Mutual Fund Investing in the Chinese A-share Market*

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Abstract

This chapter investigates whether stock mutual funds in the Chinese A-share market provide economic value for investors. Stock mutual funds in China experienced a steady growth from 2006 to 2019 – the number of funds multiplied by 17-fold. These funds outperform the CSI300 Index on average, and fund returns show economically large differences in the cross-section. Fund performance exhibits persistence: the top-performing funds in a given month are also likely to be the top funds in the following month. Portfolios formed using the top-performing funds improve the risk-return tradeoff compared to investing in the aggregate market, without increased volatility or tail risk. Our results indicate stock mutual funds provide attractive investment opportunities in the A-share market.

Keywords: mutual funds, stocks, performance attribution, A-share market

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1. Introduction

The economic value of mutual funds for investors has been of long-standing interest to financial researchers, going back at least to Jensen (1968) who uses the Capital Asset Pricing Model (CAPM) to evaluate whether mutual funds have positive risk-adjusted returns. Since the seminal work of Jensen (1968), hundreds of papers have investigated the question of whether mutual fund managers can add value for investors by outperforming their benchmark returns, including Carhart (1997), Daniel et al. (1997), Pastor and Stambaugh (2002), Cohen et al. (2005), Fama and French (2010), and Pastor et al. (2015). Although many papers have been written on mutual fund performance, there remains a debate among researchers on whether mutual funds can reliably outperform their benchmarks.

In this chapter, we investigate whether actively managed stock mutual funds provide attractive investment opportunities for retail investors in a relatively young stock market with a developing mutual fund industry. Established in 1991, the Chinese A-share market has grown to become the second largest stock market in the world. Given the size and growing importance of the A-share market, researchers have been increasingly interested in understanding the empirical patterns of asset prices and investor behavior in this market.

We set out to document foundational facts about actively managed stock mutual funds in the A-share market. For our analysis, we focus on three aspects. First, we review the size and growth of the stock mutual fund industry in the A-share market, making comparisons with commensurate figures in the U.S. markets. Second, we examine the performance of stock mutual funds – average returns, cross-sectional dispersion, and performance persistence – using portfolio sorts and Fama and MacBeth (1973) regressions. Third, we evaluate the economic value of portfolios of stock mutual funds via performance attribution regressions.

Our findings can be summarized as follows. From 2006 to 2019, stock mutual funds in the A-share market experienced explosive growth. The number of stock mutual funds increased steadily, rising 17-fold. Growth in assets under management (AUM) also showed an upward path, increasing sixfold. An equal-weight portfolio of all stock mutual funds outperforms the CSI300 Index, the mostly commonly used benchmark among funds. There is a large cross-sectional spread in average returns among funds – the top-performing funds outperform the average funds by more than 20% per year, implying large gains for investors who can reliably identify the top-performing funds.

Successful fund selection is predicated on two assumptions: some fund managers possess significant ability to generate outperformance, and this ability persists. We find evidence that supports both assumptions. Economically significant average return differences are observed across funds, and funds that perform well in one period also tend to perform well in the following period. Quintiles formed on past performance or CAPM alphas show little turnover from month to month, and performance persistence can be observed even at the annual horizon.

Since the two assumptions for successful fund selection are satisfied, investors presumably can benefit from selecting the best funds. We illustrate the feasibility of improving the risk-return tradeoff by forming portfolios of top-performing stock mutual funds, ranked by their CAPM alphas. Portfolios of top funds improve the risk-return tradeoff compared to a buy-and-hold strategy in the aggregate market, without increased volatility or tail risk. There is a tradeoff between diversification and outperformance: a portfolio of the top 5% of funds contains more idiosyncratic risk, but offers greater market-adjusted outperformance.

Take together, our results paint the following picture for stock mutual funds in the A-share market. In a young and developing stock market, stock mutual funds behave as “smart money”, outperforming the aggregate market return on average. Although many funds are able to beat market returns, fund managers are not created equal. The best fund managers possess sufficient skill to provide economically large risk-adjusted returns, and such skill persists over time. Investors who can successfully identify the top fund managers can reap great rewards, potentially outperforming the market by double-digit returns per annum. Even if an investor cannot identify the top funds, she would still likely be better off investing in several mutual funds than in the aggregate stock market.

Our work fits into the literature on evaluating the performance of mutual funds. There is a large literature, mostly based on the U.S. markets, which supports the idea that mutual funds do not outperform the aggregate stock market (Jensen, 1968; Elton et al., 1993; Fama and French, 2010). Our finding that stock mutual funds as a whole outperform the aggregate market stands in sharp contrast to these studies, and may be related to the differential maturity of the U.S. and Chinese stock markets and the saturation of institutional investors. Chi (2016) finds that in the A-share market, stock mutual funds can outperform the market. However, he only focuses on the equal-weight portfolio of all funds and does not investigate whether subsets of funds can further improve performance.

Our work is also related to the literature on the persistence of fund performance. One set of studies rejects the notion that mutual fund performance exhibit persistence. Carhart (1997) finds economically large differences in average returns in portfolios ranked by past returns, but this persistence does not extend to the following year. Bollen and Busse (2005) find short-term return persistence up to three months, but no return persistence beyond three months. Some papers argue that although funds on average generate negative abnormal returns, relative performance persists (Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Grinblatt et al., 1995; Grinblatt and Keloharju, 2000). Compared to the first set of studies, we document longer return persistence in a developing market, and we illustrate the economic value of such persistence for investors. Compared to the second set of studies, we find that not only does relative performance persist, but also stock mutual funds generate abnormal returns as a whole.

The remainder of the chapter is organized as follows. Section 2 covers some background and describes the data. Section 3 explores the performance of stock mutual funds in the A-share market. Section 4 illustrates the economic value of portfolios of funds for investors. Section 5 concludes.

2. Background and Data

2.1 Background

China's stock market has gone through rapid development since its establishment in 1991. By August 2016, the Chinese A-share market has become the second largest stock market with a total capitalization exceeding $5 trillion (Chen and Chi, 2018). As a relatively young stock market, trading in the A-share market is dominated by retail investors. According to official statistics from the Shanghai and Shenzhen stock exchanges, more than 80% of trading volume can be attributed to retail investors. In comparison, institutional investors dominate trading in the U.S. markets, and retail investors make up less than 20% of trading volume.

The first mutual fund primarily investing in the A-share stock market, a closed-end fund, launched in 1998. Three years later, the first open-end stock mutual fund was launched. As the mutual fund industry in China grew, regulation compelled funds to increase the transparency of their operations. Starting in 2003, mutual funds have had to disclose their top 10 holdings on a quarterly schedule, and their entire portfolio holdings on a semi-annual schedule. Prior to August 2015, in order to be classified as an actively managed stock mutual fund, a fund must invest at least 60% of its assets in the A-share market. In August 2015, this minimum threshold increased from 60% to 80%. As a result, many funds classified as stock mutual funds prior to August 2015 became a class of funds known as hybrid stock mutual funds, which hold between 60% and 80% of assets in the A-share market. Hybrid funds have more flexibility to invest in assets class beyond stocks, such as fixed-income instruments or financial derivatives. In our study, we focus on actively managed stock mutual funds, hereinafter simply called “stock mutual funds”.

2.2 Data

We collect our data from Wind Information® (WIND). WIND is a leading Chinese financial data provider. Founded in 1994, WIND serves more than 90% of the domestic financial enterprises. Our sample consists of actively managed stock mutual funds from July 2006 to September 2020. We start our sample in 2006 because there is only a small number of funds prior to 2006.

We start from the universe of all mutual funds in the Chinese markets, and we construct our sample of stock mutual funds using the following three filters. First, we exclude passive index funds. Second, we examine the quarterly fund holdings data, and we select funds that have at least 55% of assets invested in the A-share market in any given quarter, and on average have more than 60% of assets invested in stocks. Third, we exclude funds whose benchmark allocates more than 5% into a non-A-share stock index such as the Hang Seng Index.

Since the first stock mutual fund was introduced in 1998 in China, the mutual fund industry has experienced steady and robust growth. Figure 1 plots the number of stock mutual funds in the Chinese A-share market. In 2006, there were only 79 stock mutual funds. This figure has grown steadily, reaching 1,368 by 2019. In a short span of just 13 years, the number of funds in the A-share market has multiplied 17-fold.

Table 1 reports summary statistics for the actively managed stock mutual funds. While the number of funds increased every year, the total assets under management of these funds experienced a less clear upward trend. In 2006, the total AUM of stock mutual funds was ¥229 billion[3], which ballooned to ¥1,424 billion in 2007, but subsequently fell to just under ¥800 billion in the early 2010's, before rising again to ¥1,370 billion in 2019. Overall, the AUM of stock mutual funds showed significant growth, increasing sixfold from 2006 to 2019, but the path was very volatile. This erratic growth illustrates a rather young industry which has not reached maturity.

The period between 2006 and 2020 was marked by significant growth in the total stock market capitalization in the Chinese A-share market, which rose from ¥2.3 trillion to over ¥49 trillion. As a fraction of the total stock market capitalization, the total stock mutual fund AUM peaked in 2007 at over 15%, before falling down to a stable level between 2-3% in the late 2010's. Currently, stock mutual fund makes up a relatively small percentage of market participants in the A-share market.

Figure 1 and Table 1 provide an informative overview of stock mutual funds in the A-share market. The growth of this industry in China does not resemble that of the U.S. funds from the same time period, but is reminiscent of an earlier period in the U.S. fund history. Khorana and Servaes (2012) document that in the infancy of the U.S. mutual fund industry, the AUM increased sixfold over a nine-year span from 1976 to 1984, a rate of growth similar to the observed pattern in the A-share market from 2006 to 2019. By the 2000s, the U.S. mutual fund industry had matured, and from 2000 to 2009 the growth rate in the number of funds or the assets under management had slowed down. In this period, the AUM of all mutual funds increased 83%.

The market share of actively managed stock mutual funds is significantly larger in the U.S. markets compared to that of the Chinese A-share market. Barber et al. (2016) assert that

[3] The USD($)/RMB(¥) exchange rate ranged from 6.05 to 7.72 in our sample period.

“most mutual fund investors allocate their savings to actively managed mutual funds”, a statement supported by data. According to Pastor et al. (2017), as of 2013, mutual funds in the U.S. had a total AUM of $15 trillion, about $7.5 trillion of which are focused on stock investments. Of these stock funds, 82% were actively managed, giving a total of over $6 trillion in actively managed stock mutual funds. In comparison, the U.S. stock market was $24 trillion in 2013, which means stock mutual funds made up 25% of the total market capitalization.

A more recent figure can be derived from Ma et al. (2019), who state the total AUM of mutual funds in the U.S. was over $16 trillion in 2016. If the proportion of actively managed stock mutual funds remained roughly constant between 2013 and 2016, there would have been $6.5 trillion in actively managed stock mutual funds in the U.S. in 2016, when the total stock market capitalization was $27 trillion. The total assets under management for actively managed stock mutual funds in the U.S. markets was then 24% of the total stock market capitalization. The market share estimates from Pastor et al. (2017) and Ma et al. (2019) are six to 10 times larger compared to the market share observed in the A-share market.

3. Performance of Stock Mutual Funds

From the perspective of an investor in the Chinese A-share market who wants to delegate her investment decisions to mutual fund managers, there are two natural questions to ask: 1) How do stock mutual funds perform in China? 2) Can an investor do better than the average stock mutual fund by selecting a sub-sample of the top-performing funds? To answer these questions, we investigate the performance of Chinese stock mutual funds. We will first compare aggregate fund performance to the market benchmark, then examine the cross-sectional variation in fund performance.

3.1 Stock Mutual Funds in Aggregate

The CSI300 Index represents the 300 largest stocks listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. It is the most commonly used performance benchmark for mutual funds as well as exchange-traded funds. To evaluate the behavior of the aggregate set of stock mutual funds, we construct an equal-weight portfolio of all funds, rebalance monthly. Figure 2 compares the cumulative returns of this equal-weight portfolio with the returns of the CSI300 Index. From 2007 to 2020, the portfolio of all stock mutual funds significantly outperformed the CSI300 Index. The equal-weight portfolio of stock mutual funds grew from 1 to 2.71, for an annualized average return of 10.8%, whereas the CSI300 Index's grew from 1 to 1.31 in the same period, for an annualized average return of 6.2%. The equal-weight portfolio of funds has a lower volatility compared to the CSI300 Index; the annualized volatility of the equal-weight portfolio of stock mutual funds is 25.2%, whereas the volatility of the CSI300 Index is 28.7%. Despite the CSI300 Index's 6.2% annualized average returns, its cumulative returns over 13 year are just 31%. The index experienced high volatility, which drove a large wedge between the arithmetic and geometric returns.

Given its higher average returns and lower volatility, the equal-weight portfolio of all stock mutual funds provides investors with a more attractive risk-return tradeoff. Its Sharpe ratio is 0.35, more than twice as high as that of the CSI300 Index. The tail risk of the equal-weight portfolio of funds is also smaller than that of the CSI300 Index. The maximum drawdown of the portfolio of funds is 58.0%, compared to 70.5% for the CSI300 Index.

Our finding that aggregate stock mutual funds outperform the market is consistent with the results in Chi (2016), who also finds outperformance using data up to December 2013. Aggregate fund performance differs in the A-share market and the U.S. markets. There is a large literature, based on the U.S. markets, that supports the idea that mutual funds do not outperform the aggregate stock market (*inter alia*, Jensen, 1969; Elton et al., 1993; Fama and French, 2010). A separate set of papers argue that although mutual funds on average underperform the market, relative performance across funds may persist (Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Grinblatt et al., 1995; Grinblatt and Keloharju, 2000). We turn our attention to the relative performance across stock mutual funds in the next section.

3.2 The Cross-Section of Fund Returns

A-share investors who invest in an equal-weight portfolio of stock mutual funds can outperform the aggregate stock market. Could investors do better by selecting funds that are likely to outperform in the future? Successful fund selection requires two necessary conditions. First, some fund managers must possess significant ability to generate outperformance. Second, this ability must be persistent, so the selected top managers continue to produce outperformance. If these two conditions were satisfied, then provided the investor has a method of identifying the top funds, her selected portfolio of funds will have a higher return compared to the equal-weight portfolio of all funds.

There is an economically large spread in the average returns of stock mutual funds. The average return difference between the top 5% of funds and the average of all funds is a staggering 23.3% per year. The top 20% of funds outperform the average of all funds by 14.9% per year. The bottom 20% of funds, in turn, underperform the average of all funds by 14.4% per year. These differences could be due to random chance, or fund manager skill – persistent outperformance by a select set of funds would favor a skill-based explanation or a luck-based one.

To better understand the return distribution of stock mutual funds in the A-share market, we rank funds into quintiles by their returns over the past 12 months. The highest quintile contains 20% of funds with the highest cumulative returns over the previous 12 months, whereas the lowest quintile contains 20% of funds with the lowest cumulative returns. Quintiles are equal-weight among their constituent funds, and reconstituted monthly. To understand the behavior of these quintiles, we track the portfolio characteristics before and after portfolio formation. We examine the average returns of the quintiles, and we use the Capital Asset Pricing Model to partition the returns into a systematic component and an idiosyncratic component:

$$R_{j,t} - R_{ft} = \alpha_j + b_j RmRf_t + \varepsilon_{j,t} \quad (1)$$

where $R_{j,t}$ is the portfolio return of quintile j. R_{ft} is the risk-free rate in month t, a monthly equivalent of the three-month fixed-term deposit rate. $RmRf_t$ is the aggregate Chinese stock market return, proxied by the CSI300 Index, in month t in excess of the risk-free rate. α_j is the intercept, the part of average returns unexplained by the CAPM.

The pre- and post-formation statistics are shown in Panel A of Table 2. By construction, average returns prior to portfolio formation increase monotonically from the lowest quintile to the highest quintile, ranging from -0.05% per month to 2.39% per month. The difference in average returns between the highest and lowest quintiles is 2.44% per month, which is economically large and statistically significant at the 1% level. Because the ranking period is 12 months and the rebalance frequency is one month, two adjacent rebalances have an 11-month overlap in the portfolio signals, and portfolio statistics from two adjacent months are not independent. We account for potential serial correlation using Newey and West (1987) standard errors. 11 lags are used to compute the Newey-West errors to allow for serial correlation up to 11 months.

We do not observe much variation in the market betas of the portfolios, which lie in a tight range between 0.82 and 0.86. Quintiles with higher average returns in the pre-formation period tend to have somewhat lower market betas. Because there are large differences in average returns, but limited variation in market betas, portfolio average returns are not explained by the CAPM. The unexplained portion of average returns – the

CAPM alphas – follows a similar pattern as the average returns themselves. The difference in CAPM alphas between the highest and lowest quintiles is 2.19% per month, economically and statistically large.

In the month after portfolio formation, average portfolios returns are still monotonic in the quintile ranks, although the return differences are not as large as those in the pre-formation period. The average return spread between the highest and lowest quintiles is 2.26%, somewhat smaller compared to the pre-formation value. The market betas for the quintiles range from 0.83 to 0.86, virtually unchanged from their pre-formation values. The spread in CAPM alphas is still economically large, 2.04% per month, albeit smaller compared to that of the pre-formation period.

Another way to measure fund performance is by their abnormal returns relative to the CAPM (Jensen, 1969; Carhart, 1997). We estimate CAPM alphas for each fund based on past 12-month returns, and sort all funds into quintiles: the highest quintile contains 20% of funds with the largest CAPM alphas in the pre-formation period, whereas the lowest quintile contains 20% of funds with the smallest CAPM alphas. Each portfolio is reconstituted at the beginning of every month. The portfolio statistics are shown in Panel B of Table 2.

By forming quintiles based on CAPM alphas, we are maximizing the spread in pre-formation CAPM alphas by design, rather than the spread in average returns. Nevertheless, in the pre-formation period, the average portfolio returns are monotonically increasing in the quintile ranks. The lowest quintile formed on CAPM alphas shows an average monthly return of 0.11%, followed by 0.76% for the next quintile, 1.13% for the middle quintile, 1.53%, and 2.23% for the highest quintile. There is a 2.12% spread in average returns between the highest and lowest quintiles. We observe slightly more variation in the market betas for these quintiles compared to Panel A, ranging from 0.81 to 0.88, but the difference in market exposure between the highest and lowest quintiles is still economically small (0.81 - 0.88 = -0.07) and statistically indistinguishable from zero. The CAPM alphas show significant variation across the quintiles, from -0.82% for the lowest quintile to 1.80% for the highest quintile, for a difference of 2.61%.

In the post-formation period, the average return difference between the highest and lowest quintiles is 1.97%, statistically significant at a 1% level. There is still minimal variation in the market betas; the range is only 0.06. The differences in CAPM alphas remain economically and statistically large: 2.4% per month between the highest and lowest ranked quintile portfolios.

Figure 3 shows a time series plot of the cumulative returns of the five quintiles formed on CAPM alphas. All portfolios are initialized at 1 in 2007. The five portfolios are highly correlated with one another, primarily due to their market exposure, hence they are also positively correlated with the CSI300 Index returns. We observe persistent performance commensurate with the quintile rankings: the top 20% of funds consistently outperform, following by the next 20%, and so on. Ordered by quintiles, the annual average returns of the quintiles are 14.9%, 12.7%, 10.4%, 9.2%, and 6.8%. The bottom 20% of funds have a cumulative return of 64%, compared to 341% for the top 20% of funds – 1 RMB invested in the bottom 20% of funds in 2007 would have turned into 1.64 RMB by September 2020, whereas 1 RMB invested in the top 20% of funds in 2007 would have turned into 4.41 RMB by 2020.

3.3 Persistence in Performance

Portfolio turnover gives a measure of the persistence of fund performance. A high portfolio turnover for the top quintile would imply that most top-performing funds in one month are not the top-performing funds in the following month, suggesting little to no performance persistence. Alternatively, a low portfolio turnover would imply that the top-performing funds in one month tend to also be the top-performing funds in the following month, indicating a high degree of persistence in fund performance.

Fund performance exhibits persistence from month to month. The top quintile of funds, based on past 12-month returns, has a monthly turnover of 20.8%. This figure implies that approximately four out of five top-performing funds in a given month will also be top-performing funds in the following month. We observe similar portfolio turnover for the bottom 20% of funds based on past returns; the monthly turnover is 20.6%.

Portfolios based on the CAPM alphas exhibit similar levels of turnover. A portfolio of the top 20% of funds based on the CAPM alphas has a monthly turnover of 21.5%, which means 78.5% of funds tend to remain in the top-quintile portfolio at each monthly portfolio rebalance. A portfolio of the bottom 20% of funds based on CAPM alphas exhibit a monthly turnover of 21.2%. The evidence surrounding monthly portfolio turnover strongly suggest there is performance persistence for stock mutual funds at the monthly horizon.

At each monthly portfolio rebalance, the portfolio formation signal is based on a trailing 12-month period. In two adjacent monthly rebalances, the two sets of signals have an 11-month overlap, which mechanically makes the two sets of signals highly correlated. The low turnover values may be an artifact of a higher rebalance frequency relative to the portfolio formation signal. To overcome this potential limitation to our analysis, suppose we rebalance the portfolios once a year, such that two adjacent rebalance periods do not share overlapping portfolio formation signals. The turnover figures of these annually rebalanced portfolios do not suffer from any potential downward bias due to overlapping signals.

The turnover of the top 20% of funds, based on past year's returns, is 74.6%, indicating that about one quarter of the top-performing funds in a given year continue to be the top-performing funds in the following year. The bottom 20% of funds also shows some persistence – the portfolio turnover is 68.5%, which means almost one third of the worst-performing funds tend to continue to perform relatively poorly in the following year. Annual portfolio rebalances based on CAPM alphas show similar levels of persistence. The top 20% of funds have a portfolio turnover of 73.8%, whereas the bottom 20% of funds have a turnover of 75.8%.

While portfolio turnover provides suggestive evidence of performance persistence, a more formal test is needed to more rigorously quantify this finding. We use the methodology of Fama and MacBeth (1973) to test performance persistence at an annual horizon. Every year, we compute the cumulative returns and the CAPM alphas for each stock mutual fund, and we evaluate whether the top-performing funds in one year are also the top-performing funds in the following year. Because the returns and CAPM alphas in one year do not overlap with those from another year, there is no mechanical reason for these measures to persist.

Each year, we run cross-sectional regressions of fund returns and on their lagged values:

$$r_{i,t} = a_t^r + b_t^r r_{i,t-1} + \varepsilon_t^r \quad (2)$$

where $r_{i,t}$ is return of fund *i* in year *t*. If a fund that performs well in one year also tend to perform well in the following year, we would expect a positive regression coefficient b_t^r. After running separate cross-sectional regressions for each year, we compute the point estimates and standard errors of the regression coefficients from their time series.

We also investigate the persistence of the CAPM alphas of individual stock mutual funds:

$$\alpha_{i,t} = a_t^\alpha + b_t^\alpha \alpha_{i,t-1} + \varepsilon_t^\alpha \quad (3)$$

where $a_{i,t}$ is CAPM alpha of fund *i* in year *t*. Similar to the interpretation of Equation (2), if the top-performing funds, measured by their CAPM alphas, tend to continue to outperform, we should expect to observe a positive estimate for b_t^{α}.

Table 3 presents the Fama-MacBeth regression results. We observe economically large regression coefficients associated with past performance. From the perspective of a given fund, a 1% increase in fund returns relative to other funds is associate with a 0.18% increase in relative performance in the following year. Similarly, a 1% increase in the CAPM alpha relative to other funds is associated with a 0.19% increase in the CAPM alpha in the following year, compared to the other funds. The point estimates are not only economically large, but also statistically significant at the 1% level.

In the context of existing literature, the persistence of fund returns in the A-share market is striking. Papers focused on the U.S. markets almost uniformly find no performance persistence at the annual frequency. Carhart (1997) finds economically large differences in average returns in portfolios ranked on past returns at a monthly rebalance frequency, but this persistence does not extend to the following year. Funds ranked by one-year returns do not show performance persistence, except for the extreme losers that continue to underperform. Bollen and Busse (2005) document short-term return persistence in mutual funds up to three months, but no return persistence beyond three months. Taking a different approach to measure the skill of mutual fund managers that does not focus on fund returns, Berk and van Binsbergen (2015) find that the average mutual fund adds values for investors for up to 10 years. In the A-share market, fund returns tell a compelling story: top fund managers are able to add value for investors through persistent outperformance relative to other funds and benchmark returns.

4. The Economic Value of Stock Mutual Funds

4.1 Portfolios of Top-Performing Funds

We have demonstrated that stock mutual fund returns exhibit significant cross-sectional variation that persists over time. In this section, we take the perspective of an investor and explore the benefit of constructing portfolios of the top-performing funds. We examine the return profiles of these portfolios to gain insight into the economic value of stock mutual funds for market participants.

Barber et al. (2016) find that CAPM alphas are the best predictor of fund flows, suggesting investors strongly value market-adjusted fund returns. As such, we use CAPM alphas as the selection criteria for top-performing funds. At the end of each month, we calculate the CAPM alphas of each stock mutual fund in our sample, using past 12 month returns. Next, we sort all available funds by their CAPM alphas and select the top 5% of funds, allocating equal portfolio weights to these funds. At the beginning of our sample in 2007, when the top 5% included fewer than 10 selected funds, we select the top 10 funds.

Figure 4 compares the performance of this portfolio with the CSI300 Index. From 2007 to 2020, the cumulative return of the CSI300 Index was 31%. In comparison, a portfolio of the top 5% of all stock mutual funds showed a cumulative return of 466%, turning 1 RMB in 2007 into 5.66 RMB by September 2020.

Robust outperformance of the CSI300 Index is not limited to the top 5% of stock mutual funds. Investors can achieve better diversification by considering a larger set of top-performing funds. As the number of funds increases, the portfolio becomes more diversified, but the ability of the portfolio to generate outperformance also decreases. Table 4 presents the performance statistics for these portfolios. The top 5% of funds have an average return of 17.2% per year from 2007 to 2020, compared to 16.0% for the top 10%, 14.6% for the top 25%, and 13.1% for the top 50% of funds. A portfolio that simply invests in all available stock mutual fund every month has an average return of 10.8% per year. Clearly, portfolios made up of stock mutual funds easily outperform the CSI300

Index in our sample. Investors could do even better by selectively investing in the top-performing funds.

Table 4 presents additional performance statistics for portfolios of top-performing stock mutual funds. Among all portfolios, the equal-weight portfolio of all stock mutual funds has the lowest volatility, 25.2% per year. Portfolio volatility increases as the set of top-performing funds becomes smaller. A portfolio of the top 5% of funds, with a volatility of 28.2%, is the most volatile. However, it is still less volatile than the CSI300 Index, which has an annual volatility of 28.7%.

Although more concentrated portfolios have higher volatility, they still offer a more attractive risk-return tradeoff for investors due to their high average returns. A portfolio of the top 5% of funds has the highest Sharpe ratio, 0.54, of all the portfolios. The Sharpe ratios decrease monotonically as the portfolios become more diversified. All the portfolios of funds have higher Sharpe ratios compared to that of the CSI300 Index.

Less diversified portfolios could be more susceptible to idiosyncratic effects associated with individual funds. However, more concentrated portfolios of stock mutual funds do not exhibit greater tail risk. As we move to more concentrated positions from an equal-weight portfolio of all funds, to the top 50%, top 25%, top 10%, and the top 5% of funds, the maximum drawdowns of these portfolios are remarkably similar, hovering around 58%. It appears that the more concentrated portfolios of stock mutual funds do not suffer larger occasional losses compared to the more diversified portfolios. All the portfolios experienced smaller drawdowns compared to the CSI300 Index, which has a maximum drawdown of 70.5%.

4.2 Performance Attribution

Portfolios of stock mutual funds can generate economically meaningful outperformance relative to the CSI300 Index. How do these different portfolios behave? To answer this question, we employ a standard performance attribution setup:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf} RmRf_t + \varepsilon_t \quad (4)$$

In this regression, $R_{mf,t}$ is the return of the portfolio of mutual funds in month t. R_{ft} is the risk-free rate in month t, computed as a monthly value of the three-month fixed-term deposit rate. $RmRf_t$ represents the aggregate Chinese stock market return in month *t* in excess of the risk-free rate. α_{mf} is the portion of average returns unexplained by the CAPM.

An equal-weight portfolio that includes every available stock mutual fund has a market beta of 0.78, and a CAPM alpha of 5.5% per year. Market returns explain a significant fraction of the return variation of the aggregate set of funds; only 21.2% of the return variation remains unexplained. The aggregate set of stock mutual funds in the A-share market behaves differently compare to the aggregate set of funds in the U.S. markets. Fama and French (2010) demonstrate that in the U.S. markets, stock mutual funds in aggregate have a market beta of 1.01, and a performing attribution regression using market returns results in an R-squared of 96%. Evidently, stock mutual funds as a whole highly resembles the market in the U.S. markets, whereas in the Chinese markets, aggregate stock mutual funds do not track the market as closely.

An equal-weight portfolio of the top half of funds, rebalanced monthly, has a market beta of 0.77 and an unexplained average return of 7.9%. For investors who are able to identify the best-performing 50% of stock mutual funds, their annual average returns can be improved by 2.4%. If an investor were to form an equal-weight portfolio of the 25% top funds, the market beta of such a portfolio would be 0.77, and the residual average return would be 9.4%. As we move to more selective portfolios, the regression intercept – unexplained average returns by the CAPM – rises to 11.9% for a portfolio of the top 5%

of funds. Selecting the best-performing funds not only achieves highest average returns (see Table 4), but also the largest risk-adjusted outperformance. Interestingly, the market exposure of more concentrated portfolios does not appear to increase; a portfolio of the top 5% of funds still has a market beta of 0.78, equivalent to that of the aggregate portfolio of stock mutual funds.

Perhaps not surprisingly, portfolios with more concentrated positions in the top performing funds have more idiosyncratic risk. The CAPM can explain almost 80% of the return variation associated with the aggregate portfolio of stock mutual funds, but only 63% of the return variation associated with a portfolio of the top 5% of funds. In fact, the explanatory power of the CAPM steadily decreases as the portfolios become more concentrated: 73.8% for the top 50% of funds, 70.5% for the top 25%, and 65.2% for the top 10%. Although the systematic risks of these portfolios are all the same, they contain increasing idiosyncratic risks not captured by market returns.

Stable market betas across portfolios formed on past performance is consistent with previous work on stock mutual funds. Chi (2016) also finds that the aggregate set of stock mutual funds in the A-share market has a beta statistically significantly less than one, between 0.71 and 0.78 depending on whether other factors such as value or momentum are included in the performance attribution regression. Carhart (1997) asserts that market betas are not able to capture differences in average returns of stock mutual funds; deciles formed on past 12-month returns all have market betas around one.

The outperformance of Chinese stock mutual funds relative to the aggregate stock market stands in contrast to the findings in the U.S. markets. Among others, Fama and French (2010) document that U.S. stock mutual funds, whether in aggregate or a selected set, have not been able to beat the U.S. stock market in the past few decades. Investors in the A-share market would have beaten the market handily by holding in portfolios of stock mutual funds.

Concluding Remarks

In this chapter, we study the economic value of stock mutual funds for investors in the Chinese A-share market. From 2006 to 2019, stock mutual funds in the A-share market experienced rapid growth. The number of funds multiplied 17-fold, whereas the assets under management grew sixfold. An equal-weight portfolio of all stock mutual funds outperforms the CSI300 Index, the most common benchmark for these funds.

We investigate the average performance, cross-sectional dispersion, and performance persistence of Chinese stock mutual funds, and we uncover a marketplace well-suited for fund selection. Economically large average return differences are observed across funds, and funds that perform well in one period also tend to perform well in the subsequent periods. Our results suggest actively managed stock mutual funds provide attractive investment opportunities for investors. We illustrate the economic value of stock mutual funds by forming portfolios of the top-performing funds based on their past risk-adjusted returns, and we find these portfolios improve the risk-return tradeoff compared to a buy-and-hold strategy in the aggregate stock market.

In this research, we have explored two measures of past performance: past returns and CAPM alphas. A natural extension of our work is to explore a larger suite of performance measures, including information ratio, Sortino ratio, and multi-factor model alphas. Moreover, fund holdings could provide a different perspective on skill and persistence. Performance measures derived from holdings data such as industry concentration (Kacperczyk et al., 2005), holding similarity (Cohen et al., 2005), and return gap (Kacperczyk et al., 2008) all provide interesting research directions. Lastly, one could run a horse race between different performance measures in predicting future fund returns, or blend several performance measures into an optimal portfolio of funds.

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Figure 1: Number of Stock Mutual Funds

This figure plots the number of actively managed stock mutual funds in the Chinese A-share market from 2006 to 2019.

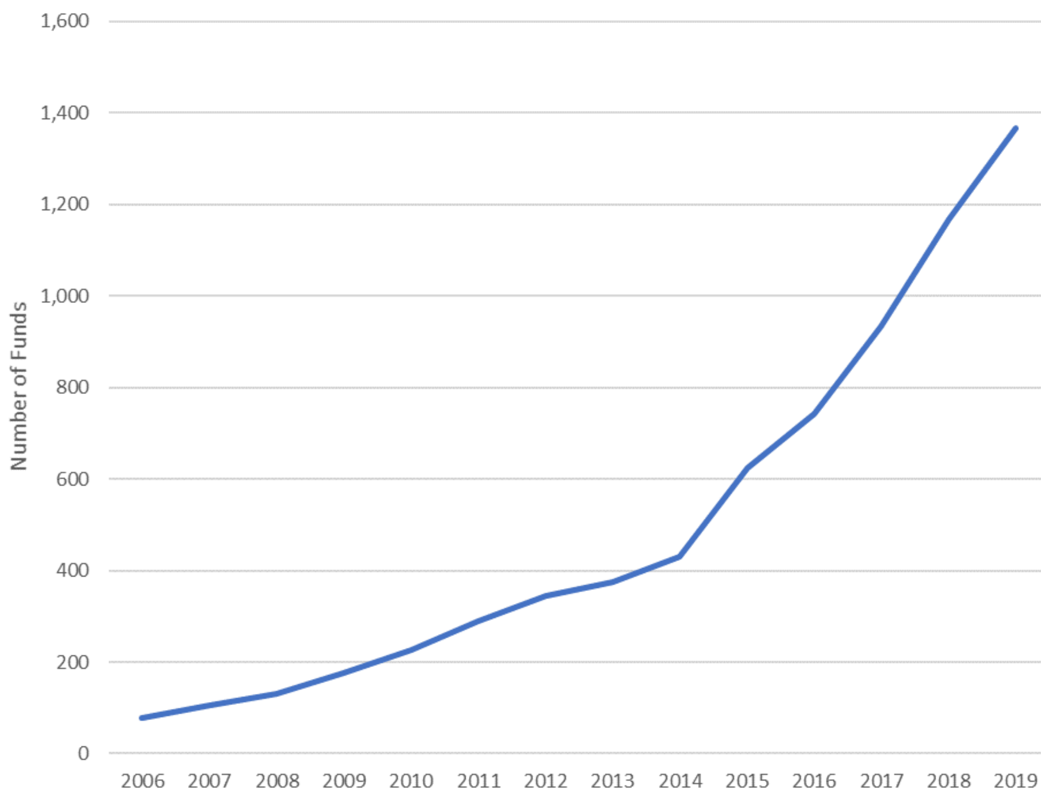

Figure 2: Aggregate Stock Mutual Fund Performance

This figure plots the portfolio value (initialized at 1) for an equal-weight portfolio of all stock mutual funds, compared to the CSI300 Index. The sample period is August 2007 to September 2020.

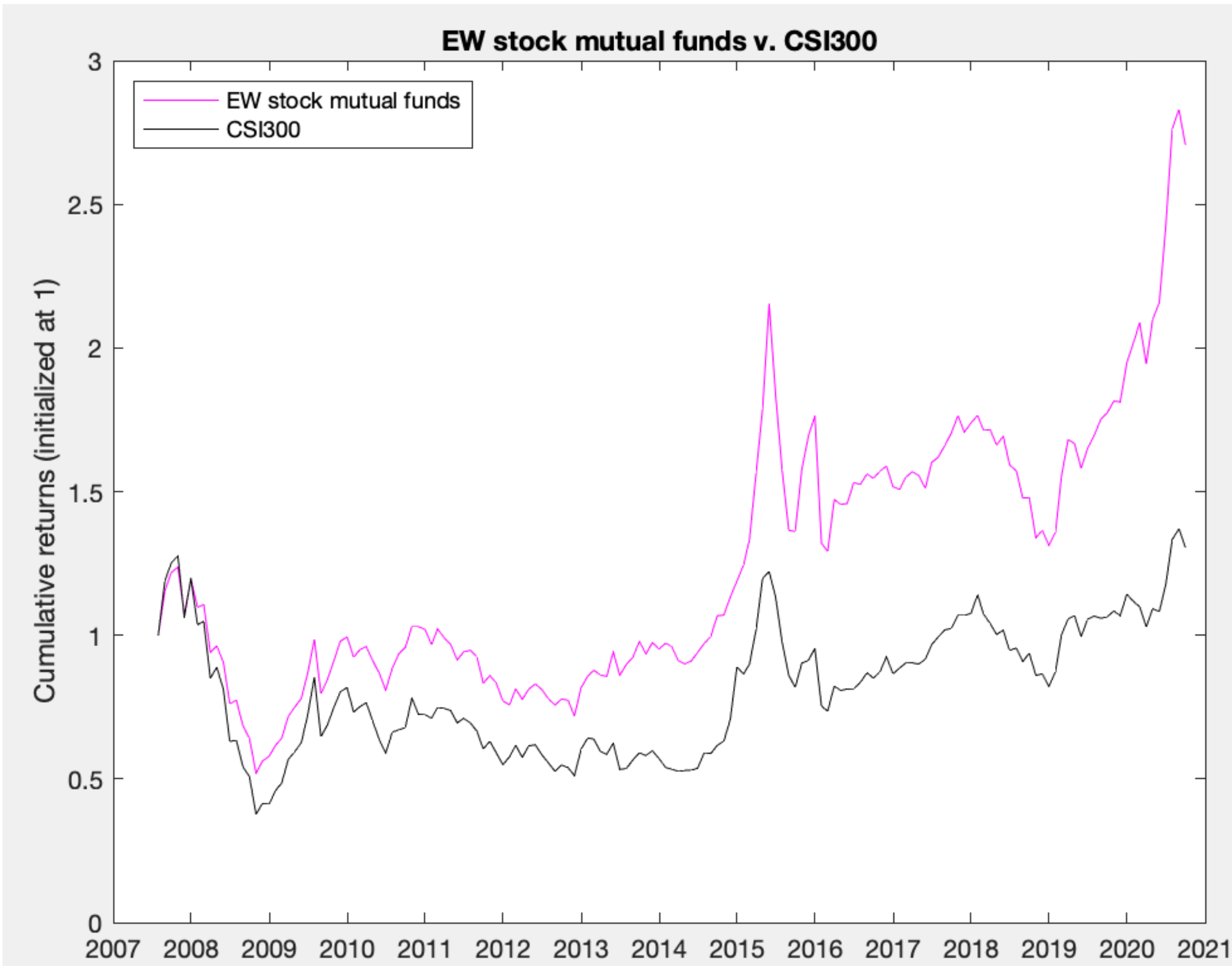

Figure 3: Cumulative Returns of Fund Quintiles

This figure plots the portfolio value (initialized at 1) for five quintile portfolios, sorted by past 12-month CAPM alpha:

$$R_{j,t} - R_{ft} = \alpha_j + b_j RmRf_t + \varepsilon_{j,t}$$

where $R_{j,t}$ is the portfolio return of quintile j. R_{ft} is the risk-free rate in month t, a monthly equivalent of the three-month fixed-term deposit rate. $RmRf_t$ is the aggregate Chinese stock market return, proxied by the CSI300 Index, in month t in excess of the risk-free rate. Five portfolios are formed based on the intercept α_j, rebalanced monthly. The sample period is from August 2007 to September 2020.

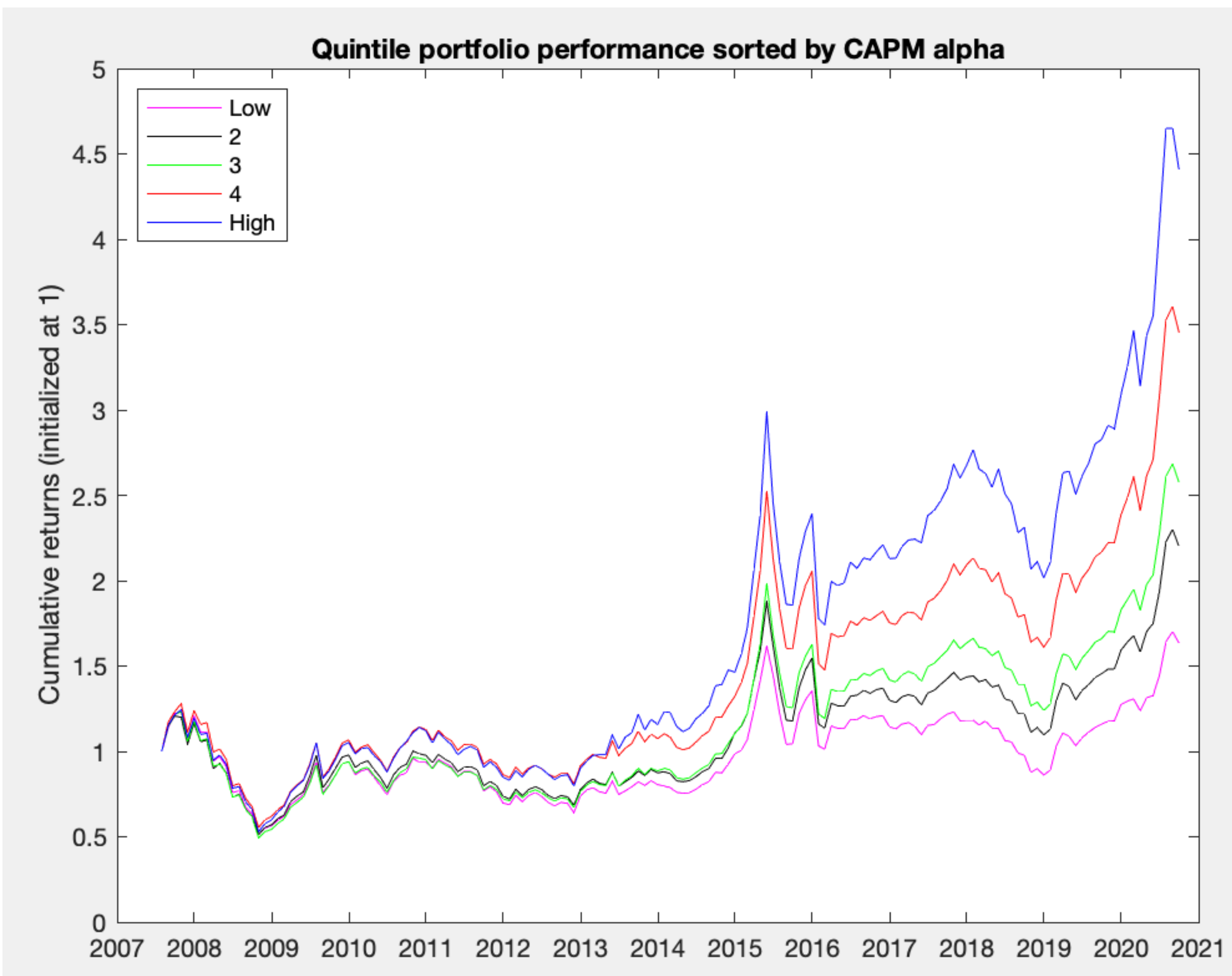

Figure 4: Cumulative Returns of the Top 5% of Funds

This figure plots the portfolio value (initialized at 1) for a portfolio of the top 5% of funds, measured by the CAPM alphas, rebalanced monthly. The sample period is August 2007 to September 2020.

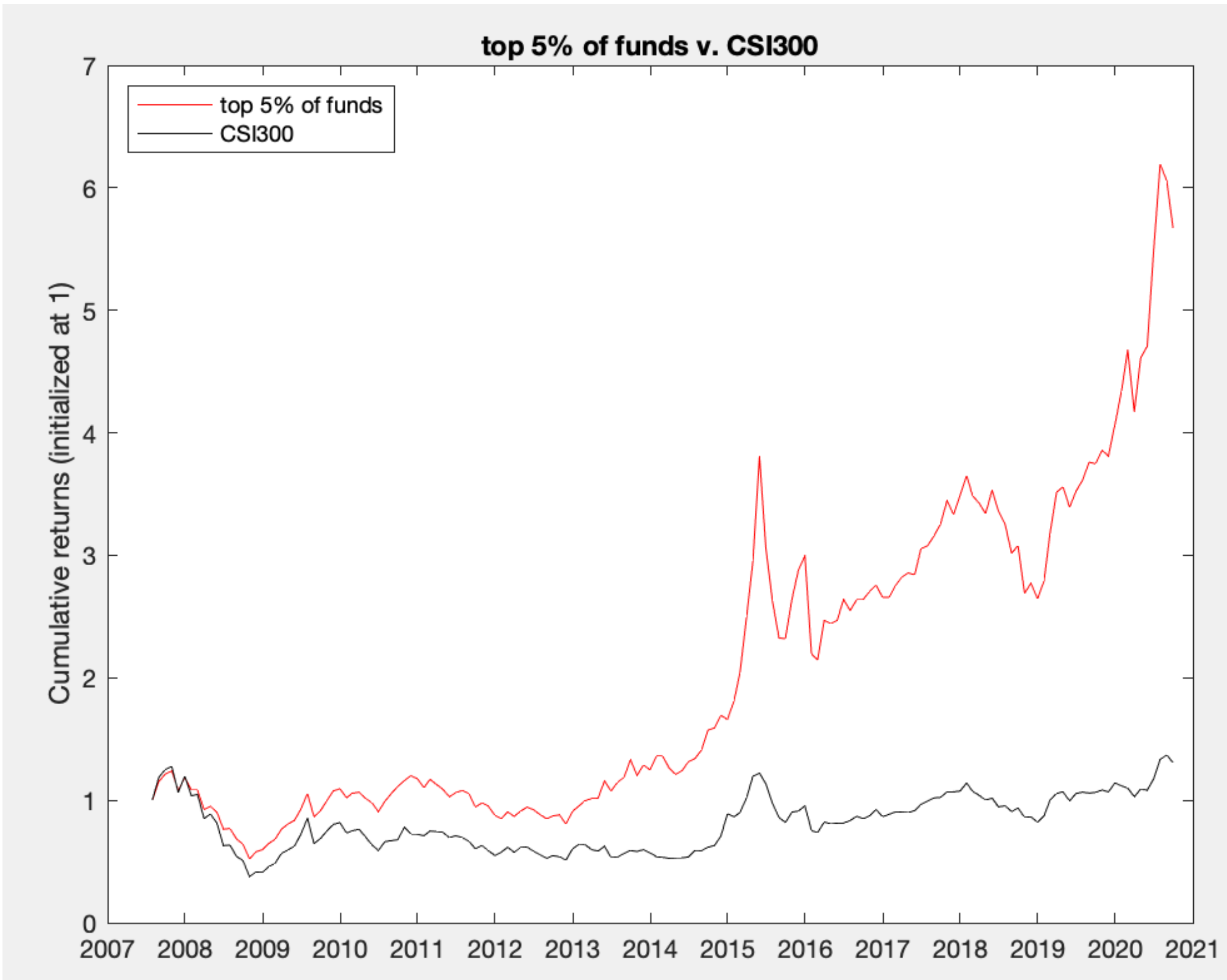

Table 1: Summary Statistics of Actively Managed Stock Mutual Funds

The table reports the year-end summary statistics of the actively managed stock mutual funds in the A-share market. The second column reports the number of stock mutual funds. The third column reports the total asset under management of the stock mutual funds, in ¥billion. The fourth column reports the total market capitalization of the Chinese A-share stock market, in ¥billion. The rightmost column reports the total AUM of stock mutual funds as a fraction of the total stock market capitalization.

Year	Number of Funds	Total AUM (¥billion)	Total Stock Market Capitalization (¥billion)	AUM/Mktcap
2006	79	229	2,366	9.7%
2007	105	1,424	9,043	15.7%
2008	132	606	4,436	13.7%
2009	176	1,031	14,938	6.9%
2010	226	998	19,069	5.2%
2011	289	791	16,329	4.8%
2012	346	770	17,985	4.3%
2013	375	777	19,789	3.9%
2014	430	747	31,465	2.4%
2015	624	1,087	41,544	2.6%
2016	742	896	39,081	2.3%
2017	935	1,056	44,674	2.4%
2018	1,168	942	35,228	2.7%
2019	1,368	1,370	49,131	2.8%

Table 2: Performance of Quintiles formed on Past Returns

Each month, we rank the stock mutual funds by their past 12-month performance, and form equal-size quintile portfolios. We then track the quintile portfolio's performance in the following month. The three columns on the left report the pre-formation average monthly returns, market betas, and CAPM alphas. The three columns on the right report the post-formation statistics. In the bottom two rows, we report the portfolio statistics for a portfolio that takes a long position in the highest quintile and a short position in the lowest quintile. Newey and West (1987) t-statistics are reported in the parentheses, with the number of lags set to 11. Panel A ranks funds by their past 12-month returns; Panel B ranks funds by their past 12-month CAPM alphas. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Panel A: Quintiles based on 12-Month Returns

	Pre-formation			Post-formation		
	Avg Return	β	α	Avg Return	β	α
1 (low)	-0.05%	0.86	-0.60%	0.00%	0.86	-0.56%
2	0.71%	0.84	0.06%	0.70%	0.85	0.08%
3	1.14%	0.84	0.45%	1.11%	0.84	0.44%
4	1.58%	0.83	0.84%	1.52%	0.83	0.80%
5 (high)	2.39%	0.82	1.59%	2.26%	0.83	1.48%
5-1	2.44%***	-0.04	2.19%***	2.26%***	-0.04	2.04%***
	(11.8)	(-1.07)	(9.7)	(11.5)	(-1.11)	(9.0)

Panel B: Quintiles based on 12-Month CAPM Alphas

	Pre-formation			Post-formation		
	Avg Return	β	α	Avg Return	β	α
1 (low)	0.11%	0.88	-0.82%	0.15%	0.88	-0.73%
2	0.76%	0.85	-0.01%	0.75%	0.85	0.00%
3	1.13%	0.83	0.44%	1.10%	0.83	0.43%
4	1.53%	0.82	0.92%	1.47%	0.82	0.87%
5 (high)	2.23%	0.81	1.80%	2.12%	0.82	1.67%
5-1	2.12%***	-0.07	2.61%***	1.97%***	-0.06	2.40%***
	(9.4)	(-1.55)	(10.7)	(9.1)	(-1.37)	(9.7)

Table 3: Performance Persistence of Funds

The table reports the results to the Fama-MacBeth procedure applied to fund performance. We conduct cross-sectional regression for each year, following one of the two setups below:

$$r_{i,t} = a_t^r + b_t^r r_{i,t-1} + \varepsilon_t^r$$
$$\alpha_{i,t} = a_t^\alpha + b_t^\alpha \alpha_{i,t-1} + \varepsilon_t^\alpha$$

where $r_{i,t}$ is the total return of fund *i* during the 12-month period ending in month *t* and $\alpha_{i,t}$ is the CAPM alpha of fund *i* during the 12-month period ending in month *t*. Point estimates and standard errors of regression coefficients are computed from their time series. The first column shows the regression results for returns, and the second column shows the results for CAPM alphas. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)
a	0.08	0.00
	(1.3)	(1.5)
b	0.18***	0.19***
	(4.2)	(4.4)
Avg R-Squared	3.52%	4.76%

Table 4: Portfolios of Stock Mutual Funds

This table reports the performance of portfolios formed using stock mutual funds. Every month, all available stock mutual funds are ranked by their trailing 12-month CAPM alphas, and a subset of the best-performing funds are selected. "Top x%" is a portfolio of the x% best-performing funds. "All Funds" is an equal-weight portfolio of all stock mutual funds.

	Annualized Returns	Annualized Volatility	Sharpe Ratio	Maximum Drawdown
Top 5%	17.2%	28.2%	0.54	58.0%
Top 10%	16.0%	27.3%	0.52	58.0%
Top 25%	14.6%	26.4%	0.48	57.3%
Top 50%	13.1%	25.8%	0.43	57.9%
All Funds	10.8%	25.2%	0.35	58.0%
CSI300 Index	6.2%	28.7%	0.15	70.5%

Table 5: Performance Evaluation of Portfolios of Funds

The table reports the performance evaluation regressions for portfolios formed on stock mutual funds. We use the Capital Asset Pricing Model:

$$R_{j,t} - R_{ft} = \alpha_j + b_j RmRf_t + \varepsilon_{j,t}$$

where $R_{j,t}$ is the portfolio return of quintile j. R_{ft} is the risk-free rate in month t, a monthly equivalent of the three-month fixed-term deposit rate. $RmRf_t$ is the aggregate Chinese stock market return, proxied by the CSI300 Index, in month t in excess of the risk-free rate. "Top x%" is a portfolio of the x% best-performing funds. "All Funds" is an equal-weight portfolio of all stock mutual funds. T-statistics are reported in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Top 5%		
Intercept	RmRf	R-squared
11.96%**	0.78***	63.2%
(2.5)	(16.4)	
Top 10%		
Intercept	RmRf	R-squared
10.77%**	0.77***	65.3%
(2.4)	(17.1)	
Top 25%		
Intercept	RmRf	R-squared
9.38%**	0.77***	70.7%
(2.4)	(19.4)	
Top 50%		
Intercept	RmRf	R-squared
7.89%**	0.77***	73.9%
(2.2)	(21.0)	
All Funds		
Intercept	RmRf	R-squared
5.53%*	0.78***	78.8%
(1.7)	(24.1)	