family-level HHI. In our sample, we find that all funds in the large-fund group belong to the largest ten fund families (around 97% of these fund observations even belong to the largest five fund families), and all funds in the small-fund group belong to fund families with size ranks of the bottom 20%. Thus, our funds in the large-fund (small-fund) group are also in fund families that are sufficiently large (small) relative to others, and based on our theoretical prediction, we should find similar results on the dynamics of family-level HHI. Table 5 confirms this. In particular, an increase in stock market volatility significantly decreases family-level HHI; increase in the performances of funds in the large-fund (small-fund) group exerts significantly positive (insignificantly negative) impacts on family-level HHI, and higher performance variations in these funds mitigate the positive (negative) impacts.

Robustness

We also do multiple robustness checks on our test results. We estimate the shocks in VIX as the out-of-sample residuals of an AR(1) model or an AR(2) model on VIX on a 24-month rolling-widow basis, and use these shocks to measure the (unexpected) changes in VIX instead of dif_VIX_t. We redefine the large-fund group as the largest ten funds. We also redefine the small-fund group as the funds with fund TNA values from the tenth percentile to the fifteenth percentile, or as those with fund TNA values from the fifth percentile to the fifteenth percentile. Furthermore, we use standard error clustered by year instead of Newey-West estimates of standard error. We redo the tests and find results that are highly consistent with those in Table 4 and Table 5. For brevity, we omit the results of these robustness checks here. In summary, our empirical results are consistent with our theoretical predictions.

4 Conclusion

We introduce continuous-time rational models of dynamics of AFMI HHI in which unobservable fund manager abilities are heterogeneous and dynamic. In equilibrium, managers with higher inferred abilities receive larger fund sizes, so their relative inferred abilities determine HHI. Our model predicts that, when we measure HHI at the fund level, if a manager's inferred ability is sufficiently large (small) relative to the inferred abilities of others, then an increase in this manager's inferred ability exerts positive (negative) impact on HHI. Also, when funds' performance variations are larger, investors rely less on the shocks of managers' relative performances to infer manager abilities, making investment flows less sensitive to these shocks. Consequently, the positive (negative) impacts of higher relative performances of sufficiently large (small) funds on HHI are mitigated and have smaller absolute magnitudes.

In addition, in our nonlinear framework where sensitivities of gross alphas to manager abilities decrease with stock market volatility, higher stock market volatility decreases all funds' equilibrium sizes. If there are extremely large funds, then the effect of higher stock market volatility on these funds dominates that of other funds, inducing a negative aggregate effect on HHI. Linear frameworks of manager abilities and gross alphas that are used in the current literature cannot directly model this effect and effects of other economic factors on the dynamics of HHI, as we do in our nonlinear frameworks.

We also show a special case in which unobservable fund manager abilities are constant in a linear framework. In this case, as time goes to infinity, managers' inferred abilities converge to their true ability levels and do not change, making both equilibrium fund sizes and HHI stay unchanged. All our results hold whether investors are risk neutral or mean-variance risk averse and whether there are fund entrances or exits. Moreover, when we measure HHI at the fund family level, we find results on the HHI dynamics similar to those when we measure HHI at the fund level, as long as similar requirements on the fund families' aggregate inferred abilities/family sizes are satisfied. In addition, our results hold when HHI affects proportionally gross alpha sensitivities to abilities and fund size factors.

Our empirical results are consistent with our theoretical findings. In particular, an increase in stock market volatility significantly decreases fund-level HHI. An increase in the large-fund group's market share, which proxies this group's relative performance, exerts a significantly positive impact on fund-level HHI; and a larger performance variation in this group significantly decreases such positive impact. An increase in the small-fund group's market share tends to exert a negative effect on fund-level HHI, although this effect is insignificant. However, we find evidence that a larger performance variation in this group mitigates the effect of the group's change in market share on fund-level HHI. In addition, funds in our large-fund (small-fund) group are also in sufficiently large (small) fund families, and we find similar empirical results when we measure HHI at the fund family level.

Moreover, our empirical evidence that the sizes of funds that enter the market and that exit the market are trivial compared to the AFMI size supports our framework that fund entrance and exit do not affect HHI dynamics immediately but change the set of funds. Also, the fluctuation of the empirical HHI (whether at the fund level or fund family level) over time is consistent with our theoretical results in which manager abilities are dynamic and unobservable, but it is inconsistent with a model with constant unobservable manager abilities in a linear framework. Also, the fact that the empirical HHI moves more closely with large funds' market shares than the inverse of the number of competitors shows the importance of modeling heterogeneous managers, where HHI captures managers' relative inferred abilities, instead of homogeneous managers, where HHI is simply the inverse of the number of competitors. In addition, our model explains the following literature findings in a compatible way: 1) from the 1990s to early 2000s, new entrants who have portfolio holdings similar to those of incumbents decrease fund performances and fund flows, 2) outperforming managers are scarce, and 3) HHI decreases during this period.

Our paper sheds light on future research on the dynamics of AFMI concentration. In particular, future research in this area can focus on factors that affect fund managers' relative inferred abilities. For example, current literature finds that fund family members can compete or cooperate with each other [see, for example, Evans, Prado, and Zambrana (2020), Eisele, Nefedova, Parise, and Peijnenburg (2020), and Xu (2023)]. Other literature shows that mutual funds compete in different dimensions, such as by trading assets in specific industries and style markets (defined by, for example, stock's total capitalization and book-to-market-ratio), by selling fund shares in specific retail market segments (such as direct-sold and broker-sold), by concentrating research on stocks that are informationally intense, and by offering unique products [see, for example, Kacperczyk, Sialm, and Zheng (2005), Guercio and Reuter (2014), Hoberg, Kumar, and Prabhala (2018), Jiang, Shen, Wermers, and Yao (2018), and Kostovetsky and Warner (2020)]. Because the methods that fund managers use to compete in the market affect managers' relative inferred abilities, these methods would consequently exert impacts on AFMI concentration. Our study also suggests that a nonlinear framework of gross alphas and manager abilities can directly model the effects of these factors and offer more insights to the market equilibrium.

Although our paper studies the dynamics of AFMI concentration, our framework can be extended to study the dynamics of concentration in other industries in which incomplete information exists: producers' performance depends on dynamic states that are unobservable to customers and producers.

Data Appendix

This section details the definitions and constructions of the variables.

- $Flow_{i,t}$ is the fund flow, which is the difference between the monthly growth rate of the fund's TNA and the fund's monthly net return. It is in decimal.
- $NetAlpha_{i,t}$ is the fund net alpha, calculated as the fund's net return in excess of risk-free return minus the benchmark's return, which is estimated by an empirical asset pricing model on a 24-month rolling-window basis. It is in decimal.
- dif_HHI_t is $HHI_t - HHI_{t-1}$, where HHI_t is calculated as the sum of squares of all funds' (fund families') market shares in month t when it is fund-level (family-level) HHI. It is in decimal.
- dif_VIX_t is $VIX_t - VIX_{t-1}$, where VIX_t is the average value of the daily option-implied volatility index values in month t, divided by 100. It is in decimal.
- $dif\_MarketShare_t^L$ ($dif\_MarketShare_t^S$) is the change in market share of the large-fund group (small-fund group) from time $t-1$ to t. It is in decimal.
- $Perf\_Var_t^L$ ($Perf\_Var_t^S$) is the weighted average of the measure of performance variation within the large-fund group (small-fund group) at time t, using funds' net assets under management at this time as weights. A fund's measure of performance variation, $Perf\_Var_{i,t}$, is $OMR2_{i,t}$, $NetAlpha\_Std_{i,t}$, or $GrossAlpha\_Std_{i,t}$. It is in decimal.
- $OMR2_{i,t}$ is the $1-R^2$ of the empirical asset pricing model estimated on a 24-month rolling-window basis. It is in decimal.
- $NetAlpha\_Std_{i,t}$ is the fund net alpha standard deviation, calculated as using the fund net alphas in the last 12 months. It is in decimal.
- $GrossAlpha\_Std_{i,t}$ is the fund gross alpha standard deviation, calculated as using the fund gross alphas in the last 12 months, where fund gross alpha is fund net alpha plus annual fund expense ratio divided by 12. It is in decimal.
- $NumGrowth_t$ is the change in the number of funds in the market from time $t-1$ to t, divided by the number of funds at $t-1$. It is in decimal.

- $\ln Age_{i,t}$ is the natural logarithm of fund age, which is calculated as the number of months since the inception of the fund's oldest share class.
- $\ln Size_{i,t}$ is the natural logarithm of the fund's TNA in the December 2020 dollar, which is equal to the original TNA divided by the total market capitalization of the U.S. equity market at time t, and then multiplied by the total market capitalization of the U.S. equity market in December 2020. TNA is in billion dollars.
- $Expense_{i,t}$ is fund expense ratio, the ratio of total investment that shareholders pay for the fund's operating expenses, including 12b-1 fees. It is in decimal.
- $TurnOver_{i,t}$ is fund turnover ratio, calculated as the minimum of aggregated sales and aggregated purchases of securities, divided by the average 12-month total net assets under management of the fund. It is in decimal.
- $StyleFlow_{i,t}$ is style flow, calculated as the weighted-average flow of the fund class based on Lipper fund classification, and is in decimal.
- $FamAlpha_{i,t}$ is fund family net alpha, calculated as the weighted average of the members' net alphas excluding the net alphas of fund i, where the lagged net asset under management is the weight. It is in decimal.
- $\ln FamNo_{i,t}$ is the natural logarithm of the number of active equity funds that have net alpha observations in the family. The number of active equity funds is in integer.

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Figure 1 U.S. AFMI Concentration Dynamics

Figure 1 plots the monthly values of variables from January 1993 to December 2020 using the U.S. active equity mutual fund data from the Center for Research in Security Prices (CRSP). The two graphs at the top plot the fund-level HHI and the number of funds in the market, respectively. The two graphs in the middle plot the family-level HHI and the number of fund families in the market, respectively. The two graphs at the bottom plot the market shares of the large-fund group and small-fund group, respectively. HHI is the Herfindahl-Hirschman Index, calculated as the sum of market shares squared. The number of funds is counted as the number of the U.S. active equity mutual funds that have observations satisfying our criteria. The number of fund families is counted as the number of fund families that have fund observations satisfying our criteria. Market shares are calculated based on total net assets under management. The large-fund group contains the largest five funds in the market, whereas the small-fund group contains funds that have fund size values from the fifth percentile to the tenth percentile. These two groups are redefined each month. The gray areas represent the two recessions, from March 2001 to November 2001, and from December 2007 to June 2009, respectively.

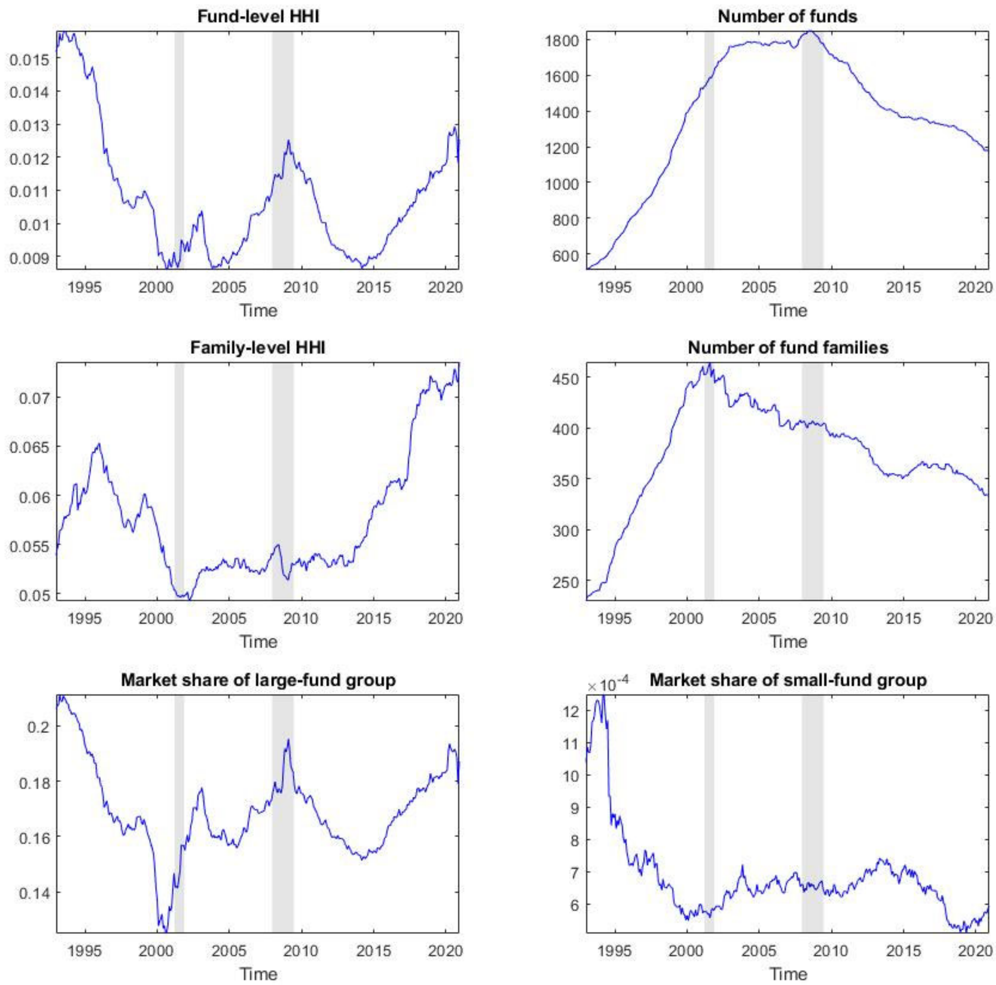

Table 1. Summary Statistics on Variables for Fund-Level Analysis

Table 1 reports the summary statistics on the variables for our fund-level analysis. Our sample period is from January 1990 to December 2020, and we use monthly data. FF5 is the five-factor model developed by Fama and French (2015), and FFC4 is the four-factor model developed by Fama and French (1993) and Carhart (1997). We estimate the models on a 24-month rolling-window basis, and over time, calculate the $1 - R^2$ and out-of-sample prediction of fund net alphas. The definitions and constructions of all the variables are reported in the Data Appendix.

				Percentile		
Variable	Observation	Mean	Standard deviation	25th	50th	75th
Fund characteristics						
Fund flow (decimal)	369589	0.0027	0.8675	-0.0152	-0.0050	0.0068
Fund net return (decimal)	369589	0.0077	0.0624	-0.0191	0.0118	0.0381
Fund TNA (in 1 billion December 2020 dollars)	369589	4.6323	16.1613	0.2767	0.9473	3.1540
Fund age (number of months)	369589	203.5	171.4	89.0	155.0	250.0
Fund expense (decimal)	369589	0.0117	0.0042	0.0093	0.0114	0.0139
Fund turn over ratio (decimal)	369589	0.7868	0.6987	0.3400	0.6167	1.0200
Style flow (decimal)	369589	-0.0012	0.0103	-0.0068	-0.0024	0.0035
Estimates from FF5						
Fund net alpha (decimal)	369589	-0.0009	0.0427	-0.0100	-0.0011	0.0076
$1 - R^2$ of the factor model (decimal)	369589	0.0769	0.0746	0.0312	0.0566	0.0977
Fund net alpha standard deviation (decimal)	369589	0.0170	0.0388	0.0093	0.0133	0.0195
Fund gross alpha standard deviation (decimal)	369589	0.0170	0.0388	0.0093	0.0133	0.0195
Estimates from FFC4						
Fund net alpha (decimal)	369589	-0.0010	0.0437	-0.0098	-0.0011	0.0074
$1 - R^2$ of the factor model (decimal)	369589	0.0813	0.0763	0.0339	0.0610	0.1037
Fund net alpha standard deviation (decimal)	369589	0.0166	0.0391	0.0092	0.0131	0.0191
Fund gross alpha standard deviation (decimal)	369589	0.0166	0.0391	0.0092	0.0131	0.0191
Fund family characteristics						
Fund family net alpha by FF5 (decimal)	68552	-0.0006	0.1020	-0.0089	-0.0012	0.0064
Fund family net alpha by FFC4 (decimal)	68552	-0.0006	0.1027	-0.0088	-0.0012	0.0062
Number of member funds in fund families (number)	68552	5.9023	6.0191	2.0000	4.0000	7.0000
Fund family TNA (in 1 billion December 2020 dollars)	68006	25.1030	90.1054	0.8643	3.8815	15.7357
Market characteristics						
VIX (decimal)	336	0.1954	0.0805	0.1361	0.1750	0.2345

Table 2. Flow–Net Alpha Sensitivity, Stock Market Volatility, and Performance Variation

Table 2 reports the results of the model in Equation (52). The dependent variable is the fund percentage flow, $Flow$, and it is in decimal. The independent variables are lagged by one month. The first three columns report the results of the model using the measures of fund performance and performance variation estimated by the FF5 model, and the last three columns report the results of the model using the measures estimated by the FFC4 model. The detailed definitions of the variables are in the Data Appendix. Standard errors that are clustered by fund and by year are presented in parentheses. The symbols ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively, in a two-tail t-test.

	FF5			FFC4		
	(1)	(2)	(3)	(4)	(5)	(6)
NetAlpha	0.3075***	0.3143***	0.3143***	0.4089***	0.3935***	0.3935***
	(0.0731)	(0.0771)	(0.0771)	(0.0848)	(0.0817)	(0.0817)
*NetAlpha*VIX*	-0.1719**	-0.2077**	-0.2077**	-0.1704*	-0.2142**	-0.2142**
	(0.0814)	(0.0867)	(0.0867)	(0.0884)	(0.0815)	(0.0815)
VIX	-0.0035	-0.0042	-0.0042	-0.0031	-0.0040	-0.0040
	(0.0040)	(0.0039)	(0.0039)	(0.0039)	(0.0037)	(0.0037)
*NetAlpha*OMR2*	-0.1648***			-0.2035***		
	(0.0342)			(0.0337)		
OMR2	0.0040			0.0040		
	(0.0087)			(0.0082)		
*NetAlpha*NetAlpha_Std*		-0.0443***			-0.0543***	
		(0.0102)			(0.0109)	
NetAlpha_Std		0.0135			0.0132	
		(0.0135)			(0.0129)	
*NetAlpha*GrossAlpha_Std*			-0.0443***			-0.0543***
			(0.0102)			(0.0109)
GrossAlpha_Std			0.0135			0.0132
			(0.0135)			(0.0129)
*NetAlpha*lnSize*	-0.0069	-0.0053	-0.0053	-0.0074	-0.0075	-0.0075
	(0.0050)	(0.0059)	(0.0059)	(0.0056)	(0.0065)	(0.0065)
*NetAlpha*lnAge*	-0.0280**	-0.0344***	-0.0344***	-0.0437***	-0.0469***	-0.0469***
	(0.0117)	(0.0123)	(0.0123)	(0.0127)	(0.0124)	(0.0124)
lnSize	-0.0048***	-0.0049***	-0.0049***	-0.0048***	-0.0048***	-0.0048***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
lnAge	-0.0239***	-0.0239***	-0.0239***	-0.0239***	-0.0239***	-0.0239***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Expense	-0.9627***	-0.9680***	-0.9680***	-0.9580***	-0.9628***	-0.9628***
	(0.2410)	(0.2429)	(0.2429)	(0.2414)	(0.2435)	(0.2435)
TurnOver	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Flow	0.0233	0.0233	0.0233	0.0232	0.0233	0.0233
	(0.0182)	(0.0182)	(0.0182)	(0.0181)	(0.0182)	(0.0182)
StyleFlow	0.4361***	0.4372***	0.4372***	0.4367***	0.4377***	0.4377***
	(0.0564)	(0.0565)	(0.0565)	(0.0572)	(0.0573)	(0.0573)
FamAlpha	0.0012	0.0006	0.0006	0.0004	0.0003	0.0003
	(0.0016)	(0.0020)	(0.0020)	(0.0026)	(0.0026)	(0.0026)
lnFamNo	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Constant	0.1330***	0.1333***	0.1333***	0.1327***	0.1331***	0.1331***
	(0.0119)	(0.0115)	(0.0115)	(0.0119)	(0.0115)	(0.0115)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	369,589	369,589	369,589	369,589	369,589	369,589
R-squared	0.0451	0.0451	0.0451	0.0454	0.0453	0.0453
Adjusted R-squared	0.0387	0.0387	0.0387	0.0390	0.0389	0.0389

Table 3. Summary Statistics on Variables for Market-Level Analysis

Table 3 reports the summary statistics on the variables for our market-level analysis. Our sample period is from January 1990 to December 2020, and we use monthly data. HHI is the Herfindahl-Hirschman Index, calculated as the sum of market shares squared, and it is in decimal. VIX is the average of daily option-implied volatility index values in each month. The large-fund group contains the largest five funds (based on fund size values), and the small-fund group contains those with fund size values from the fifth percentile to the tenth percentile. FF5 is the five-factor model developed by Fama and French (2015), and FFC4 is the four-factor model developed by Fama and French (1993) and Carhart (1997). We estimate these models on a 24-month rolling-window basis, and over time, calculate the $1 - R^2$ and the out-of-sample prediction of fund net alphas. The definitions and constructions of all the variables are reported in the Data Appendix.

Variable	Observation	Mean	Standard deviation	Percentile 25th	Percentile 50th	Percentile 75th
Market characteristics						
Fund-level HHI (decimal)	336	0.0108	0.0019	0.0092	0.0104	0.0115
Change in fund-level HHI (decimal)	336	-0.0003	0.0047	-0.0001	0.0000	0.0001
Family-level HHI (decimal)	336	0.0575	0.0061	0.0528	0.0550	0.0608
Change in family-level HHI (decimal)	336	-0.0006	0.0120	-0.0002	0.0001	0.0003
VIX (decimal)	336	0.1954	0.0805	0.1361	0.1750	0.2345
Change in VIX (decimal)	336	0.0003	0.0433	-0.0177	-0.0027	0.0119
Market share of large-fund group (decimal)	336	0.1692	0.0163	0.1594	0.1674	0.1774
Change in market share of large-fund group (decimal)	336	-0.0012	0.0206	-0.0012	-0.0001	0.0010
Market share of small-fund group (decimal)	336	0.0007	0.0001	0.0006	0.0007	0.0007
Change in market share of small-fund group (decimal)	336	-3.50E-07	2.86E-05	-9.75E-06	4.59E-07	1.02E-05
Number of funds (number)	336	1379	374	1219	1405	1727
Growth rate of the number of funds (decimal)	336	0.0198	0.3164	-0.0028	0.0011	0.0072
Estimates from FF5						
Large-fund group's 1 - R2 of the factor model (decimal)	336	0.0744	0.0506	0.0313	0.0580	0.1155
Large-fund group's net alpha standard deviation (decimal)	336	0.0092	0.0031	0.0076	0.0082	0.0104
Large-fund group's gross alpha standard deviation (decimal)	336	0.0092	0.0031	0.0076	0.0082	0.0104
Small-fund group's 1 - R^2 of the factor model (decimal)	336	0.1111	0.0459	0.0759	0.1065	0.1405
Small-fund group's net alpha standard deviation (decimal)	336	0.0157	0.0058	0.0125	0.0144	0.0195
Small-fund group's gross alpha standard deviation (decimal)	336	0.0155	0.0058	0.0124	0.0142	0.0190
Estimates from FFC4						
Large-fund group's 1 - R2 of the factor model (decimal)	336	0.0818	0.0572	0.0357	0.0613	0.1284
Large-fund group's net alpha standard deviation (decimal)	336	0.0092	0.0029	0.0076	0.0087	0.0108
Large-fund group's gross alpha standard deviation (decimal)	336	0.0092	0.0029	0.0076	0.0087	0.0108
Small-fund group's 1 - R^2 of the factor model (decimal)	336	0.1165	0.0471	0.0812	0.1117	0.1421
Small-fund group's net alpha standard deviation (decimal)	336	0.0153	0.0057	0.0123	0.0142	0.0183
Small-fund group's gross alpha standard deviation (decimal)	336	0.0151	0.0057	0.0122	0.0141	0.0179

Table 4. Dynamics of Fund-Level HHI, Changes in Stock Market Volatility and Fund Performance, and Performance Variation

Table 4 reports the results of the model in Equation (53), where the dependent variable is the change in fund-level HHI, dif_HHI, which is in decimal. The independent variables are lagged by one month. The columns (2) to (4) report the results of the model using the measures of fund performance and performance variation estimated by the FF5 model, and columns (5) to (7) report the results of the model using the measures estimated by the FFC4 model. The detailed definitions of the variables are in the Data Appendix. The standard errors are presented in parentheses, which are estimated by the Newey-West estimator, with the maximum lag of 12 to be considered in the autocorrelation structure of the regression error. The symbols ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively, in a two-tail t-test.

		FF5			FFC4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dif_VIX	-0.0185***	-0.0128***	-0.0072***	-0.0071***	-0.0148***	-0.0063***	-0.0062***
	(0.0061)	(0.0046)	(0.0018)	(0.0018)	(0.0046)	(0.0019)	(0.0019)
Dif_MarketShare ^{L}	1.1648***	1.8136***	1.8950***	1.8854***	1.7348***	1.8431***	1.8356***
	(0.3545)	(0.3655)	(0.1312)	(0.1323)	(0.3926)	(0.1166)	(0.1179)
Dif_MarketShare ^{S}	-10.4878	-38.9940	-11.7915	-13.3416	-47.3898*	-14.2290	-15.0738
	(10.4128)	(24.7941)	(11.6700)	(11.5912)	(28.2525)	(11.5485)	(11.4543)
Dif_MarketShare ^{L} **OMR2* ^{L}		-13.7309***			-11.1934***		
		(3.3880)			(2.9644)		
OMR2 ^{L}		-0.0041			-0.0030		
		(0.0035)			(0.0028)		
Dif_MarketShare ^{S} **OMR2* ^{S}		223.3505*			240.3995*		
		(128.9604)			(136.4108)		
OMR2 ^{S}		-0.0091			-0.0084		
		(0.0077)			(0.0078)		
Dif_MarketShare ^{L} **NetAlpha_Std* ^{L}			-146.8074***			-142.0496***	
			(18.4656)			(16.9828)	
NetAlpha_Std ^{L}			-0.0039			0.0031	
			(0.0706)			(0.0752)	
Dif_MarketShare ^{S} **NetAlpha_Std* ^{S}			1,457.3450*			1,700.5736**	
			(870.1754)			(862.9170)	
NetAlpha_Std ^{S}			-0.0197			-0.0268	
			(0.0332)			(0.0327)	
Dif_MarketShare ^{L} **GrossAlpha_Std* ^{L}				-146.1784***			-141.6057***
				(18.3745)			(16.9451)
GrossAlpha_Std ^{L}				-0.0046			0.0035
				(0.0714)			(0.0767)
Dif_MarketShare ^{S} **GrossAlpha_Std* ^{S}				1,634.9686*			1,832.8401**
				(883.6655)			(875.0814)
GrossAlpha_Std ^{S}				-0.0177			-0.0264
				(0.0366)			(0.0349)
NumGrowth	0.0764***	0.0795***	0.1002***	0.0999***	0.0811***	0.0989***	0.0986***
	(0.0231)	(0.0154)	(0.0062)	(0.0063)	(0.0179)	(0.0056)	(0.0056)
Constant	-0.0027	-0.0003	-0.0012*	-0.0011*	-0.0006	-0.0011*	-0.0011*
	(0.0017)	(0.0018)	(0.0006)	(0.0006)	(0.0020)	(0.0006)	(0.0006)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	336	336	336	336	336	336	336

Table 5. Dynamics of Family-Level HHI, Changes in Stock Market Volatility and Fund Performance, and Performance Variation

Table 5 reports the results of the model in Equation (53) where the dependent variable is the change in family-level HHI, dif_HHI, which it is in decimal. The independent variables are lagged by one month. The columns (2) to (4) report the results of the model using the measures of fund performance and performance variation estimated by the FF5 model, and columns (5) to (7) report the results of the model using the measures estimated by the FFC4 model. The detailed definitions of the variables are in the Data Appendix. The standard errors are presented in parentheses, which are estimated by the Newey-West estimator, with the maximum lag of 12 to be considered in the autocorrelation structure of the regression error. The symbols ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively, in a two-tail t-test.

		FF5			FFC4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dif_VIX	-0.0478***	-0.0332***	-0.0190***	-0.0187***	-0.0385***	-0.0167***	-0.0165***
	(0.0157)	(0.0120)	(0.0047)	(0.0047)	(0.0119)	(0.0050)	(0.0050)
Dif_MarketShare ^{L}	2.9809***	4.6419***	4.8479***	4.8233***	4.4473***	4.7160***	4.6966***
	(0.9067)	(0.9354)	(0.3371)	(0.3399)	(1.0027)	(0.2985)	(0.3018)
Dif_MarketShare ^{S}	-25.9133	-103.2295	-27.7098	-32.0121	-124.7267*	-33.6284	-36.0972
	(26.8073)	(63.6037)	(28.8948)	(28.8223)	(72.0076)	(28.4053)	(28.2913)
Dif_MarketShare ^{L} **OMR2* ^{L}		-35.1589***			-28.7937***		
		(8.6739)			(7.5898)		
OMR2 ^{L}		-0.0102			-0.0071		
		(0.0095)			(0.0075)		
Dif_MarketShare ^{S} **OMR2* ^{S}		601.0876*			642.9683*		
		(330.8901)			(347.9415)		
OMR2 ^{S}		-0.0267			-0.0258		
		(0.0192)			(0.0194)		
Dif_MarketShare ^{L} **NetAlpha_Std* ^{L}			-374.9015***			-362.5442***	
			(47.9735)			(44.1819)	
NetAlpha_Std ^{L}			0.0258			0.0667	
			(0.1886)			(0.2029)	
Dif_MarketShare ^{S} **NetAlpha_Std* ^{S}			3,601.9172*			4,189.1962**	
			(2,150.3450)			(2,125.7289)	
NetAlpha_Std ^{S}			-0.0564			-0.0778	
			(0.0930)			(0.0890)	
Dif_MarketShare ^{L} **GrossAlpha_Std* ^{L}				-373.2812***			-361.4011***
				(47.7271)			(44.0714)
GrossAlpha_Std ^{L}				0.0250			0.0693
				(0.1900)			(0.2061)
Dif_MarketShare ^{S} **GrossAlpha_Std* ^{S}				4,078.8145*			4,546.4599**
				(2,193.0905)			(2,165.1525)
GrossAlpha_Std ^{S}				-0.0527			-0.0784
				(0.1013)			(0.0944)
NumGrowth	0.1955***	0.2034***	0.2564***	0.2556***	0.2075***	0.2531***	0.2523***
	(0.0592)	(0.0394)	(0.0160)	(0.0161)	(0.0456)	(0.0142)	(0.0143)
Constant	-0.0066	-0.0000	-0.0029*	-0.0028*	-0.0005	-0.0026*	-0.0026*
	(0.0043)	(0.0046)	(0.0015)	(0.0015)	(0.0050)	(0.0015)	(0.0015)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	336	336	336	336	336	336	336

Internet Appendix

(For Online Publication Only)

This appendix provides the proofs and additional discussions of our theoretical results and offers the simulation results.

Mathematical Proofs and Additional Discussions

This section provides the proofs of the results in the corresponding sections.

Proof of Results in Section 2.2

In the managers' problems shown in Equation (15), to maximize $A_i m_{i,t} q_{i,t}^a - c_i {q_{i,t}^a}^2$, we apply the first-order condition with respect to $q_{i,t}^a$, and find the optimal value $q_{i,t}^{a^*}$ as

$$q_{i,t}^{a^*} = \frac{A_i m_{i,t}}{2c_i}. \quad \text{(A1)}$$

The second-order condition $-2c_i < 0$ shows that $q_{i,t}^{a^*}$ induces a maximum. Substituting Equation (A1) into Equation (14) and rearranging, we find the fund i' optimal fund sizes as

$$q_{i,t}^* = \frac{\left(A_i m_{i,t}\right)^2}{4c_i f_i}. \quad \text{(A2)}$$

Similar to Berk and Green (2004) and Feldman and Xu (2022), we assume that manager i, $i = 1, \ldots, n$, sets f_i sufficiently low such that the constraint $0 \leq q_{i,t}^{a^*} \leq q_{i,t}^*$ is automatically satisfied and we do not incorporate this constraint in the optimization.

Q.E.D.

Proof of Results in Section 2.4

In Equation (27), if $q_{i,t}^* > \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}$ $\left(q_{i,t}^* < \frac{\sum_{j=1}^n q_{j,t}^{*2}}{\sum_{j=1}^n q_{j,t}^*}\right)$, then $\frac{\partial HHI_t^*}{\partial m_{i,t}} > 0$ $\left(\frac{\partial HHI_t^*}{\partial m_{i,t}} < 0\right)$. This proves Corollary RN2.1a.

In Equation (28), if $q_{i,t}^*$ is sufficiently small relative to $q_{j,t}^*$'s for $j \neq i$, then the term $-\sum_{j=1}^n q_{j,t}^{*2}$ dominates in the expression $3q_{i,t}^* \sum_{j=1}^n q_{j,t}^* + \frac{6q_{i,t}^*\left(\sum_{j=1}^n q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^n q_{j,t}^*\right)} - 8q_{i,t}^{*2} - \sum_{j=1}^n q_{j,t}^{*2}$, making this expression negative. If $q_{i,t}^*$ is sufficiently large relative to $q_{j,t}^*$'s for $j \neq i$, then $3q_{i,t}^* \sum_{j=1}^n q_{j,t}^* + \frac{6q_{i,t}^*\left(\sum_{j=1}^n q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^n q_{j,t}^*\right)} < 9q_{i,t}^{*2}$ and $-8q_{i,t}^{*2} - \sum_{j=1}^n q_{j,t}^{*2} < -9q_{i,t}^{*2}$, making $3q_{i,t}^* \sum_{j=1}^n q_{j,t}^* + \frac{6q_{i,t}^*\left(\sum_{j=1}^n q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^n q_{j,t}^*\right)} - 8q_{i,t}^{*2} - \sum_{j=1}^n q_{j,t}^{*2} < 9q_{i,t}^{*2} - 9q_{i,t}^{*2} = 0$. If all funds' sizes are sufficiently close, then the expression is $3q_{i,t}^* \sum_{j=1}^n q_{j,t}^* + \frac{6q_{i,t}^*\left(\sum_{j=1}^n q_{j,t}^{*2}\right)}{\left(\sum_{j=1}^n q_{j,t}^*\right)} - 8q_{i,t}^{*2} - \sum_{j=1}^n q_{j,t}^{*2} \approx (2n-2)q_{i,t}^{*2} > 0$ as $n \geq 2$. This proves Corollary RN2.1b.

Q.E.D.

Proof of Results in Section 2.7

Regarding the net returns of the $n+1$ assets, we have the following results. For the ith asset, $i = 1, \dots, n$,

$$\begin{aligned} R_{i,t} &= \frac{dS_{i,t}}{S_{i,t}} + \frac{d\eta_t}{\eta_t} \\ &= \left(\frac{q_{i,t}^a}{q_{i,t}} A_i m_{i,t} - \frac{c_i {q_{i,t}^a}^2}{q_{i,t}} - f_i + \mu_p\right) dt + \frac{q_{i,t}^a}{q_{i,t}} B_i d\bar{W}_{i,t} + \sigma_p dW_{p,t} \end{aligned} \tag{A3}$$

and for the last asset

$$R_{n+1,t} = \frac{d\eta_t}{\eta_t} = \mu_p dt + \sigma_p dW_{p,t}. \tag{A4}$$

We define the following:

- the mean net return vector of the $n+1$ assets, $\boldsymbol{\mu}_\mathbf{t}$, is an $(n+1) \times 1$ vector, with $\mu_{i,t} = \left(\frac{q_{i,t}^a}{q_{i,t}} A_i m_{i,t} - \frac{c_i {q_{i,t}^a}^2}{q_{i,t}} - f_i + \mu_p\right) dt$, $i = 1, \dots, n$, and $\mu_{n+1,t} = \mu_p dt$;
- the covariance matrix of the $n+1$ assets, $\mathbf{Q_t}$, is an $(n+1) \times (n+1)$ positive definite symmetric matrix, with diagonal elements $Q_{ii,t} = \left[\left(\frac{q_{i,t}^a}{q_{i,t}}\right)^2 B_i^2 + \sigma_p^2\right] dt$, $i = 1, \dots, n$, $Q_{ii,t} = \sigma_p^2 dt$, $i = n+1$, and off-diagonal elements $Q_{ij,t} = \sigma_p^2 dt$, $\forall i \neq j$.

Then, we have

$$\mathrm{E}\left[\frac{dp_t}{p_t}\middle| \mathcal{F}_t^{\boldsymbol{\xi}}\right] = \mathbf{v_t}'\boldsymbol{\mu}_\mathbf{t} \tag{A5}$$

$$\mathrm{Var}\left[\frac{dp_t}{p_t}\middle|\mathcal{F}_t^{\xi}\right] = \mathbf{v_t}'\mathbf{Q_t}\mathbf{v_t}. \tag{A6}$$

Next, we write down the Lagrange function

$$F_t(\mathbf{v_t}, \lambda_t) = \frac{\mathbf{v_t}'\boldsymbol{\mu}_\mathbf{t}}{\sqrt{\mathbf{v_t}'\mathbf{Q_t}\mathbf{v_t}}} + \lambda_t(1 - \mathbf{v_t}'\mathbf{1}). \tag{A7}$$

We later will argue that the condition $0 \le v_{i,t} \le 1,\ \forall t, i = 1, \dots, n+1$ is automatically satisfied in our model, so it does not affect our optimization process and is not incorporated in Equation (A7). First-order conditions generate

$$\nabla_{\mathbf{v_t}} F_t(\mathbf{v_t^*}, \lambda_t^*) = \frac{(\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{\frac{1}{2}}\boldsymbol{\mu}_\mathbf{t} - (\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{-\frac{1}{2}}\mathbf{Q_t}\mathbf{v_t^*}\mathbf{v_t^*}'\boldsymbol{\mu}_\mathbf{t}}{\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*}} - \lambda_t^*\mathbf{1} = \mathbf{0} \tag{A8}$$

$$\nabla_{\lambda_t} F_t(\mathbf{v_t^*}, \lambda_t^*) = 1 - \mathbf{v_t^*}'\mathbf{1} = \mathbf{0}. \tag{A9}$$

Multiplying both sides of Equation (A8) by $\mathbf{v_t^*}'$ on the left, we have

$$\frac{(\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{\frac{1}{2}}\mathbf{v_t^*}'\boldsymbol{\mu}_\mathbf{t} - (\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{-\frac{1}{2}}\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*}\mathbf{v_t^*}'\boldsymbol{\mu}_\mathbf{t}}{\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*}} = \lambda_t^* = 0. \tag{A10}$$

Then,

$$(\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{\frac{1}{2}}\boldsymbol{\mu}_\mathbf{t} - (\mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*})^{-\frac{1}{2}}\mathbf{Q_t}\mathbf{v_t^*}\mathbf{v_t^*}'\boldsymbol{\mu}_\mathbf{t} = \mathbf{0}. \tag{A11}$$

The second-order condition is satisfied and omitted here for brevity. Then, $\mathbf{v_t^*}$ is a maximizer. Next, we solve $\mathbf{v_t^*}$ explicitly. Define $\mu_v^* dt \triangleq \mathbf{v_t^*}'\boldsymbol{\mu}_\mathbf{t}$ and $\sigma_v^{2*} dt \triangleq \mathbf{v_t^*}'\mathbf{Q_t}\mathbf{v_t^*}$, which are the portfolio mean return and variance of return at the optimal weight allocations in dt, respectively. Rearranging Equation (A11), we have

$$\mathbf{Q_t}\mathbf{v_t^*} = \boldsymbol{\mu}_\mathbf{t}\frac{\sigma_v^{2*}}{\mu_v^*}. \tag{A12}$$

Then, the ith element of $\mathbf{Q_t}\mathbf{v_t^*}$ is $\left[v_{i,t}^*\left(\frac{q_{i,t}^a}{q_{i,t}}\right)^2 B_i^2 + \sigma_p^2\right]dt$, for $i = 1, \dots, n$, and $\sigma_p^2 dt$ for $i = n+1$. Also, the ith element of $\boldsymbol{\mu}_\mathbf{t}\frac{\sigma_v^{2*}}{\mu_v^*}$ is $\frac{\sigma_v^{2*}}{\mu_v^*}\left(\frac{q_{i,t}^a}{q_{i,t}}A_i m_{i,t} - \frac{c_i {q_{i,t}^a}^2}{q_{i,t}} - f_i + \mu_p\right)dt$, for $i = 1, \dots, n$ and $\frac{\sigma_v^{2*}\mu_p}{\mu_v^*}dt$ for $i = n+1$. We have the following relation by dividing the ith element for $i = 1, \dots, n$ by the last element for both sides of Equation (A12):

$$\frac{v_{i,t}^{*}\left(\frac{q_{i,t}^{a}}{q_{i,t}}\right)^{2} B_i^2+\sigma_p^2}{\sigma_p^2}=\frac{\frac{\sigma_v^{2*}}{\mu_v^{*}}\left(\frac{q_{i,t}^{a}}{q_{i,t}}A_i m_{i,t}-\frac{c_i {q_{i,t}^{a}}^{2}}{q_{i,t}}-f_i+\mu_p\right)}{\frac{\sigma_v^{2*}\mu_p}{\mu_v^{*}}} \tag{A13}$$

for $i=1,\dots,n$. Rearranging the expression above, we have

$$v_{i,t}^{*}=\frac{\left(\frac{q_{i,t}^{a}}{q_{i,t}}A_i m_{i,t}-\frac{c_i {q_{i,t}^{a}}^{2}}{q_{i,t}}-f_i\right)\sigma_p^2}{\left(\frac{q_{i,t}^{a}}{q_{i,t}}\right)^{2} B_i^2\mu_p} \tag{A14}$$

for $i=1,\dots,n$.

Then, funds' sizes can be expressed as, for $i=1,\dots,n$,

$$q_{i,t}=Vv_{i,t}^{*}=V\frac{\left(\frac{q_{i,t}^{a}}{q_{i,t}}A_i m_{i,t}-\frac{c_i {q_{i,t}^{a}}^{2}}{q_{i,t}}-f_i\right)\sigma_p^2}{\left(\frac{q_{i,t}^{a}}{q_{i,t}}\right)^{2} B_i^2\mu_p}. \tag{A15}$$

Substitute the expression above into Equation (44), and rearrange to get

$$f_i q_{i,t}=-\frac{{q_{i,t}^{a}}^{2}B_i^2\mu_p}{V\sigma_p^2}-c_i{q_{i,t}^{a}}^{2}+q_{i,t}^{a}A_i m_{i,t}. \tag{A16}$$

Manager i's problem is to maximize $f_i q_{i,t}$ by choosing $q_{i,t}^{a}$. Applying the first-order condition on the right-hand side of Equation (A16), we have

$$q_{i,t}^{a^*}=\frac{A_i m_{i,t}V\sigma_p^2}{2\left(B_i^2\mu_p+c_iV\sigma_p^2\right)}. \tag{A17}$$

The second-order condition is $-\frac{2B_i^2\mu_p}{V\sigma_p^2}-2c_i<0$, showing that $q_{i,t}^{a^*}$ is a maximizer. Then substituting $q_{i,t}^{a^*}$ back to Equation (A15), we have

$$q_{i,t}^{*}=\frac{\left(A_i m_{i,t}\right)^2V\sigma_p^2}{4f_i\left(B_i^2\mu_p+c_iV\sigma_p^2\right)}. \tag{A18}$$

We can see that

$$\frac{q_{i,t}^{a^*}}{q_{i,t}^{*}}=\frac{2f_i}{A_i m_{i,t}}. \tag{A19}$$

We assume that manager i sets f_i sufficiently low such that the condition $0\le q_{i,t}^{a^*}\le q_{i,t}^{*}$ is automatically satisfied and we do not incorporate this constraint in the optimization problem in Equation (44). Also, by Equations (A15) and (A18), we have, for $i = 1, \dots, n$,

$$v_{i,t}^* = \frac{q_{i,t}^*}{V} = \frac{\left(A_i m_{i,t}\right)^2 \sigma_p^2}{4f_i\left(B_i^2 \mu_p + c_i V \sigma_p^2\right)}. \tag{A20}$$

As $m_{i,t} \geq \underline{m_{i,t}} \geq 0$ and all other parameters on the right-hand side of Equation (A20) are positive, $v_{i,t}^*$, $i = 1, \dots, n$ is nonnegative; i.e., investors do not short sell active funds. That is, as long as funds provide positive expected net alphas, investors do not short sell them. Also, summing up Equation (A20) for $i = 1, \dots, n$, we have

$$\sum_{i=1}^{n} v_{i,t}^* = \sum_{i=1}^{n} \frac{\left(A_i m_{i,t}\right)^2}{4f_i\left(\frac{B_i^2 \mu_p}{\sigma_p^2} + c_i V\right)}. \tag{A21}$$

With a sufficiently large μ_p or a sufficiently small σ_p^2, we have $\sum_{i=1}^{n} v_{i,t}^* \leq 1$. As $v_{i,t}^*$, $i = 1, \dots, n$ is nonnegative and $\sum_{i=1}^{n} v_{i,t}^* \leq 1$, we have $v_{i,t}^* \leq 1$, for $i = 1, \dots, n$. With all these conditions, we also have $0 \leq v_{n+1,t}^* \leq 1$; i.e., investors invest part of their wealth into the passive benchmark. The intuition is that as long as the passive benchmark portfolio provides sufficiently high expected return or sufficiently low risk, investors do not short sell it. These results are realistic because in reality, we observe investors invest part of their wealth in active funds and another in passive benchmark portfolios. Then, the condition $0 \leq v_{i,t} \leq 1$, $\forall, i = 1, \dots, n+1$ is automatically satisfied and we do not incorporate this constraint in solving the investors' optimization problems.

Q.E.D.

Proof of Results in Section 2.9

Let investors be risk-neutral. When HHI is calculated at fund family level as shown in Equation (50) and fund i belongs to fund family k, we have

$$\frac{\partial HHI_t^*}{\partial m_{i,t}} = \frac{\partial HHI_t^*}{\partial Q_{k,t}^*} \frac{\partial Q_{k,t}^*}{\partial q_{i,t}^*} \frac{\partial q_{i,t}^*}{\partial m_{i,t}} = 4X_i A_i^2 m_{i,t} \times \frac{Q_{k,t}^* \sum_{j=1}^{l} Q_{j,t}^* - \sum_{j=1}^{l} Q_{j,t}^{*2}}{\left(\sum_{j=1}^{l} Q_{j,t}^*\right)^3}. \tag{A22}$$

Notice that in the above analysis, $\frac{\partial Q_{k,t}^*}{\partial q_{i,t}^*} = 1$ because $Q_{k,t}^* = \sum_{h=1}^{n_k} q_{h,t}^*$ where fund h is any fund in family k. Then, we have $Q_{k,t}^* > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^*} > 0$ $(Q_{k,t}^* > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^*} < 0)$ if and only if

$\frac{\partial HHI_t^*}{\partial m_{i,t}} > 0$ ($\frac{\partial HHI_t^*}{\partial m_{i,t}} < 0$). With analysis similar to that of Section 2.4, we have the results in Proposition FAa and FAb. Also, we have

$$\begin{aligned}\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} &= \frac{\partial HHI_t^*}{\partial Q_{k,t}^*}\frac{\partial Q_{k,t}^*}{\partial q_{i,t}^*}\frac{\partial q_{i,t}^*}{\partial A_i(\lambda_t)} \\ &= 4X_i A_i^2(\lambda_t) m_{i,t} \times \frac{Q_{k,t}^* \sum_{j=1}^{l} Q_{j,t}^* - \sum_{j=1}^{l} Q_{j,t}^{*2}}{\left(\sum_{j=1}^{l} Q_{j,t}^*\right)^3}.\end{aligned} \tag{A23}$$

Then, we have $Q_{k,t}^* > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^*} > 0$ ($Q_{k,t}^* > \frac{\sum_{j=1}^{l} Q_{j,t}^{*2}}{\sum_{j=1}^{l} Q_{j,t}^*} < 0$) if and only if $\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} > 0$ ($\frac{\partial HHI_t^*}{\partial A_i(\lambda_t)} <$ 0). With analysis similar to that of Section 2.5, we have the result in Proposition FAc.

When investors are mean-variance risk-averse instead of risk-neutral, we only need to change X_i to X_i^{RA}, and the above results still hold.

Q.E.D.

Simulation Results

We use simulation to illustrate the dynamics of HHI. In our following numerical analyses, we consider a two-fund AFMI, i.e., $n = 2$, and assume that investors are risk neutral. The numerical analyses with mean-variance risk-averse investors are similar, and we omit them for brevity.

We first illustrate how HHI changes with different values of relative inferred manager abilities, fund size factors, and sensitivity of gross alphas to abilities. We set $m_{2,t} = 1$, $A_2 = 1$, and $X_2 = 100$. We set the range of $m_{1,t}$ as $[0, 4]$. As $m_{2,t} = 1$, the value of $m_{1,t}$ can be regarded as manager 1's inferred ability relative to manager 2's. We simulate the values of HHI for three cases,

- Case One: $A_1 = A_2 = 1$ and $X_1 = X_2 = 100$;
- Case Two: $A_1 = A_2 = 1$ and $X_1 = 2X_2 = 200$;
- Case Three: $A_1 = 2A_2 = 2$ and $X_1 = X_2 = 100$.

Figure A1 illustrates the results. In Case One, the two funds have the same size factor and sensitivity of gross alpha to ability. Where $m_{1,t}$ is smaller (larger) than one, fund 1's equilibrium size is smaller (larger) than that of fund 2, and the AFMI is concentrated at fund 2 (fund 1). Then, a higher $m_{1,t}$ increases fund 1's size and makes the AFMI less (more) concentrated. The lowest level of HHI_t^* is 0.5, achieved where $m_{1,t} = 1$; i.e., the two managers have the same inferred ability thus the same equilibrium size. The highest HHI_t^* is 1, achieved where $m_{1,t} = 0$ or $m_{1,t} \to \infty$; i.e., either manager 2 or manager 1 has infinite relative ability such that AFMI becomes monopolistic. Moreover, in the figure, we can see that where $m_{1,t}$ is close to zero (close to four), HHI_t^* is concave in $m_{1,t}$, as it is more difficult to increase HHI_t^* by further decreasing (increasing) $m_{1,t}$. Also, where $m_{1,t}$ is close to one, HHI_t^* is convex in $m_{1,t}$, as it is easier to increase HHI_t^* if $m_{1,t}$ has a larger deviation from one that makes fund 1's size deviate farther from fund 2's size.

In Case Two, fund 1 has a larger size factor but the same sensitivity of gross alpha to ability. Comparing Case Two with Case One, we can see that the graph of Case Two shrinks to the left. In particular, where HHI_t^* decreases (increases) with $m_{1,t}$, at the same $m_{1,t}$ level, HHI_t^* has a lower (higher) value. Also, in Case Two, where HHI_t^* is concave (convex) in

$m_{1,t}$, HHI_t^* is more sensitive with $m_{1,t}$.

In Case Three, fund 1 has a larger sensitivity of gross alpha to ability but the same size factor. Because a higher sensitivity of gross alpha to ability has a stronger effect on equilibrium fund size than the size factor [by Equation (20), A_i has a power of two whereas X_i has a power of one]. The graph of Case Three shrinks more to the left and has larger concavity and convexity in the corresponding intervals, compared with Case Two.

Next, we simulate these two funds' inferred abilities, $m_{1,t}$ and $m_{2,t}$, and then HHI_t^*. We discretize our continuous-time processes into discrete-time processes, setting $dt = \Delta t$ to be one month and $d\overline{W}_{1,t} = \Delta\overline{W}_{1,t}$ and $d\overline{W}_{2,t} = \Delta\overline{W}_{2,t}$, to follow a normal distribution of mean zero and variance Δt. We set some of the two funds' parameter values based on the summary statistics of our sample: for $i = 1, 2$, $f_i = 0.095\%$, $B_i = 4.275\%$, and $m_{i,0} = 0.982\%$. We also set $\gamma_{i,0} = 0.0006$, $i = 1, 2$. Additionally, we set $c_i = 0.0002$ and $A_i = 1$, $i = 1, 2$. We conduct the simulation for two frameworks, one with dynamic abilities and the other with constant abilities. In particular, the parameters specific to these two frameworks are set as follows.

- Dynamic Abilities: for $i = 1, 2$, $a_{0,i} = 0.01$, $a_{1,i} = -0.02$, $b_{1,i} = 0.02$, and $b_{2,i} = 0.01$.
- Constant Abilities: for $i = 1, 2$, $a_{0,i} = 0$, $a_{1,i} = 0$, $b_{1,i} = 0$, and $b_{2,i} = 0$.

We simulate $\Delta\overline{W}_{1,t}$ and $\Delta\overline{W}_{2,t}$ as two independent series of increments of Brownian motions and use the same set of simulated $\Delta\overline{W}_{1,t}$ and $\Delta\overline{W}_{2,t}$ values for both cases.

We simulate the results for 400 months. Figure A2 plots the simulation results. In both frameworks, we can see that, when $m_{1,t}$ is farther away from (closer to) $m_{2,t}$, HHI_t^* becomes larger (smaller). Also, with constant abilities, the two managers' inferred abilities change little after 250 months. This is because the estimation precisions are very high after 250 months, making the inferred abilities insensitive to innovation shocks. Consequently, equilibrium fund sizes change little after 250 months, making HHI_t^* stable at a value close to 0.90 after 250 months. On the other hand, with dynamic abilities, the two managers' inferred abilities fluctuate greatly over time, even after 250 months. As the estimation precisions are low, the inferred abilities are still sensitive to innovation shocks. Consequently, equilibrium fund sizes fluctuate greatly after 250 months, making HHI_t^* volatile after 250 months in the interval from 0.50 to 0.75.

Figure A1. AFMI Equilibrium HHI and Relative Inferred Abilities

Figure A1 illustrates the results of an AFMI with two funds, fund 1 and fund 2. The vertical axis is the equilibrium AFMI Herfindahl-Hirschman Index, HHI_t^*, and the horizontal axis is manager 1's inferred ability, $m_{1,t}$. Manager 2's inferred ability $m_{2,t}$ is set to be one, so that $m_{1,t}$ can be regarded as manager 1's inferred ability relative to manager 2's. In Case One, the two managers have the same size factor, $X_1 = X_2 = 100$, and the same sensitivity of gross alpha to ability, $A_1 = A_2 = 1$. In Case Two, $X_1 = 2X_2 = 200$ and $A_1 = A_2 = 1$, whereas in Case Three, $X_1 = X_2 = 100$ and $A_1 = 2A_2 = 2$. The solid curve, dashed curve, and dotted dashed curve illustrate the results of Case One, Case Two, and Case Three, respectively.

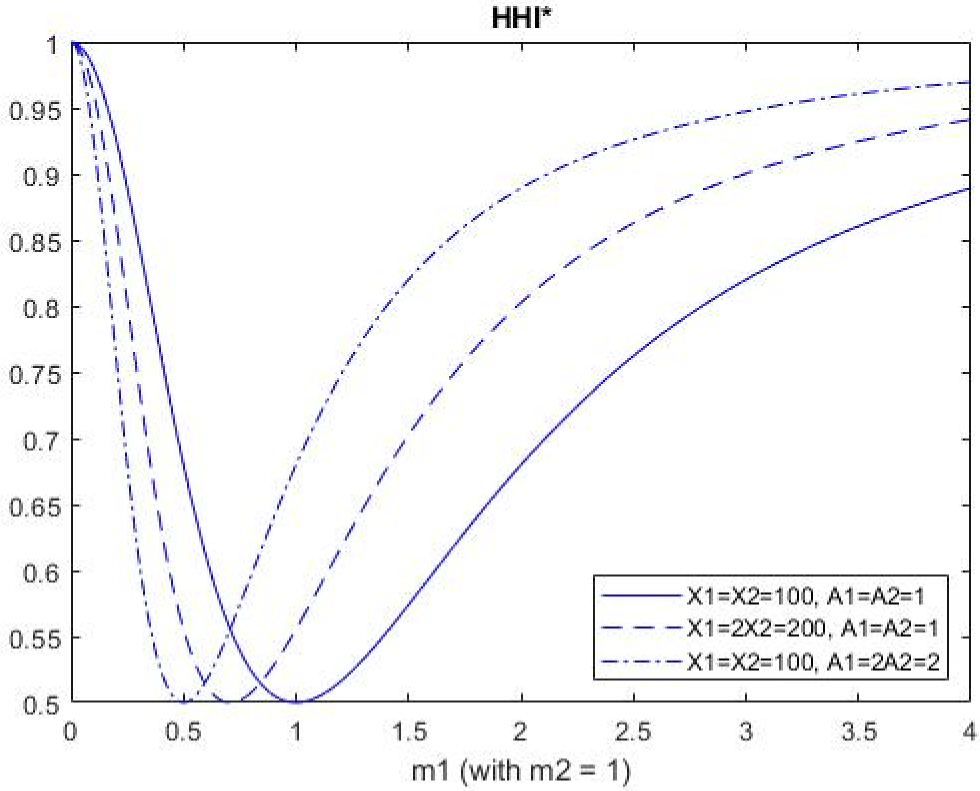

Figure A2. AFMI Equilibrium HHI and Inferred Abilities with Dynamic Abilities and Constant Abilities

Figure A2 illustrates the results of an AFMI with two funds, fund 1 and fund 2, with dynamic abilities in the two upper subplots and with constant abilities in the two lower subplots, respectively. For each case, on the left-hand side, we illustrate the simulated inferred abilities, $m_{1,t}$ and $m_{2,t}$, in blue lines and red stars, respectively. On the right-hand side, we illustrate the equilibrium AFMI Herfindahl-Hirschman Index, HHI_t^*. We plot these simulation results from Month 0 to Month 400.