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The performance distribution and managerial skill of passive funds: evidence from the Korean market

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Abstract

This study investigates the performance distribution of passive funds in the Korean market and compares it with the performance distribution of active funds. The key findings are as follows, first, the performance distribution of passive funds has a thicker tail compared to that of active funds. There are passive funds that achieve outstanding performance, and both the false discovery rate (FDR) analysis and simulation analysis suggest that their outperformance is driven by managerial skill rather than luck. Second, passive fund performance is more persistent compared to active fund performance. Third, investors are less responsive to passive fund performance compared to active fund performance. The fund flow-performance relationship is significantly positive for active funds but not for passive funds. This implies that investors may not recognize the managerial skills of passive funds.

Keywords Passive funds, Active funds, Fund performance, Performance persistence

Paper type Research paper

1. Introduction

The performance and persistence of equity funds have been important topics in finance. In academics, it is highly related to the market efficiency, and superior performance and performance persistence justify the existence of the asset management industry on the practical side. From this perspective, starting with the work of Jensen (1968), there has been a large literature on the performance and persistence of equity funds in the US market. Most studies report poor performance of equity funds (Grinblatt and Titman, 1989; Wermers, 2000; Kacperczyk *et al.*, 2005; French, 2008; Cremers and Petajisto, 2009). Similarly, studies in the Korean market generally report underperformance of equity funds (Yoo and Kim, 2012; Kim *et al.*, 2020).

While there are numerous studies on the performance of equity funds, previous studies usually focus on active funds and exclude passive funds because fund performance is believed to be driven by active management. Passive funds may be considered homogeneous assets because their essential objective is tracking the benchmark. Overturning this belief, Crane and Crotty (2018) find that there are significant differences in the performance of passive funds in the US market. Given this prior evidence, in this paper, we examine whether there is significant difference in performance among passive funds in the Korean market. Specifically, we attempt to answer the following two research questions.

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First, we examine whether there are significant performance differences among Korean passive funds. Crane and Crotty (2018) consider US passive funds from 1995 to 2013 and find that the proportion of index funds with skill is similar to that of active funds with skill and that their performance is persistent. In addition, the fund selection process of Korean asset managers implies that there are performance differences among passive funds. For example, the OCIOs (Outsourced Chief Investment Officers) of pension funds invest in equities by dividing them into active and passive types and then subdividing each type into subtypes called styles. Although it is not surprising to categorize active funds into large/small-cap, growth/value, managers are selected even for passive funds with the same mandate, which implies that practitioners expect significant performance differences among passive funds. In short, there could be significant performance differences among passive funds. Thus, we need to examine their existence and the sources of performance in passive funds.

Second, we examine how the performance distribution of passive funds differs from that of active funds. The size of outperformance, often measured as the fund's alpha, can be greater in active funds than in passive funds, even if their managerial skills are similar because passive funds are subject to tighter management constraints than active funds. Although the performance of an active fund could be affected by both active management and managerial skills, the performance of a passive fund only depends on managerial skills due to its management constraints. Given this difference, to compare the performance of active and passive funds, it is necessary to estimate the performance distributions of passive and active funds separately and match funds in similar positions within each performance distribution. In addition, this comparison is important for practice considering the process of determining the weights of active and passive funds. For example, OCIOs need to determine the proportion of active and passive investments in the equity asset class, and comparing the performance distributions of active and passive funds is essential in implementing a mean-variance framework.

Our key empirical findings are as follows. First, when comparing the *t*-value distributions of alpha between passive and active funds, the distribution of passive funds has fatter tails compared to active funds, indicating the existence of passive funds that exhibit extremely high performance. The analysis of the False Discovery Rate (FDR) by Barras *et al.* (2010), which estimates the proportion of funds with significant managerial skill, also suggests a relatively high proportion of passive funds with good performance. Moreover, when comparing the actual performance distribution of passive funds with a simulated one assuming no superior performance, it shows that the performance differences among passive funds are due to managerial skill rather than luck. The frequency of actual *t*-values exceeding the simulated *t*-values is significantly higher than 50%. As a result, the empirical evidence consistently supports the managerial skills of passive funds.

Second, we observe the performance persistence of passive funds compared to active funds. We divide the entire sample period into three subsample periods: 2010–2013, 2014–2017, and 2018–2021. During each period, we estimate the alpha for both active and passive funds. Based on these estimated alphas, we classify the funds into five subgroups and calculate the transition matrix of fund performance from the earlier period to the later period. For active funds, no clear performance persistence is observed. However, all transition probabilities for passive funds are above 30%. Notably, the probability of the highest-performing passive funds being retained from one period to the next is estimated at 57.89% between 2010–2013 and 2014–2017, and 66.67% between 2014–2017 and 2018–2021. It suggests that managerial skills may be more pronounced in passive funds than in active funds. Persistent fund performance in passive funds indicates the existence of managerial ability.

Third, we observe that investors' reactions to good fund performance are less pronounced in passive funds compared to active funds. When examining the relationship between past performance and fund flows, we find a positive association for active funds, but not for passive funds. This suggests that investors may be paying less attention to differences in passive fund performance attributed to managerial ability, unlike their response to active funds. However, it is worth noting that the performance-flow relationship for passive funds has strengthened recently. This indicates a growing awareness among investors regarding significant management capabilities associated with passive funds.

This study stands apart from previous research as it specifically analyzes the performance of passive funds in the Korean market. Prior studies in Korea, such as Kho and Kim (2013) and Kim *et al.* (2020), primarily focus on active funds. Considering the recent outperformance of passive funds and the implementation of alpha-generating strategies within passive funds, understanding their performance and sources becomes crucial. Additionally, our study distinguishes itself by comparing the performance of passive funds with that of active funds, providing a foundation for evaluating whether the reported outperformance by certain active funds is a result of active management.

Our empirical findings have huge implications particularly concerning the need for improved methodologies in comparing fund performance. Our study reveals that differences in managerial skills among Korean passive funds significantly impact their performance. Consequently, when assessing the active management of active funds, a more appropriate approach involves comparing their relative position in the active fund performance distribution with the performance of passive funds in the same position within the passive fund performance distribution, rather than merely examining the size of the outperformance. From a practical standpoint, this study justifies the selection of sub-managers after a thorough review of the fund manager's investment strategy even for passive funds with identical mandates. Our findings imply that passive funds are not homogenous, thus investors should distinguish between good and bad more carefully.

The remainder of the paper is structured as follows. Section 2 provides related literature. Section 3 describes the data and methodology in this study. Section 4 reports the empirical findings. Finally, Section 5 provides the concluding remarks of the study.

2. Literature review

Since Jensen (1968)'s seminal work, extensive research has been conducted on fund performance in the US market. Most of these studies report that active funds occasionally outperform their benchmarks before fees and expenses, but they fail to do so after deducting these costs. For instance, Grinblatt and Titman (1989) examine quarterly holdings of active funds from 1975 to 1984 and identify significant risk-adjusted returns for growth funds. However, these returns lose their significance after fees and expenses are accounted for. Similarly, Wermers (2000) finds that active funds outperform the benchmark by 1.3% per year before expenses, but they underperform the benchmark by 1.0% per year after expenses. Using data from 1980 to 2006, French (2008) also concludes that active funds underperform passive funds by 0.67% per year. On a different note, Barras *et al.* (2010) introduce the False Discovery Rate (FDR) as a measure to estimate the frequency of funds in the performance distribution. They note that the presence of poorly managed funds, especially those with no outperformance, and those with outperformance, influence the overall distribution of fund performance. Utilizing this measure, they find a significant presence of poorly managed funds in the market before 1996, but such presence dwindles considerably thereafter.

On the contrary, even though the performance of average actively managed fund is not superior, there is noteworthy outperformance observed in a small number of funds. Kacperczyk *et al.* (2005) reports that funds heavily invested in specific sectors tend to perform better on average. They interpret this as indirect evidence linking sector expertise to managerial ability. Similarly, Ali *et al.* (2008) discover that funds with a higher proportion of investment in stocks favorable in terms of accruals anomaly exhibit outperformance. Moreover, Grinblatt *et al.* (1995) reveal that many equity funds employ momentum strategies, with funds utilizing such strategies showing superior performance. Particularly, Cremers and Petajisto (2009) propose a measure of active share based on the difference between a fund's share and the benchmark index's share. They demonstrate that funds with higher active share tend to outperform the benchmark after expenses. Fama and French (2010) report that while active funds do not outperform their benchmarks on average, there are specific active funds that significantly outperform the benchmark through bootstrapping. These studies collectively contribute to understanding the outperformance observed in certain active funds.

While extensive research has been conducted on the performance of active funds, there has been a scarcity of studies exploring the differences in performance among passive funds. This lack of research can be attributed to the prevailing notion that different passive funds are essentially homogenous products. However, two exceptions stand out in this regard: Elton *et al.* (2004) and Crane and Crotty (2018), both of which investigate the performance of index funds. Elton *et al.* (2004) examine index funds from 1996 to 2001 and find that those tracking the S&P 500 index have an annualized expense ratio of 2%, with a performance differential between index funds of 2.09% per year. Interestingly, they observe no significant correlation between past performance and future inflows, raising questions about the rationality of investors' fund selection process.

Crane and Crotty (2018) find significant performance differences among passive funds, comparable to performance differences within active funds, indicating that passive funds should not be considered as homogeneous assets. Employing Carhart's (1997) four-factor model, they additionally find that over 20% of passive funds outperform their benchmarks, and these outperforming funds exhibit strong performance persistence. Finally, they observe that the performance of passive funds is on par with active funds. Specifically, the alpha of the top 5% of active (passive) funds is estimated at 48 basis points per month (42 basis points). However, when accounting for residual risk, the outperformance of active funds does not surpass that of passive funds as active funds are inherently riskier. As a result, the study argues that the outperformance seen in active funds is not significantly superior to the outperformance of funds within passive funds and suggests that passive funds may offer a more favorable risk-reward profile, making them a potentially superior investment vehicle.

Like the US market, research on the Korean market has predominantly focused on active funds, with most studies revealing underperformance for such funds. For instance, Yoo and Kim (2012) find that domestic active funds underperform the KOSPI index by an average of 0.13% points per year. Similarly, Kim *et al.* (2020) observe that active funds in Korea generally fail to outperform their benchmarks due to a lack of holdings in undervalued stocks relative to those benchmarks. However, there are studies reporting outperformance of some funds. Yun *et al.* (2011) demonstrate that funds with higher industry concentration achieve better risk-adjusted excess returns than those with lower industry concentration. Kho and Kim (2013) study the stock picking ability of active funds and show that the portion of stock picking ability attributed to existing stock positions significantly influences fund performance and is unrelated to the information processing ability of the fund manager. Furthermore, Kim *et al.* (2020) find that some active funds hold consistently undervalued stocks relative to their benchmarks, leading to relatively superior performance.

In contrast, there is a scarcity of research on the performance and distribution of passive funds in the Korean market. One exception is Ban *et al.* (2016), who analyze the performance of KOSPI200 index funds and report significant differences in the cross-sectional distribution, ranging from 3% to 13%. They find that these differences in performance are explained by the proportion of holdings in derivatives, suggesting that the performance variation among domestic index funds is primarily due to arbitrage rather than stock selection. However, their study only covers a limited number of passive funds and does not compare the distribution of passive funds with the performance distribution of active funds.

An important implication of the existing literature is the scarcity of studies examining the performance of passive funds in the Korean fund market. This can be attributed to the predominant focus of previous research on equity funds, specifically analyzing the stock picking and timing abilities of fund managers. Consequently, the scope of analysis has primarily been limited to active funds, leading to the exclusion of passive funds from most studies. Passive funds are often considered homogeneous financial instruments, merely tracking market indices, which further contributes to their exclusion from the literature.

However, given the recent research on passive funds in the US market and the observed investment behavior of fund managers, there is a growing need for more comprehensive research on domestic equity passive funds. Ultimately, a study comparing the performance and performance sustainability of passive and active funds would be valuable to enhance our understanding of their differences and implications. Such research would provide insights into the distinct characteristics and potentials of both types of funds, offering essential guidance to investors and fund managers in making informed decisions.

3. Data and methodology

3.1 Data

This study examines all equity funds in the Korean market, categorizing them into two groups: passive and active funds. The required data on returns and fund characteristics come from the Korea Fund Ratings.

Each equity fund is identified with a unique code and includes information on its fund type. Funds are categorized into various types, such as general equity, other equity (theme), dividend equity, small and mid-cap equity, sector equity, equity ETF, KOSPI200 Index, and KRX300 Index. Based on these categories, active funds are classified as general equity, other equity, dividend equity, small and mid-cap equity, or sector equity, while passive funds include equity ETFs, KOSPI200 Index, and KRX300 Index. Equity ETFs are excluded from this study due to their distinct characteristics following Ban *et al.* (2016). We also exclude funds that have changed their type over time to maintain consistency. For the analysis, only funds that benchmarked against the KOSPI200 Index are included to avoid difficulties arising from changes in the benchmark index when different indexes are used. Most active funds set the KOSPI200 Index as their benchmark, and all passive funds, except the KRX300 Index type, are included in the analysis.

The fund return data set consists of daily returns for both the fund and the benchmark index, from which monthly returns are calculated. Fund characteristics data provide information on total assets, net asset value, inception date, management fee, sales fee, custodial fee, and other fees for each fund. The period of operation is calculated from the initial establishment date, and the total fee is derived by summing up the four fees. Furthermore, the fund holdings data and the value of each security at the end of the month are provided, enabling the calculation of the fund's weight in each security. Securities are identified as derivatives with standardized codes, with those having codes of 4 (futures and options), 6 (debentures, including ELS and DLS), or A (warrants, including ELW). Securities are identified as bonds if their codes are 1 (government bonds), 2 (municipal bonds), 3 (special bonds), B (foreign bonds), C (strips), E (certificates of deposit), or F (commercial paper). The ratio of the value of the derivatives in the total assets of the fund and that of the bonds are considered as the derivatives holding ratio and the bond holding ratio, respectively.

Fund characteristics data are available from 2008. However, due to the exceptional performance of funds during the financial crisis, the sample period is from January 2010 to December 2021. To further understand the evolution of fund performance in the more recent period, the full sample period is divided into three four-year periods: 2010 to 2013, 2014 to 2017, and 2018 to 2021.

Funds are included in our sample six months after their inception as new funds often exhibit significantly different characteristics. Moreover, only funds that have been operational for at least 24 months are considered as shorter periods might lead to unreliable performance assessments. Additionally, our study only includes funds with an average net asset value of KRW 1 billion or more as funds with very low assets may not have typical return-risk characteristics.

For fund performance, the literature often evaluates a fund's managerial skill based on its asset selection and market timing. This evaluation is expressed through the cross-sectional and time-series difference between the fund's returns and those of its benchmark. If a fund's managerial skill influences its outperformance, then funds that display greater aggressiveness by investing in different stocks or at different times compared to the benchmark are likely to achieve higher outperformance. Cremers and Petajisto (2009) investigate the impact of two crucial factors on fund performance: active shares and tracking error. These variables are defined as follows:

$$AS_{i,t} = \frac{1}{2}\sum_{j=1}^{N_{i,t}}\left|w_{i,j,t} - W_{i,j,t}\right|,\ TE_{i,t} = Std(R_{i,t,d} - r_{i,t,d}) \quad (1)$$

$N_{i,t}$ represents the number of stocks held by the fund i. Additionally, $W_{i,j,t}$ and $w_{i,j,t}$ represent the proportion of the asset j held by the benchmark and that of the fund i, respectively. If a fund holds an asset not included in the benchmark, the benchmark's weight on this asset is considered zero. Similarly, if a fund does not hold a benchmark component, the fund's investment in that asset is taken as zero as well. Tracking error is calculated as the standard deviation of the difference between the monthly return ($R_{i,t,d}$) of the benchmark and the monthly return ($r_{i,t,d}$) of the fund. These returns are derived from a time series of returns over the past 12 months.

Table 1 displays the descriptive statistics of the fund characteristics. The statistics are computed by first calculating the time series averages of the fund characteristics variables for each fund and then presenting the cross-sectional statistics of these time series averages.

The sample comprises 580 active funds and 142 passive funds. However, since each fund is not present in the sample at all time points, the actual number of funds present at each time point is lower, with an average of 362.97 active funds and 99.24 passive funds observed at each time point. The number of passive funds is relatively small compared to active funds.

Active funds exhibit an average net asset value of $36.9bn, while passive funds have an average net asset value of $26.2bn. However, the median size of active and passive funds is considerably lower at 7.6 billion won and 7.3 billion won, respectively. This discrepancy between the mean and median is due to a few large funds that significantly impact the average size. Considering that the median fund size is quite similar for both active and passive funds, there does not appear to be a substantial difference in the size of these funds in the sample, except for a few large funds.

The average duration of active and passive funds in our sample is approximately 7 years. However, there is a notable difference in the compensation structure between active and passive funds. Active funds, which pursue active management strategies, typically require management fees around twice as high as those of passive funds, resulting in a significant disparity in total fees. This difference is further evident in the proportion of funds with active and passive management. Active funds constitute 56.61% of the sample, whereas passive funds account for 41.88%. Interestingly, the average tracking error is similar for both active and passive funds. However, the active share and median tracking error of passive funds are notably lower than the average, indicating that some passive funds exhibit relatively higher

Panel A. Active funds	N	580	Average N	362.97				
	NAV	Age	Total fee	Expense ratio	AS	TE	DHR	BHR
Average	368.57	7.85	1.56%	0.63%	56.61%	6.34%	0.12%	0.91%
Std.	897.36	3.97	0.53%	0.19%	13.46%	2.63%	0.69%	3.68%
Median	75.75	7.45	1.57%	0.65%	53.80%	5.76%	0.00%	0.00%

Panel B. Passive funds	N	142	Average N	99.24				
	NAV	Age	Total fee	Expense ratio	AS	TE	DHR	BHR
Average	261.62	7.02	0.81%	0.31%	41.88%	6.40%	0.42%	3.21%
Std.	440.02	3.48	0.45%	0.17%	30.29%	9.77%	2.78%	11.41%
Median	73.03	7.12	0.79%	0.29%	27.35%	1.86%	0.00%	0.00%

Note(s): This table presents the descriptive statistics of the monthly data for the funds. Panels A and B show the statistics for active and passive funds, respectively. Following Korean Fund Ratings, the authors classify general equity, small and mid-cap equity, sector equity, dividend equity, and other equity (theme) funds as active funds, while the KOSPI200 Index, other equity indexes, equity ETFs, and KRX300 are considered passive funds. The sample period covers from January 2010 to December 2021. The statistics are the cross-sectional statistics of time series average. The number of funds refers to the total number of all funds in the sample while the average number of funds represents the time series average of the number of funds at a given time point. Net asset value is denoted in Korean Won (KRW) billion, and the age is expressed in years. The active share is calculated as half of the sum of the absolute values of the weight difference between the fund and the benchmark index. The tracking error is measured as the standard deviation of the difference between the fund's return and the benchmark index return over the past 12 months
Source(s): Table by authors

Table 1.
Descriptive statistics

levels of activity compared to other passive funds despite being classified as passive. This tendency could potentially lead to outperformance among certain passive funds.

On the other hand, active funds have greater flexibility in investing in bonds compared to passive funds. It is possible that performance differences stemming from rebalancing between stocks and bonds, in addition to differences in stock management ability, may impact active funds more than passive funds. To examine this possibility, we investigate the bond holdings of active and passive funds. The data in Table 1 indicates that active funds have a median bond allocation of 0.91%, whereas passive funds have a slightly higher median bond allocation of 3.21%. However, when considering the median and standard deviation of bond holdings, the difference between active and passive funds is not significant. The data suggest that equity funds are not significantly overweight in bonds for either active or passive funds indicating that the impact of rebalancing between stocks and bonds is unlikely to have a substantial effect on the performance distribution of passive and active funds.

3.2 Fund performance models

This study involves utilizing performance measures for both active and passive funds. Specifically, we estimate the alpha of individual funds and the t-value of the alpha using a time series model as the performance metrics. Among the 6 benchmark models considered by Crane and Crotty (2018) [1], we calculate the alpha and t-value of individual funds based on 4 benchmark models commonly used in performance evaluation.

$$\text{Model 1: } r_{i,t} - r_t^{index,i} = \alpha + \varepsilon_{i,t} \tag{2}$$

$$\text{Model 2: } r_{i,t} - r_{f,t} = \alpha + \beta MKT_t + \varepsilon_{i,t} \quad (3)$$

$$\text{Model 3: } r_{i,t} - r_{f,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{i,t} \quad (4)$$

$$\text{Model 4: } r_{i,t} - r_{f,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \sum_{j=1}^{4} \beta_{5,j} Z_{j,t-1} MKT_t + \varepsilon_{i,t} \quad (5)$$

In the above models, $r_{i,t}$ represents the return of fund i at time t, and $\varepsilon_{i,t}$ is the error term with a zero mean and constant variance. Additionally, $r_t^{index,i}$ denotes the return at time t of the benchmark index set by fund i. The alpha in the model is estimated as the mean of the time series of the fund's outperformance relative to the benchmark. To construct the Carhart 4 risk factors, we require data on the return and company characteristics of individual stocks in Korea, and we obtain them from FnGuide's DataGuide database. We specifically consider common stocks listed on the stock market, excluding stocks in the financial/utility sectors, and stocks with capital losses. The returns used are total returns after accounting for dividends.

The market risk factor in the Capital Asset Pricing Model (CAPM) is the excess return of the KOSPI index, including dividends. The excess return is defined as the difference between the risk-free rate at time t and the monthly yield of 364-day monetary stabilization bonds.

The Carhart's (1997) 4-factor model includes SMB, HML, and UMD, representing the size, value, and momentum factors, respectively. To estimate each factor, we construct factor portfolios as follows. At the end of June each year, we divide all stocks in the sample into two groups based on their market capitalization, separating the top 50% and bottom 50%. Within each size group, we further categorize the stocks into three subgroups based on the ratio of their last fiscal year's book value to the market value at the end of December of the previous year. These subgroups are the top 30%, middle 40%, and bottom 30% based on the book-to-market value ratio. We then calculate the value-weighted average return of the six portfolios created. The size factor is defined as the difference between the average return of the three portfolios with smaller market capitalization and the average return of the remaining three portfolios with larger market capitalization. The value factor is defined as the difference between the average return of the top two portfolios with the highest book-to-market value ratio and the average return of the bottom two portfolios with the lowest book-to-market value ratio. To construct the momentum factor, we follow a similar approach as the value factor. We categorize stocks within each size group into three subgroups based on their monthly historical returns: top 30%, middle 40%, and bottom 30%, resulting in six portfolios. The momentum factor is defined as the difference between the average return of the top two portfolios with the highest historical returns and the average return of the bottom two portfolios with the lowest historical returns.

$Z_{j,t}$ refers to the state variables in the conditional model, which includes the cross term between each state variable and the market factor as an additional risk factor. The state variables $Z_{1,t}$ to $Z_{4,t}$ consist of the short-term risk-free rate (91-day CD rate), dividend yield (KOSPI index dividend yield over the past 12 months), term spread (difference between 10-year government bond yield and 1-year government bond yield), and credit spread (difference between the corporate bond BBB- yield and corporate bond AA-yield), respectively as proposed in Ferson and Schadt (1996). The time series data for these variables are collected from the Bank of Korea Economic Statistics System (ECOS).

The estimated alpha may be influenced by the size of the fund's idiosyncratic risk. Specifically, the alpha of a fund with a larger standard deviation of the error term may be larger than the alpha of a fund with a smaller standard deviation of the error term under the same conditions. To account for this, we also consider the t-value of alpha as a measure of fund performance. The t-value of alpha can be interpreted as the fund's excess performance reward for a unit of risk.

4. Empirical findings

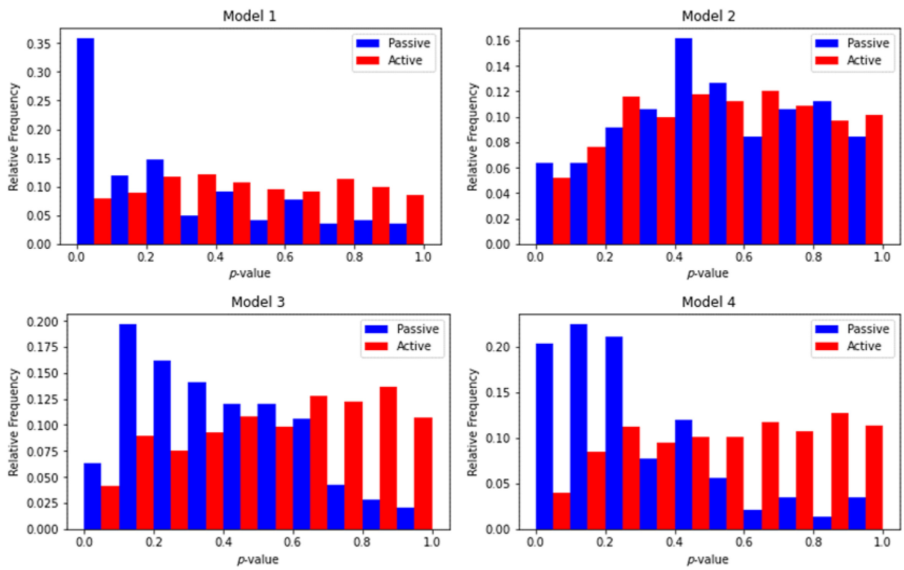
4.1 Distribution of passive fund performance

If there are significant performance differences within passive funds, using the size of alpha alone may not be an appropriate measure to assess the active management skill of an active fund. This is because active and passive funds operate under different constraints, and the same level of alpha can have different implications for each group of funds. Therefore, it is more appropriate to focus on the standardized t-value of alpha rather than the alpha itself. Specifically, it is essential to compare a particular fund's t-value of alpha relative to the overall distribution within both passive and active fund populations.

By examining the distribution of t-value, particularly for active funds, we can identify whether active funds achieve significant outperformance compared to passive funds. Although this approach may not be as informative for alpha itself, comparing the distribution of t-values provides valuable insights into the performance disparity between active and passive funds.

We analyze the distribution of alpha p-values, which represents the relative position of the t-values of alpha estimated from the benchmark model for each passive and active fund. Figure 1 illustrates the distribution of alpha p-values estimated for each fund.

If there does not exist significantly higher or lower performing fund, the performance differences may be attributed to chance. As a result, the distribution of alpha p-values will



Note(s): This figure shows the distribution of alpha's p-values across funds. Blue bars show the distribution of alpha's p-values of passive funds and red bars show the distribution of alpha's p-values of active funds

Source(s): Figure by authors

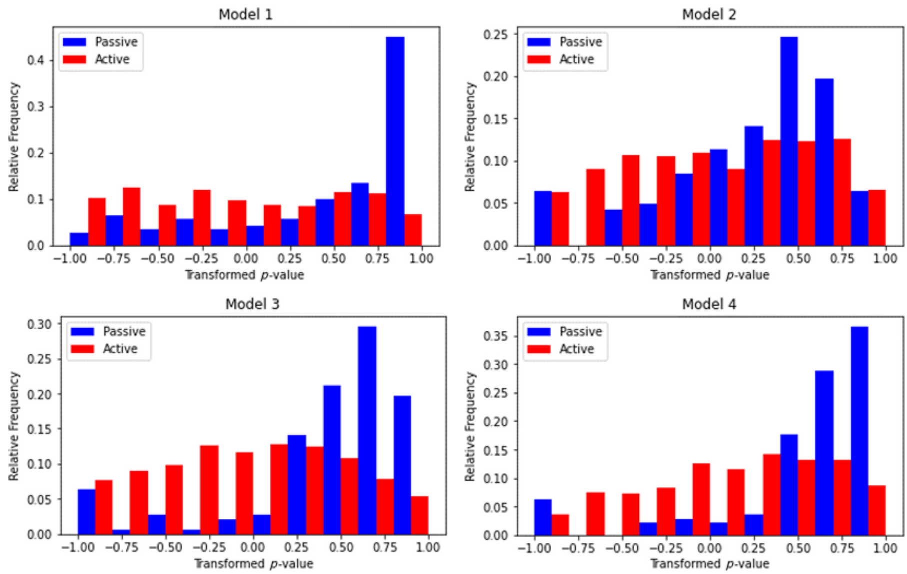
Figure 1.
Distribution of p-values

tend to be closer to a uniform distribution with more funds having lower p-values compared to higher ones. Conversely, if some funds exhibit superior or inferior performance due to managerial skill, the distribution of alpha p-values will show a left-skewed pattern indicating a concentration of funds with more extreme performance levels.

In Figure 1, it is evident that the alpha p-value distributions of passive funds display a left-skewed pattern, except for Model 2 (CAPM model). This suggests that there are a substantial number of passive funds with superior performance that are significantly different from what would be expected by chance alone. On the other hand, the alpha p-values of active funds exhibit a more uniform distribution. This distribution pattern indicates that there is greater potential for significantly higher or lower performing funds within the passive funds compared to active funds.

To differentiate between extremely low p-values in funds with superior performance and those in funds with inferior performance, we consider the distribution of p-values based on the sign of the estimated alpha. To achieve this, we introduce the concept of transformed p-values. For funds with a positive estimated alpha, the transformed p-value is calculated as the p-value minus one while for funds with a negative estimated alpha, the transformed p-value is calculated as the p-value minus one. In the distribution of transformed p-values, funds with superior performance are represented by high transformed p-values close to 1, while funds with inferior performance are represented by low transformed p-values near -1. Figure 2 displays the distribution of transformed p-values.

The frequency of high transformed p-values near one is consistently higher for passive funds, irrespective of the benchmark model. This indicates that the high frequency of low



Note(s): This figure shows the distribution of transformed alpha's p-values. Blue bars show the distribution of transformed alpha's p-values of passive funds and red bars show the distribution of transformed alpha's p-values of active funds. The transformed p-value is the p-value minus one if the estimated alpha is negative, and one minus the p-value if it is positive

Source(s): Figure by authors

Figure 2. Distribution of transformed p-value

p-values in passive funds is primarily driven by funds with superior performance rather than funds with inferior performance. Conversely, the transformed p-values of active funds exhibit a distribution close to a uniform distribution similar to the previous p-values [2].

However, it is important to be cautious in interpreting high alpha or alpha t-values as conclusive evidence of significant managerial skill. It is plausible that some zero alpha funds may generate high performance purely by chance, and vice versa. Conversely, funds with genuine managerial skill are expected to consistently perform at or above their expected performance levels, leading to high alpha or alpha t-values. Consequently, the group of funds identified as superior performers based on alpha t-values may include some zero alpha funds alongside most of the truly skilled performers. Therefore, to determine the proportion of funds with genuine good performance, we need to deduct the share of zero alpha funds that happen to perform well from the share of funds that exhibit superior performance based on their alpha t-values.

In this context, Barras *et al.* (2010) introduce the False Discovery Rate (FDR) methodology to estimate the proportion of funds with superior performance. The FDR can be computed based on the alpha p-values of funds assuming that three types of funds coexist: unskilled, zero-alpha, and skilled funds. Under this methodology, it is assumed that the alpha p-values of funds with no managerial skill will be uniformly distributed between 0 and 1. In contrast, the alpha p-values of unskilled and skilled funds will be concentrated near zero while funds with high alpha p-values near one will have a negligible weight. Consequently, the distribution of alpha p-values close to one would mostly comprise zero alpha funds.

To estimate the proportion (W) of all funds with alpha p-values above a certain value (λ^*) which indicates funds with no significant alpha, we set lambda close to 1. Consequently, the proportion ($\widehat{\pi}_0$) of zero alpha funds can be estimated as follows.

$$\widehat{\pi}_0 = \frac{W}{1-\lambda^*} \tag{6}$$

If we consider funds with alpha t-values lower than $-t_{\gamma^*/2}$ as underperformers and funds with alpha t-values higher than $t_{\gamma^*/2}$ as outperformers based on a significance level of gamma for alpha t-values, then there will be zero alpha funds that are misclassified as underperformers or outperformers purely by chance (i.e., $\widehat{\pi}_0 \times \frac{\gamma^*}{2}$). To calculate the proportion of unskilled funds ($\widehat{\pi}_-$) and the proportion of skilled funds ($\widehat{\pi}_+$), we adjust the proportions of underperformers (S_-) and outperformers (S_+) by subtracting the proportion of zero-alpha funds included by chance, as follows.

$$\widehat{\pi}_- = S_- - \widehat{\pi}_0 \times \frac{\gamma^*}{2}, \widehat{\pi}_+ = S_+ - \widehat{\pi}_0 \times \frac{\gamma^*}{2} \tag{7}$$

Nonetheless, Barras *et al.* (2010) demonstrate that the FDR estimation is relatively robust to the choice of parameters if they are sufficient to accurately determine the average fund's weight. To estimate the share of skilled passive funds in this study, we consider the combinations of $\lambda^* = 0.75$, 0.80, and 0.85 and $\gamma^* = 0.30$ and 0.35, which are consistent with values suggested in prior work. The proportion of fund types among passive funds based on the FDR methodology is presented in Table 2 [3].

Across all models, the percentage of passive funds exhibiting superior performance is notably high. Even for the smallest model (Model 3), over 30% of passive funds are classified as having superior performance, and for Models 1 and 4, more than half of all funds are deemed to perform well. Conversely, the proportion of poorly managed funds remains consistently estimated to be significantly lower, at less than 4%. The FDR methodology further supports the notion that a substantial presence of outperforming funds within passive funds is not merely a result of chance.

Model	λ^*	γ^*	Unskilled	Zero alpha	Skilled
Model 1	0.75	0.30	1.27%	33.80%	51.27%
	0.80	0.30	0.53%	38.73%	50.53%
	0.85	0.30	1.41%	32.86%	51.41%
	0.75	0.35	2.54%	33.80%	51.13%
	0.80	0.35	1.67%	38.73%	50.26%
	0.85	0.35	2.70%	32.86%	51.29%
Model 3	0.75	0.30	3.24%	25.35%	31.41%
	0.80	0.30	3.35%	24.65%	31.51%
	0.85	0.30	2.82%	28.17%	30.99%
	0.75	0.35	2.61%	25.35%	40.63%
	0.80	0.35	2.73%	24.65%	40.76%
	0.85	0.35	2.11%	28.17%	40.14%
Model 4	0.75	0.30	3.38%	19.72%	54.79%
	0.80	0.30	2.64%	24.65%	54.05%
	0.85	0.30	1.41%	32.86%	52.82%
	0.75	0.35	2.89%	19.72%	58.52%
	0.80	0.35	2.02%	24.65%	57.66%
	0.85	0.35	0.59%	32.86%	56.22%

Note(s): This table shows the proportion of unskilled, zero alpha, and skilled passive funds estimated according to the FDR method of Barras *et al.* (2010). The authors consider six combinations of the two parameters: $\lambda^* = 0.75$, 0.80, and 0.85 and $\gamma^* = 0.30$ and 0.35 Model 1, Model 3, and Model 4 correspond to the fund performance evaluation benchmark models in Equation (2), Equation (4), and Equation (5), respectively
Source(s): Table by authors

Table 2. Classification of passive funds based on FDR method

The distribution of estimated alpha p-values suggests the possibility of some passive funds significantly outperforming active funds. However, it should be noted that this distribution of p-values only indicates that the t-distribution of estimated alpha exhibits a thicker tail compared to a typical t-distribution, rather than comparing it directly to the t-distribution of alpha at zero alpha. If the outperformance exceeds the distribution with zero alpha, particularly on the high side, it might be attributed to factors beyond chance, such as the fund's managerial skill.

Indeed, as highlighted in Fama and French (2010), the estimation of alpha and its cross-sectional distribution of t-values is not done under the null hypothesis that alpha is zero. Therefore, to ascertain the distribution of alpha t-values when alpha is zero, a simulation approach is required. In this simulation, we begin by subtracting the estimated alpha from the general time series model from each fund's return to create a sample of returns with zero alpha. From this sample, we perform bootstrap resampling of the cross-sectional observations, including the monthly returns and fund characteristics of all funds at a given point in time, to construct a hypothetical sample with the same size as the actual sample. By applying the same benchmark model to this virtual sample and repeating the process numerous times and averaging the results, we can estimate the cross-sectional distribution of t-values of alpha under the assumption of zero alpha.

To assess whether the observed overperformance can be attributed to skill or mere luck, we divide the alpha t-values into quartiles and examine how frequently the quartile of actual alpha t-values exceeds the quartile of alpha t-values in the hypothetical sample with zero alpha. If the overperformance is purely due to chance, the frequency will converge to 50%, whereas if it stems from skill, the frequency will be higher than 50%. The results of this comparison are presented in Table 3.

For active funds, the quartiles of actual alpha t-values tend to be lower than the corresponding quartiles of hypothetical alpha t-values when the t-value is low, and higher

Table 3.
t-value distributions of the simulated and actual fund performance

Quantile	Model 1 Simulation	Model 1 Actual	Model 1 Actual > Simulation	Model 2 Simulation	Model 2 Actual	Model 2 Actual > Simulation	Model 3 Simulation	Model 3 Actual	Model 3 Actual > Simulation	Model 4 Simulation	Model 4 Actual	Model 4 Actual > Simulation
Panel A. Active funds												
0.05	−1.412	−1.638	30.90%	−1.312	−1.353	45.60%	−1.260	−1.465	33.60%	−1.295	−1.175	55.30%
0.1	−1.095	−1.287	33.80%	−1.014	−1.086	44.20%	−0.966	−1.134	35.40%	−0.995	−0.891	54.10%
0.2	−0.713	−0.959	30.50%	−0.654	−0.709	47.30%	−0.613	−0.770	36.60%	−0.642	−0.462	62.90%
0.3	−0.438	−0.619	35.10%	−0.392	−0.432	47.80%	−0.358	−0.425	45.10%	−0.388	−0.173	66.60%
0.4	−0.205	−0.338	38.80%	−0.165	−0.176	50.30%	−0.139	−0.237	42.50%	−0.169	0.029	65.50%
0.5	0.012	−0.078	43.80%	0.047	0.054	52.00%	0.067	−0.013	44.20%	0.035	0.235	66.50%
0.6	0.229	0.189	48.10%	0.260	0.340	56.60%	0.274	0.187	43.60%	0.239	0.422	65.80%
0.7	0.461	0.509	54.50%	0.486	0.548	55.70%	0.495	0.405	44.40%	0.454	0.652	67.70%
0.8	0.733	0.782	55.40%	0.749	0.800	55.10%	0.756	0.627	41.90%	0.706	0.891	66.10%
0.9	1.112	1.097	52.20%	1.112	1.128	53.60%	1.122	0.953	39.40%	1.057	1.239	65.40%
0.95	1.425	1.361	49.00%	1.415	1.416	52.20%	1.428	1.310	44.40%	1.354	1.446	59.50%
Panel B. Passive funds												
0.05	−1.509	−1.126	72.00%	−1.184	−1.610	16.80%	−1.154	−1.522	19.50%	−1.177	−2.463	1.90%
0.1	−1.175	−0.726	78.80%	−0.860	−0.531	70.80%	−0.821	−0.321	87.60%	−0.853	−0.080	98.00%
0.2	−0.768	−0.124	89.10%	−0.500	−0.135	73.00%	−0.458	0.413	94.40%	−0.493	0.625	98.80%
0.3	−0.484	0.444	95.50%	−0.266	0.145	73.60%	−0.224	0.572	90.30%	−0.253	0.767	95.70%
0.4	−0.251	0.817	97.60%	−0.098	0.319	72.10%	−0.048	0.704	85.60%	−0.064	0.982	93.20%
0.5	−0.038	1.148	98.50%	0.032	0.537	75.50%	0.083	0.839	84.60%	0.083	1.170	92.10%
0.6	0.171	1.388	98.40%	0.162	0.688	77.50%	0.215	0.990	85.40%	0.226	1.237	90.20%
0.7	0.390	1.851	99.50%	0.328	0.778	76.70%	0.378	1.141	86.10%	0.387	1.352	89.80%
0.8	0.660	2.421	99.90%	0.566	0.898	73.40%	0.603	1.277	86.20%	0.593	1.567	91.30%
0.9	1.039	2.913	100%	0.944	1.163	70.70%	0.962	1.431	80.90%	0.920	1.702	90.20%
0.95	1.321	3.643	100%	1.285	1.342	62.70%	1.290	1.505	71.30%	1.233	1.984	90.10%

Note(s): This table compares the distribution of alpha's t-values for the simulated and actual fund performance. Panels A and B show the results of active and passive funds, respectively. The simulated sample consists of a sample of the same size as the actual sample by bootstrapping from the alpha-subtracted sample with 1,000 iterations. "Simulation" is the quantile of the alpha's t-value of the simulated sample, which represents the average of the quantiles of the alpha's t-values. "Actual" represents the quantiles of alpha's t-values calculated from the actual sample. "Actual > Simulation" indicates the proportion of simulated alpha's t-value quantiles that are smaller than the actual alpha t-value quantiles. The Model 1 to Model 4 correspond to the fund performance benchmark models in Equation (2) to Equation (5), respectively.
Source(s): Table by authors

when the t-value is high. However, even for high alpha t-value quartiles that represent potential outperforming funds, the frequency with which the actual alpha t-value quartile surpasses the hypothetical alpha t-value quartile is not significantly different from the 50% level, except in Model 4. This distribution of alpha t-values suggests that active funds do not particularly underperform. Also, it means that active funds do not outperform.

On the other hand, for passive funds, the alpha t-value quintiles consistently exceed the hypothetical alpha t-value quintiles, irrespective of the model, except for the very low quintiles (e.g., the 5th quintile). Moreover, the frequency of the actual alpha t-value quintiles being higher than the hypothetical alpha t-value quintiles is estimated to be substantial, around 70%, even for the lowest model, Model 2. This indicates that the outperformance of passive funds significantly exceeds what would be expected by chance in the absence of specific alpha. In conclusion, there are indeed significant outperformers among passive funds.

4.2 Passive fund performance persistence and flow-performance relationship

To assess the performance persistence of passive funds, we divide the full sample period (2010–2021) into three equal-sized sub-samples (2010–2013, 2014–2017, and 2018–2021) and separately estimate the alphas of the funds for each sub-sample period. Based on the estimated alphas' magnitude, we categorize all funds within each sub-sample period into five equally sized subpopulations. We then calculate the transition probabilities.

If there is persistence in fund performance, we expect that funds in the lower (higher) fund performance group in the previous sub-sample period will have a higher likelihood of remaining in the lower (higher) fund performance group in the subsequent sub-sample period. In contrast, if there is no persistence in fund performance, the probability of being in each fund performance group would be close to 20%, implying that fund performance in the previous sub-sample period is unrelated to fund performance in the subsequent sub-sample period. Table 4 presents the fund performance transition matrix for both active and passive funds.

Table 4. Fund performance transition matrix

	(2010–2013) → (2014–2017)						(2014–2017) → (2018–2021)				
	Low	q2	q3	q4	High		Low	q2	q3	q4	High
Panel A. Active funds											
Low	26.92%	24.36%	20.51%	15.38%	12.82%	Low	20.97%	20.97%	20.97%	19.35%	17.74%
q2	19.70%	16.67%	27.27%	13.64%	22.73%	q2	19.48%	24.68%	19.48%	23.38%	12.99%
q3	16.46%	17.72%	22.78%	22.78%	20.25%	q3	17.81%	26.03%	21.92%	23.29%	10.96%
q4	12.50%	23.75%	23.75%	22.50%	17.50%	q4	13.33%	16.00%	22.67%	18.67%	29.33%
High	17.86%	21.43%	15.48%	25.00%	20.24%	High	*37.74%*	5.66%	20.75%	11.32%	24.53%
Panel B. Passive funds											
Low	*57.14%*	14.29%	4.76%	14.29%	9.52%	Low	*55.00%*	20.00%	15.00%	0.00%	10.00%
q2	5.26%	*52.63%*	21.05%	5.26%	15.79%	q2	8.70%	*56.52%*	21.74%	8.70%	4.35%
q3	15.00%	25.00%	*30.00%*	15.00%	15.00%	q3	8.70%	8.70%	*39.13%*	*39.13%*	4.35%
q4	11.11%	5.56%	*33.33%*	*50.00%*	0.00%	q4	13.64%	0.00%	27.27%	*40.91%*	18.18%
High	5.26%	0.00%	*31.58%*	5.26%	*57.89%*	High	26.67%	6.67%	0.00%	0.00%	*66.67%*

Note(s): This table reports the fund performance transition matrix. The entire sample is divided into subsamples for three subperiods: 2010–2013, 2014–2017, and 2018–2021. The fund's alphas are estimated for each subperiod. The alphas are estimated based on Model 4 (conditional four-factor model). Funds in each sub-sample are categorized into five equally sized subgroups (Low, q2-q4, High) based on their alpha. The transition matrix of fund performance is computed from the earlier period to the later period. Panels A and B show the fund performance transition matrices for active and passive funds, respectively

Source(s): Table by authors

Analyzing the diagonal of the transition matrix, which represents the probability of retaining the same fund performance cohort, we observe distinct patterns for active and passive funds. Active funds exhibit transition probabilities below 30% across all time periods, resembling the 20% probability that would occur in the absence of any relationship. In contrast, for passive funds, all transition probabilities exceed 30%, with the highest performance cohort demonstrating substantial retention rates: 57.89% from the first subperiod (2010–2013) to the second subperiod (2014–2017) and 66.67% from the second subperiod (2014–2017) to the third subperiod (2018–2021). This implies that passive funds exhibit more pronounced performance persistence compared to active funds.

Another approach to identify a fund's management ability is to examine performance-flow relationship. If investors rationally update their assessment of a fund's performance based on its past performance, then funds with superior performance are likely to attract more investors. Thus, fund performance-flow relationship emerges, where funds that have performed well in the past create larger inflows than their underperforming counterparts.

To indirectly assess the presence of managerial ability in passive fund performance, we employ a panel regression model. This analysis seeks to identify whether the fund flow patterns align with the notion that superior performance stems from managerial skills in passive funds.

$$\begin{aligned} Flow_{i,t} = \alpha_i + \alpha_t + \beta_1 PF_{i,t-1} + \gamma(PF_{i,t-1} \times DP_i) + \beta_2 \ln(TNA_{i,t-1}) + \beta_3 \ln(AGE_{i,t-1}) \\ + \beta_4 AS_{i,t-1} + \beta_5 TE_{i,t-1} + \beta_6 DHR_{i,t-1} \end{aligned} \tag{8}$$

The risk-adjusted performance of a fund (PF) is calculated as the difference between the fund's actual return ($r_{i,t}$) and the predicted return ($\widehat{r}_{i,t}$) excluding the alpha component. This difference, denoted as ($r_{i,t} - \widehat{r}_{i,t}$), represents the risk-adjusted performance, where $\widehat{r}_{i,t}$ represents the portion of the fund's performance that can be attributed to the risk factors considered in the benchmark model. To control for various factors and potential biases in the analysis, we include several control variables [4]. We utilize time series and cross-sectional fixed effects (α_t, α_i) that take the value of 1 for passive funds and 0 for active funds. Additionally, we incorporate the logarithm of fund total assets (TNA) and the fund's age (AGE) as control variables. Considering the findings of Ban *et al.* (2016), who examine the performance characteristics of the KOSPI200 index funds, we also include the derivatives holding ratio (DHR) of the fund as a control variable. The variable *Flow* represents the inflow of funds.

$$Flow_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t}) \times TNA_{i,t-1}}{TNA_{i,t-1}} \tag{9}$$

If the fund performance-flow relationship exists, the coefficient of past performance (β_1) should be positive. The coefficients of the passive fund dummy variable and the risk-adjusted performance (γ) would be positive if investors are more sensitive to the performance of passive funds compared to active funds, and negative if they are more insensitive (see Table 5).

Table 5 shows the estimation result of the fund performance-flow relationship. When we estimate the panel regression for the entire sample period, we find a positive coefficient of past risk-adjusted performance, indicating that investors do respond to fund performance. However, this coefficient is not statistically significant, implying that there is no significant fund performance-flow relationship during the entire period. Nevertheless, when we estimate the panel regression for the latest period (2018–2021), we observe a significant fund performance-flow relationship at the 5% significance level in Model 1 and at the 10%

	Entire sample (2010–2021)				Recent sample (2018–2021)		
Variable	Coefficient	*t*-value	*p*-value	Variable	Coefficient	*t*-value	*p*-value
Panel A. Model 1							
AS	−0.0259	−0.4981	0.6184	AS	0.1004	2.0650	0.0389
DHR	0.0748	0.8620	0.3887	DHR	−0.0997	−0.6790	0.4972
TE	0.4800	1.3028	0.1926	TE	0.1324	0.6663	0.5052
ln(AGE)	0.0017	0.0308	0.9755	ln(AGE)	−0.0848	−1.4185	0.1561
ln(TNA)	−0.1390	−2.1425	0.0322	ln(TNA)	−0.1874	−3.7201	0.0002
PF	1.2287	1.3546	0.1756	PF	0.7156	1.9919	0.0464
PF × DP	−1.5518	−1.6833	0.0923	PF × DP	−1.0222	−2.8587	0.0043
Panel B. Model 2							
AS	−0.0251	−0.4863	0.6267	AS	0.1011	2.0831	0.0373
DHR	0.0712	0.8326	0.4051	DHR	−0.1068	−0.7302	0.4653
TE	0.4842	1.3159	0.1882	TE	0.1647	0.8003	0.4235
ln(AGE)	0.0011	0.0206	0.9836	ln(AGE)	−0.0854	−1.4230	0.1548
ln(TNA)	−0.1390	−2.1408	0.0323	ln(TNA)	−0.1873	−3.7263	0.0002
PF	1.0194	1.3696	0.1708	PF	0.5524	1.8547	0.0637
PF × DP	−0.4335	−1.3279	0.1842	PF × DP	−0.0501	−0.1894	0.8498
Panel C. Model 3							
AS	−0.0244	−0.4741	0.6355	AS	0.1008	2.0803	0.0375
DHR	0.0691	0.8166	0.4142	DHR	−0.1075	−0.7341	0.4629
TE	0.4863	1.3183	0.1874	TE	0.1714	0.8310	0.4060
ln(AGE)	0.0012	0.0222	0.9823	ln(AGE)	−0.0876	−1.4549	0.1457
ln(TNA)	−0.1389	−2.1414	0.0322	ln(TNA)	−0.1874	−3.7285	0.0002
PF	1.1342	1.3694	0.1709	PF	0.6103	1.7141	0.0865
PF × DP	−0.3669	−0.8397	0.4011	PF × DP	0.0784	0.2981	0.7657
Panel D. Model 4							
AS	−0.0246	−0.4779	0.6328	AS	0.1003	2.0618	0.0392
DHR	0.0692	0.8138	0.4158	DHR	−0.1072	−0.7244	0.4688
TE	0.4874	1.3205	0.1867	TE	0.1738	0.8375	0.4023
ln(AGE)	0.0011	0.0198	0.9842	ln(AGE)	−0.0894	−1.4797	0.1390
ln(TNA)	−0.1389	−2.1426	0.0321	ln(TNA)	−0.1875	−3.7289	0.0002
PF	1.2233	1.3272	0.1844	PF	0.6527	1.7131	0.0867
PF × DP	−0.3227	−0.6488	0.5165	PF × DP	0.1413	0.5043	0.6141

Note(s): This table shows the estimated results of the panel regression of fund inflows on performance. The independent variables are risk-adjusted performance (PF), the interaction term between risk-adjusted performance and a passive fund dummy variable (PF × DP), log total assets (ln(TNA)), log age (ln(AGE)), active share (AS), tracking error (TE), and derivatives holding ratios (DHR). Panels A, B, C, and D show the results of the fund performance benchmark model in equations (2) through (5) to calculate risk-adjusted performance, respectively. The authors report estimation results for the entire sample period and for the recent period of 2018–2021. The panel regression model includes time series and cross-sectional fixed effects
Source(s): Table by authors

Table 5. Fund performance-flow relationship

significance level in the other benchmark models. This suggests that the fund performance-flow relationship for funds has become stronger in recent years compared to the past.

Interestingly, the coefficient of the interaction term between the passive fund dummy variable and risk-adjusted performance is negative or insignificant. This implies that investors are less sensitive to past performance for passive funds. Considering that there exist the significant outperforming passive funds, this result suggests that investors may not fully perceive the extent of passive funds' outperformance. However, it is worth noting that the fund performance-flow relationship for passive funds has strengthened in the recent period, indicating that investors have become more aware of the significant performance of passive funds in recent years.

5. Conclusion

Previous studies on equity funds have typically focused on active funds and exclude passive funds from their analysis. It is based on the common ideas that fund managers' asset selection and market timing abilities may be more relevant to active funds. Passive funds are often considered as homogenous assets and just track market indices. However, given recent studies on passive funds in the US market, it is essential to examine the performance distribution of passive funds in the Korean market.

This study shows that there is a more significant performance difference among passive funds than active funds. Furthermore, we find that this difference is not simply due to chance, but is due to managerial skills, comparing the actual performance distribution and the simulated distribution. The superior performance of passive funds tends to persist in subsequent periods more than that of active funds. Despite the significant performance differences in passive funds than active funds, investors have been less responsive to the performance of passive funds than active funds. This implies that investors in passive funds are paying less attention to performance differences than investors in active funds.

Our findings suggest that evaluation of active management could be improved. The significant performance differences among Korean passive funds indicate that active management may not be the only factor contributing to the outperformance of active funds, but also general asset management that could contribute to performance differences among passive funds. To evaluate the performance of an active fund, it is necessary to compare the performance of the active fund to that of similarly situated passive funds within the performance distribution. In practice, it suggests that fund manager's strategies should be reviewed carefully even for passive funds because they are not homogenous.

Notes

1. The authors exclude the 11-factor model based on Vanguard indices and the seven-factor model based on Russell indices.
2. Appendix further reveals that the alpha for active funds, regardless of the model, follows a nearly symmetric distribution resembling a t-distribution. In contrast, for passive funds, the distribution is more right skewed with zero representing no outperformance. This pattern is particularly observed in Models 3 and 4, which aligns with the alpha-transformed p-value distribution.
3. For the FDR to be meaningful, it is crucial that the proportion of funds with alpha p-values close to one is negligibly small among both unskilled and skilled funds. This ensures that the distribution of alpha p-values is heavily concentrated near very small values and becomes less frequent as alpha p-values increase. If the distribution of alpha p-values does not significantly deviate from a uniform distribution, calculation of the FDR becomes challenging. Consequently, the authors only estimate the FDR for passive fund models 1, 3, and 4 in Figure 1, and not for active fund models 2 and 3 as the alpha p-value distribution in the latter cases does not significantly differ from a uniform distribution, leading to a disproportionately large number of funds with alpha p-values near 1.
4. The authors do not include fund fees as a control variable in this analysis. Usually, the size of fee is fixed over time, which could not be distinct from the cross-sectional fixed effects.

References

Ali, A., Chen, X., Yao, T. and Yu, T. (2008), "Do mutual funds profit from the accruals anomaly?", *Journal of Accounting Research*, Vol. 46 No. 1, pp. 1-26.

Ban, J., Kim, S. and Kwon, S. (2016), "Performance characteristics of KOSPI 200 Index funds", *Korean Journal of Financial Studies*, Vol. 45 No. 5, pp. 1035-1074.

Barras, L., Scaillet, O. and Wermers, R. (2010), "False discoveries in mutual fund performance: measuring luck in estimated alphas", *Journal of Finance*, Vol. 65 No. 1, pp. 179-216.

Carhart, M.M. (1997), "On persistence in mutual fund performance", *Journal of Finance*, Vol. 52 No. 1, pp. 57-82.

Crane, A.D. and Crotty, K. (2018), "Passive versus active fund performance: do index funds have skill?", *Journal of Financial and Quantitative Analysis*, Vol. 53 No. 1, pp. 33-64.

Cremers, K.M. and Petajisto, A. (2009), "How active is your fund manager? A new measure that predicts performance", *Review of Financial Studies*, Vol. 22 No. 9, pp. 3329-3365.

Elton, E.J., Gruber, M.J. and Busse, J.A. (2004), "Are investors rational? Choices among index funds", *Journal of Finance*, Vol. 59 No. 1, pp. 261-288.

Fama, E.F. and French, K.R. (2010), "Luck versus skill in the cross-section of mutual fund returns", *Journal of Finance*, Vol. 65 No. 5, pp. 1915-1947.

Ferson, W.E. and Schadt, R.W. (1996), "Measuring fund strategy and performance in changing economic conditions", *Journal of Finance*, Vol. 51 No. 2, pp. 425-461.

French, K.R. (2008), "Presidential address: the cost of active investing", *Journal of Finance*, Vol. 63 No. 4, pp. 1537-1573.

Grinblatt, M. and Titman, S. (1989), "Mutual fund performance: an analysis of quarterly portfolio holdings", *Journal of Business*, Vol. 62 No. 3, pp. 393-416.

Grinblatt, M., Titman, S. and Wermers, R. (1995), "Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior", *American Economic Review*, Vol. 85 No. 5, pp. 1088-1105.

Jensen, M. (1968), "The performance of mutual funds in the period 1945-1964", *Journal of Finance*, Vol. 23 No. 2, pp. 389-416.

Kacperczyk, M., Sialm, C. and Zheng, L. (2005), "On the industry concentration of actively managed equity mutual funds", *Journal of Finance*, Vol. 60 No. 4, pp. 1983-2011.

Kho, B. and Kim, J. (2013), "Stock selection ability and information processing ability of mutual funds in Korea", *Korean Journal of Financial Studies*, Vol. 42 No. 3, pp. 493-527.

Kim, C., Lee, J. and Lee, C. (2020), "Mutual fund performance and stock market anomalies", *Korean Journal of Financial Studies*, Vol. 49 No. 1, pp. 41-72.

Wermers, R. (2000), "Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses", *Journal of Finance*, Vol. 55 No. 4, pp. 1655-1695.

Yoo, S. and Kim, D. (2012), "Style, performance, market timing of equity mutual funds in Korea", *Asian Review of Financial Research*, Vol. 25 No. 3, pp. 409-450.

Yun, Y., Sohn, P. and Kim, S. (2011), "Do industry focused funds create the superior performance?: the evidence from Korean fund market", *Korean Journal of Financial Management*, Vol. 28 No. 1, pp. 61-92.

(The Appendix follows overleaf)

Appendix

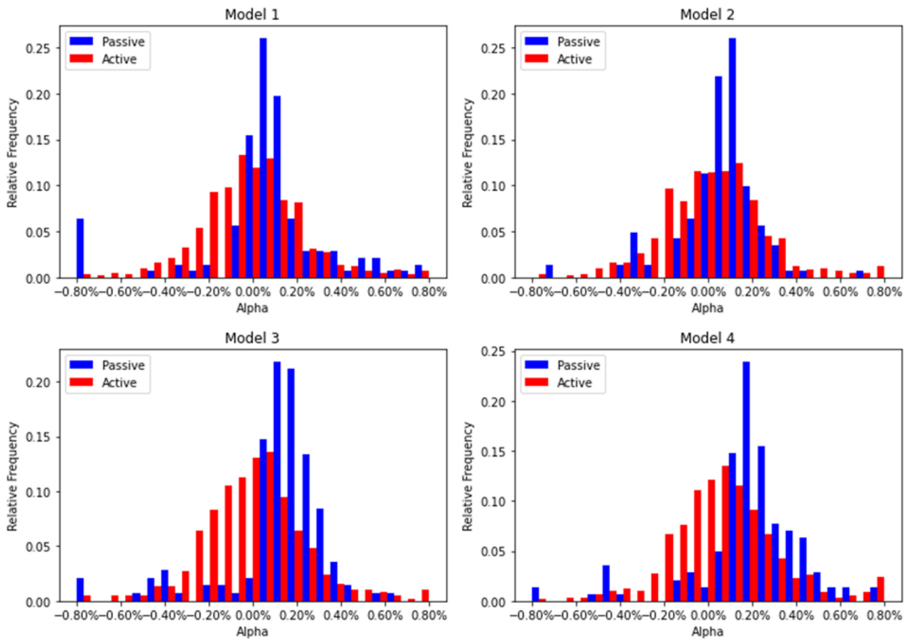


Figure A1.
Distribution of alpha

Note(s): This figure shows the distribution of fund's alpha. Blue bars show the distribution of alpha of passive funds and red bars show the distribution of alpha of active funds
Source(s): Figure by authors

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