Passive Investing, Mutual Fund Skill, and Market Efficiency*

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August 30, 2022

*I thank Rajesh Aggarwal, Elena Asparouhova, Niki Boyson, Jonathan Brogaard, Mike Cooper, Andra Ghent, Rachel Hayes, Davidson Heath, J Li, Ľuboš Pástor, Elena Patel, Matt Ringgenberg, Nathan Seegert, Chong Shu and seminar participants at University of Utah for helpful comments. I thank Talis Putnins for sharing his code and data. Email: da.huang@eccles.utah.edu.

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Abstract

This paper examines how the rise of passive investing affects active management. I develop a parsimonious model of passive and active investment in which greater passive investment accelerates investors' learning about active managers' skill. The model provides a rational explanation, namely the rise of passive investing, for several empirical observations: A more skilled active mutual fund industry, more closet indexing by active funds, and compression of the performance distribution of active investing. I test the model's predictions using a novel shift-share instrumental variable design and show they are borne out in the data. I also find that high levels of passive investing improve market efficiency, consistent with a more skilled active mutual fund industry.

JEL: G11, G14, G20

Keywords: Passive investment, active investment, learning, skill, market efficiency

I. Introduction

Mutual fund managers have stock-picking skills (Berk & van Binsbergen, 2015). In fact, it appears that the active management industry has become more skilled over time (Pástor, Stambaugh, & Taylor, 2015).[1] However, many investors have been abandoning active management in favor of passive investing in the last two decades. As of 2021, passive investment in U.S. equity is on the verge of overtaking active investment, a sharp increase from 20% of the industry in 2004 (see Figure 1). In this paper, I show the rise of passive investing is a reason for, rather than an anomalous outcome of, a more skilled mutual fund industry.[2] This is because greater passive investment accelerates investors' learning about managers' skill. I find empirical evidence that the rise of passive investment accelerates the exit of unskilled managers, reduces risk-taking of surviving fund managers, and shrinks the performance dispersion of the active management industry. I also find that higher levels of passive investment improve stock market efficiency, consistent with a more skilled mutual fund industry.

I develop a parsimonious Bayesian model based on Pástor and Stambaugh (2012) in which investors learn about managers' skill through past performance. I show that with a greater proportion of passive investment, underperforming against a fund's benchmark becomes a more credible signal that the fund manager has low skill. Therefore, the model predicts that

[1] In addition, there is a voluminous literature suggesting mutual fund managers have skill – for example, see Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Baks, Metrick, and Wachter (2001), Berk and Green (2004), Kosowski, Timmermann, Wermers, and White (2006), Cremers and Petajisto (2009), Cohen, Polk, and Silli (2009), Baker, Litov, Wachter, and Wurgler (2010), Guercio and Reuter (2014), Kacperczyk, Nieuwerburgh, and Veldkamp (2014), Barber, Huang, and Odean (2016), D. C. Brown and Davies (2017a), Song (2020), among others. On the other hand, some studies suggest mutual fund managers may not have skill (Fama & French, 2010).

[2] It is possible for the mutual fund industry to become more skilled through two channels – on the intensive margin, all active fund managers could become more skilled; and on the extensive margin, the proportion of skilled managers could go up. In this paper, I focus on the latter and refer to a higher proportion of skilled active managers when I use the term "more skilled mutual fund industry."

underperforming fund managers exit faster and the active management industry becomes more skilled. The model also predicts that surviving managers, who on average are more skilled, protect their survival by taking less risk to produce a consistent stream of outperformance in order to reveal their type to investors faster, providing a rational explanation as to why active funds have holdings similar to the index, or the "closet indexing" behavior, consistent with K. C. Brown, Harlow, and Starks (1996). The third model prediction is that the performance dispersion of the active management industry declines as passive investment grows. The model also implies that greater passive investment may improve market efficiency as a consequence of a more skilled active management industry.

I test these predictions with a shift-share instrumental variable (SSIV) design. The SSIV is constructed with a base share and a shock – the base share of the SSIV is the fund-family's style level asset allocation; and the shock is the fund-family asset growth. The SSIV establishes casual inference by isolating variation in the size of passive investment based on the exogenous base share that is orthogonal to potential endogenous variables (Goldsmith-Pinkham, Sorkin, & Swift, 2020). I find empirical evidence consistent with the model predictions. I also find that greater passive investment improves market efficiency, consistent with a more skilled active management industry.

This paper makes two main contributions. First, I show that passive investment systematically impacts the active management industry through a unique learning channel – the rise of passive investment accelerates investors' learning about managers' skill. This insight provides a rational explanation for several empirically observed patterns that may otherwise seem counter-intuitive, including investors' abandonment of active management, active funds' closet indexing behavior, and the performance compression among active funds given a more skilled active management industry. Second, this paper addresses an important question – what is the optimal level of passive investment in the market? My results suggest that the current level of passive investment may be lower than optimal from a market efficiency perspective.

Active mutual funds exhibit decreasing returns to scale on both fund level and industry level (Berk & Green, 2004; Pástor & Stambaugh, 2012; Pástor et al., 2015; D. C. Brown & Davies, 2017b) for reasons including liquidity cost that increases in fund size (Nanda, Narayanan, & Warther, 2000), optimal information production policy (Grossman & Stiglitz, 1980), etc. Based on industry-level decreasing returns to scale, I develop a model and generate three predictions about how passive investment impacts active management.

First, the model predicts that greater passive investment accelerates the exit of underperforming active funds. As passive investment grows, i.e., the relative size of active management shrinks, it becomes easier for active funds to outperform passive benchmarks. In a Bayesian learning framework, when a fund underperforms against the benchmark, investors update their prior and form a posterior belief that the manager has low skill. A manager goes out of business when investors allocate capital away from the fund because they believe the manager cannot outperform the benchmark in expectation according to their posterior belief about the manager's skill. The Bayes factor used to form the posterior belief is higher when the level of passive investment is higher. In other words, when passive investment is high, underperformance is a more credible signal that the active manager has low skill. As a result, underperforming funds, which on average are run by low-skilled managers, are replaced by outperforming funds faster and the active management industry becomes more skilled.

Second, the model predicts that higher relative passive investment reduces the risk-taking of surviving fund managers, who are on average more skilled. This is because high risk-taking, i.e., high variance of fund returns, slows the rate at which investors learn about the skill of the manager. As a result, a high-skilled manager prefers lower risk to accelerate investors' learning of her true type. Intuitively, she chooses a low return variation in order to minimize the possibility of underperforming the passive benchmark and therefore accelerates investors' learning that she has high skill. The opposite is true for a low-skilled manager, who prefers high risk to maximize the chance of outperforming the benchmark. This prediction is consistent with the tournament incentive documented in K. C. Brown et al. (1996) and provides a rational explanation for the closet indexing behavior displayed by active funds in recent years.

Third, the model predicts the performance dispersion of the active management industry decreases with passive investment. This is a result of a more skilled active management industry – on the extensive margin, low-skilled managers who take higher risk exit faster; and on the intensive margin, surviving high-skilled managers take less risk. Taken together, the risk-taking level of the entire active management industry goes down and therefore performance dispersion shrinks.

I empirically test the above predictions in a panel of active U.S. equity mutual funds. I measure the relative size of passive investment as the fraction of passively managed assets to total assets in each investment style.[3] Even though passive investment has exhibited a steady growth trend, it has grown asymmetrically across different investment styles at a different pace over time. The cross-sectional heterogeneity in the levels of passive investment mitigates the concern of spurious correlation arising from potential non-stationarity in

[3]Investment style is measured with the CRSP Objective Code, the MFDB variable *crsp_obj_cd*. CRSP Objective Code consists of four digits. The first digit indicates the asset class in which the fund invests (e.g., E stands for equity and I stands for fixed income). Within equity funds, the second digit indicates the region in which the fund invests (e.g., D stands for domestic and F stands for foreign with respect to the U.S.). Within domestic equity funds (ED), the last two digits indicate the investment style (e.g., CM stands for mid-cap, SH stands for healthcare sector, YG stands for growth, etc.).

passive investment (Phillips & Moon, 2000).

The identification challenge in my study lies with potential omitted variables that simultaneously drive passive investment size and outcome variables, such as a popularity shock to investment styles. For example, if a certain style becomes more popular and attracts a large inflow, all active funds within the style earn a lower expected return due to decreasing returns to scale, which makes passive investment more appealing and pushes up the relative size of passive investment. At the same time, active funds within that style may be more likely to survive simply because the style is popular among investors. In this example, passive size correlates with fund survival but the effect is not causal.

To address the omitted variable bias, I develop a shift-share instrumental variable (SSIV) for the growth rate of style-level active management, which shifts the level of *relative* passive investment size. The SSIV is constructed with lagged monthly fund-family-level active asset allocation across styles as the base share and fund-family-level active asset growth as the shock. Specifically, the SSIV is the inner product of the vector of family-style-level shares and the vector of family-level growth rates for each investment style. Intuitively, the SSIV is a composite style-level growth rate contributed by mutual fund families. With the assumption that the monthly base share is exogenous (Goldsmith-Pinkham et al., 2020), the SSIV isolates the variation in passive size that is uncorrelated with endogenous variables, allowing the two-stage least square (2SLS) estimates to identify causal effects.

Violation of the exogenous share assumption is unlikely. Such a violation would mean that mutual fund families' asset allocation across styles shifts from month to month *in reaction to* popularity shocks. This popularity-chasing behavior in base share is improbable for many institutional reasons from both mutual fund families' and investors' perspectives. Empirically, I find evidence for the exogenous share assumption – the month-to-month change in asset allocation across styles of fund families is largely unchanged throughout time, suggesting that the base share is uncorrelated with style-specific month-to-month omitted variables.

Consistent with the model's first prediction, I find that the interaction of relative passive size and lagged excess return negatively predicts fund survival. Conditional on any level of exit risk from underperformance, a one standard deviation increase in passive size exacerbates such exit risk by 21.1% on average. This result is consistent with the idea that higher relative passive investment accelerates the revelation of low-skilled managers and makes their funds go out of business faster. As a result, the active management industry becomes more skilled over time due to the rise of passive investment.

I also find that higher passive investment reduces surviving managers' risk-taking, supporting the model's second prediction. I measure risk-taking with the forward volatility of the fund's excess return and the portfolio turnover ratio in the next year. A one standard deviation increase in passive size causes a 0.23 standard deviation decrease in forward volatility and a 0.14 standard deviation decrease in future portfolio turnover. The results are consistent with a more skilled active management industry – more skilled surviving managers take less risk in order to reveal their high skill faster by generating consistent outperformance. The results provide a rational explanation to active fund's closet indexing behavior, consistent with Basak and Pavlova (2013) but through a different economic channel – the rise of passive investing.

I find evidence for the model's third prediction that higher passive size shrinks the performance dispersion of active funds. I measure performance dispersion as the standard deviation of the excess return over the passive benchmark of all active funds in the investment style. A one standard deviation increase in passive size shrinks the performance dispersion in the next 3 months to 12 months by 0.25 standard deviation on average. The results suggest active fund returns become more homogeneous due to the rise of passive investing.

Finally, I examine the implications of passive investment for the market as a whole. Low-skilled mutual fund managers are likely to add noise to stock prices because they do not possess stock-picking skill and are obliged to take high risk to maximize the chance of outperforming the benchmark. As passive investment grows, low-skilled managers exit faster and the surviving active management industry becomes more skilled, which results in higher price efficiency of stock prices. I find empirical evidence supporting this conjecture. Measuring price efficiency following Brogaard, Nguyen, Putniņš, and Wu (2022), a one standard deviation increase in relative passive size improves price efficiency of stocks in corresponding styles by about 0.2 standard deviation. The results suggest that low-skilled managers harm market efficiency by adding noise to stock prices and high-skilled managers do not completely offset this noise. As passive investment grows, accelerating the exit of low-skilled managers and making active management more skilled, the stock market becomes more efficient as less noise is added. The results suggest that the current level of passive investment may be lower than optimal from a market efficiency perspective.

II. Literature Review

This paper contributes to a growing literature on the interaction between active and passive investment. Pástor and Stambaugh (2012) develop a model in which active industry size self-corrects to a stable level despite poor past performance because investors understand industry-level decreasing returns to scale. Pástor et al. (2015) find empirical evidence for decreasing returns to scale and document that the active management industry appears to have become more skilled over time. I provide an economic mechanism for the growing skill of the active management industry – low-skilled managers exit at a faster pace as a result of more accurate inference of skill from investors in a high passive investment environment. This also provides an additional explanation to the closet indexing behavior by active managed funds documented in Basak and Pavlova (2013) and Petajisto (2013). D. C. Brown and Davies (2017a) develop a model with moral hazard, i.e., manager's unobserved effort to earn excess returns, and predict a decline in management fee as a result of growth in passive investment. This paper offers additional insight on how passive investment affects other key outcomes of active mutual funds beyond the fees they charge. Song (2020) studies the interaction between skill and scale on the fund level while I focus on this interaction at the industry level. In contemporaneous work, Dannhauser and Spilker III (2022) study the impact of passive funds on the behavior of active funds focusing on moral hazard, i.e., unobserved action, within the fund family. I expand the scope of the analyses and examine the effects of the rise of passive investing on active funds' behavior on a broad market-wide level focusing on a learning channel.

A large academic literature studies mutual fund performance and attempts to identify skilled managers.[4] Mutual fund investors do so as well. My paper examines the impact of the rise of passive investing, one of the most important structural changes in capital market in last two decades, on investors' learning about active mutual fund managers' skill. In the spirit of Baks et al. (2001), I develop a Bayesian model where investors infer active managers' skill from past performance, but in relation to a passive investment alternative. This paper adds to studies of investors' learning in other contexts such as convexity in the flow-return relation (Lynch & Musto, 2003), investor's participation costs (Huang, Wei, & Yan, 2007),

[4]For examples, see Daniel et al. (1997), Pástor and Stambaugh (2002), Berk and Green (2004), Kacperczyk, Sialm, and Zheng (2005), Avramov and Wermers (2006), Baker et al. (2010), Fama and French (2010), Guercio and Reuter (2014), Kacperczyk et al. (2014), Berk and van Binsbergen (2015), Barber et al. (2016), Song (2020), among others.

and fund family's employment decisions (Dangl, Wu, & Zechner, 2008).

Lastly, this paper proposes a novel channel through which passive investment affects broad market efficiency and adds to the voluminous literature that studies the effect of the rise of ETFs (which are largely passively managed) on the capital market. Ben-David, Franzoni, and Moussawi (2018) document that higher ETF ownership leads to higher stock volatility due to index-arbitrage trades on the ETF price against its net asset value. Glosten, Nallareddy, and Zou (2021) find that a higher ETF ownership of a stock leads to better information efficiency because ETFs are hedging instruments against broad market return and therefore facilitate informed trade in individual stocks using long-short strategies. Greenwood (2007) documents a positive relation between index weight and stock comovement due to commonality in trading behavior while Da and Shive (2018) attribute this to arbitrage activity. I contribute to the literature by identifying a unique economic channel through investors' learning of fund managers' skill. Growing passive investment accelerates the exit of low-skilled managers, who add noise to stock prices because they do not possess stock-picking skill and are obliged to take high risk. As a result, the rise of passive investment (largely through ETFs) improves market efficiency. The economic channel in my paper, however, is not specific to the institutional design of ETFs, and is applicable to the rise of passive investment more broadly.

III. Model

In this section, I construct a model of active and passive investment in which investors learn about active fund managers' skill based on Pástor and Stambaugh (2012). I derive three testable predictions about the effect of passive investment on two fund-level outcomes and one aggregate outcome. The key insight is that passive investment accelerates investors' learning of mutual fund managers' skill, which affects fund survival, fund risk-taking, and ultimately industry-level performance dispersion.

Players. The model consists of three types of players – active fund managers, active investors, and passive investors. M atomistic fund managers, indexed by i, operate M active mutual funds. Fund managers are endowed with unobservable portfolio management skill a_i – high-skilled managers are expected to generate an excess return of $a_i = a$ while low-skilled managers are expected to generate an excess return of $a_i = -a$ ($a > 0$) for the first dollar of wealth invested in active management. The mass of high- and low-skilled managers are $1-q$ and q with $q \in (0, 1)$. The heterogeneous manager setting extends Pástor and Stambaugh (2012) which have homogeneous managers. N active investors, indexed by j, competitively allocate their wealth W between a passive fund and M active funds. Passive investors are endowed with wealth W_p and always invest in the passive fund.

Strategies. Manager i chooses a percentage fee f_i she charges for the portfolio service and a risk-taking level σ_i of the portfolio she manages with the following return production technology:

$$\tilde{r}_{i,t} = \tilde{r}_{P,t} + (a_i - b\frac{\sum_i s_i}{W + W_P}) + \tilde{x}_t + \tilde{\epsilon}_{i,t} \tag{1}$$

where $\tilde{r}_{i,t}$ is the gross return of fund i and $\tilde{r}_{P,t} \sim N(\mu_P, \sigma_P^2)$ is the return of benchmark at time t. $\tilde{x}_t \sim N(0, \sigma_x^2)$ is the common factor among active mutual funds and $\tilde{\epsilon}_{i,t} \sim N(0, \sigma_i^2)$ is the idiosyncratic return of each fund. s_i is the assets under management of active fund i, $\sum_i s_i$ is the size of the active management industry in dollars, and $\frac{\sum_i s_i}{W + W_P}$ is the relative size of the active management industry. The term $-b\frac{\sum_i s_i}{W+W_P}$ captures the decreasing returns to scale ($b>0$) nature of active fund management (Pástor & Stambaugh, 2012; Pástor et al., 2015; D. C. Brown & Davies, 2017a). I assume high-skilled managers are always able to outperform the passive benchmark in expectation, i.e., $a-b>0$. Neither managers nor investors know manager's skill in the beginning and learn it throughout time from historical performance. The time subscript is suppressed in subsequent expressions to simplify notation.

Active investor j choose a vector $\boldsymbol{\omega}_j = [\omega_{j,1}, \cdots, \omega_{j,M}]$ of weights with which she invests her wealth in M active funds. I assume short-selling of the passive fund is not possible, i.e., $\boldsymbol{\omega}_j \boldsymbol{\iota}_M \leq 1 \ \forall \ j$.

Payoff. Active fund manager i maximizes her dollar amount management fee by choosing optimal percentage fee and risk-taking:

$$\max_{f_i,\sigma_i} f_i s_i \tag{2}$$

Active investor j maximizes the expected net-of-fee portfolio return[5] by choosing the optimal asset allocation across active funds with $1-\boldsymbol{\omega}_j\boldsymbol{\iota}_M$ invested in the passive fund:

$$\max_{\{\omega_{j,i}\}} \left[\mu_P + \sum_{i=1}^{M} (E[a_i|D] - b\frac{\sum_i s_i}{W+W_P} - f_i)\omega_{j,i} \right] \tag{3}$$

where D is the information set that is available to investor j.

Beliefs. Both investors and managers use Bayesian updating to learn managers' skill. They infer managers' skill with the return production technology (which is public knowledge),

[5]I assume active investors are risk-neutral for tractability. Mean-variance investors produce qualitatively similar results.

the relative size of active management industry (a public signal), and their a priori belief of managers' skill (a private signal). For example, if the first return realization $\hat{r}_i$ underperforms against the passive benchmark, investor's posterior belief that the manager has low skill is updated as:

$$\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P) = \frac{P(\hat{r}_i < \hat{r}_P|a_i = -a) \cdot P(a_i = -a)}{P(\hat{r}_i < \hat{r}_P)} \tag{4}$$

where $P(\hat{r}_i < \hat{r}_P|a_i = -a)$ is the Bayes factor given underperformance and $P(a_i = -a)$ is the priori belief that the manager has low skill.

Denoting the relative size of the active management industry $\dfrac{\sum_i s_i}{W + W_P}$ as y to simplify notation, the posterior belief can be written as:

$$\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P) = \frac{\Phi_1(by + a)q}{\Phi_1(by + a)q + \Phi_1(by - a)(1 - q)} \tag{5}$$

where $\Phi_1(\cdot)$ is the cumulative distribution function (CDF) of a normal distribution with mean of zero and standard deviation of $\sqrt{\sigma_x^2 + \sigma_i^2}$.

There is information asymmetry about managers' skill implicitly built in the model. Fund managers choose the level of σ_i while investors do not observe σ_i and can only infer its value from historical performance. This means the learning process in equation (4) is more accurate for managers than investors, i.e., managers understand their own skill level better than investors do, consistent with Berk, van Binsbergen, and Liu (2017) and D. C. Brown and Davies (2017a). If investors and managers have the same information set, managers' choice of σ_i would have no impact.

A. Equilibrium

The equilibrium of this economy is a collection of $\{\{w_{j,i}\}, f_i, \sigma_i\}$ that solves the optimization problems for all investors and all active fund managers.

When $W_P = 0$, the equilibrium collapses to Pástor and Stambaugh (2012). This is because over time low-skilled managers have their type revealed to investors due to under-performance and go out of business. In each period, investors update their beliefs about a fund manager's skill, i.e., a subjective probability, and form a subjective expectation of the fund's return. When investors update their beliefs to a point at which the subjective expectation of return is lower than the passive benchmark, they stop allocating any wealth to the fund, which will then go out of business. When $t \to \infty$, investors perfectly infer manager's skill and all low-skilled managers' funds exit. Therefore, active fund managers are homogeneous and Pástor and Stambaugh (2012) equilibrium obtains.[6]

For the purpose of my empirical analyses, I focus on the comparative statics on the investors' posterior beliefs rather than the equilibrium outcome when $t \to \infty$. When $W_P > 0$, the model allows exogenous changes in relative passive industry size, which generates key predictions for my empirical analyses.

B. Comparative Statics

I generate three testable predictions in this section. Exogenous changes in relative passive industry size have implications on active fund's survival, active fund risk-taking, and the active management industry.

[6]See detailed equilibrium outcomes in Pástor and Stambaugh (2012).

Proposition 1. High passive investment makes underperforming funds more likely to exit:

$$\frac{\partial}{\partial y}\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P) < 0 \tag{6}$$

Proof. See Appendix A1.

Insert **Figure 2** About Here

Figure 2 illustrates how greater relative passive investment makes underperforming active managers more likely to exit. The green and red curves represent the excess return distribution of a fund run by a high- and low-skilled manager. Given a bad realization (an excess return of -4% as an example in the figure), investors update their belief that the manager has low skill by a Bayes factor that equals the ratio of the height of the red dot (L) to the height of the green dot (H). Panel A plots this dynamic when passive investment is low and panel B plots this dynamic when passive investment is high by moving both distributions to the right due to decreasing returns to scale. In response, the Bayes factor increases, i.e., investors update their belief more harshly given a bad realization. Intuitively, as a higher relative passive size makes outperforming the benchmark easier for an active manager with skill, investors take underperformance as a more credible signal that the manager has low skill. A greater passive investment therefore makes underperforming managers, who on average are more likely to have low skill, exit faster and leaves the surviving managers more skilled on average, consistent with Pástor et al. (2015).

Proposition 2. High passive investment makes surviving managers take less risk because higher risk-taking slows down the rate at which investors learn managers' skill:

$$\frac{\partial}{\partial \sigma_i} \hat{P}(a_i = -a | \hat{r}_i < \hat{r}_P) < 0 \tag{7}$$

Proof. See Appendix A1.

Insert **Figure 3** About Here

Figure 3 illustrates how risk-taking affects the revelation of managers' type. Panel A plots the excess return distributions of a low-skilled manager with different levels of risk-taking. The green area represents the probability of outperforming the passive benchmark. As low-skilled manager is obliged to take high risk to maximize the chance of a good realization[7], slowing down the revelation of her skill. Panel B plots the dynamics of a high skilled manager who prefers low risk so that her high skill is revealed to investors faster. As passive investment grows, surviving managers become more skilled, and therefore takes less risk in their portfolio, providing a rational explanation to closet indexing, consistent with Basak and Pavlova (2013) but through a different channel – investors' learning about managers' skill. This prediction is also consistent with the tournament incentive documented in K. C. Brown et al. (1996) – funds with a mid-year outperformance have an incentive to reduce the risk-taking, and vice versa. In my model, active mutual funds behave in a similar fashion but due to managers' heterogeneous skill levels instead of mid-tournament performance.

Proposition 3. High passive investment makes the return dispersion of the active manage-

[7] In reality, for institutional reasons, there is an upper bound on how much risk a manager can take. I abstract away from this constraint in the model without loss of generality.

ment industry go down.

Proof. See Appendix A1.

Passive investment reduces the return dispersion of the active management industry on both the extensive margin and intensive margin. On the extensive margin, low-skilled managers who take high risk exit faster because investors learn about their skills more quickly due to higher relative passive investment; and on the intensive margin, surviving managers take low risk to reveal their high skill to investors faster. Taken together, the actively managed funds become more homogeneous and the performance dispersion declines over time, consistent with a more skilled active mutual fund industry.

Next, I test these three model predictions empirically using U.S. equity mutual fund data.

IV. Variable Construction and Identification Strategy

A. Variable Construction

In this section, I describe the data I use to construct the fund-level and style-level variables needed to test the three propositions from the model. I also construct stock-level variables to test additional implications of the model. The main data used in this paper comes from Center for Research in Security Prices (CRSP) Survival-Bias-Free U.S. Mutual Fund Database (MFDB). The sample period is from 2004 to 2020[8]. The sample includes all U.S. domestic equity funds (including mutual funds and ETFs) in investment styles, measured by MFDB variable *crsp_obj_cd*, that have 100 or more active funds (whose *index_fund_flag* not equal D) at all times during the sample period.

[8]The sample starts in 2004 because one key variable, *index_fund_flag*, becomes available in June 2003.

A.1. Fund-Level Variables

I calculate monthly excess returns of the active fund by subtracting the average return of the passive funds in the corresponding style from the active fund's gross return. I measure active funds' risk-taking with two variables – forward return volatility, calculated as the standard deviation of the excess return for the next six months, and future portfolio turnover, measured as MFDB variable *turn_ratio* in the following year.

A.2. Stock-Level Variables

I calculate two market efficiency measures following Brogaard et al. (2022). Specifically, I run a vector autoregression (VAR) that includes stock return, stock order flow, and market return, correspondingly decomposing the variation in stock return into public firm-specific information, private firm-specific information, and market-wide information, respectively. The innovation in the VAR is the noise in stock returns. I use the two firm-specific information measures for my empirical test, consistent with the idea that high-skilled managers have the ability to identify good (bad) companies and allocate capital to (away from) them, which impounds firm-specific information into stock prices.

A.3. Style-Level Variables

I calculate return dispersion in each fund style as the standard deviations of excess returns of all active funds in the style within a 3-, 6-, and 12-month window in the future.

Finally, the main independent variable of interest, passive size, is calculated for each fund style on a monthly level as the fraction of assets under management (AUM) of passive funds to the total AUM:

$$\text{Passive Size}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t}}$$

where k denotes fund style and t denotes month. **Figure 4** shows the passive size and number of active funds for all sample fund styles over time.

Insert **Figure 4** About Here

As shown in panel A of **Figure 4**, all eight styles see a growth of passive investment over time. Passive investment in each fund style grows at a different rate and passive size is meaningfully heterogeneous across fund styles. The cross-sectional heterogeneity helps mitigate the concern of spurious correlation arising just from a time trend (Phillips & Moon, 2000). The relative passive size for each fund style is the main independent variable of interest for all subsequent analyses. Panel B shows that different fund styles have dramatically different numbers of active funds but the trend is largely similar across styles. **Table 1** shows the summary statistics.

Insert **Table 1** About Here

B. Identification Strategy

In this section, I discuss the identification challenge of my study, develop a shift-share instrumental variable (SSIV) to address the issue, and confirm the validity of the SSIV.

B.1. Shift-Share Instrumental Variable

One potential identification challenge is omitted variable bias that is specific to styles and varies from month to month. If an unobserved variable simultaneously positively correlates with passive size and outcome variables, OLS estimates will be biased upwards. An example is a popularity shock across styles from month to month. If style k becomes more popular and attracts a large inflow on style level, active funds are expected to earn a lower excess return due to decreasing returns to scale on both industry and fund levels (Berk & Green, 2004; Pástor & Stambaugh, 2012; Pástor et al., 2015; D. C. Brown & Davies, 2017a). As a result, passive investment in style k becomes relatively more attractive and grows in relative size. At the same time, active funds in style k may be more likely to survive simply because the style is popular among investors. In this example, passive size correlates with fund survival but the effect is not causal.

I employ a shift-share instrumental variable (SSIV) design to identify exogenous variation in relative passive size by mutual fund style against unobserved omitted variables (Goldsmith-Pinkham et al., 2020; Borusyak, Hull, & Jaravel, 2022). I construct the SSIV on growth of active investment[9], which exogenously changes the relative passive size:

$$\widehat{\text{Passive Size}}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t-1} \cdot \hat{g}_{k,t}} \tag{8}$$

where $\hat{g}_{k,t}$ is fitted value of active investment growth rate using the instrument from the first stage.[10] The SSIV, $B_{k,t}$, is constructed with lagged monthly fund family level active

[9]The growth of passive investment is a secular trend that asset managers understand and try to take advantage of, suggesting neither exogenous shock nor exogenous share design is plausible. Therefore I do not construct a SSIV for growth of passive investment.

[10]See a discussion about the "forbidden regression" in section VI.B.1.

asset allocation across styles as base share and fund family level active asset growth as shock:

$$B_{k,t} = \sum_{f} z_{k,f,t-1} \cdot g_{f,t} \tag{9}$$

where $z_{k,f,t-1}$ is fund family f's active asset allocation in style k in lagged month and $g_{f,t}$ is the asset growth of the fund family f in month t.

B.2. The Validity of SSIV

Relevance. The first stage of the two-stage least square (2SLS) process estimates the following equation:

$$g_{k,t} = \alpha + \beta \cdot B_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t} \tag{10}$$

where $g_{k,t}$ is the growth rate of active investment in style k in month t and $B_{k,t}$ is the SSIV. κ_k and τ_t are style and month fixed effects. The point estimate of β is 0.039 and statistically significant at 1% level, suggesting the instrument is relevant.[11]

Exogeneity and Exclusion Restriction. The omitted variable bias arises from style-specific month-to-month unobserved variables (e.g., a popularity shock). The key assumption for SSIV to address this issue is that the ex-ante base share, $z_{k,f,t-1}$, is as good as exogenous against the omitted variable, which also supports the exclusion restriction for the instrument (Goldsmith-Pinkham et al., 2020).

Violation of the exogenous share assumption is unlikely. Such a violation would mean that mutual fund families' asset allocation across styles shifts from month to month *in reaction to*

[11]The F-stat of the first stage is 8.10, suggesting potential weak instrument problem. I provide additional robustness checks on weak instrument in section VI.B.2.

popularity shocks. This popularity-chasing behavior in base share is improbable for several institutional reasons. First, from the perspective of the mutual fund families, they usually offer a fixed set of fund styles that do not change from month to month, because launching new funds in a previously unspecialized style to chase popularity is difficult as it takes a long time to file regulatory documents, hire fund managers, implement a marketing campaign, etc. Second, from the perspective of mutual fund investors, they do not rebalance their investment across mutual funds on a monthly basis for several reasons, including attention constraint (most retirement accounts' allocation decision is made at the beginning of the employment and rarely changes over time), exit constraint (some mutual funds have a back-end load, preventing investors to re-allocate their assets on a high frequency), etc. Therefore fund family level lagged monthly asset allocation across styles is unlikely to respond to style-specific month-to-month shocks.

I find empirical evidence supporting the exogenous share assumption. While it is not possible to directly perform tests proposed by Goldsmith-Pinkham et al. (2020) due to potential confounding variables being unobservable (popularity shock), we do observe base shares to be slow-moving, if not constant, over time. For example, **figure 5** plots the asset allocation of Vanguard, one of the largest asset managers in the industry and top-Rotemberg-weight [12] fund families in the sample. The percentage allocation in most fund styles is strikingly stable over time. Two styles exhibit a time trend (Growth Income and Growth) substituting each other but are very slow-moving over the course of almost two decades, with monthly change averaging at around 10 basis points. A similar pattern holds for other large and/or top-Rotemberg-weight fund families. The stable within-family asset

[12] Rotemberg weight measures how much each fund family contributes to the SSIV estimates. It depends on the correlation between the k^{th} instrument's fitted value of the endogenous variable and the endogenous variable itself.

allocation shows that the base share for SSIV does not change in anticipation of the month-to-month popularity shock. Therefore the monthly lagged allocation is plausibly as good as exogenous against unobserved confounding variables.[13]

Insert **Figure 5** About Here

The SSIV design plausibly rules out that the results are driven by style-specific month-to-month unobserved confounding variables, e.g., popularity shocks, because the exogenous base share drives the 2SLS estimates in subsequent analyses.

V. Empirical Analysis

In this section, I empirically test the model predictions. The model predicts greater passive investment accelerates the exit of underperforming funds (proposition 1), makes surviving funds take less risk (proposition 2), and shrinks the performance dispersion of the active management industry (proposition 3).

A. Active Fund Survival

Underperforming funds are more likely to go out of business with greater passive investment (proposition 1). This is because as passive investment continues to grow, shrinking the relative active management size, outperforming the benchmark becomes easier due to decreasing returns to scale. Recognizing this effect, investors take underperformance as a more credible signal that the active manager has low skill.

[13]Even though the exogenous base share ($z_{k,f,t}$) assumption is likely satisfied, one may still be concerned with potential common trend in SSIV shock ($g_{f,t}$). I perform additional robustness checks on this concern in section VI.B.3.

I test this prediction with the semi-parametric Cox Proportional Hazard model. The Cox model estimates parameters in a hazard function to maximize the likelihood of funds' exits in the cross-section sequentially. Specifically, the hazard (risk of exit) for fund i at time t is:

$$h(t|\boldsymbol{X}_i) = h_0(t)\exp(\boldsymbol{X}_i\boldsymbol{\beta}) \tag{11}$$

where $h_0(t)$ is the baseline hazard and $\boldsymbol{X}_i$ is a vector of explanatory variables including active fund's past excess return, passive size in its style category, and the interaction of the two. The Cox model does not impose any parametric assumptions on the baseline hazard $h_0(t)$ and leaves it unestimated. This is achieved by a less restrictive assumption – the baseline hazard is the same for all funds in the sample, therefore their hazard risk is proportional. In other words, the Cox model treats any one fund's exit risk as a multiplicative (governed by $\exp(\boldsymbol{X}_i\boldsymbol{\beta})$) replica of that of any other fund. Figure 6 supports this assumption. It plots the hazard function in analysis time (i.e., time at risk) for active funds that outperform and underperform the benchmark. We can see the hazard functions for the two groups are largely parallel, suggesting that the underlying assumption for the Cox model is satisfied. I standardize all continuous variables – Lagged Excess Return and Passive Size – to a standard deviation of 1 for ease of interpretation in the Cox model estimate.

Insert **Table 2** About Here

Table 2 reports the results that greater passive investment accelerates the exit of underperforming funds. Column 1 shows that a one standard deviation decrease in one-year Lagged Excess Return increases the exit risk by 23%, consistent with the idea that underperforming funds are more likely to go out of business. A one standard deviation increase in passive investment makes all active funds in the style 13.6% less likely to go out of business, as all active funds are expected to generate a higher return in a high passive environment, consistent with the decreasing returns to scale. The interaction between Lagged Excess Return and Passive Size is the main variable of interest. Given a fund with a negative one standard deviation excess return, a one standard deviation increase in passive size subjects the fund to an additional 4.8% exit risk, consistent with the model prediction that greater passive investment accelerates the exit of underperforming funds. The compounding of exit risk has an economically meaningful magnitude – conditional on any level of exit risk from underperformance, a one standard deviation increase in passive investment exacerbates the exit risk by 21.1% in the specification under column 1. Columns 2 and 3 use past 2- and 3-year excess return and yield qualitatively similar results.

Columns 4 to 6 repeat the analyses in columns 1 to 3 with SSIV and show consistent results. We see that the exacerbation factors from passive investment in SSIV estimation are slightly lower but of similar magnitude compared to OLS, suggesting the unobserved style-specific month-to-month shocks (e.g., popularity) mildly drive both passive size and fund survival in the same direction. The SSIV design mitigates the omitted variable bias by identifying exogenous variation in active asset growth from fund-family level ex-ante asset allocation. The magnitude of the causal effect (from columns 4 to 6) in exacerbation is about 21% on average. The results document a novel economic channel to explain the observation made by Pástor et al. (2015) that the active management industry becomes more skilled over time. As passive investment grows, low-skilled managers exit faster, making managers who survive on average more skilled.

A.1. Falsification Test

I take advantage of the costly search literature (Sirri & Tufano, 1998) and the reporting convention in mutual fund industry to devise a falsification test – if a past performance is not observed by the investors, greater passive investment should not improve their learning from such unobserved performance. Mutual fund performance is reported in lagged period of full years. For example, **figure 7** shows that Vanguard and Blackrock report past 1-, 3-, 5-, and 7-year performance. That is, it is relatively easy for investors to learn a fund's past performance over whole years but costly to obtain the information about past performance over periods that are not whole years. Based on this insight, I repeat the survival analyses but replace the past 1-, 2-, and 3-year performance with past 11-, 23-, 35-month performance as falsification. The difference between 1-year and 11-month, 2-year and 23-month, and 3-year and 35-month performances is otherwise minimal except the whole-year performance is readily observable and the just-shy-of-whole-year performance is costly to obtain. Therefore, there is little to no improved learning from greater passive investment on these just-shy-of-whole-year performances, which are plausibly unobserved by average investors. As a result, I expect a muted exacerbation effect on past 11-, 23-, and 35-month performances.

Insert **Figure 7** About Here

Table 3 presents the falsification results and supports the economic channel through which investors learn about managers' skill. Columns 1 to 3 copy the results from columns 4 to 6 in table 2 for ease of comparison. Columns 4 to 6 report the falsification results. We see that the exit risk from underperformance is comparable under whole-year and just-shy-of-whole-year performances, suggesting that they are otherwise similar to each other except for the observability to investors. The exacerbation effect from passive investment under falsification is much smaller than that under the treatment. The exacerbation effect under falsification is also largely statistically indistinguishable from zero. Put differently, exit risk associated with unobserved underperformance is not exacerbated by increases in passive investment, highlighting the importance of the observability in past performance. The distinction in observability is consistent with the economic channel that passive investment accelerates investors' learning about managers' skill – when the underperformance is not observable, there is no improved learning.

Insert **Table 3** About Here

I provide additional robustness checks in section VI.C that uses an alternative definition of underperformance and addresses potential cross-sectional heterogeneity in funds' survival.

B. Active Fund Risk-Taking

Next, I test the model prediction that surviving funds take less risk when passive investment is higher (proposition 2) because their high skill is revealed to investors faster. I measure active funds' risk-taking with two measures – the forward volatility of excess return in the next six months and the portfolio turnover ratio in the following year. I estimate the following regression:

$$Y_{i,t} = \beta \times \text{Passive Size}_{k,t} + \zeta_i + \tau_t + \epsilon_{i,t} \tag{12}$$

where $Y_{i,t}$ is forward Return Volatility or Portfolio Turnover and ζ_i and τ_t are fund and year-month fixed effects.[14] Fund fixed effects sweeps out any fund-specific time-invariant effect such as the family that the fund belongs to, established reputation, and so on. Time fixed effects control for broad economic conditions in each time period that apply to all sample funds. Continuous variables – Return Volatility, Portfolio Turnover, and Passive Size – are scaled to a standard deviation of 1 for ease of interpretation.

Insert **Table 4** About Here

Table 4 presents the regression results of equation (12) and shows greater passive investment reduces surviving funds' risk taking. Columns 1 and 2 report the OLS estimates and columns 3 and 4 report the SSIV estimates. The SSIV estimates show that one standard deviation increase in passive size causes a 0.17 standard deviation decrease in risk-taking, consistent with the model prediction that surviving fund managers prefer to take lower risk in a high passive environment because their high skill is revealed to investors at a faster rate. The causal effect from the SSIV is close to the OLS estimates, indicating that omitted variable bias is minimal.

C. Active Management Industry Performance Dispersion

Passive investment also shrinks the performance dispersion of the active management industry (proposition 3). On the extensive margin, low-skilled managers – who take higher risk in order to have a chance of beating the benchmark – exit at an accelerated pace with greater passive investment. On the intensive margin, higher passive investment makes surviving

[14]Fund style fixed effects are included in the first stage in equation (10) and in principle should also be included in equation (12). However, I include fund fixed effects which subsume fund style fixed effects. Also, using fund style fixed effects instead of fund fixed effects in equation (12) yields qualitatively similar results.

high-skilled managers content with taking less risk. As a result, the return dispersion of the active management industry declines as passive investment grows. To test this prediction, I estimate the following regression:

$$\text{Dispersion}_{k,t+j} = \beta \times \text{Passive Size}_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t+j} \tag{13}$$

where $\text{Dispersion}_{k,t+j}$ is the return dispersion of all active funds in fund style k starting from month $t+j$ to $t+j+5$, i.e., a forward rolling window with a length of six months. κ_k are fund style fix effects that sweep out all style-specific time-invariant effects such as investor's inherent and slow-moving preferences across different fund styles. τ_t are year-month fixed effects that control for broad economic conditions that apply to all cross-sections of fund styles in the same way such as investor's loss of income from a financial crisis. Continuous variables – Dispersion and Passive Size – are scaled to a standard deviation of 1 for ease of interpretation.

Insert **Table 5** About Here

Table 5 presents the regression results of equation (13) using the first six periods of the rolling window and shows consistently that passive investment shrinks the performance dispersion in the active management industry. Panel A reports the OLS estimates and panel B reports the SSIV estimates. The passive size of the fund style strongly negatively predicts future dispersion in the style across different forward periods of the rolling window. The SSIV results suggest that a one standard deviation increase in passive size causes a 0.25 standard deviation reduction of return dispersion in the immediate future.

Insert **Figure 8** About Here

The dispersion-shrinking effect persists for about two years and becomes statistically indistinguishable from zero afterwards. **Figure 8** plots the estimates of the causal effect reported in **table 5** panel B further into the future with 95% confidence intervals. The statistical insignificance in the distant future is not driven by the increase in standard errors, which are strikingly stable, suggesting a persistent impact of passive investment on performance dispersion with a half-life of about a year. **Figure 9** repeats the analyses in **figure 8** with alternative forward rolling-windows of 3-month and 12-month and shows qualitatively the same patterns. The dispersion-shrinking effect from passive investment is robust to different configurations of dispersion calculation.

Insert **Figure 9** About Here

We can clearly see the force of endogeneity by comparing the OLS and SSIV estimates in **table 5**. OLS consistently over-estimates the magnitude of the causal effects by about 20%. An example of the endogeneity is the following: suppose biotech firms specializing in oncology research become popular due to successful cancer treatments, and attract inflows to healthcare sector funds. Due to decreasing returns to scale, all active healthcare funds earn a lower excess return, making passive investment more attractive. Therefore the relative size of passive investment in healthcare sector funds increases. At the same time, all healthcare fund managers realize the investment opportunity and invest in oncology companies, i.e., the portfolio composition among healthcare funds becomes homogeneous which results in a lower return dispersion among active healthcare sector funds. The unobserved popularity shock simultaneously drives passive size up and dispersion down, and therefore biases the magnitude of OLS estimates upwards. The SSIV design mitigates this bias by ensuring the instrumented passive size only reflects the variation from ex-ante base shares that are independent of the popularity shock, and therefore exogenous.

VI. Discussion

In this section, I examine the implications of the rise of passive investment on active funds' future performance and market efficiency. I also perform additional analyses to support the robustness of the instrumental variable and empirical results.

A. Implication of Passive Investing

A.1. Passive Investing and Active Fund Performance

I examine the impact of passive investing on active funds' performance. The rise of passive investing leads to better excess return of active funds on both the extensive and intensive margins. On the extensive margin, low-skilled managers who produce worse performance are driven out faster; and on the intensive margin, higher passive investment mechanically makes all funds earn a higher return due to industry level decreasing returns to scale. I estimate the following regression:

$$Y_{i,t} = \beta \times \text{Passive Share}_{k,t} + \zeta_i + \tau_t + \epsilon_{i,t} \tag{14}$$

where $Y_{i,t}$ is the future 1-, 2-, and 3-year excess return per annum of active fund i in style k. ζ_i and τ_t are fund and year-month fixed effects. Passive Size is scaled to a standard deviation of 1 for ease of interpretation.

Insert **Table 6** About Here

Table 6 presents the regression results of equation (14) and shows a positive relation between passive investment size and fund future returns. The results using OLS and the SSIV are similar. We see that a one standard deviation increase in passive size causes active fund returns to improve by 1.3 percentage point in the next year and by 0.7 percentage in the upcoming three years based on the SSIV results. One interpretation is that the results in column 6 capture the long term structural change in active management – managers on average become more skilled; and results in column 4 capture the skill increase and the decreasing returns to scale together. In sum, we see a robust pattern that increase in passive investment causes active funds to earn a higher benchmark adjusted return, consistent with the idea that the active management industry becomes more skilled.[15]

A.2. Passive Investing and Market Efficiency

I next examine the impact of passive investing on market efficiency. Low-skilled managers are often unable to identify good stocks and are obliged to take high risk. As a result, they add noise to stock prices through their trades, hurting market efficiency. These managers then exit at an accelerated pace due to greater passive investment. Therefore passive investment potentially improves market efficiency.

[15]The fact that the active mutual fund industry as a whole earns a higher return is not a violation of Sharpe's arithmetic (Sharpe, 1991). The alpha of outperforming funds comes from not only the underperforming funds within the mutual fund industry, but also other market participants outside of the mutual fund industry, including retail investors, hedge funds, etc.

There are additional reasons why passive investment could improve market efficiency. In theory, in an economy in which all assets are priced at equilibrium, noise traders – in this case low-skilled managers – have no effect on price efficiency because informed traders act as contrarians and always trade away the mispricing caused by noise traders' uninformed trades. Then why should we expect any effect here? There are two empirical reasons. First, the stock market is not at an equilibrium – otherwise all active funds would earn exactly zero alpha, which we know is not the case. Therefore, the equilibrium argument that skilled managers always counter-act against unskilled managers doesn't apply. Second, in reality, mutual fund managers face frictions such as liquidity constraint, size of a single position constraint, and short-selling constraint, which prevents them from fully cancelling out the noise in stock prices added by unskilled managers. Therefore it is an empirical question whether substituting out noise-adding low-skilled managers would improve, worsen, or have no impact on market efficiency.

To answer this question, I estimate the following regression:

$$Y_{s\in k,y} = \beta \times \text{Passive Share}_{k,t} + \kappa_k + \xi_s + \tau_t + \epsilon_{s,y} \tag{15}$$

where $Y_{s\in k,y}$ is the market efficiency measure for stock s that is held by the largest passive fund in style k in year y. This reflects the idea that the passive size in healthcare style shouldn't affect real estate stocks and the passive size in midcap style shouldn't affect small cap stocks, etc. The two market efficiency measures capture the amount of public and private firm-specific information impounded in stock price following Brogaard et al. (2022).[16] κ_k, ξ_s, and τ_t are fund style, stock, and year-month fixed effects. Continuous variables – Public

[16]Specifically, I run a vector autoregression (VAR) that includes stock return, stock order flow, and market return, correspondingly decomposing the variation in stock return into public firm-specific information, private firm-specific information, and market-wide information, respectively.

Information, Private Information, and Passive Size – are scaled to a standard deviation of 1 for ease of interpretation.

Insert **Table 7** About Here

Table 7 presents the regression results of equation (15). Columns 1 and 2 report OLS estimates and columns 3 and 4 report SSIV estimates. We see systematic evidence that greater passive investment causes improvement in market efficiency. A one standard deviation increase in passive size causes the stock price efficiency to increase by around 0.107 standard deviation. The magnitude of the causal effect in SSIV estimates is close to that of OLS estimates, suggesting the omitted variable bias is limited. That greater passive investment improves market efficiency provides suggestive evidence that the current level of passive investing is below optimal from a market efficiency perspective, consistent with greater passive investment resulting in a more skilled active mutual fund industry on average.

B. Robustness of the Shift-Share Instrumental Variable

In this section, I perform robustness tests on potential issues arising from the "forbidden regression" in the instrumental variable context. I also perform two robustness tests for the SSIV to address concerns of a potential weak instrument and common trend in the shocks used to construct SSIV.

B.1. Forbidden Regression

A "forbidden regression" occurs when the endogenous variable in the second stage is obtained by a non-linear transformation from the fitted value in the first stage regression (Wooldridge, 2010). A forbidden regression may result in an inconsistent 2SLS estimator because the linear projection (from the first stage to the second stage) of a non-linear transformation (e.g., equation (8)) is not the same as the non-linear transformation of the linear projection.

I address this issue in two ways – a 3SLS process and a bootstrap process. The 3SLS process runs the same first stage regression in equation (10) and produces $\widehat{\text{Passive Size}}_{k,t}$ using equation (8). Then $\widehat{\text{Passive Size}}_{k,t}$ is used as the IV for Passive $\text{Size}_{k,t}$ with a 2SLS process for **tables 2**, **4**, **5**, and **7**. The "intermediate first stage", in which $\widehat{\text{Passive Size}}_{k,t}$ is used to predict Passive $\text{Size}_{k,t}$, ensures the final stage estimate is consistent with an asymptotically valid t-stat (Wooldridge, 2010). The 3SLS results, which account for potential issues arising from a forbidden regression, are qualitatively similar as reported results. I also block-bootstrap the estimates by fund family, fund or fund style (whichever is applicable in the second stage), and year-month. The bootstrap standard errors are calculated as the standard deviation of the point estimate across the iterations. The bootstrapped standard errors are qualitatively similar to the analytical standard errors used to calculate the t-stats reported in the table. The results from the 3SLS procedure and the bootstrap suggest the concern from a forbidden regression is minimal.

B.2. Weak Instrument

I address the potential weak instrument problem by estimating the reduced form following Chernozhukov and Hansen (2008). They establish that rejecting the null hypothesis in a reduced form estimation is a sufficient condition of rejecting null hypothesis in the second stage in a 2SLS estimation so long as the exclusion restriction is satisfied, even if the instrument is weak. I estimate the reduced form regressions corresponding to the 2SLS SSIV results reported in **tables 2**, **4**, **5**, and **7** and find that the null hypothesis $\beta_{B_{k,t}} = 0$ is consistently rejected on similar statistical level. The results mitigate the concern of upward bias arising from a weak instrument and support the validity of the SSIV.

B.3. Common Trend in SSIV Shocks

Another potential concern for the validity of the SSIV is that the shocks used to construct the SSIV may exhibit a common time trend (Borusyak et al., 2022). If true, even if the base share is plausibly exogenous, the SSIV itself could simply pick up a time trend from the shocks, rendering the instrument useless. This concern is particularly relevant in the canonical labor setting because most industries tend to grow or shrink following the economic cycle. However, a common trend in the shocks is unlikely in a mutual fund setting because at any time some fund families grow their business while others lose business. To more concretely address this concern, I plot the cumulative growth in assets managed by mutual fund families used to construct the SSIV in **figure 10**. We clearly see that the cumulative growth across fund families does not exhibit a common time trend. At any time, some fund families see a growth in their assets while others see a decline. The results suggest that a common trend in the SSIV shocks that threatens the validity of the instrument is unlikely to be an issue in my study.

Insert **Figure 10** About Here

C. Robustness of Fund Survival Results

In this section, I perform three additional robustness checks on the main results on the active funds' survival. I use an alternative definition of underperformance and address potential cross-sectional heterogeneity in funds' baseline hazard.

C.1. Alternative Definition of Underperformance

I first use management fees as an alternative threshold to define underperformance. The analyses in **table 2** is based on funds excess return over the passive benchmark, consistent with equation 4 where a bad realization is defined as underperforming the passive benchmark. The model is robust to alternative threshold to define underperformance. I test robustness by repeating the analyses in **table 2** and replace the excess return with net-of-fee return, another performance evaluation measure commonly used by investors.

Insert **Table 8** About Here

Table 8 presents the results and shows the model prediction is robust to this alternative definition of underperformance. Compared to the estimates in **table 2**, the magnitude of the exacerbation from passive investment (reported at the bottom row) is slightly weaker with 1-year net-of-fee returns and comparable with 2- and 3-year net-of-fee returns. This is consistent with the idea that investors see a negative net-of-fee return as a lack of skill and greater passive investment accelerates investors' learning of managers' skill.[17]

C.2. Cross-sectional Heterogeneity in Baseline Hazard

I relax the identifying assumption of the Cox model and test the robustness of the model specification. The Cox model leaves baseline hazard unspecified and unestimated, but as-

[17]Although in theory, fund managers strategically set management fees to extract all the rent associated with skill (Berk & Green, 2004), which renders net-of-fee returns uninformative at all from a learning perspective, in reality management fees are set at the inception of the fund and rarely adjusted later. Therefore, net-of-fee is plausibly informative from an investor's learning perspective.

sumes that it is the same for all sample funds. A potential concern is that the baseline hazard function is different for funds in different styles. For example, a sector fund could be less likely to go out of business than a broad market fund because sector funds' managers usually have industry experience in the sector that their fund operates in and therefore are more likely to generate good performance. This violates the proportional hazard assumption for the Cox model.

I estimate the maximum likelihood estimator in Cox model in a stratified sample by investment style to address this issue. In essence, each style is treated as a separate sample, assigned a style-specific baseline hazard that is the same across all funds *within* the style, and given a joint likelihood function. The model then jointly maximizes the likelihood for all styles. Intuitively, this is similar to adding style fixed effects to the estimation which sweeps out style-specific time-invariant omitted variables, including the unobserved baseline hazard.

Insert **Table 9** About Here

Table 9 presents the results and shows the estimates are robust to a more saturated specification. The exit risk exacerbation using SSIV is economically meaningful, ranging from 7% to 20%. Comparing the results with table 2, the estimates in the stratified model are 25% to 50%, suggesting the unobserved potential difference in baseline hazard across styles may slightly upwardly bias but do not fully explain the effect that greater passive investment exacerbates the exit risk of underperforming funds.

VII. Conclusion

This paper studies the effects of the rise of passive investing on active management. I develop a Bayesian learning model in which investors learn about active fund manager's skill through historical performance. Greater passive investment reveals active managers' skill to investors at an accelerated pace, causing unskilled managers to exit faster and making the mutual fund industry more skilled on average. As a result, surviving funds take less risk and the return dispersion of the active management industry declines. Empirically, I develop a novel shift-share IV design, and I find causal evidence that is consistent with the model's predictions. The results provide rational explanations for several empirically observed patterns that may otherwise seem counter-intuitive, including investor's abandonment of active management, active fund's closet indexing behavior, and the compression of performance of active management industry given a more skilled active management industry.

Greater passive investment may be beneficial to market efficiency due to a more skilled active mutual fund industry. I find empirical support that greater passive investment causes stock prices to be more efficient, suggesting that current level of passive investment may be lower than optimal from a market efficiency perspective.

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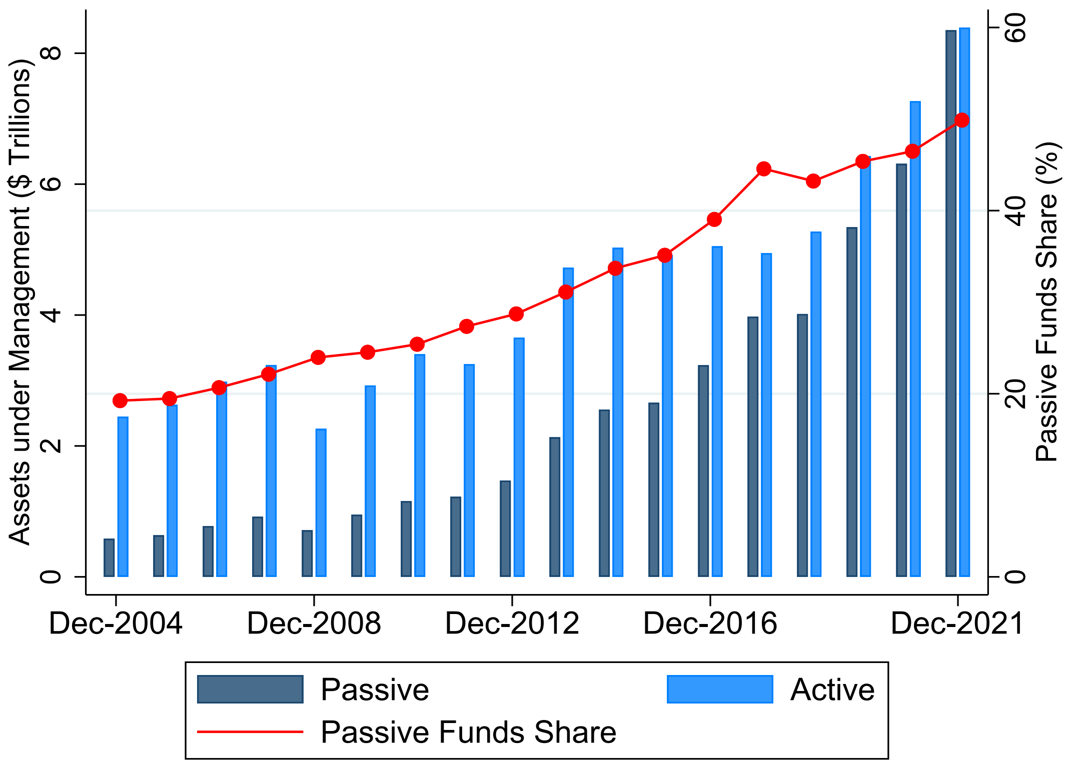
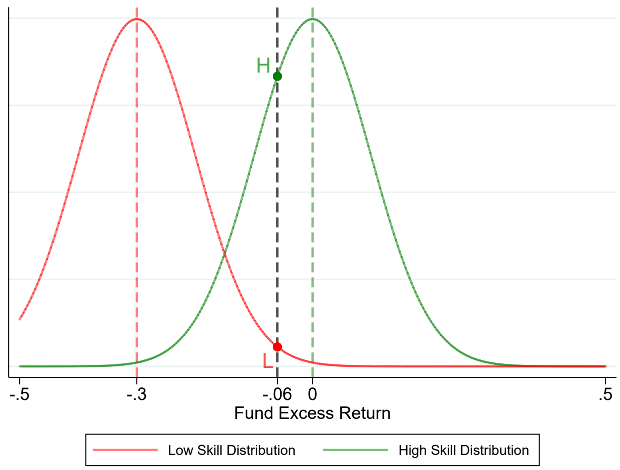
Figure 1. Passive Overtakes Active Overtime



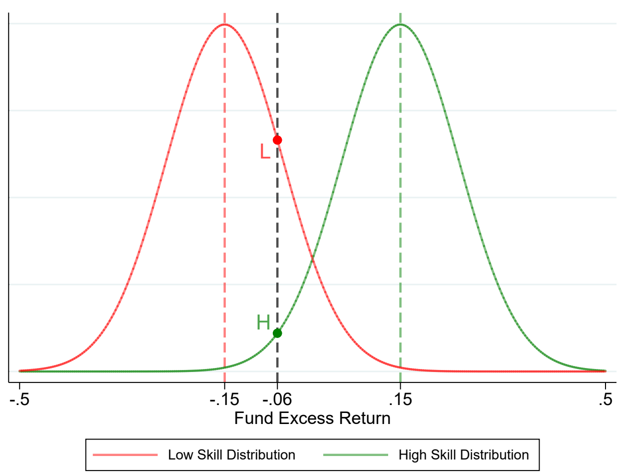
The figure plots the assets under management of U.S. domestic equity mutual funds that are actively and passively managed from 2004 to 2021.

Figure 2. Bayesian Inference of Manager's Skill

(a) Low Passive Investment



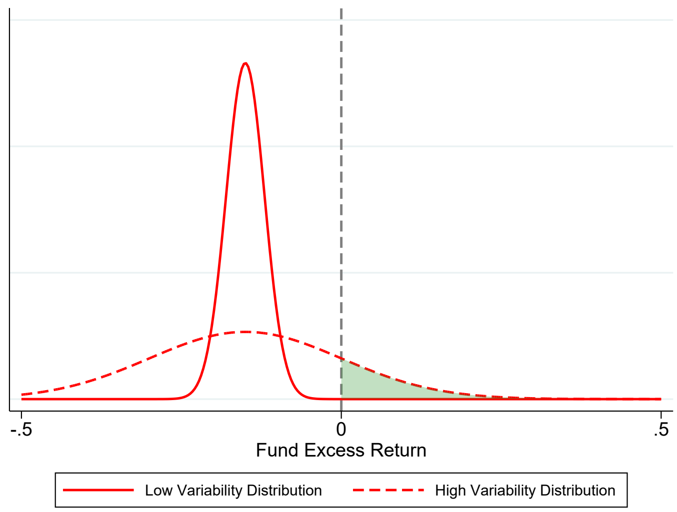
(b) High Passive Investment



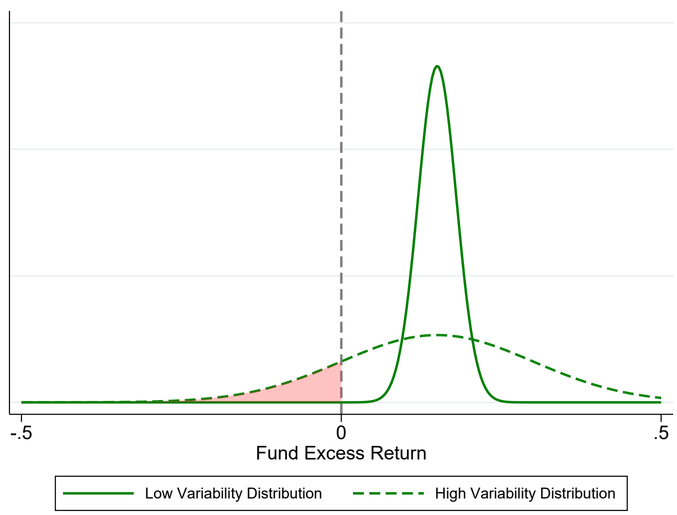
Panel A of the figure plots investor's Bayesian learning of fund manager's type when passive investment is low and panel B plots that when passive investment is high. The red curve stands for the distribution of excess returns of a low-type fund and the green curve stands for that of a high-type fund. The red and green dashed lines stand for the mean of the distribution. Given a realization of bad return (black dashed line), investor's posterior belief that the manager has low skill is updated by the value of L/H.

Figure 3. Fund Manager's Optimal Risk-Taking

(a) Low-Skilled Manager



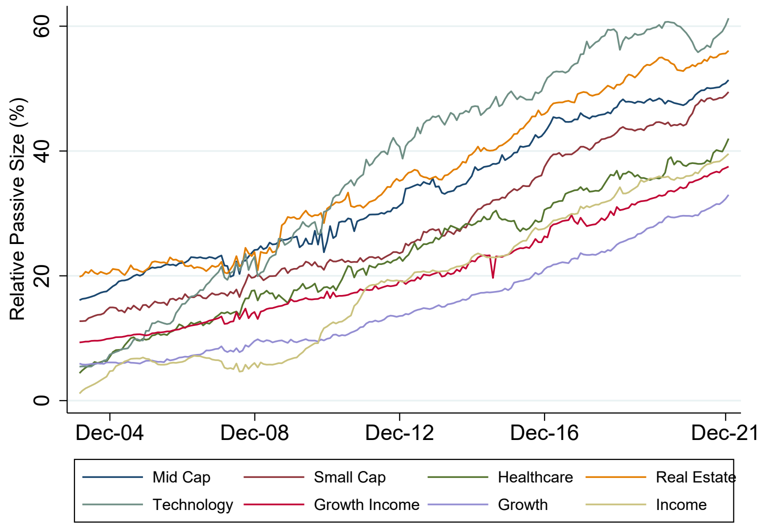
(b) High-Skilled Manager



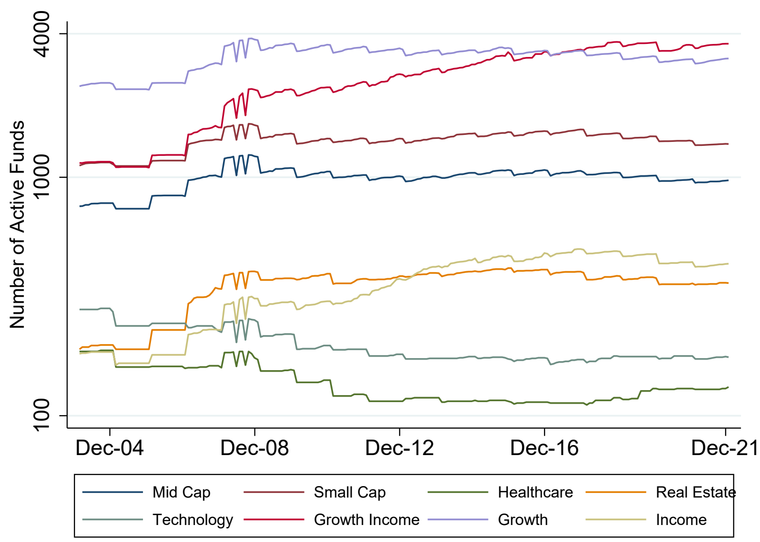
Panel A of the figure plots low-skilled manager's dynamic of risk-taking choices and panel B plots that of the high-skilled manager. In panel A, the green shaded area stands for the probability of a low-skilled manager outperforming the passive benchmark. In panel B, the red shaded area stands for the probability of a high-skilled manager underperforming the passive benchmark.

Figure 4. Competitive Landscape by Fund style

(a) Relative Size of Passive Investment

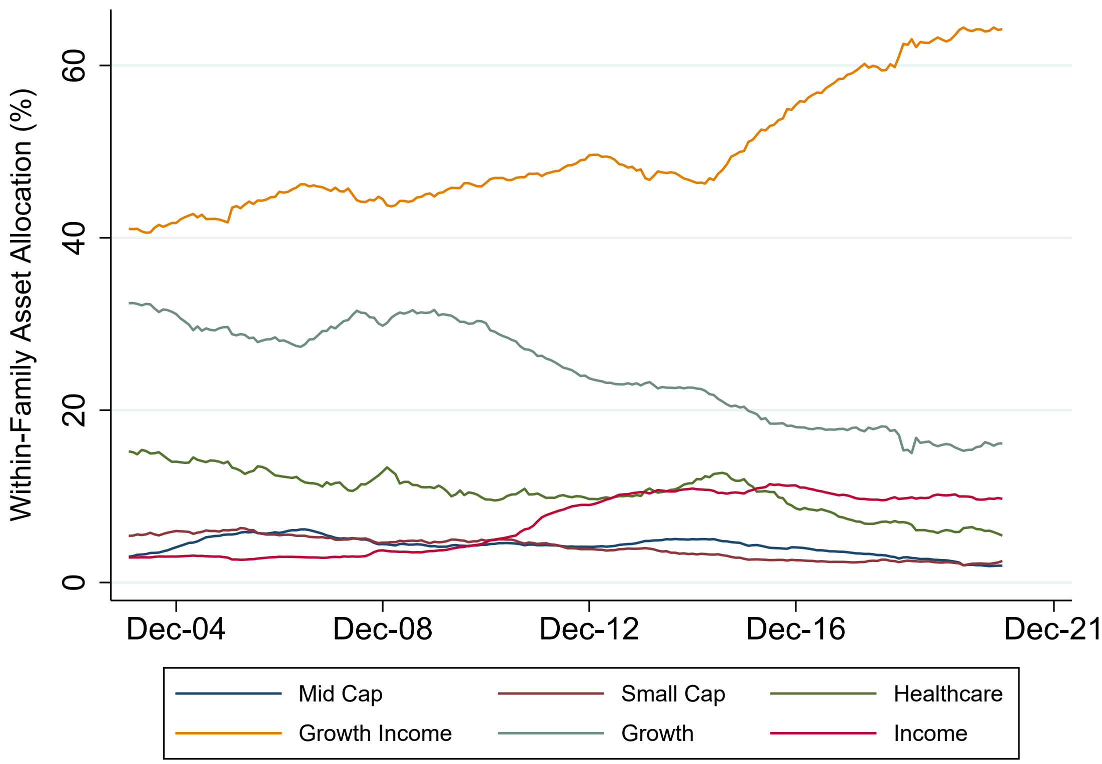


(b) Number of Active Funds



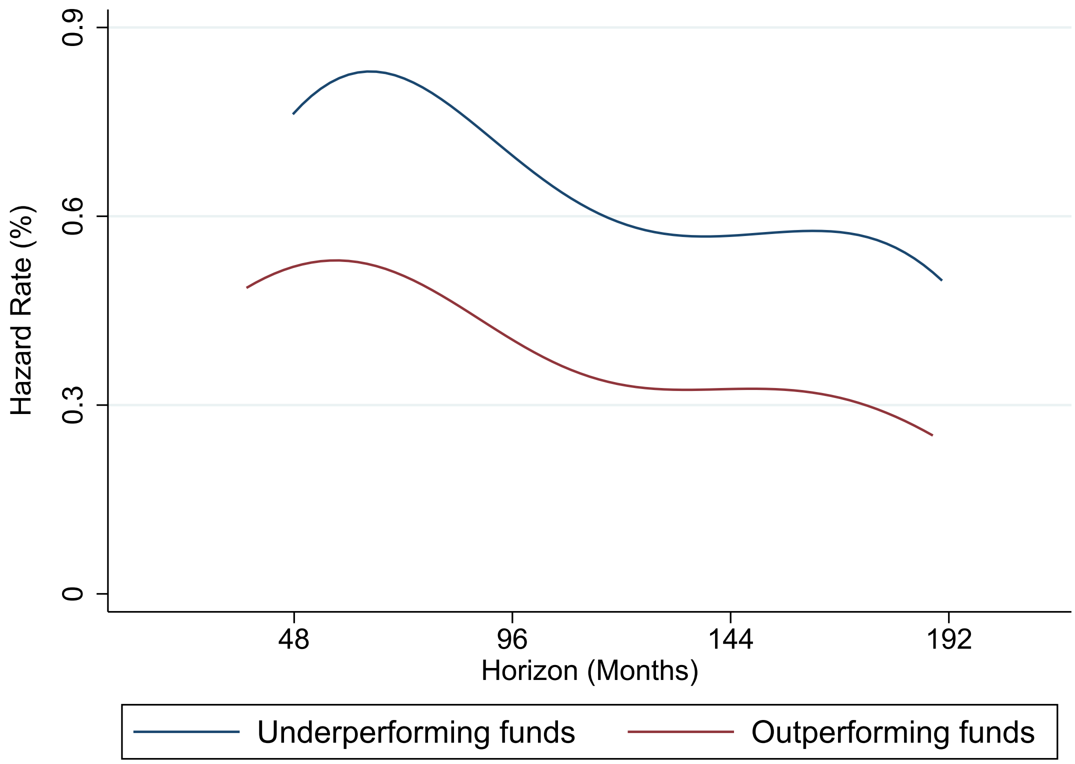
Panel A of the figure plots relative size of passive investment by mutual fund styles that have 100 or more active funds at any time during the sample period from 2004 to 2021. Panel B plots the number of actively managed mutual funds in each fund style, presented in log scale.

Figure 5. Vanguard Asset Allocation across Styles Over Time



This figure plots Vanguard's asset allocation across mutual fund styles over time as a percentage of the total asset of the sample active funds managed by Vanguard.

Figure 6. Hazard Rate of Fund Survival by Past Performance



The figure plots the estimates of hazard rate of active fund survival by its trailing 12-month net return over its benchmark. The y-axis stands for the probability of the fund exiting. The x-axis stands for analysis time, i.e., time-at-risk, in months.

Figure 7. Mutual Fund Performance Disclosure

(a) Vanguard Performance Disclosure

Average annual returns—updated monthly
as of 02/28/2022

	1-yr	3-yr	5-yr	10-yr	Since inception 05/23/1984
Health Care Fund Inv	7.88%	10.33%	10.00%	13.98%	15.73%
Spliced Health Care Index* (Benchmark)	10.05%	12.44%	11.49%	12.79%	10.98%

Important fund performance information

Cumulative, yearly, and quarterly historical returns

After-tax returns—updated quarterly
as of 12/31/2021

	1-yr	3-yr	5-yr	10-yr	Since inception 05/23/1984
Health Care Fund Inv					
Returns before taxes	14.30%	16.53%	13.87%	15.32%	16.03%
Returns after taxes on distributions	11.99%	13.91%	11.47%	13.00%	—
Returns after taxes on distributions and sales of fund shares	9.79%	12.57%	10.60%	12.22%	—
Average Health Fund					
Returns before taxes	6.88%	18.84%	15.55%	16.17%	—
Returns after taxes on distributions	—	—	—	—	—
Returns after taxes on distributions and sales of fund shares	—	—	—	—	—

Learn more about after-tax returns

(b) Blackrock Performance Disclosure

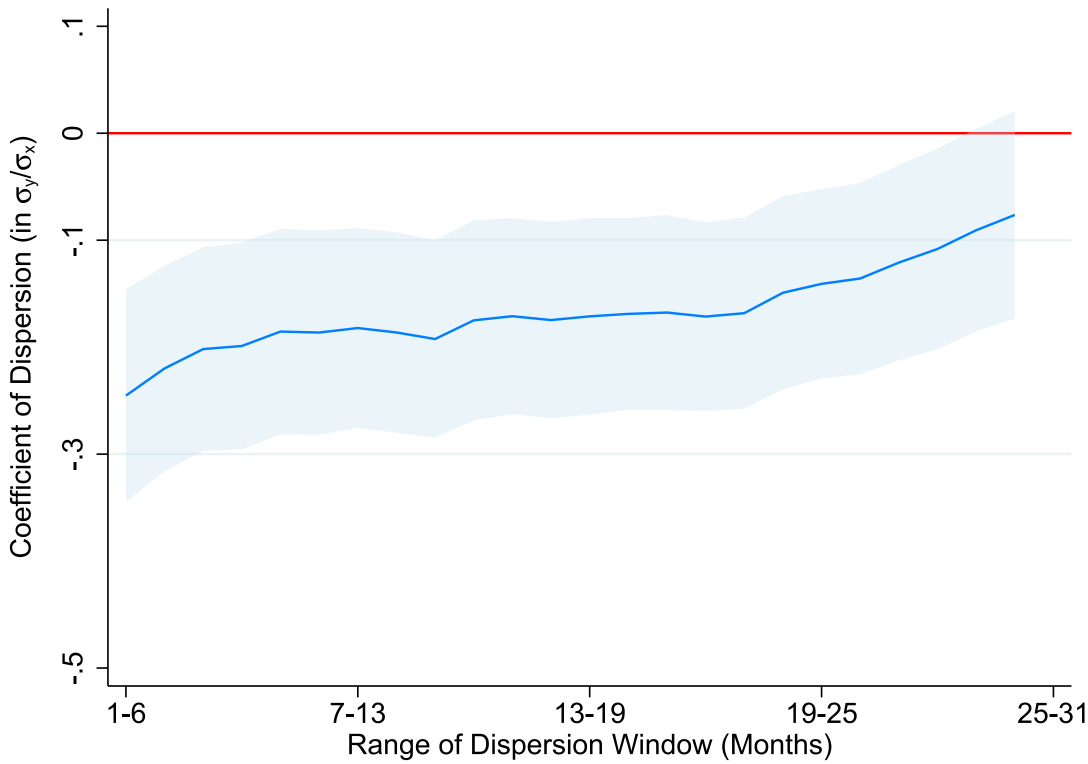
Average Annual | Cumulative | Calendar Year

as of Feb 28, 2022

	1y	3y	5y	10y	Incept.
Total Return (%)	14.58	38.70	30.69	24.98	10.95
Market Price (%)	14.58	38.72	30.71	24.99	10.95
Benchmark (%)	15.12	39.40	31.33	25.61	11.44
After Tax Pre-Liq. (%)	14.38	38.34	30.34	24.63	10.76
After Tax Post-Liq. (%)	8.77	31.32	25.58	21.81	9.56

Panel A (B) shows a screenshot of a Vanguard (Blackrock) fund's performance disclosure on its website.

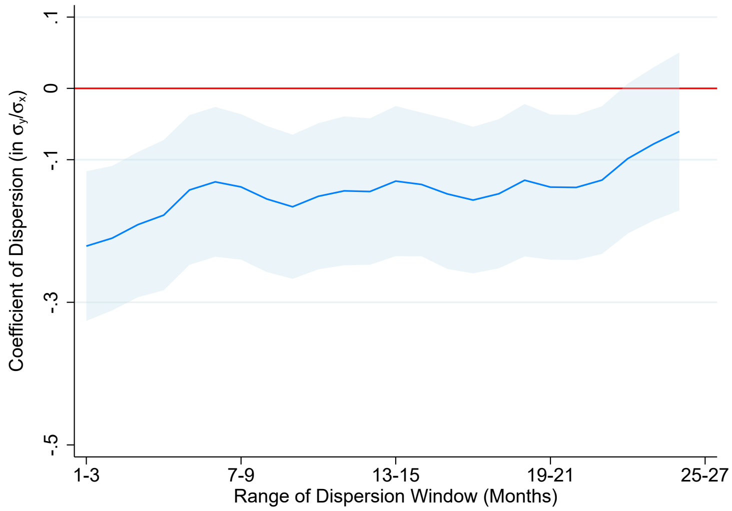
Figure 8. Passive Investment Shrinks Active Fund Return Dispersion – the SSIV estimates



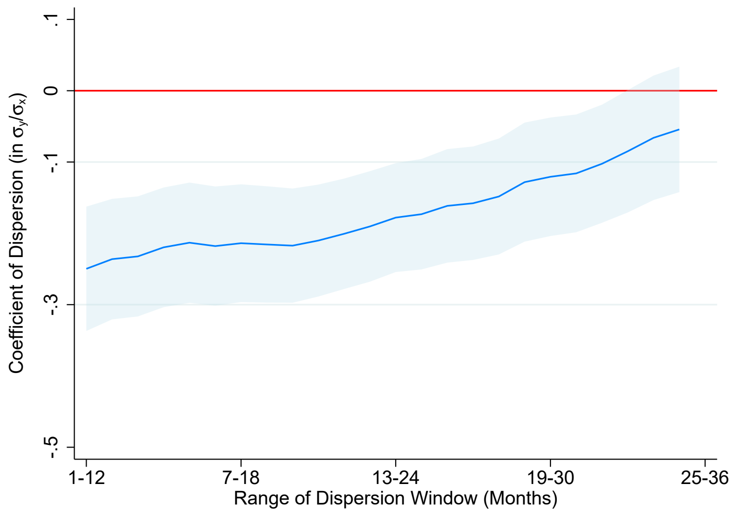
The figure plots the regression coefficients presented in **Table 5** panel B further into the future. The y-axis stands for the change in active fund return dispersion (measured in its standard deviation) in response to one standard deviation increase in instrumented passive size. Passive size is calculated as the passive assets under management (AUM) over total AUM by fund style category, instrumented with SSIV. Return dispersion is calculated as the standard deviation of active mutual funds' excess returns using a forward 6-month rolling window. The x-axis stands for the starting month of the 6-month window. The shaded area represents the 95% confidence interval of the estimates.

Figure 9. Passive Investment Shrinks Active Fund Return Dispersion with Different Horizons

(a) 3-month Rolling Window

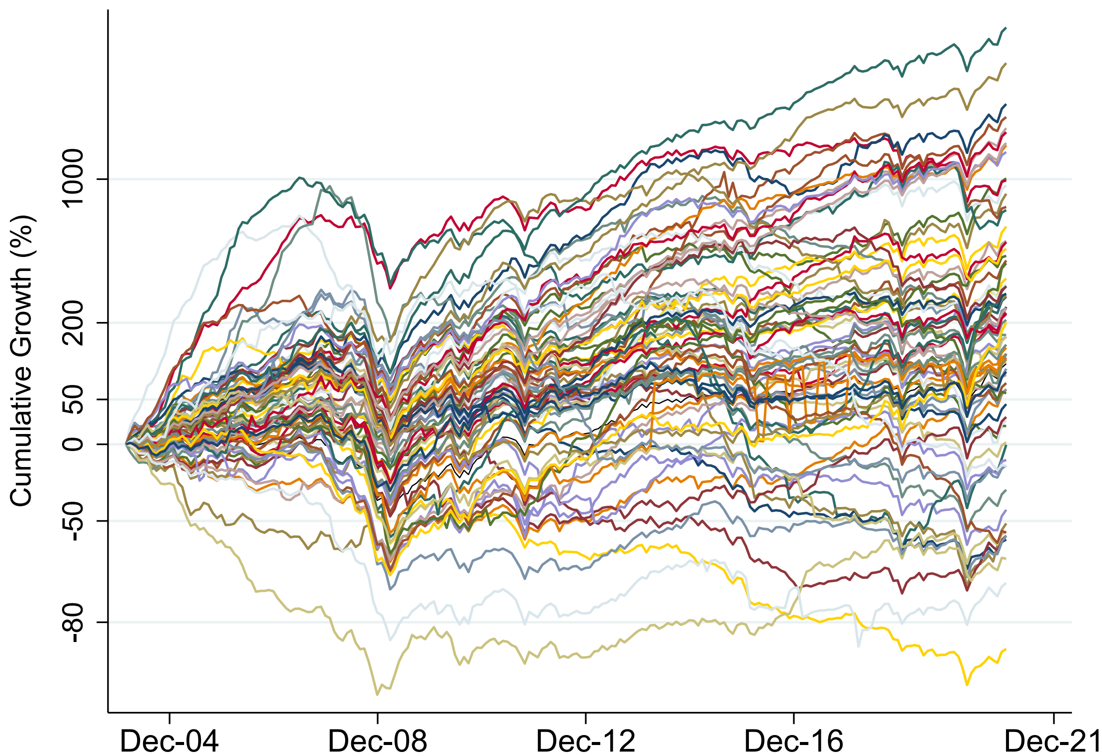


(b) 12-month Rolling Window



The figure repeats the exercise in **Figure 8** using different windows in dispersion calculation. Panel A uses a rolling 3-month window and panel B uses a rolling 12-month window. The shaded area represents the 95% confidence interval of the estimates.

Figure 10. Fund Family Asset Growth



The figure shows the cumulative growth in assets managed by mutual fund families used to construct the SSIV in percentage (y-axis in log scale).

Table 1
Summary Statistics

The table presents the summary statistics of the variables used in the analyses. Lagged Excess Return is the gross return of the fund minus the passive benchmark return (defined as the average return of the passive funds in the style) in the past 1, 2, and 3 years. Return Volatility is the standard deviation of the excess return of the fund in the next six months. Turnover Ratio is CRSP MFDB variable *turn_ratio*. Private Info and Public Info are variance decomposition components following Brogaard et al. (2022). Forward Return Dispersion is the standard deviation of excess returns of all funds in a fund style category during a specified forward window. Passive size is the passive AUM divided by the total AUM for a fund style category. Count of active funds is the number of active fund in a certain fund style category.

	Mean	StDev	P10	Median	P90	#Obs.
Active Funds (N=20,789)						
Lagged Excess Returns (%)						
1 Year	-1.05	10.25	-8.67	-1.27	6.64	1,710,183
2 Year	-1.96	15.65	-13.85	-2.63	10.22	1,490,371
3 Year	-3.04	19.48	-19.37	-3.92	13.10	1,291,198
Return Volatility (%)	1.54	0.94	0.66	1.28	2.74	2,103,914
Turnover Ratio (%)	4.42	381.78	15.00	52.00	150.00	1,600,759
Stocks (N=4,663)						
Private Info (bps)	3.52	5.31	0.30	1.59	9.00	30,333
Public Info (bps)	3.76	5.96	0.39	1.70	9.26	30,333
Fund Styles (N=8)						
Forward Return Dispersion (%)						
1-3 month	1.62	0.58	0.99	1.50	2.38	1,720
1-6 month	1.67	0.54	1.09	1.56	2.42	1,720
1-12 month	1.70	0.50	1.16	1.59	2.40	1,720
Passive size (%)	26.63	13.92	9.26	23.82	47.77	1,728
Count of active funds	1,148	1,136	160	619	3,293	1,728

Table 2
Passive Investment and Active Funds Survival

The table presents the results from survival analyses of active mutual funds using the semi-parametric Cox Proportional Hazard model. The Cox model estimates $h(t|\boldsymbol{X}_i) = h_0(t)\exp(\boldsymbol{X}_i\boldsymbol{\beta})$, where $h(t|\boldsymbol{X}_i)$ is the hazard rate for fund i at month t, $\boldsymbol{X}$ is the vector of independent variables, $h_0(t)$ is the baseline hazard function that takes the same value for all funds, and $\boldsymbol{\beta}$ is the maximum likelihood estimator of the vector of coefficients. The dependent variable is the exit risk of the fund. $\boldsymbol{X}_i$ includes the relative passive size (passive assets divided by total assets) by fund style k measured by MFDB variable *crsp_obj_cd*, the lagged (1-, 2-, and 3-year) excess return of the active fund, and the interaction of the two. Columns 1-3 report the OLS estimates and columns 4-6 report the SSIV estimates. The sample contains active mutual funds that belong to a fund style (measured by CRSP objective code) that has 100 or more active funds at all times during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of hazard ratio for ease of interpretation. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effects of the interaction and of the lagged excess return. Z-scores are calculated based on robust standard error clustered on fund level and reported in parentheses. The Z-score of risk exacerbation factor is estimated using delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	MLE			SSIV		
Passive Size	-0.048***	-0.073***	-0.056***	-0.037***	-0.067***	-0.057***
× Lagged Excess Return	(-3.30)	(-2.82)	(-1.84)	(-2.48)	(-2.51)	(-1.89)
Lagged Excess Return	-0.230***	-0.223***	-0.293***	-0.247***	-0.233***	-0.292***
	(-7.84)	(-3.31)	(-3.89)	(-8.58)	(-3.38)	(-3.95)
Passive Size	-0.136***	-0.129***	-0.113***	-0.135***	-0.128***	-0.111***
	(-3.30)	(-2.82)	(-1.84)	(-2.48)	(-2.51)	(-1.89)
Lagged Return Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	1,593,709	1,379,993	1,186,022	1,593,709	1,379,993	1,186,022
Exacerbation Factor	0.211	0.328	0.192	0.149	0.289	0.195
from Passive Investment	(2.51)	(1.66)	(1.36)	(2.05)	(1.57)	(1.39)

Table 3
Passive Investment and Active Funds Survival – Falsification

The table repeats the analyses in table 2. Columns 1-3 are identical to columns 4-6 in table 2 for ease of comparison. Columns 4-6 repeat the analyses in columns 1-3 with a lagged excess return for the period of one month less. The sample contains active mutual funds that belong to a fund style (measured by CRSP objective code) that has 100 or more active funds at all times during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta)-1$, instead of hazard ratio for ease of interpretation. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effects of the interaction and of the lagged excess return. Z-scores are calculated based on robust standard error clustered on fund level and reported in parentheses. The Z-score of risk exacerbation factor is estimated using delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment			Falsification		
$\widehat{\text{Passive Size}}$	-0.037**	-0.067**	-0.057*	-0.013	-0.038	-0.049*
× Lagged Excess Return	(-2.48)	(-2.51)	(-1.89)	(-0.94)	(-1.52)	(-1.81)
Lagged Excess Return	-0.247***	-0.233***	-0.292***	-0.280***	-0.267***	-0.280***
	(-8.58)	(-3.38)	(-3.95)	(-10.65)	(-4.46)	(-4.51)
Passive Size	-0.135***	-0.128***	-0.111***	-0.135***	-0.136***	-0.122***
	(-8.84)	(-7.43)	(-5.48)	(-9.05)	(-8.36)	(-6.75)
Lagged Return Period	1 Year	2 Year	3 Year	11 Month	23 Month	35 Month
Strata by Style	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,593,709	1,379,993	1,186,022	1,612,835	1,397,253	1,201,652
Exacerbation Factor	0.149	0.289	0.195	0.047	0.141	0.173
from Passive Investment	(2.05)	(1.59)	(1.39)	(0.89)	(1.21)	(1.38)

Table 4
Passive Investment and Surviving Active Funds Risk-Taking

The table presents the results from the following regression:

$$Y_{i,t} = \beta \times \text{Passive Share}_{k,t} + \zeta_i + \tau_t + \epsilon_{i,t}$$

where risk-taking measure $Y_{i,t}$ is return volatility or portfolio turnover. Return volatility is measured as the standard deviation of the six monthly excess returns from $t+1$ to $t+6$. Portfolio turnover is measured as MFDB variable *turn_ratio* in the following year after month t. Passive $\text{Share}_{k,t}$ is the passive size in fund style k (measured by MFDB variable *crsp_ojb_cd*) in month t, measured as the passive assets divided by the total assets. Columns 1 and 2 report the OLS estimates and columns 3 and 4 report SSIV estimates. ζ_i and τ_t are fund and year-month fixed effects. The sample contains active mutual funds that belong to a fund style (measured by CRSP objective code) that has 100 or more active funds at all times during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. T-stats are calculated based on robust standard errors clustered on fund and monthly level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	OLS		SSIV	
	Return Volatility	Portfolio Turnover	Return Volatility	Portfolio Turnover
Passive Size	-0.189***	-0.176***	-0.174***	-0.173***
	(-5.11)	(-5.27)	(-4.22)	(-5.32)
Fund FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	1,752,679	1,442,456	1,746,595	1,436,932
R-squared	0.562	0.750	0.562	0.750

Table 5
Passive Investment and Return Dispersion of the Active Management Industry

The table presents the results from the following regression:

$$\text{Dispersion}_{k,t+j} = \beta \times \widehat{\text{Passive Share}}_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t}$$

where $\text{Dispersion}_{k,t+j}$ is calculated as the standard deviation of excess returns all active funds in fund style k, measured by MFDB variable *crsp_ojb_cd*, using a 6-month rolling window starting from month $t+j$. $\text{Passive Share}_{k,t}$ is the passive size in style k in month t, measured as the passive assets divided by the total assets. $\widehat{\text{Passive Share}}_{k,t}$ is the predicted value of $\text{Passive Share}_{k,t}$ using the SSIV. κ_k and τ_t are fund style fixed and year-month fixed effects. The sample contains fund styles that have 100 or more active funds at any time during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. Panel A reports the OLS estimates and panel B reports the SSIV estimates. T-stats are calculated based on robust standard errors clustered on monthly level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: OLS estimates:

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion Window	$1 \rightarrow 6$	$2 \rightarrow 7$	$3 \rightarrow 8$	$4 \rightarrow 9$	$5 \rightarrow 10$	$6 \rightarrow 11$
Passive Size	-0.309***	-0.292***	-0.270***	-0.262***	-0.254***	-0.243***
	(-6.53)	(-6.26)	(-5.85)	(-5.68)	(-5.44)	(-5.27)
Fund style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,594	1,594	1,594	1,594	1,594	1,594
R-squared	0.683	0.681	0.680	0.679	0.677	0.677

Panel B: SSIV estimates:

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion Window	$1 \rightarrow 6$	$2 \rightarrow 7$	$3 \rightarrow 8$	$4 \rightarrow 9$	$5 \rightarrow 10$	$6 \rightarrow 11$
$\widehat{\text{Passive Share}}$	-0.245***	-0.220***	-0.202***	-0.199***	-0.185***	-0.186***
	(-4.87)	(-4.51)	(-4.18)	(-4.05)	(-3.81)	(-3.84)
Fund style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,594	1,594	1,594	1,594	1,594	1,594
R-squared	0.683	0.681	0.680	0.679	0.677	0.677

Table 6
Passive Investment and Active Funds' Performance

The table represents the results from the following regression:

$$Y_{i,t} = \beta \times \text{Passive Share}_{k,t} + \zeta_i + \tau_t + \epsilon_{i,t}$$

where $Y_{i,t}$ is the future 1-, 2-, and 3-year excess return per annum of active fund i. Passive $\text{Share}_{k,t}$ is the passive size in style k in month t, measured as the passive assets divided by the total assets. $\widehat{\text{Passive Share}}_{k,t}$ is the predicted value of Passive $\text{Share}_{k,t}$ using the SSIV. ζ_i and τ_t are fund and year-month fixed effects. The sample contains all stocks that are held by the passive benchmark for the eight fund styles used in previous analyses from 2004 to 2020. Passive size is scaled to a standard deviation of 1. T-stats are calculated based on robust standard errors clustered on fund and monthly level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			SSIV	
Passive Size	0.014***	0.011***	0.008***	0.013***	0.010***	0.007***
	(5.06)	(5.44)	(4.76)	(5.11)	(5.21)	(4.41)
Excess Return Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,837,749	1,837,756	1,837,756	1,831,533	1,831,540	1,831,540
R-squared	0.256	0.506	0.753	0.261	0.517	0.769

Table 7
Passive Investment and Market Efficiency

The table represents the results from the following regression:

$$Y_{s\in k,y} = \beta \times \widehat{\text{Passive Share}}_{k,t} + \xi_s + \tau_t + \epsilon_{s,y}$$

where market efficiency measure $Y_{s\in k,y}$ (on stock s that is held by the passive benchmark of style k in year y) captures the public or private information impounded in stock price using variance decomposition following Brogaard et al. (2022). Passive Share$_{k,t}$ is the passive size in style k in month t, measured as the passive assets divided by the total assets. $\widehat{\text{Passive Share}}_{k,t}$ is the predicted value of Passive Share$_{k,t}$ using the SSIV. ξ_s and τ_t are stock and year-month fixed effects. The sample contains all stocks that are held by the passive benchmark for the eight fund styles used in previous analyses from 2010 to 2021. All continuous variables are scaled to a standard deviation of 1. T-stats are calculated based on robust standard errors clustered on stock and monthly level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	OLS		SSIV	
	Private	Public	Private	Public
Passive Size	0.128***	0.113***	0.115***	0.099***
	(4.39)	(3.93)	(4.09)	(3.55)
Stock FE	Yes	Yes	Yes	Yes
Fund Style FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	421,825	421,740	421,825	421,740
R-squared	0.092	0.542	0.143	0.537

Table 8
Passive Investment and Active Funds Survival – Robustness on Performance Threshold

The table repeats the analyses in **table 2** with fund net-of-fee returns instead of excess returns. The Cox model estimates $h(t|\boldsymbol{X}_i) = h_0(t)\exp(\boldsymbol{X}_i\boldsymbol{\beta})$, where $h(t|\boldsymbol{X}_i)$ is the hazard rate for fund i at month t, $\boldsymbol{X}$ is the vector of independent variables, $h_0(t)$ is the baseline hazard function that takes the same value for all funds, and $\boldsymbol{\beta}$ is the maximum likelihood estimator of the vector of coefficients. The dependent variable is the exit risk of the fund. $\boldsymbol{X}_i$ includes the relative passive size (passive assets divided by total assets) by fund style k measured by MFDB variable *crsp_obj_cd*, the lagged (1-, 2-, and 3-year) net-of-fee return of the active fund, and the interaction of the two. Columns 1-3 report the OLS estimates and columns 4-6 report the SSIV estimates. The sample contains active mutual funds that belong to a fund style (measured by CRSP objective code) that has 100 or more active funds at all times during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of hazard ratio for ease of interpretation. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effects of the interaction and of the lagged excess return. Z-scores are calculated based on robust standard error clustered on fund level and reported in parentheses. The Z-score of risk exacerbation factor is estimated using delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	MLE			SSIV		
Passive Size	-0.028*	-0.064***	-0.062***	-0.019	-0.059***	-0.060***
× Lagged Net-of-Fee Return	(-1.82)	(-2.19)	(-2.11)	(-1.23)	(-2.04)	(-2.10)
Lagged Net-of-Fee Return	-0.404***	-0.374***	-0.422***	-0.416***	-0.380***	-0.424***
	(-11.80)	(-4.16)	(-5.04)	(-12.38)	(-4.24)	(-5.13)
Passive Size	-0.123***	-0.092***	-0.089***	-0.125***	-0.095***	-0.093***
	(-7.75)	(-4.28)	(-3.34)	(-7.86)	(-4.48)	(-3.58)
Lagged Return Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	1,593,709	1,379,993	1,186,022	1,593,709	1,379,993	1,186,022
Exacerbation Factor	0.070*	0.170***	0.146***	0.045	0.155***	0.142***
from Passive Investment	(1.68)	(1.61)	(1.67)	(1.17)	(1.54)	(1.67)

Table 9
Passive Investment and Active Funds Survival – Robustness on Baseline Hazard

The table repeats the analyses in **table 2** with relaxed baseline hazard assumption by stratifying the analyses by investment styles. The strata Cox model estimates $h(t|\boldsymbol{X}_i) = h_{0,k}(t)\exp(\boldsymbol{X}_i\boldsymbol{\beta})$, where $h(t|\boldsymbol{X}_i)$ is the hazard rate for fund i at month t, $\boldsymbol{X}$ is the vector of independent variables, $h_{0,k}(t)$ is the baseline hazard function that takes the same value for all funds in the same investment style k, and $\boldsymbol{\beta}$ is the maximum likelihood estimator of the vector of coefficients. The dependent variable is the exit risk of the fund. $\boldsymbol{X}_i$ includes the lagged (1-, 2-, and 3-year) excess return of the active fund and the interaction of the two. The passive size by style is subsumed by the style-specific baseline hazard function. Columns 1-3 report the OLS estimates and columns 4-6 report the SSIV estimates. The sample contains active mutual funds that belong to a fund style (measured by CRSP objective code) that has 100 or more active funds at all times during the sample period from 2004 to 2020. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of hazard ratio for ease of interpretation. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effects of the interaction and of the lagged excess return. Z-scores are calculated based on robust standard error clustered on fund level and reported in parentheses. The Z-score of risk exacerbation factor is estimated using delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	MLE			SSIV		
Passive Size	-0.040***	-0.070***	-0.053***	-0.021	-0.063***	-0.052***
× Lagged Excess Return	(-2.51)	(-2.32)	(-1.59)	(-1.34)	(-2.00)	(-1.55)
Lagged Excess Return	-0.281***	-0.280***	-0.331***	-0.307***	-0.291***	-0.333***
	(-8.40)	(-3.64)	(-4.09)	(-9.57)	(-3.70)	(-4.13)
Lagged Return Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Strata by Style	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,593,709	1,379,993	1,186,022	1,593,709	1,379,993	1,186,022
Exacerbation Factor	0.142	0.252	0.160	0.070	0.216	0.155
from Passive Investment	(2.09)	(1.56)	(1.24)	(1.23)	(1.49)	(1.22)

A1. Model Proof

This appendix provides proof of equations (6) and (7) in propositions 1 and 2.

Proof of Proposition 1:

Denote $\Phi_1(by + a)q$ as m and $\Phi_1(by - a)(1 - q)$ as n in equation (4), the derivative of $\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P)$ with respect to y can be written as:

$$\frac{\partial \hat{P}}{\partial y} = \frac{\dfrac{\partial m}{\partial y} \cdot n - \dfrac{\partial n}{\partial y} \cdot m}{(m + n)^2} \tag{A1}$$

Focus on the numerator in equation (A1) as the denominator is strictly positive and denote the PDF of $\Phi_1(\cdot)$ as $\phi_1(\cdot)$:

$$\frac{\partial m}{\partial y} \cdot n - \frac{\partial n}{\partial y} \cdot m = bq(1 - q)\Big(\phi_1(by + a)\Phi_1(by - a) - \phi_1(by - a)\Phi_1(by + a)\Big) \tag{A2}$$

Note that $by + a > 0$ and $by - a < 0$ (because $a - b > 0$ and $y \in [0, 1]$) are two points of equal distance to $by \geq 0$, i.e., $by + a$ is further away from 0 than $by - a$. Therefore $\phi_1(by + a) < \phi_1(by - a)$. Also with $\Phi_1(by - a) < \Phi_1(by + a)$, we have:

$$\phi_1(by + a)\Phi_1(by - a) - \phi_1(by - a)\Phi_1(by + a) < 0 \tag{A3}$$

Namely, $\partial \hat{P}/\partial y < 0$. Therefore, given a bad realization, investor's posterior belief that the manager is of low skill decreases/increases in relative size of active/passive management.

Proof of Proposition 2:

The derivative of $\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P)$ with respect to σ_i can be written as:

$$\frac{\partial \hat{P}}{\partial \sigma_i} = \frac{\dfrac{\partial m}{\partial \sigma_i} \cdot n - \dfrac{\partial n}{\partial \sigma_i} \cdot m}{(m+n)^2} \tag{A4}$$

Denote $\Phi(\cdot)$ and $\phi(\cdot)$ as the CDF and PDF of the *standard* normal distribution and re-write m and n as:

$$m = \Phi\left(\frac{by+a}{\sqrt{\sigma_x^2+\sigma_i^2}}\right)q = \Phi\left(\frac{by+a}{\sigma_i^{'}}\right)q \tag{A5}$$

$$n = \Phi\left(\frac{by-a}{\sqrt{\sigma_x^2+\sigma_i^2}}\right)(1-q) = \Phi\left(\frac{by+a}{\sigma_i^{'}}\right)(1-q) \tag{A6}$$

where $\sigma_i^{'} = \sqrt{\sigma_x^2+\sigma_i^2}$. Focus on the numerator in equation (A4) as the denominator is strictly positive:

$$\frac{\partial m}{\partial \sigma_i} \cdot n - \frac{\partial n}{\partial \sigma_i} \cdot m = \frac{\partial \sigma_i^{'}}{\partial \sigma_i}\left(\frac{\partial m}{\partial \sigma_i^{'}} \cdot n - \frac{\partial n}{\partial \sigma_i^{'}} \cdot m\right) \tag{A7}$$

$$= -\frac{\partial \sigma_i^{'}}{\partial \sigma_i}q(1-q)\left[\left(\frac{by+a}{\sigma_i^{'2}}\phi\Big(\frac{by+a}{\sigma_i^{'}}\Big)\Phi\Big(\frac{by-a}{\sigma_i^{'}}\Big)\right) - \left(\frac{by-a}{\sigma_i^{'2}}\phi\Big(\frac{by-a}{\sigma_i^{'}}\Big)\Phi\Big(\frac{by+a}{\sigma_i^{'}}\Big)\right)\right] \tag{A8}$$

Note that $\frac{\partial \sigma_i^{'}}{\partial \sigma_i} > 0$ and that the first term in the bracket is strictly positive and the second term is strictly negative, therefore $\frac{\partial \hat{P}}{\partial \sigma_i} < 0$. In other words, given a bad realization, a higher return variability slows down the inference that the manager is of low type.

Proof of Proposition 3:

Let the fraction of low-skilled manager be $\hat{q}$, we have $\hat{q} = q$ when $t = 0$, $\hat{q} = 0$ when $t \to \infty$, and $\dfrac{\partial \hat{q}}{\partial t} > 0 \ \forall t \in [0, \infty)$. The passive investment size accelerate the revelation of managers' skill therefore the exit of low-skilled managers, i.e., $\dfrac{\partial \hat{q}}{\partial y} > 0 \ \forall t$.

Low-skilled managers prefer a high risk for their portfolio. Assume without the loss of generality that the upper bound of the idiosyncratic risk a manager can take is $\bar{\sigma}$. All low-skilled managers have $\sigma_i = \bar{\sigma}$ and all high-skilled managers have $\sigma_i = 0$. The performance dispersion of the active management industry is:

$$Dispersion = \hat{p}(\sigma_x + \bar{\sigma}) + (1 - \hat{q})\sigma_x = \sigma_x + \hat{p}\bar{\sigma} \tag{A9}$$

Therefore, higher passive investment shrinks the performance dispersion of the active management industry:

$$\frac{\partial}{\partial y} Dispersion = \bar{\sigma}\frac{\partial \hat{q}}{\partial y} > 0 \tag{A10}$$