The Rise of Passive Investing and Active Mutual Fund Skill*

Da Huang

D'Amore-McKim School of Business
Northeastern University

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Abstract

This paper shows that the rise of passive investing makes the active mutual fund industry more skilled. Greater passive investing makes it easier for active funds to outperform the benchmark and accelerates the exit of underperforming funds. In response, skilled managers take less risk to outperform more consistently. Since unskilled active managers introduce noise into stock prices, accelerating their exit improves market efficiency. These findings reconcile the rise of passive investing, closet indexing, and fund homogenization, which may imply a lack of skill, with the literature documenting the presence of skills in the active mutual fund industry.

JEL: G11, G14, G20

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

1. Introduction

Extensive literature suggests that active mutual fund managers have stock-picking skills and the active management industry has become more skilled over time (Pástor, Stambaugh, & Taylor, 2015). Despite this increase in skill, the last two decades have witnessed a significant shift from active to passive investing. By 2021, passive strategies nearly overtook active management in U.S. equity mutual funds (**Figure 1**). This shift is accompanied by closet indexing and the homogenization of active funds, often interpreted as a lack of skill among active managers. This paper challenges the conventional narrative that the rise of passive investing indicates a lack of skill in active management. Instead, I demonstrate that the rise of passive investing is a reason for, rather than a contradiction to, an increasingly skilled active mutual fund industry.

The key insight of this paper is that greater passive investing makes the industry more skilled by accelerating the exit of underperforming funds. This is because the rise of passive investing, or a smaller active industry relative to the market, means less active money competing for alphas, making it easier for all funds to outperform the benchmark (Pástor & Stambaugh, 2012). Understanding this industry-level decreasing return to relative scale, investors expect skilled active managers to outperform the benchmark more frequently when passive investing is high. Therefore, underperformance becomes a stronger signal that the manager is unskilled, and underperforming funds exit the industry faster.

Understanding the increased cost of underperformance with the rise of passive investing, skilled managers now prefer strategies with lower idiosyncratic risks relative to the benchmark. They do so by implementing a few high-conviction stock ideas and anchoring a significant portion of their portfolios to the benchmark. This strategy helps them outperform the benchmark consistently. As a result, the rise of passive investing makes the active industry more skilled but also leads to closet indexing and fund homogenization. This paper reconciles these trends, often interpreted as a lack of skill, with the extensive literature that consistently documents skills in the active mutual fund industry. These results have important implications for the overall market efficiency. The rise of passive investing weeds out unskilled active managers and therefore makes stock prices less noisy. As a result, markets become more efficient.

I find empirical support for these predictions in the U.S. equity mutual fund industry. I measure the relative size of passive investing by investment style as the proportion of passively managed money relative to the total amount managed actively and passively. In a survival analysis, I find that a one standard deviation increase in passive investing compounds the closure risk of underperforming active funds by 14% to 24% in most conservative estimates. This result highlights the reason behind the increased skill level in the active mutual fund industry, as documented by Pástor et al. (2015), who offer convincing evidence for increasing skills but stop short of examining the economic mechanism. Additionally, I find that greater passive investing leads to lower future tracking error and portfolio turnover on the fund level and lower future return dispersion on the industry level. These results explain closet index and fund homogenization in the context of the rise of passive investing and increased skill levels in the active mutual fund industry. Skilled managers closet index to "lock in" outperformance, reminiscent of the behavior by top managers taking lower risk to "lock in" their lead in mutual fund tournaments (Brown, Harlow, & Starks, 1996). I also find that the rise of passive investing decreases the noise in stock prices, consistent with the idea that unskilled managers exit the industry faster.

I discuss alternative explanations, such as potential omitted variables affecting both passive investing and outcomes. For instance, one example is time-varying popularity shocks by investment style. I develop a shift-share instrumental variable (SSIV) based on mutual fund families' asset allocation across investment styles, which is primarily based on portfolio managers' investment expertise (Kacperczyk, Sialm, & Zheng, 2005). Their expertise tends to focus on a fixed set of industries and does not shift across investment styles in response to popularity. Therefore, I assume that the across-style within-family asset allocation does not respond to time-varying style-specific shocks, and I provide empirical evidence supporting this identifying assumption. The SSIV produces qualitatively similar results, alleviating concerns about omitted confounding variables.

This paper makes several contributions. First, I reconcile several trends that are often interpreted as a lack of skill, such as the rise of passive investing, closet indexing, and fund homogenization, with the extensive literature that consistently documents the presence of skills in the active mutual fund industry. The rise of passive investing is a reason for, rather than a contradiction to, an increasingly skilled active industry. As a result, skilled managers take less risk (closet indexing) and active funds become more alike (fund homogenization). This paper also addresses an important question – what is the optimal level of passive investment in the market? My results show that the rise of passive investing has led to an increase in price efficiency to date by reducing noise, suggesting that the current level of passive investment is lower than optimal from a market efficiency perspective in the U.S.

This paper contributes to the emerging literature that studies how passive investments affect the asset management industry. Among theoretical work, Feldman, Saxena, and Xu (2020), Gârleanu and Pedersen (2022), (Coles, Heath, & Ringgenberg, 2022), and (Malikov, 2024) model how passive investments interact with active investments in a general equilibrium framework. In their work, investors always directly invest in stock markets and choose to be passive or active by balancing cost to information production and return to investments.

In my framework, investors invest indirectly through mutual funds and choose passive funds when they believe active funds cannot outperform. Therefore, their work studies passive and active investments through channels reminiscent of (Grossman & Stiglitz, 1980), while I do so through mutual fund channels akin to (Berk & Green, 2004) and (Pástor & Stambaugh, 2012). In addition, their work explains the *existence* of skill in active management *despite* the rise of passive investing, whereas, in contrast, my results explain the *rise* of skill in active management *because of* the rise of passive investing. These results provide complementary evidence on how passive investing affects the active industry and market efficiency in different contexts.

On the empirical side, Cremers, Ferreira, Matos, and Starks (2016) study how active funds compete when facing pressure from passive funds with an early sample in the international context. They describe a competitive strategy of active managers that is different than what I find in the U.S. mutual fund industry. I reconcile these results through a channel of different active managers' skill levels. Cremers et al. (2016) and I provide complementary empirical evidence on how active managers compete against passive investing given different levels of skills. In contemporary work, Sun (2021) focuses on how active funds change their fees in response to the entry of index products based on active funds' distribution channel. Dannhauser and Spilker III (2023) study how passive funds affect the fees and incentives of sister active funds in the same mutual fund family. In contrast, this paper is the first to study how the rise of passive investing affects the skill levels in the active industry. It challenges the conventional view that the shift toward passive indicates a lack of skill in active management. Instead, I show this shift makes the active industry more skilled over time by weeding out unskilled active managers. Although, as mentioned by Pástor et al. (2015), the active industry can become more skilled also through the entry of skilled managers, I focus on the exit of unskilled ones since it is a direct consequence of the rise of passive investing.

This paper also contributes to the voluminous literature on passive investments, a lot of which are ETFs, and market efficiency. Ben-David, Franzoni, and Moussawi (2018) document that higher ETF ownership leads to higher stock volatility due to index arbitrage activities. Glosten, Nallareddy, and Zou (2021) find that a higher ETF ownership of stocks leads to better information efficiency because ETFs reduce the cost of arbitrage in long-short trades. Shim and Todorov (2023) find bond ETFs buffer fire sales and fuel fire purchases due to authorized participants' inventory management. Sammon (2023) finds that higher passive investments lead to less firm-specific information being incorporated into stock prices ahead of earnings announcements. This paper contributes to the literature with a novel result: the rise of passive investing weeds out unskilled active mutual fund managers, leads to less noisy stock prices, and therefore improves market efficiency.

2. Empirical Framework

In this section, I examine the economic channel through which passive investing affects skill in the active mutual fund industry. This economic channel leads to four testable hypotheses which I empirically analyze. I then describe the data and the identification strategy employed in the empirical studies.

2.1. Economic Channel

The rise of passive investing, or less active money competing for alpha, makes it easier for active managers to outperform the benchmark due to industry-level decreasing returns to relative scale (Pástor & Stambaugh, 2012). Investors understand this dynamic and expect skilled managers to outperform the benchmark more often. Therefore, they are "less forgiving" when a fund underperforms the benchmark. Put differently, underperforming could result from a mere unlucky draw or a lack of skill. Investors attribute underperformance to a lack of skill more when outperforming is easier with greater passive investing. When investors believe an active manager is unskilled, they allocate money away from her fund, which causes the fund to exit the industry.

Hypothesis 1. Underperforming funds are more likely to exit the industry with greater passive investing.

Insert **Figure 2** About Here

Figure 2 demonstrates graphically how an increase in passive investment accelerates investors' inference that an underperforming manager has low skill. The green curve to the right and the red curve to the left represent the excess return (over benchmark) distributions for funds managed by skilled and unskilled managers, respectively. Panel (a) represents the low-passive-investing scenario where competition for alpha is intense and outperforming the benchmark is difficult. Investors understand that skilled managers on average earn the same return as the benchmark whereas unskilled managers on average earn a return 30% lower than the benchmark. Both returns have the same idiosyncratic volatility, an assumption that I relax in the next hypothesis. Consider a fund that earns a -6% excess return, represented by the black dash line. Investors use this performance to infer the manager's skill level. The likelihood that this manager is skilled is H, the intersection between the skilled return distribution and the -6% return realization. Similarly, the likelihood that this manager is unskilled is L. Therefore, the likelihood ratio that this manager is unskilled is $L/H < 1$. Namely, in this numeric example, even though this manager underperforms the benchmark, investors believe she is more likely to be skilled given how difficult it is to outperform.

Panel (b) represents the high-passive-investing scenario. Due to industry-level decreasing returns to relative scale, investors now expect skilled managers to earn a 15% excess return and unskilled ones to earn a -15% excess return on average. Consider the same -6% excess return as before. The likelihood ratio that this manager is unskilled is $L/H > 1$. As a result, in this numeric example, investors believe that the active manager with the same performance is more likely to be unskilled.

Generalizing from the numeric examples, we see that the likelihood ratio, L/H increases with the level of passive investing. This is the key insight of the paper. Investors attribute underperformance to a lack of skill more with greater passive investing. As a result, the rise of passive investing accelerates the exit of underperforming funds and makes the active mutual fund industry more skilled. I provide a stylized model in **Appendix A1** that demonstrates the generalization of the numeric examples.

Hypothesis 2. Active funds take less risk as the industry becomes more skilled with greater passive investing.

As passive investing grows, surviving funds are run by more skilled managers, who prefer to take a low risk for their portfolio. As a result, the rise of passive investing leads to lower risk-taking of active funds.

Insert **Figure 3** About Here

Figure 3 illustrates the preference of risk-taking by active managers. In Panel (a), we see two excess return distributions for an unskilled manager who takes either high or low risks. Taking high risks leads to a wide return distribution, whereas taking low risks results in a more concentrated one. The green area under the curve indicates the probability of outperforming the benchmark. An unskilled manager prefers a high risk to increase the chance of outperforming the benchmark. Conversely, Panel (b) illustrates a skilled manager's preference for low risks. She minimizes the probability of underperforming the benchmark (the red area under the curve) by implementing a few best stock ideas and anchoring a significant part of her portfolio to the benchmark. This strategy allows skilled managers to outperform the benchmark consistently. As a result, the rise of passive investing makes the surviving managers more skilled, who take low risks relative to the benchmark in their portfolio. This hypothesis offers a novel explanation for closet indexing behavior, often perceived as a lack of skill. I argue that closet indexing can result from skilled managers trying to signal their high skills to investors. This insight echoes the tournament incentive characterized by Brown et al. (1996), where fund managers who outperform early in the tournament want to take low risks to "lock in" their lead for the rest of the tournament.

Hypothesis 3. Greater passive investing decreases the return dispersion of the active management industry.

This hypothesis represents an industry-level consequence of the fund-level prediction in Hypothesis 2. The rise of passive investing causes active funds to closet-index more, leading their returns to track the index more closely and resemble each other. The key is that this homogenization results from a more skilled active industry, rather than a lack of skill.

Hypothesis 4. Greater passive investing decreases the noise in stock prices.

This is because greater passive investing weeds out unskilled managers who introduce noise into stock prices due to their low skills and high risk-taking (the extensive margin). In addition, skilled managers take less risk by focusing on a few high-conviction stock ideas and closet-indexing a significant portion of their portfolio (the intensive margin). As a result, the noise in stock prices decreases with the rise of passive investing.

2.2. Data and Variable Construction

This section describes the data used to construct the fund-level, style-level, and stock-level variables in the empirical analysis. The main data used in this paper comes from the Center for Research in Security Prices (CRSP) Survival-Bias-Free U.S. Mutual Fund Database (MFDB). The sample period is from 2004 to 2020. The sample includes all U.S. domestic equity funds (including both mutual funds and ETFs) in investment styles, measured by MFDB variable *crsp_obj_cd*, with 100 or more active funds at all times during the sample period to avoid a few overly dominant funds altering the dynamic of the active industry.

2.2.1. Fund-Level Variables

I calculate the monthly excess returns of an 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 – tracking error, calculated as the standard deviation of excess returns for the next one, two, and three years, and portfolio turnover, measured as the average of MFDB variable *turn_ratio* in the following one, two, and three years.

2.2.2. Stock-Level Variables

To examine the market efficiency implication, I calculate four market efficiency measures following Brogaard, Nguyen, Putniņš, and Wu (2022). Specifically, I run a vector autoregression (VAR) that includes market return, stock return, and stock order flow, correspondingly decomposing the variation in stock returns into market-wide information, public firm-specific information, and private firm-specific information, respectively. The innovation in the VAR is the noise in stock returns. The market information component measures how much of the stock return variance is explained by past market returns. The firm-specific public information component measures how much of the stock return variance is explained by past returns of the firm. The firm-specific private information component measures how much of the stock return variance is explained by past order flow imbalances of the firm. I scale these four components by the total variance to avoid potential biases arising from non-stationary time series. The four components add up to one.

2.2.3. 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 12-month rolling 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:

$$\text{Passive Size}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t}}, \tag{1}$$

where k denotes fund style and t denotes month.

I require all funds in the sample to have a *crsp_obj_cd* unchanged over time to avoid possible style drift (Wermers, 2012). I use *index_fund_flag* equals D to identify explicit passive funds. The passive size measure excludes closet indexers and home indexers despite their substantial presence (Chinco & Sammon, 2024) because my economic channel relies on the passive size being a publicly observable signal. I provide a detailed description of the data cleaning and variable construction process in **Appendix A2**. **Table 1** shows the summary statistics.

Insert **Table 1** About Here

2.3. Identification Strategy

In this section, I discuss potential alternative explanations for the economic channel described in Section 2.1. To address this endogeneity concern, I develop a shift-share instrumental variable (SSIV) based on the mutual fund family's asset allocation across investment styles.

A potential endogeneity concern is omitted variables, such as time-varying popularity in investment styles, to simultaneously affect both passive investment and outcome variables. One example is popularity shock in investment styles. For example, advancements in oncology research spark investment interest and make healthcare funds more popular. The rise in popularity will increase passive investing in the healthcare sector because more active money competes for alpha, making passive investing more appealing (Berk & Green, 2004; Pástor & Stambaugh, 2012; Pástor et al., 2015; Barras, Gagliardini, & Scaillet, 2022). Simultaneously, the rise in popularity will also affect outcomes such as fund survival and homogenization. Healthcare funds may be less likely to exit because they are popular among investors. In addition, healthcare funds may be more homogenized because skilled active managers converge on oncology stocks based on the promising cancer-curing prospect. In this example, we see passive investing correlates with fund survival and homogenization. However, there is no causal relation between passive investing and the outcomes.

To mitigate the issue of omitted variables, I develop a shift-share instrumental variable (SSIV). The SSIV represents a composite growth rate of actively invested assets at the style level and is calculated as

$$B_{k,t} = \sum_{f} z_{k,f,t-1} \cdot g_{f,t}. \tag{2}$$

In this equation, $z_{k,f,t-1}$ is the active asset allocation of fund family f in style k in the previous month. This is called the "base share" of the SSIV. The SSIV "shock", $g_{f,t}$, is the total active asset growth for fund family f in month t. **Figure 4** provides a stylized example (with time subscript suppressed for brevity) of the SSIV construction. There are two fund families, A and B, and two investment styles, 1 and 2. The top part of the figure displays the input of the SSIV. The asset allocation matrix (the numbers in blue) consists of the SSIV base shares. The fund-family-level asset growth (the numbers in red) is the SSIV shock. The bottom part of the figure demonstrates the calculation of the instrument. The SSIV, i.e., the composite growth rate by investment style, is calculated by projecting the vector of fund-family growth onto the fund-family-to-investment-style asset allocation matrix.

Insert **Figure 4** About Here

The instrument $B_{k,t}$ captures the variations in active asset growth rate by investment style that are driven by asset allocation decisions and growth rates of fund families. If the base share is unrelated to unobserved omitted variables, the SSIV isolates the causal effect between the independent variable and the outcomes. This is commonly referred to as the exogenous base share design (Goldsmith-Pinkham, Sorkin, & Swift, 2020; Borusyak, Hull, & Jaravel, 2022).

2.3.1. Exogeneity

I use the exogenous base share design to separate the effect of passive investing from confounding factors like popularity shocks. The identifying assumption is that the base share is uncorrelated with omitted variables that could simultaneously affect both passive investment and the outcomes of interest. More specifically, I assume that fund-family asset allocation decisions are not influenced by month-to-month fluctuations in popularity across investment styles.

The identifying assumption is likely to hold because the asset allocation is primarily driven by investment expertise (Kacperczyk et al., 2005). As a result, families typically offer a fixed menu of funds and rarely launch new funds to chase fleeting trends since hiring new fund managers with the necessary expertise can be time-consuming. Additionally, finding distributing partners and obtaining regulatory approvals also take considerable time. By the time new funds are ready to launch, the hot trend may have already passed. Furthermore, mutual fund investors face significant friction in portfolio choice (Choukhmane & de Silva, 2024) and do not frequently shift their allocations due to reasons like fees and inattention. For these reasons, mutual fund families and investors are unlikely to respond to style-specific, short-term shocks in their monthly asset allocations.

I provide empirical support for the identifying assumption. Although the strict exogeneity is not testable given that the potential confounding variable is not observable, I perform the following test to validate the identification strategy. Specifically, I test whether the style-level counts and flows of active funds react to short-term past returns *within each fund family*. If the number of funds reacts to past returns, then it is likely that mutual fund families do chase popularity shocks. Similarly, if fund flows react to past returns on investment style level *within the fund family*, then investors do pay attention to popularity shocks and reallocate their assets frequently. Namely, if either count or fund flow responds to short-term past returns on style level within fund families, the identifying assumption is likely to not hold.

I estimate the following equation *for each mutual fund family* that has 100 or more fund-style level observations:

$$y_{k,t} = \beta \times \text{Return}_{k,t-1} + \kappa_k + \epsilon_{k,t} \ , \tag{3}$$

where the dependent variable $y_{k,t}$ is either $\text{Count}_{k,t}$ or $\text{Flow}_{k,t}$. $\text{Count}_{k,t}$ is the number of active funds in style k run by the fund family. $\text{Flow}_{k,t}$ is the fund flow (defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot \text{Return}_{i,t})/\text{TNA}_{i,t-1}$) aggregate to the investment-style k of the fund family. $\text{Return}_{k,t-1}$ is the average active fund return of investment-style k within the family. I include investment-style fixed effects, κ_k, to sweep out unobserved factors that are style-specific and time-invariant. **Figure 5** reports the results.

Insert **Figure 5** About Here

Panel (a) of **Figure 5** plots in red the kernel distribution of the t-stat of the estimations from **Equation 3** using $\text{Count}_{k,t}$ as the dependent variable. The distribution largely resembles the standard normal distribution in blue with a slightly leptokurtic shape. If the null hypothesis for **Equation 3** is true, i.e., there is no relation between fund counts and past returns, repeating the regression enough times would produce t-stats following a standard normal distribution (which resembles the t distribution with degree of freedom greater 100). Therefore, the similarity between the two curves suggests that fund counts do not respond to past returns. In addition, only 2 out of 256 fund families, or 0.04% of the total net asset value of the estimated sample as of 2020, have a positive coefficient with 5% statistical significance. Put together, the lack of statistical and economic significance of **Equation 3** with $\text{Count}_{k,t}$ as the dependent variable suggests that mutual fund families do not chase short-term popularity shocks.

Panel (b) of **Figure 5** plots the t-stat distribution of **Equation 3** with $\text{Flow}_{k,t}$ as the dependent variable. Similarly, the distribution closely aligns with the standard normal distribution. As a result, we fail to reject the null hypothesis – past returns do not drive future fund flow on style level within the fund family. Furthermore, 12 out of 260 fund families (or 3.57% of the total net asset value of the estimated sample as of 2020) have a positive coefficient with 5% statistical significance. Therefore, mutual fund investors do not seem to reallocate their assets frequently in response to short-term past returns on style level within fund families. In sum, the base share is likely unrelated to the potential confounding variables and the SSIV isolates the causal effect of passive investing on outcome variables of interest.

2.3.2. Relevance

The first stage uses the SSIV, namely the composite asset growth, to predict the actual asset growth on the style level:

$$g_{k,t} = \alpha + \beta \cdot B_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t}, \tag{4}$$

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 year-month fixed effects. The point estimate of β is 0.039 with statistical significance at 1% level, suggesting the instrument is relevant. The F-statistic from the first stage regression is 8.1. I conduct additional robustness tests on a potential weak instrument following Stock and Yogo (2002) and Chernozhukov and Hansen (2008) in **Appendix A4**.

I obtain the predicted value of the asset growth, $\hat{g}_{k,t}$, from the first stage and instrument for the relative size of passive investment as

$$\widehat{\text{Passive Size}}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t-1} \cdot \hat{g}_{k,t}}, \tag{5}$$

$\widehat{\text{Passive Size}}_{k,t}$ is driven by the asset growth from asset allocation decisions. Therefore the instrumented passive size is not correlated with month-to-month popularity shocks. I use the instrumented passive size along with the actual passive size in all subsequent analyses to rule out alternative explanations such as popularity shocks driving both passive size and outcome variables.

3. Empirical Results

In this section, I empirically test the hypotheses in section 2.1. The economic framework predicts that greater passive investment accelerates the exit of underperforming funds (Hypothesis 1), makes surviving funds take less risk (Hypothesis 2), shrinks the performance dispersion of the active mutual fund industry (Hypothesis 3), and reduces the noises in stock prices (Hypothesis 4).

3.1. Active Fund Survival

Underperforming funds are more likely to go out of business with greater passive investment (Hypothesis 1). This is because less active money competing for alpha means all active funds are expected to earn a higher return (Pástor & Stambaugh, 2012). Understanding this effect, investors expect skilled managers to outperform benchmark more consistently and take underperforming as a more credible signal of lack of skill.

I test this hypothesis 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 function (risk of fund closure) for fund i at time t is:

$$h(t|\boldsymbol{X}_i) = h_0(t)\exp(\boldsymbol{X}_i\boldsymbol{\beta}), \tag{6}$$

where $h_0(t)$ is the baseline hazard and $\boldsymbol{X}_i$ is a vector of explanatory variables including active funds' past excess return, passive size in its style category, the interaction of the two, and fund-level controls including age, size, and management fee. The Cox model does not make parametric assumptions on the baseline hazard $h_0(t)$ and leaves it unestimated. Instead, it only assumes that the baseline hazard function is the same for all funds in the sample. Therefore, the closure risks of all sample funds are proportional. Essentially, the Cox model treats any one fund's closure risk as a multiplicative (by $\exp(\boldsymbol{X}_i\boldsymbol{\beta})$) replica of the closure risk of any other fund. I standardize continuous variables such as Lagged Excess Return and Passive Size to have a standard deviation of 1 for ease of interpretation.

Insert **Table 2** About Here

Table 2 reports the results: greater passive investment accelerates the exit of underperforming funds. Columns 1 to 3 are the baseline results. Column 1 shows that a one standard deviation decrease in one-year Lagged Excess Return increases the exit risk by 24.5%, 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 4.6% closure risk. The results support the hypothesis that greater passive investment accelerates the exit of underperforming funds.

To assess the economic magnitude of the estimates, I calculate an exacerbation factor as the ratio of the marginal effect of the interaction and the marginal effect of the lagged performance. Reported at the bottom of **Table 2**, the exacerbation factor is economically and statistically significant. Conditional on any level of closure risk from underperformance, a one standard deviation increase in passive investment exacerbates the closure risk by

18.9% in the specification in column 1. The following is a concrete example to illustrate the economic significance. If a fund has a baseline closure risk of 50% per annum (i.e., roughly 4% per month), reducing its past year's excess return by one standard deviation would unconditionally increase the closure risk to 62.3% ($50\% \times (1 + 24.5\%)$). If the same underperformance occurs when the passive investment is one standard deviation higher, the conditional closure risk from underperformance would increase to 64.6% ($50\% \times (1 + (24.5\% \times (1 + 18.9\%)))$). The two percentage points increase in closure risk is economically significant – it translates into an additional 100 fund closures every year with 5,000 active equity funds in the market. The exacerbation factor is also statistically significant. I calculate the z-score using the standard error obtained with the delta method and report it in the parenthesis at the bottom. Columns 2 and 3 use past 2- and 3-year excess returns and yield qualitatively similar results.

Columns 4 to 6 repeat the analyses in columns 1 to 3 with a stratified Cox model. The stratified model only assumes the same baseline hazard function for funds in the same style (instead of all funds). As a result, any observed or unobserved variables that affect all funds in the same style will be absorbed into the style-specific hazard function that is ultimately left unestimated. The stratification by style in the Cox model is analogous to style fixed effects in a panel regression. We see that all estimates remain qualitatively the same, suggesting that the exacerbation of closure risk is robust to style-specific factors. Columns 7 to 9 add fund-level controls including age, size, and management fee. Holding all else constant, fund age is positively associated with closure risk while fund size is negatively associated with closure risk. Management fee has a statistically and economically insignificant effect on fund closure. The magnitude of the coefficient of the interaction term increases after adding fund-level controls, while the coefficient of past performance decreases. As a result, the exacerbation of the closure risk, calculated as the ratio of the two, becomes even stronger. These results show that the relation between passive investing and the closure of underperforming funds is robust to different specifications. The results are also robust to alternative definitions of excess returns. Using return over fees, CAPM alpha, and Fama-French 3-factor alpha yields qualitatively similar results.

An endogeneity concern is that unobserved confounding variables, such as the popularity shock described in section 2.3, could affect both the passive size and fund survival. I repeat the analyses in **Table 2** with the passive size instrumented by the shift-share instrumental variable (SSIV). The base share of the SSIV, fund families' asset allocation, is determined by longstanding investment expertise and is unrelated to short-term unobservable shocks. Therefore, the results using instrumented passive size are free from biases caused by potential omitted variables such as the popularity shock. **Table 3** shows the estimates using passive size instrumented by the SSIV.

Insert **Table 3** About Here

The point estimates in **Table 3** are close to those in **Table 2**. The main variable of interest and the exacerbation factor remain statistically and economically significant for all but one column. The results suggest that the MLE estimates likely do not suffer from the omitted variable problem.

The results in **Table 2** and **3** provide a novel explanation as to why the active mutual fund industry becomes more skilled over time – unskilled managers are driven out of business faster due to the rise of passive investing. My results explain the empirical observation made by Pástor et al. (2015). They show that the active industry becomes more skilled while holding individual manager's skill constant. They propose two possibilities – skilled managers' entry and unskilled managers' exit – and speculate that the former is more likely. My results show that the latter is also an important channel through which the active industry becomes more skilled, especially in the context of the rise of passive investing.

3.1.1. Falsification Test of the Economic Channel

I conduct a falsification test of the economic channel in this section. As mentioned in detail in section 2.1, the economic channel is that investors observe past performance to infer active managers' skill conditional on the level of passive investment. Namely, investors Bayesian-update their private belief about managers' skills using public signals. As a result, an ideal experiment to test this channel would be to make the past performance not observable (so that it is no longer a public signal) but otherwise unchanged and see whether the exacerbation of closure risk diminishes. If the exacerbation diminishes with the unobserved but otherwise identical past returns, it strongly supports the Bayesian learning channel.

The key is to change the observability of past returns without changing other return characteristics. I exploit an arbitrary discontinuity in the reporting norm of mutual funds – they all report their past performance in full-year increments at all times. For example, **Figure 6** shows that Vanguard and Blackrock report past performance only in full-year increments on their websites. This reporting norm makes obtaining the non-full-year performance extremely difficult for most investors without subscriptions to professional databases. As a result, while the past 1-, 2-, and 3-year performances are easily obtainable, the past 11-, 23-, and 35-month performances are near unobservable to most investors. In addition, the year-minus-one-month performances are otherwise identical to the full-year performances because one month is a small increment compared to full years, especially for two- and three-year returns. For example, at the end of June 2017, the three-year past returns starting from July 2014 are very close to the 35-month past returns starting from August 2014. The discontinuous difference is that the former is readily observable but the latter is not observable without significant search cost (Sirri & Tufano, 1998).

Insert **Figure 6** About Here

I conduct the falsification test by repeating the analysis in **Table 3** using year-minus-one-month past performances instead of full-year ones. The results are reported in **Table 4**. We see that the coefficient of the interaction term and the exacerbation factor become smaller for all specifications. In 7 out of 9 specifications, the exacerbation factor with year-minus-one-month performances shrinks by more than half compared to that with full-year performances. In more than half of the specifications, the effect is statistically indistinguishable from zero. The lack of exacerbation of closure risk using unobserved returns strongly supports the Bayesian learning channel. Since the year-minus-one-month returns are not observed, they cannot be used in the Bayesian learning of the investors and therefore cannot be exacerbated by the rise of passive investing. However, these year-minus-one-month returns do predict closure with similar magnitude compared to the full-year ones because they are still strongly correlated with the manager's skill. The similar magnitude of the coefficient in Lagged Excess Return further supports the "otherwise identical" condition of the discontinuity design. The results using uninstrumented passive size are qualitatively the same and are reported in **Appendix A5**.

Insert **Table 4** About Here

3.2. Active Fund Closet Indexing

Next, I examine the relation between passive investing and active manager's risk-taking. Greater passive investing leads to a more skilled active industry, and therefore skilled active managers take less risk to reveal their skills more quickly (Hypothesis 2). I measure active funds' risk-taking in the next year with two metrics – the tracking error and portfolio turnover ratio. I estimate the following regression:

$$Y_{i,t} = \beta \times \widehat{\text{Passive Size}}_{k,t} + X_{i,t} + \zeta_i + \tau_t + \epsilon_{i,t}, \tag{7}$$

where $Y_{i,t}$ is the future Tracking Error or Portfolio Turnover, and ζ_i and τ_t are fund and year-month fixed effects. Fund fixed effects sweep out any fund-specific time-invariant effect such as the family that the fund belongs to, established reputation, and so on. Year-month fixed effects control for broad economic conditions in each month that apply to all sample funds. $X_{i,t}$ a vector of fund-level controls including lagged fund size and management fee (fund age is absorbed by fund and time fixed effects jointly). I standardize continuous variables such as Tracking Error, Portfolio Turnover, and Passive Size to have a standard deviation of 1 for ease of interpretation.

Insert **Table 5** About Here

Table 5 presents the regression results of **Equation (7)** and shows that greater passive investment makes active fund managers take less risk. Columns 1 to 3 report results with future tracking errors and columns 4 to 6 report results with future portfolio turnover ratios. We see that the level of passive investment negatively predicts the risk that funds take. The estimates are economically and statistically significant. A one standard deviation increase in passive investment leads to a 0.12 to 0.15 standard deviation decrease in risk-taking. Consistent with Hypothesis 2, surviving fund managers prefer a lower risk given the rise of passive investment because they can reveal their high skill to investors faster. The OLS results are qualitatively the same and are reported in **Appendix A5**.

The results reconcile the closet indexing behavior, which is often interpreted as a sign of lack of skill, and the large literature that documents skill in the active mutual fund industry. The economic channel of Hypothesis 2 resembles the tournament incentive characterized in Brown et al. (1996). In their setting, top managers prefer a low risk to "lock in" their lead in the tournament, whereas in my setting, skilled managers prefer a low risk to "lock in" their outperformance against the benchmark. This closet indexing behavior also helps explain why the passive ownership is much higher than what many people think it is (Chinco & Sammon, 2024).

My results in the U.S. mutual fund industry contrast with those of Cremers et al. (2016), who examine the international market with a sample ending in 2010. They find that passive investing makes active funds more active. A potential explanation for this difference is that the behavior of *unskilled* active managers dominates in the international markets in the early years, while the behavior of *skilled* managers dominates in the U.S. more recently. As demonstrated in **Figure 3**, unskilled managers compete against passive investing by taking higher risks to maximize their chances of outperforming the benchmark. In contrast, skilled managers compete by taking less risk to minimize their chances of underperforming the benchmark. Therefore, Cremers et al. (2016) and this paper provide complementary empirical evidence on how active managers compete against passive investing given different levels of skills.

3.3. Active Fund Homogenization

A direct consequence of the closet indexing behavior on the entire active industry is that the performance dispersion of active funds decreases (Hypothesis 3). As a result, the rise of passive investing makes the active management industry more homogenized. To test this hypothesis, I estimate the following regression:

$$\text{Dispersion}_{k,t+j} = \beta \times \widehat{\text{Passive Size}}_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t+j}, \tag{8}$$

where $\text{Dispersion}_{k,t+j}$ is the return dispersion of all active funds in fund style k starting from month $t+j$ to $t+j+11$, i.e., a forward rolling window with a length of 12 months starting from $t+j$. κ_k are fund style fixed effects that sweep out all style-specific, time-invariant effects such as investors' 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 investors' loss of income from a financial crisis. I standardize continuous variables such as Dispersion and Passive Size to have a standard deviation of 1 for ease of interpretation.

Insert **Table 6** About Here

Table 6 presents the regression results of **Equation (8)** using the first six periods of the rolling window. The results show that passive investment shrinks the performance dispersion in the active mutual fund industry. A one standard deviation increase in passive size leads to a 0.25 standard deviation reduction of return dispersion in the immediate future. The estimate remains robust using a rolling window starting in the more distant future, with slight decay in the magnitude. The estimate is also robust to using different lengths of rolling windows to calculate the industry-level return dispersion. The results reconcile the recent homogenization trend in the active mutual fund industry, which is often seen as a lack of skill, and the large literature that documents skill in the active mutual fund industry. The OLS results are qualitatively similar and are reported in **Appendix A5**.

3.4. Noise and Market Efficiency

In this section, I examine the relation between passive investing and the noise in stock prices. The economic channel predicts that the rise of passive investing makes stock prices less noisy (Hypothesis 4). There are two reasons for this prediction. On the extensive margin, unskilled managers, who take high risks with low skills and therefore introduce noise into stock prices, are weeded out faster. On the intensive margin, skilled managers take less risk by focusing on a few high-conviction stock ideas and closet-indexing a significant portion of their portfolio. The change in the behavior of skilled managers, driven by the rise of passive investing, could also affect the types of information incorporated in stock prices. Thus, I separately examine the effect of passive investing on the information content in stock prices.

I decompose stock returns into a noise component and three information components following Hasbrouck (1993) and Brogaard et al. (2022). Specifically, I run a vector autoregression (VAR) that includes market return, stock return, and stock order flow imbalance. The fraction of stock return variation not explained by the VAR, i.e., the innovation of the VAR, is the noise component. The fraction of stock return variation explained by the VAR represents the information content in stock prices, which is further decomposed into three components. The fraction of stock return variation explained by market return in the VAR is the market-wide information component. The fractions explained by stock return and stock order flow imbalance are the firm-specific public information component and the firm-specific private information component, respectively. I scale these four components (noise, market-wide information, firm-specific public information, and firm-specific private information) by the variance of the stock return to avoid potential biases arising from non-stationary time series. Together, these four components sum to unity and provide a comprehensive measure of the noise and information content in stock prices.

I estimate the following regression:

$$Y_{s\in k,t} = \beta \times \widehat{\text{Passive Share}}_{k,t} + X_{s,t} + \kappa_k + \xi_s + \tau_t + \epsilon_{s,t}, \tag{9}$$

where $Y_{s\in k,t}$ is the market efficiency measure for stock s. I match each stock to the relevant investment style if stock s is held in the largest passive fund in style k. This procedure approximates the index ownership of stock s in style k. κ_k, ξ_s, and τ_t represent fund style, stock, and year-month fixed effects, respectively. $X_{s,t}$ is a vector of stock-level controls, including lagged market capitalization and trading volume. I standardize continuous variables, including all market efficiency measures and Passive Size, to have a standard deviation of 1 for ease of interpretation.

Insert **Table 7** About Here

Table 7 presents the regression results of **Equation (9)**. Column (1) examine the effect of passive investing on noise. Consistent with Hypothesis 4, the rise of passive investing leads to less noise in stock prices. The magnitude of the effect is statistically and economically significant. A one standard deviation increase in passive investing leads to a 0.1 standard deviation decrease in noise fraction in stock prices, which is about 7.5% of the median noise fraction. Columns (2) to (4) examine the type of information incorporated in stock prices. A one standard deviation increase in passive investing leads to a 0.16 standard deviation increase in market-wide information. The firm-specific information decreases – the public information decreases by 0.08 standard deviation and the private information decreases by 0.03 standard deviation (although not statistically significant). The reduction in firm-specific information is consistent with the closet indexing behavior by skilled active fund managers, who reduce their information production in specific stocks (Petajisto, 2013; Basak & Pavlova, 2013). These results are consistent with Sammon (2023), who documents a decline in the firm-specific information incorporated in stock prices before earnings announcements as passive investments grow. However, this reduction in firm-specific information is more than made up by the increase in market-wide information in stock prices. One plausible explanation is that even though active managers engage less in stock picking and keep their portfolios close to the passive benchmark, their primary focus pivots to timing the market. My results suggest that skilled fund managers shift their attention from stock-picking to market-timing with the rise of passive investing. This shift is an additional dimension of the time-varying skill of active managers, complementing the empirical observation by Kacperczyk, Nieuwerburgh, and Veldkamp (2014), who document skilled active managers focus on stock-picking in bull markets and market-timing in bear markets.

My economic framework is different than that of the recent work by Coles et al. (2022) and Malikov (2024), who provide important insight on passive investing and market efficiency with theoretical and empirical evidence. In their work, investors directly invest in stock markets and endogenize their choice of being active or passive with information cost and returns on investment. In my framework, investors always invest through mutual funds and choose to invest in passive funds when they believe active funds cannot outperform.

Therefore, they study passive investing and market efficiency through the information production channel akin to Grossman and Stiglitz (1980), while I do so through the mutual fund industry channel akin to Berk and Green (2004) and Pástor and Stambaugh (2012). These results provide complementary evidence on how passive investing affects market efficiency in different contexts.

Taken together, the rise of passive investing leads to less noise and more overall information in stock prices, thereby improving market efficiency. Since the rise of passive investing improves market efficiency to date, the current level of passive investing is potentially lower than optimal from a market efficiency perspective in the U.S.

4. Conclusion

This paper provides a new perspective on the role of passive investing within the active mutual fund industry. Contrary to common perceptions, I find that the rise of passive investing is a reason for, rather than a contradiction to, a more skilled mutual fund industry. Greater passive investing accelerates the exit of underperforming funds. Skilled managers choose to closet index to outperform consistently and reveal their high skill faster – contrary to the common belief that closet indexing suggests a lack of skill. As a result, the active mutual fund industry becomes increasingly homogenized but more skilled at the same time. Finally, the rise of passive investing reduces the noise in stock prices and improves stock market efficiency.

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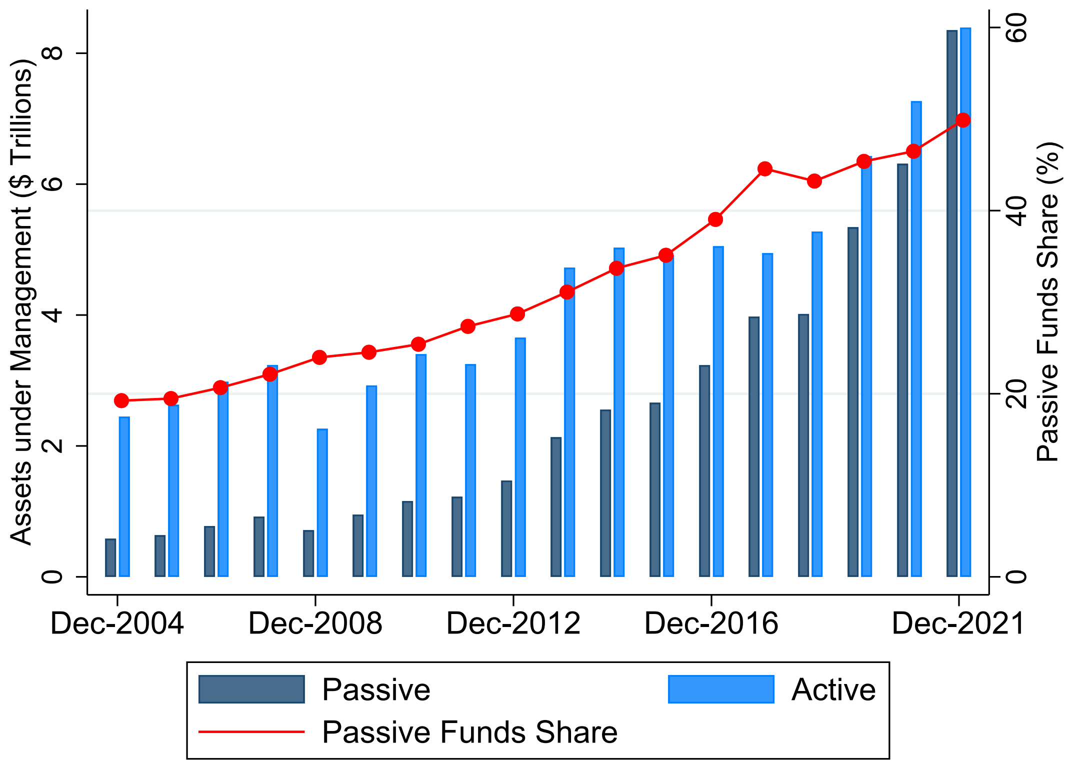
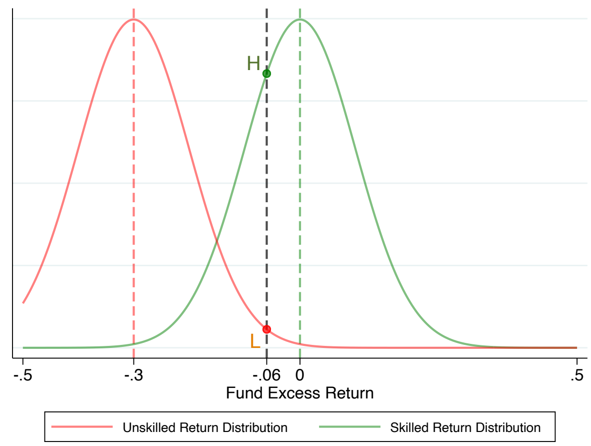
Figure 1. Passive Investing Overtakes Active Investing



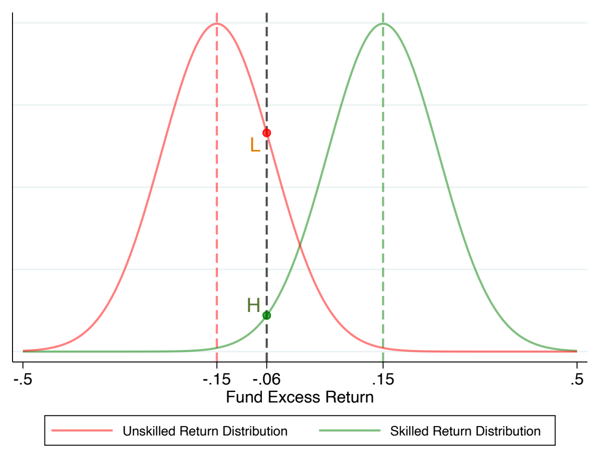
The figure plots the assets under management of U.S. domestic equity mutual funds that are actively and passively managed from 2004 to 2021.

Figure 2. Investors' Inference of Active Managers' Skill

(a) With Low Passive Investment



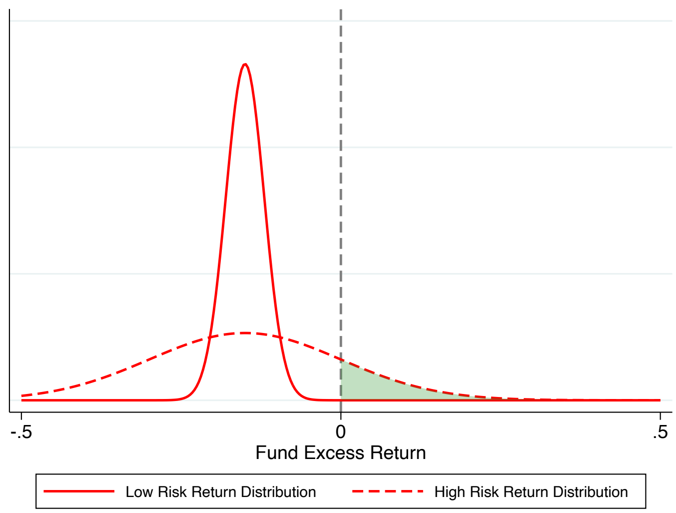
(b) With High Passive Investment



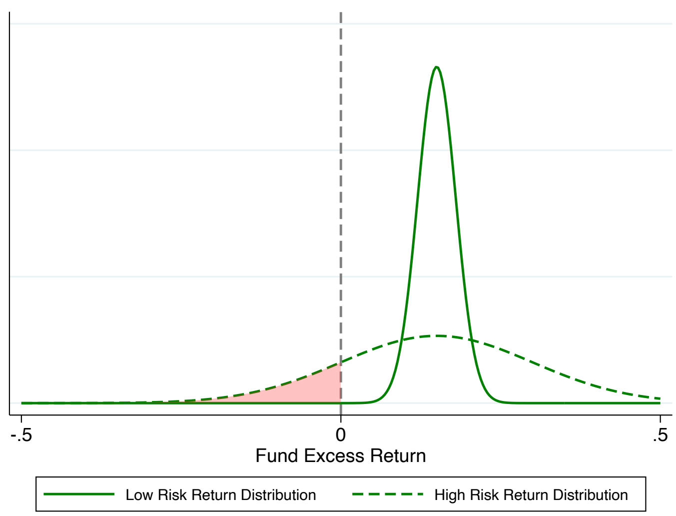
The figure plots how investors infer the active manager's skill level with the same performance, -6% below benchmark, with different levels of passive investing. The red curve to the left plots the excess return distribution of an unskilled manager and the green curve to the right plots the excess return distribution of a skilled manager. Panel (a) plots the dynamic where passive investing is low and all funds have a lower expected return and panel (b) plots the dynamic where passive investing is high and all funds have a higher expected return. H is the intersection of the return realization and the skilled return distribution and L is the intersection of the return realization and the unskilled return distribution. The likelihood (odds) ratio that the investors believe this manager is unskilled rather than skilled is L/H.

Figure 3. Active Managers' Risk Taking by Skill Level

(a) Unskilled Manager



(b) Skilled Manager



Panel (a) of the figure plots the excess return distribution of unskilled active managers with different level of risk-taking. The dashed flat curve plots the distribution with high risk and the solid peak curve plots the distribution with low risk. The green area under the curve represents the probability of an unskilled manager outperforming the benchmark. Panel (b) of the figure plots the dynamic for skilled active managers. The red area under the curve represents the probability of a skilled manager underperforming the benchmark.

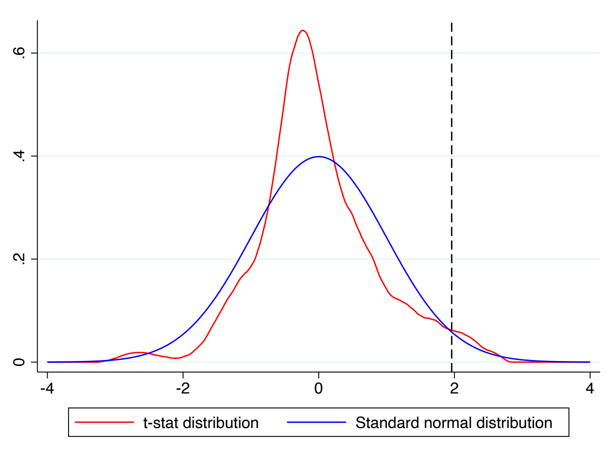
Figure 4. Shift-Share Instrumental Variable (SSIV): Numeric Example

	Fund family A Asset growth $g_A = 30\%$	Fund family B Asset growth $g_B = 10\%$
Style 1	Fund family A's allocation in style 1 $z_{1,A} = 80\%$	Fund family B's allocation in style 1 $z_{1,B} = 40\%$
Style 2	Fund family A's allocation in style 2 $z_{2,A} = 20\%$	Fund family B's allocation in style 2 $z_{2,B} = 60\%$
	Composite growth (SSIV)	
Style 1	$B_1 = 30\% \times 80\% + 10\% \times 40\% = 28\%$	
Style 2	$B_2 = 30\% \times 20\% + 10\% \times 60\% = 12\%$	

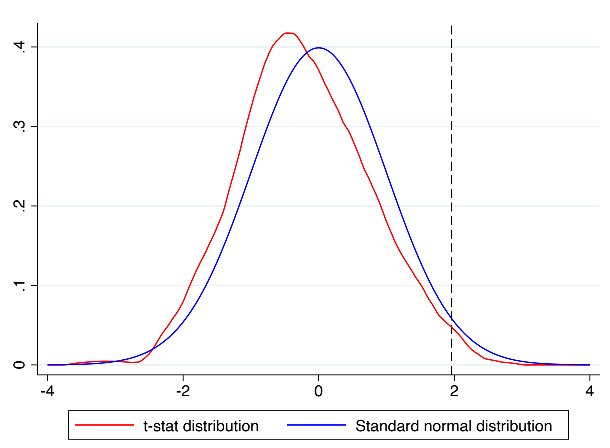
The figure provides a numeric example of the construction of the shift-share instrumental variable with two investment styles and two fund families.

Figure 5. Style-Level Fund Flow, Count, and Return by Fund Family

(a) Fund Count



(b) Fund Flow



The figure plots in red the distribution of the t-stat of the following regression *by each fund family*:

$$y_{k,t} = \beta \times \text{Return}_{k,t-1} + \kappa_k + \epsilon_{k,t} \ ,$$

where the dependent variable $y_{k,t}$ is either $\text{Count}_{k,t}$ or $\text{Flow}_{k,t}$. $\text{Count}_{k,t}$ is the number of active funds in style k run by the fund family. $\text{Flow}_{k,t}$ is the fund flow (defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot \text{Return}_{i,t})/\text{TNA}_{i,t-1}$) aggregate to the investment-style k within the fund family. $\text{Return}_{k,t-1}$ is the average fund return of investment-style k within the family. κ_k is investment-style fixed effects. The robust standard error used to calculate the t-stat is clustered on investment-style and year-month level. The standard normal distribution is also plotted in blue for ease of comparison.

Figure 6. 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

Panels (a) and (b) show a screenshot of a fund's performance disclosed on its website run by Vanguard and Blackrock, respectively.

Table 1
Summary Statistics

The table presents the summary statistics of the variables used in the analyses. Past 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 and in the past 11, 23, and 35 months. Forward Tracking Error is the standard deviation of the excess return of the fund for the following three years. Forward Turnover Ratio is CRSP MFDB variable *turn_ratio* for the following three years. Variance decomposition shares are estimated in a vector autoregression (VAR) following Brogaard et al. (2022). The decomposition components are scaled by the variance of stock price into shares such that they add up to 1. Noise corresponds to the innovation term in the VAR. Market-wide info corresponds to the market return in the VAR. Firm-specific public info corresponds to the stock return in the VAR. Firm-specific private info corresponds to the stock order flow imbalance in the VAR. Forward 1-Year Return Dispersion is the standard deviation of excess returns of all funds in a fund style for the next year. Passive Size is the passive AUM divided by the total AUM for a fund style. Count of active funds is the number of active funds in a fund style.

	Mean	StDev	P10	Median	P90	#Obs.
Active Funds (N=20,789)						
Past Excess Returns (%)						
11-Month	-0.97	9.70	-8.22	-1.16	6.30	1,729,947
1-Year	-1.05	10.25	-8.67	-1.27	6.64	1,710,183
23-Month	-1.86	15.27	-13.38	-2.51	9.94	1,508,118
2-Year	-1.96	15.65	-13.85	-2.63	10.22	1,490,371
35-Month	-2.96	19.18	-18.93	-3.83	12.87	1,307,368
3-Year	-3.04	19.48	-19.37	-3.92	13.10	1,291,198
Forward Tracking Error (%)						
1-Year	1.45	0.82	0.65	1.24	2.56	1,912,263
2-Year	1.46	0.72	0.73	1.27	2.45	1,490,167
3-Year	1.44	0.67	0.75	1.30	2.37	1,291,033
Foward Turnover Ratio (%)						
1-Year	70.09	107.74	15.00	50.00	136.00	1,266,695
2-Year	69.54	103.33	16.50	51.00	130.00	1,271,293
3-Year	69.13	101.58	17.00	51.33	128.00	1,271,700
Stocks (N=4,663)						
Variance Decomposition Shares (%)						
Noise	13.60	8.44	5.74	11.39	24.20	421,825
Market-wide Info	21.56	15.33	3.27	18.86	43.89	421,825
Firm-specific Public Info	32.32	14.58	13.96	31.20	51.95	421,825
Firm-specific Private Info	32.52	16.75	10.70	31.51	55.79	421,825
Fund Styles (N=8)						
Forward 1-Year Return Dispersion (%)	1.69	0.49	1.15	1.59	2.37	1,602
Passive Size (%)	25.94	13.28	9.57	23.21	45.91	1,602

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 closure 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 estimates under the assumption that all funds have the same underlying parametric hazard function (although left unestimated). Columns 4-6 report the estimates under the assumption that funds in the same investment style have the same underlying parametric hazard function (also left unestimated). Columns 7-9 add fund-level controls to columns 4-6 such as fund age, size, and management fee. 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 the hazard ratio for ease of interpretation. Z-scores are reported in parentheses. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effect of the interaction and the marginal effect of the lagged excess return. The Z-score of the risk exacerbation factor is estimated using the delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Passive Size	-0.046***	-0.074***	-0.056***	-0.040***	-0.070***	-0.051***	-0.049***	-0.112***	-0.092***
× Lagged Excess Return	(-3.21)	(-4.78)	(-3.21)	(-2.70)	(-4.22)	(-2.83)	(-3.20)	(-6.35)	(-4.79)
Lagged Excess Return	-0.245***	-0.234***	-0.307***	-0.292***	-0.292***	-0.347***	-0.269***	-0.173***	-0.227***
	(-9.10)	(-7.42)	(-9.04)	(-10.94)	(-9.03)	(-10.10)	(-9.49)	(-4.60)	(-5.61)
Passive Size	-0.140***	-0.134***	-0.116***						
	(-8.64)	(-7.63)	(-6.01)						
Fund Age							0.061***	0.053***	0.048***
							(15.07)	(11.60)	(9.37)
Fund Size							-0.201***	-0.210***	-0.216***
							(-48.24)	(-46.56)	(-43.72)
Management Fee							0.000	-0.001*	-0.001*
							(0.11)	(-1.91)	(-1.71)
Strata by Style	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Return Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	1,710,183	1,490,371	1,291,198	1,710,183	1,490,371	1,291,198	1,424,381	1,241,597	1,074,759
Exacerbation Factor	0.189***	0.319***	0.182***	0.137***	0.241***	0.148***	0.181***	0.646***	0.407***
from Passive Investment	(2.539)	(3.193)	(2.567)	(2.303)	(3.170)	(2.388)	(2.570)	(2.958)	(2.873)

Table 3
Passive Investment and Active Funds Survival – SSIV Estimates

The table repeats the analysis in **Table 2** using the instrumented passive size as the independent variable. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of the hazard ratio for ease of interpretation. Z-scores are reported in parentheses. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effect of the interaction and the marginal effect of the lagged excess return. The Z-score of the risk exacerbation factor is estimated using the delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{\text{Passive Size}}$	-0.038***	-0.069***	-0.059***	-0.022	-0.065***	-0.054***	-0.033**	-0.106***	-0.093***
× Lagged Excess Return	(-2.72)	(-4.67)	(-3.60)	(-1.53)	(-4.03)	(-3.09)	(-2.24)	(-6.23)	(-4.98)
Lagged Excess Return	-0.254***	-0.239***	-0.302***	-0.315***	-0.298***	-0.343***	-0.288***	-0.175***	-0.223***
	(-9.23)	(-7.61)	(-8.98)	(-11.52)	(-9.17)	(-10.00)	(-9.98)	(-4.62)	(-5.50)
Passive Size	-0.135***	-0.128***	-0.111***						
	(-8.66)	(-7.63)	(-6.03)						
Fund Age							0.061***	0.052***	0.047***
							(14.94)	(11.41)	(9.17)
Fund Size							-0.201***	-0.210***	-0.215***
							(-48.12)	(-46.41)	(-43.54)
Management Fee							0.000	-0.001*	-0.001*
							(0.12)	(-1.91)	(-1.72)
Strata by Style	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Return Period	1 Year	2 Year	3 Year	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	1,340,331	1,162,267	999,316
Exacerbation Factor	0.150**	0.290***	0.196***	0.070	0.217***	0.156**	0.115*	0.605***	0.415***
from Passive Investment	(2.232)	(3.175)	(2.798)	(1.400)	(3.075)	(2.562)	(1.933)	(2.935)	(2.908)

Table 4
Passive Investment and Active Funds Survival – Falsification

The table repeats the analysis in **Table 3** using the past 11-, 23, and 35-month returns instead of past 1-, 2-, and 3-year returns as the independent variable. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of the hazard ratio for ease of interpretation. Z-scores are reported in parentheses. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effect of the interaction and the marginal effect of the lagged excess return. The Z-score of the risk exacerbation factor is estimated using the delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{\text{Passive Size}}$	-0.014	-0.039***	-0.050***	0.005	-0.017	-0.028*	-0.002	-0.056***	-0.067***
× Lagged Excess Return	(-1.03)	(-2.72)	(-3.16)	(0.39)	(-1.18)	(-1.67)	(-0.17)	(-3.58)	(-3.85)
Lagged Excess Return	-0.287***	-0.273***	-0.289***	-0.351***	-0.378***	-0.396***	-0.334***	-0.286***	-0.280***
	(-11.37)	(-9.57)	(-9.21)	(-14.09)	(-13.71)	(-13.06)	(-12.71)	(-9.08)	(-7.93)
Passive Size	-0.135***	-0.136***	-0.122***						
	(-8.85)	(-8.34)	(-6.94)						
Fund Age							0.060***	0.053***	0.046***
							(14.84)	(11.87)	(9.23)
Fund Size							-0.193***	-0.204***	-0.210***
							(-48.21)	(-47.26)	(-44.79)
Management Fee							0.000	0.000	-0.001
							(0.29)	(0.33)	(-1.47)
Strata by Style	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Return Period	11 Month	23 Month	35 Month	11 Month	23 Month	35 Month	11 Month	23 Month	35 Month
Observations	1,612,835	1,397,253	1,201,652	1,612,835	1,397,253	1,201,652	1,354,902	1,176,783	1,012,440
Exacerbation Factor	0.048	0.142**	0.174**	-0.015	0.046	0.070	0.007	0.196***	0.241***
from Passive Investment	(0.966)	(2.252)	(2.531)	(-0.394)	(1.122)	(1.553)	(0.164)	(2.799)	(2.851)

Table 5
Passive Investment and Active Funds Closet Indexing

The table presents the results from the following regression:

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

where closet-indexing measure $Y_{i,t}$ is the future tracking error or portfolio turnover. Tracking error is measured as the standard deviation of the return difference between the fund and its benchmark from $t+1$ to $t+12$, $t+24$, or $t+36$. Portfolio turnover is measured as the average of MFDB variable *turn_ratio* for the next one, two, or three years after month t. $\widehat{\text{Passive Size}}_{k,t}$ is the passive size in fund style k in month t, instrumented by the SSIV. $X_{i,t}$ is a vector of fund-level controls including fund size and management fee. 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)	(5)	(6)
	Tracking Error			Portfolio Turnover		
$\widehat{\text{Passive Size}}$	-0.142***	-0.125***	-0.116***	-0.151***	-0.138***	-0.129***
	(-3.70)	(-3.69)	(-3.77)	(-5.30)	(-4.72)	(-4.39)
Fund Size	-0.003	-0.001	-0.000	-0.013***	-0.011***	-0.010***
	(-1.04)	(-0.51)	(-0.17)	(-4.62)	(-4.17)	(-3.57)
Management Fee	-0.000***	0.000	-0.000	0.001**	0.001**	0.001**
	(-3.49)	(0.45)	(-0.45)	(2.06)	(2.18)	(2.44)
Look-ahead Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,447,622	1,185,046	1,022,331	1,185,995	1,190,260	1,190,612
R-squared	0.673	0.775	0.818	0.741	0.798	0.831

Table 6
Passive Investment and Active Funds Homogenization

The table presents the results from the following regression:

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

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_obj_cd*, using a 12-month rolling window starting from month $t+j$. $\widehat{\text{Passive Size}}_{k,t}$ is the passive size in style k in month t, instrumented by 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion Window	$1 \rightarrow 12$	$2 \rightarrow 13$	$3 \rightarrow 14$	$4 \rightarrow 15$	$5 \rightarrow 16$	$6 \rightarrow 17$
$\widehat{\text{Passive Size}}$	-0.250***	-0.236***	-0.232***	-0.220***	-0.213***	-0.218***
	(-5.65)	(-5.51)	(-5.44)	(-5.16)	(-4.98)	(-5.14)
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	0.706	0.705	0.703	0.702	0.701	0.702

Table 7
Passive Investment and Market Efficiency

The table represents the results from the following regression:

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

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 shares of the four components from the variance decomposition following Brogaard et al. (2022). Specifically, the variation in stock return is decomposed into one noise component and three components that correspond to market information, public firm-specific information, and private firm-specific information. $\widehat{\text{Passive Size}}$ is the passive size in style k in month t, instrumented by the SSIV. $X_{i,t}$ is a vector of stock-level controls including the market capitalization and trading volume in the last month. κ_k, ξ_s, and τ_t are fund style, 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) Noise	(2) Market-wide Info	(3) Firm-specific Public Info	(4) Firm-specific Private Info
$\widehat{\text{Passive Size}}$	-0.100***	0.162***	-0.076**	-0.032
	(-3.54)	(3.50)	(-2.47)	(-1.00)
Market Capitalization	-0.007	0.099***	-0.111***	0.010
	(-0.42)	(6.26)	(-6.64)	(0.72)
Trading Volume	-0.020**	-0.038***	0.019**	0.028***
	(-2.10)	(-3.34)	(2.47)	(2.93)
Fund Style FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	421,740	421,740	421,740	421,740
R-squared	0.389	0.556	0.300	0.418

Internet Appendix

A1. Stylized Model

This appendix provides a stylized model of active and passive investment in which investors learn about active fund managers' skill based on Pástor and Stambaugh (2012). I derive two predictions corresponding to Hypothesis 1 and Hypothesis 2. The key insight is that passive investment accelerates investors' learning of mutual fund managers' skill and affects fund managers' incentive for risk-taking.

Players. The model consists of three types of players – active fund managers, active investors, and one passive investor. M atomistic fund managers, indexed by i, operate M active mutual funds. Fund managers are endowed with an unobservable portfolio management skill a_i. Skilled managers are expected to generate an excess return of $a_i = a$, while unskilled managers are expected to generate an excess return of $a_i = -a$ (with $a > 0$) 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), who model managers to have homogeneous skills. N active investors, indexed by j, competitively allocate their wealth W between the passive fund and M active funds. The passive investor is endowed with wealth W_p and always invests in the passive fund, which is the benchmark for all active funds.

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:

$$\tilde{r}_{i,t} = \tilde{r}_{P,t} + (a_i - b\frac{\sum_i s_i}{W + W_P}) + \tilde{x}_t + \tilde{\epsilon}_{i,t}, \tag{A1}$$

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 the passive fund 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 industry-level decreasing returns to relative scale ($b > 0$) in active fund management (Pástor & Stambaugh, 2012). I assume $a - b \geq 0$, namely skilled managers are always able to weakly outperform the passive benchmark in expectation even if the entire market invests actively. Neither managers nor investors know managers' skill in the beginning but rather 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 that 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:

$$\max_{f_i, \sigma_i} f_i s_i. \tag{A2}$$

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

$$\max_{\{\omega_{j,i}\}} \left[\mu_P + \sum_{i=1}^{M} (E[a_i|D] - b \frac{\sum_i s_i}{W + W_P} - f_i) \omega_{j,i} \right], \tag{A3}$$

where D is the information set that is available to investor j. I assume active investors are risk-neutral for tractability. Assuming mean-variance investors produces qualitatively similar results.

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

$$\hat{P}(a_i = -a | \hat{r}_i < \hat{r}_P) = \frac{P(\hat{r}_i < \hat{r}_P | a_i = -a) \cdot P(a_i = -a)}{P(\hat{r}_i < \hat{r}_P)}, \tag{A4}$$

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

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

$$\hat{P}(a_i = -a | \hat{r}_i < \hat{r}_P) = \frac{\Phi_1(by + a)q}{\Phi_1(by + a)q + \Phi_1(by - a)(1 - q)}, \tag{A5}$$

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

The model features an information asymmetry about fund managers' skill. Fund managers have direct knowledge of σ_i because they set the level of risk-taking of their fund. In contrast, investors do not observe σ_i and can only infer its value from historical performance. This information asymmetry makes the learning process characterized in **Equations (A4)** and **(A5)** faster and more accurate for managers than investors. Consequently, managers in this model understand their own skill level better than investors do after the first period, consistent with the empirical observation by Berk, van Binsbergen, and Liu (2017). Managers' information advantage allows them to strategically set their level of risk-taking σ_i depending on their own belief of their skill level (discussed in greater detail in proposition 2). If investors and managers have the same information set, managers' choice of σ_i would have no impact on the speed with which their skill is revealed to investors.

A1.1. 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 there is no always-passive investor, i.e., $W_P = 0$, active managers become homogeneous over time because unskilled managers exit the industry due to investors' learning of their lack of skills. Specifically, in each period, investors update their beliefs about a fund manager's skill level, forming a subjective probability on fund returns, and thereby adjusting their expectations of the fund's future performance. When all investors' expected return for a fund falls below the passive benchmark, they stop allocating capital to the fund, leading to its closure. As time approaches infinity ($t \to \infty$), investors perfectly infer managers' skill, resulting in the exit of all low-skilled managers. As a result, the levels of passive and active investments are fully endogenized and determined by exogenous inputs which include the skill level (a) and the decreasing returns to scale coefficient (b). In this case, the equilibrium fund fee is zero due to perfect competition among active managers, and the equilibrium expected alpha is also zero due to perfect competition among investors. The equilibrium relative size of the active industry is a/b and all managers possess the skill to outperform the benchmark by a with the first dollar invested actively. This equilibrium converges to that in Pástor and Stambaugh (2012).

Outside of this special case with $W_P = 0$, my model differ from Pástor and Stambaugh (2012) in two important ways. First, active managers have heterogeneous skills in my model but are homogeneous in theirs. To highlight this distinction, my analysis concentrates on the time before $t \to \infty$, when both skilled and unskilled managers are present in the market and investors are still learning. Second, I model an always-passive investor with an exogenously set wealth W_P. This feature could be interpreted as creating a partial equilibrium because it introduces variations in passive investment levels that are not fully explained by the interplay between investors and managers. This exogenous always-passive investor is motivated by the empirical observation that trading decisions, including the choice between active and passive investing, are influenced by factors beyond pure utility maximization (Bikhchandani, Hirshleifer, & Welch, 1992; Brown et al., 1996; Odean, 1998; Barber & Odean, 2000).

My subsequent analysis explores the implications of changes in the level of passive investments, which is (partially) exogenously set by W_P. Exogenous changes in the level of passive investments generate important predictions that corresponds to Hypothesis 1 and Hypothesis 2 in the main paper.

A1.2. Comparative Statics

I generate two predictions in this section. Exogenous changes in the relative size of passive investments (y) have implications for active funds' survival and active fund's risk-taking.

Prediction 1. Greater passive investment makes underperforming funds more likely to exit:

$$\frac{\partial}{\partial y}\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P) < 0. \tag{A6}$$

Proof. Denote $\Phi_1(by + a)q$ as m and $\Phi_1(by - a)(1 - q)$ as n in **Equation (A4)**, the derivative of $\hat{P}(a_i = -a|\hat{r}_i < \hat{r}_P)$ with respect to y can be written as:

$$\begin{aligned}\frac{\partial \hat{P}}{\partial y} &= \frac{\frac{\partial m}{\partial y}\Bigg(m+n\Bigg) - m\Bigg(\frac{\partial m}{\partial y} + \frac{\partial n}{\partial y}\Bigg)}{(m+n)^2} \\ &= \frac{\frac{\partial m}{\partial y}\cdot n - \frac{\partial n}{\partial y}\cdot m}{(m+n)^2}.\end{aligned} \tag{A7}$$

Focus on the numerator in **Equation (A7)** as the denominator is strictly positive and denote the PDF of $\Phi_1(\cdot)$ as $\phi_1(\cdot)$:

$$\begin{aligned}\frac{\partial m}{\partial y}\cdot n - \frac{\partial n}{\partial y}\cdot m &= \phi_1(by+a)bq\cdot\Phi_1(by-a)(1-q) - \phi_1(by-a)b(1-q)\cdot\Phi_1(by+a)q \\ &= bq(1-q)\Big(\phi_1(by+a)\Phi_1(by-a) - \phi_1(by-a)\Phi_1(by+a)\Big).\end{aligned} \tag{A8}$$

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:

$$\phi_1(by + a)\Phi_1(by - a) - \phi_1(by - a)\Phi_1(by + a) < 0. \tag{A9}$$

Namely, $\partial \hat{P}/\partial y < 0$. Therefore, given an underperformance, investor's posterior belief that the manager is unskilled increases in the relative size of passive management. ■

Prediction 2. Skilled managers take less risk with greater passive investing:

$$\frac{\partial}{\partial \sigma_i} \hat{P}(a_i = -a | \hat{r}_i < \hat{r}_P) < 0, \tag{A10}$$

so that they reveal their high skill levels to investors faster.

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

$$\frac{\partial \hat{P}}{\partial \sigma_i} = \frac{\dfrac{\partial m}{\partial \sigma_i} \cdot n - \dfrac{\partial n}{\partial \sigma_i} \cdot m}{(m + n)^2}. \tag{A11}$$

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

$$m = \Phi\left(\frac{by+a}{\sqrt{\sigma_x^2+\sigma_i^2}}\right)q = \Phi\left(\frac{by+a}{\sigma_i^{'}}\right)q, \tag{A12}$$

$$n = \Phi\left(\frac{by-a}{\sqrt{\sigma_x^2+\sigma_i^2}}\right)(1-q) = \Phi\left(\frac{by+a}{\sigma_i^{'}}\right)(1-q), \tag{A13}$$

where $\sigma_i^{'} = \sqrt{\sigma_x^2+\sigma_i^2}$. Focus on the numerator in **Equation (A11)** as the denominator is strictly positive:

$$\frac{\partial m}{\partial \sigma_i}\cdot n - \frac{\partial n}{\partial \sigma_i}\cdot m = \frac{\partial \sigma_i^{'}}{\partial \sigma_i}\left(\frac{\partial m}{\partial \sigma_i^{'}}\cdot n - \frac{\partial n}{\partial \sigma_i^{'}}\cdot m\right) \tag{A14}$$

$$= -\frac{\partial \sigma_i^{'}}{\partial \sigma_i}q(1-q)\left[\left(\frac{by+a}{\sigma_i^{'2}}\phi\left(\frac{by+a}{\sigma_i^{'}}\right)\Phi\left(\frac{by-a}{\sigma_i^{'}}\right)\right) - \left(\frac{by-a}{\sigma_i^{'2}}\phi\left(\frac{by-a}{\sigma_i^{'}}\right)\Phi\left(\frac{by+a}{\sigma_i^{'}}\right)\right)\right]. \tag{A15}$$

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, a low return variability accelerates investors' learning of managers' skill. ■

A2. Data Process

This appendix describe two details in the data cleaning process when using MFDB.

A2.1. CRSP Objective Code

The four-digit CRSP Objective Code generally does a good job aggregating information from Strategic Insights, Wiesenberger, and Lipper and providing continuous coverage. The first letter denote asset classes, which I restrict to "E" to filter for equity funds. As mentioned in the main paper, I require that all sample funds to have the same CRSP Objective Code throughout the sample to avoid issues arising from potential style drift (Wermers, 2012). There is one exception with the second digit for equity funds denotes whether the fund is domestic (D) or foreign (F). For example, from 2008 to 2009, there is a change in the second digit of the objective code of a few funds from one fund family from "D" to "F". However, their portfolio composition does not have meaningful change. A likely explanation is that in 2009 these funds state that they *may* invest in international equity but in reality never meaningfully do. The problem is not trivial – in one case, two share classes of the same fund that has this issue have a combined asset over $50 billion. Ignoring this issue would result in big discontinuous jumps in the total asset by CRSP Objective Code. As a result, whenever there is a change in the second digit of the CRSP Objective Code, I check the portfolio holdings to confirm whether the change is a mistake. In the case when portfolio holdings are not available (MFDB's holding coverage becomes relatively comprehensive starting about 2010), I manually check the fund prospectus to see if it explicitly state that they shift their focus from domestic to foreign equity (or the other way around). Unless the change in the second digit of the objective code is corroborated by the portfolio holdings or the prospectus, I ignore the change and use the old classification in terms of domestic or foreign.

A2.2. Index Fund Flag

MFDB also does a decent job identifying pure passive funds (with Index Fund Flag equals "D"), compared to search for "Index" in the fund name which can mis-classify active funds as passive (mostly index-enhanced funds, with Index Fund Flag equals "B" or "E"). There is also an exception with using Index Fund Flag equals "D". For example, in 2021, for unknown reasons, MFDB labels two funds, each with over $50 billion AUM, with Index Fund Flag equals "B" instead of "D", when these two funds are purely passive and track two popular Russell indices. Prior to 2021, these two funds have been consistently labeled with Index Fund Flag equals "D". Leaving this problem untreated also leads to big discontinuous jumps in the passive size calculation. There are two potential solutions to this problem. First, one could consider using Index Fund Flag equals either "D" or "B" to identify passive funds. However, this filter casts a nest that is way too wide and gathers way too many obviously active funds. Therefore, I use the second solution as the following. I treat the fund as a passive one if its Index Fund Flag has ever taken the value "D" throughout the sample. Admittedly, this method is also not perfect, but the funds that end up being labeled passive but are actually active generally have a small AUM. Therefore, this method provides the most precise measurement of the size of passive investing in a systematic fashion with minimal discretion from the researcher.

A3. Table A1: Variable Definitions

Variable Names	**Description**
i	An index denoting funds.
k	An index denoting investment styles.
f	An index denoting fund families.
s	An index denoting stocks.
t	An index denoting year-months.
Lagged Excess Return$_{i,t}$	The return of fund i minus the return of the largest passive fund in the style that it belongs to in month t.
Tracking Error$_{i,t}$	The forward 1-year tracking error of fund i compared to its benchmark, calculated as the standard deviation of Lagged Excess Return$_{i,t}$ in the following 12 periods.
Portfolio Turnover$_{i,t}$	The future portfolio turnover ratio for fund i during the year after month t.
Passive AUM$_{k,t}$	The total asset under management for all passive funds in investment style k in month t. See a detailed discussion around MFDB variables *index_fund_flag* and *crsp_obj_code* in **Appendix A2**.
Active AUM$_{k,t}$	The total asset under management for all active funds in investment style k in month t. See a detailed discussion around MFDB variables *index_fund_flag* and *crsp_obj_code* in **Appendix A2**.
Passive Size$_{k,t}$	$$\text{Passive Size}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t}}.$$

Continued on next page

Table A1 – continued from previous page

Variable Definitions	Description
$\widehat{\text{Passive Size}}_{k,t}$	$$\widehat{\text{Passive Size}}_{k,t} = \frac{\text{Passive AUM}_{k,t}}{\text{Passive AUM}_{k,t} + \text{Active AUM}_{k,t-1} \cdot \hat{g}_{k,t}}.$$
$\text{Dispersion}_{k,t+j}$	The standard deviation of $\text{Lagged Excess Return}_{i,t}$ of all funds in style k during a 12-month rolling window starting from $t+j$ to $t+j+11$.
$B_{k,t}$	The shift-share instrumental variable that is the composite asset growth for style k in month t driven by the asset allocation and asset growth by mutual fund families. $$B_{k,t} = \sum_f z_{k,f,t-1} \cdot g_{f,t}.$$
$z_{k,f,t}$	The weight of active assets in style k in month t within fund family f.
$g_{f,t}$	The growth rate of total active assets managed by fund family f in month t.
$g_{k,t}$	The growth rate of total active AUM in style k in month t.
$\hat{g}_{k,t}$	The predicted growth rate of total active AUM in style k in month t from the following equation: $$g_{k,t} = \alpha + \beta \cdot B_{k,t} + \kappa_k + \tau_t + \epsilon_{k,t}.$$
$\text{Return}_{k,t}$	The average return of all funds managed by a specific fund family in style k in month t (in **Equation 3**).

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Table A1 – continued from previous page

Variable Definitions	Description
$\text{Count}_{k,t}$	The number of funds managed by a specific fund family in style k in month t (in **Equation 3**).
$\text{Flow}_{k,t}$	The aggregate flow of all funds managed by a specific fund family in style k in month t (in **Equation 3**). The disaggregate individual fund flow is defined as $$\text{Flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot \text{Return}_{i,t}}{\text{TNA}_{i,t-1}},$$
$\text{Noise}_{s,t}$	The noise share in the return of stock s in month t following Brogaard et al. (2022).
Market-wide $\text{Info}_{s,t}$	The share for market-wide information in the return of stock s in month t following Brogaard et al. (2022).
Firm-specific Public $\text{Info}_{s,t}$	The share for firm-specific public information in the return of stock s in month t following Brogaard et al. (2022).
Firm-specific Private $\text{Info}_{s,t}$	The share for firm-specific private information in the return of stock s in month t following Brogaard et al. (2022).

A4. Robustness of the SSIV

This appendix discusses the additional robustness of the shift-share instrumental variable (SSIV).

Using the SSIV in fund risk-taking, fund homogenization, and market efficiency analyses and testing for weak IV problems is straightforward. Since the second stage is linear and the model is just-identified, the weak IV is as simple as comparing the first-stage F-statistic, which is the same as the Cragg-Donald statistic with just-identified IV, to the Stock-Yogo critical value. The F-statistic (8.1) exceeds the 5% critical value with 10% size distortion.

The implementation of the SSIV in fund survival analysis with a weak IV test deserves a technical note. Since the Cox model uses MLE to estimate a non-linear relation, the 2SLS procedure will produce wrong estimators for standard errors. Therefore, I first transform the Cox model, which predicts hazard risk $h(t|\boldsymbol{X}_i)$, to a Poisson regression that predicts hazard events, i.e., fund closures. This Poisson regression is equivalent to the Cox model used in the paper. Then I estimate the Poisson regression by GMM to obtain consistent estimators for the coefficients and standard errors. In the non-stratified specification, there are two endogenous variables (the standalone passive size and the interaction with past performance) and two instruments. In the stratified specification (transformed into a Poisson regression with style fixed effects), there is only one endogenous variable (the standalone passive size is subsumed by style fixed effects) and one instrument. In both cases, the first-stage F-statistic is greater than the corresponding Stock-Yogo critical values with 10% size distortion.

Two more factors are worth considering here. First, Angrist and Kolesár (2024) point out that the Staiger-Stock rule of thumb (F-statistic $>$ 10) is usually too high for single-instrument just-identified specifications. This is because if the instrument is so weak that it induces meaningful bias, it usually increases the second-stage standard errors to a point that the null cannot be rejected. As a result, the single-IV just-identified results in this paper are unlikely to suffer from weak instrument problems. Second, the Stock-Yogo test is designed for linear specifications. Therefore, the non-stratified Cox model, which is non-linear and has two instruments, deserves a closer look. Chernozhukov and Hansen (2008) develop a clever test for weak instrument test with the reduced-form estimates. I run the reduced-form specification of fund survival on the SSIV and estimate the standard error with the delta method. The reduced-form specification yields statistically significant results and therefore alleviates the weak instrument concern.

Another potential concern is that the instrumented passive size is a generated regressor using a non-linear transformation in **Equation (5)**. To address this concern, I use a "3SLS procedure" recommended (Wooldridge, 2010). Specifically, I added an intermediate step between the first and second stages. In this "1.5-stage" regression, I use the instrumented passive size, $\widehat{\text{Passive Size}}_{k,t}$, to predict the actual passive size, $\text{Passive Size}_{k,t}$. I then use the predicted value from this 1.5-stage regression for the second-stage estimates. The 3SLS estimates are essentially the same as the 2SLS ones in untabulated results. Therefore, for brevity and ease of interpretation in the main paper, I omit the discussion of the 3SLS procedure and only report the 2SLS results.

A5. Uninstrumented Results

This appendix reports MLE and OLS results using the actual uninstrumented passive size.

Table A2
Passive Investment and Active Funds Survival – Falsification, Uninstrumented

The table repeats the analysis in **Table 4** using the actual uninstrumented passive size. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect, $\exp(x\beta) - 1$, instead of the hazard ratio for ease of interpretation. Z-scores are reported in parentheses. The risk exacerbation factor from passive investment is reported as the ratio between the marginal effect of the interaction and the marginal effect of the lagged excess return. The Z-score of the risk exacerbation factor is estimated using the delta method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Passive Size	-0.019	-0.041***	-0.047***	-0.011	-0.022	-0.023	-0.017	-0.061***	-0.066***
× Lagged Excess Return	(-1.40)	(-2.74)	(-2.77)	(-0.74)	(-1.43)	(-1.36)	(-1.13)	(-3.75)	(-3.63)
Lagged Excess Return	-0.281***	-0.271***	-0.295***	-0.330***	-0.371***	-0.400***	-0.315***	-0.282***	-0.284***
	(-11.37)	(-9.47)	(-9.33)	(-13.49)	(-13.47)	(-13.19)	(-12.16)	(-8.98)	(-8.06)
Passive Size	-0.141***	-0.140***	-0.126***						
	(-8.88)	(-8.25)	(-6.91)						
Fund Age							0.060***	0.053***	0.047***
							(14.97)	(12.05)	(9.43)
Fund Size							-0.193***	-0.204***	-0.211***
							(-48.39)	(-47.41)	(-44.97)
Management Fee							0.000	0.000	-0.001
							(0.29)	(0.33)	(-1.46)
Strata by Style	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Return Period	11 Month	23 Month	35 Month	11 Month	23 Month	35 Month	11 Month	23 Month	35 Month
Observations	1,729,947	1,508,118	1,307,368	1,729,947	1,508,118	1,307,368	1,439,435	1,256,475	1,088,347
Exacerbation Factor	0.069	0.152**	0.158**	0.032	0.059	0.058	0.053	0.217***	0.233***
from Passive Investment	(1.289)	(2.268)	(2.288)	(0.711)	(1.339)	(1.277)	(1.060)	(2.895)	(2.745)

Table A3
Passive Investment and Active Funds Closet Indexing, Uninstrumented

The table repeats the analysis in **Table 5** using the actual uninstrumented passive size. 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)	(5)	(6)
	Tracking Error			Portfolio Turnover		
Passive Size	-0.184***	-0.146***	-0.125***	-0.167***	-0.154***	-0.145***
	(-4.99)	(-4.30)	(-3.94)	(-5.45)	(-4.88)	(-4.57)
Fund Size	-0.004	-0.002	-0.001	-0.014***	-0.012***	-0.010***
	(-1.54)	(-0.71)	(-0.50)	(-4.99)	(-4.43)	(-3.75)
Management Fee	-0.006*	0.002	0.002	0.008**	0.006**	0.005*
	(-1.71)	(0.66)	(0.50)	(2.24)	(2.04)	(1.89)
Look-ahead Period	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,533,423	1,198,488	1,034,943	1,199,579	1,203,886	1,204,246
R-squared	0.664	0.774	0.816	0.740	0.798	0.831

Table A4
Passive Investment and Active Funds Homogenization, Uninstrumented

The table repeats the analysis in **Table 6** using the actual uninstrumented passive size. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion Window	$1 \rightarrow 12$	$2 \rightarrow 13$	$3 \rightarrow 14$	$4 \rightarrow 15$	$5 \rightarrow 16$	$6 \rightarrow 17$
Passive Size	-0.288***	-0.276***	-0.265***	-0.252***	-0.246***	-0.239***
	(-7.09)	(-6.86)	(-6.60)	(-6.30)	(-6.09)	(-6.03)
Fund style FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,602	1,602	1,602	1,602	1,602	1,602
R-squared	0.708	0.706	0.704	0.703	0.702	0.701

Table A5
Passive Investment and Market Efficiency, Uninstrumented

The table repeats the analysis in **Table 7** using the actual uninstrumented passive size. 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) Noise	(2) Market-wide Info	(3) Firm-specific Public Info	(4) Firm-specific Private Info
Passive Size	-0.110***	0.155***	-0.071**	-0.025
	(-3.73)	(3.22)	(-2.19)	(-0.75)
Market Capitalization	-0.007	0.099***	-0.111***	0.010
	(-0.42)	(6.25)	(-6.63)	(0.72)
Trading Volume	-0.020**	-0.038***	0.019**	0.028***
	(-2.10)	(-3.33)	(2.47)	(2.93)
Fund Style FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	419,630	419,630	419,630	419,630
R-squared	0.390	0.558	0.302	0.419