# Performance Evaluation, Factor Models, and Portfolio Strategies: Evidence from Chinese Mutual Funds*

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**Abstract**

Actively managed stock mutual funds in the Chinese A-share market offer good investment opportunities. In aggregate, they outperform stock market indices. Individual funds show a wide cross-sectional dispersion in performance, with the best funds offering economically large risk-adjusted returns that persist over time. Performance persistence observed at the individual fund level is robust to various factor-model specifications. A portfolio of the top-performing funds offers an improved investment opportunity compared to a portfolio of all funds. Hedging out market risk in this portfolio increases the Sharpe ratio, lowers volatility, and reduces tail risk. These results suggest that in the young and still-developing Chinese A-share market, mutual funds can add value for investors.

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# 1. Introduction

Academic researchers and practitioners are both interested in the economic value of mutual funds for investors: Academics study mutual fund performance through the lens of market efficiency, and practitioners for the possible investment opportunities. Jensen (1968) set the stage on using factor models to evaluate whether mutual funds have positive risk-adjusted returns. Since Jensen's seminal work, a large strand of literature surrounding the question of whether mutual funds can outperform their benchmarks has emerged[5]. In the U.S. markets, the prevailing wisdom seems to be that in aggregate, mutual funds do not outperform the aggregate stock market, and past performance of individual funds does not persist into the future.

Do the above findings hold for other stock markets? With a long history and several periods of consolidation, the U.S. markets are perhaps the most liquid and efficient of all stock markets. It is possible that the behavior of mutual funds in such a mature market does not generalize to other markets. In our paper, we revisit central issues in mutual fund investing: How does the aggregate set of mutual funds compare to market benchmarks, and is it possible to identify individual funds that continue to perform well over time? Our laboratory is 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 its size and importance, academics and practitioners are increasingly interested in understanding the empirical patterns of asset prices and investor behavior in the Chinese A-share market.

We evaluate the performance of the aggregate set of actively managed stock mutual funds in the Chinese A-share market from 2006 to 2020. In our sample period, a value-weight portfolio of all funds, weighted by their total net assets (TNA), earned a return of 0.73% per month net of fees. In comparison, the CSI300 Index, a value-weight index of the 300 largest firms in the A-share market, earned 0.45% per month. We examine risk-adjusted

[5] Among others, Carhart (1997), Daniel et al. (1997), Pastor and Stambaugh (2002), Cohen et al., (2005), Fama and French (2010), and Pastor et al. (2015) all study whether mutual funds can add value beyond their benchmarks.

returns of mutual funds through performance-attribution regressions that consider six models: Capital Asset Pricing Model (CAPM) with two different market proxies, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and three and four-factor models of Liu et al. (2019). Across different models, we observe additional outperformance relative to the benchmark factors: 0.40% or 0.46% for the CAPM, depending on the market proxy; 0.28% for the Fama-French three-factor model; 0.15% for the Carhart four-factor model; 0.62% and 0.55% for the two models proposed by Liu et al. (2019). The gross returns of this value-weight portfolio, before fees, shows even more striking performance. Its average monthly return is 0.88%, which remains economically large after accounting for risk factors with alphas ranging between 0.29% to 0.76%. An equal-weight portfolio of all funds, which has an average monthly net return of 0.84% and 0.98% gross of fees, show similar findings as the value-weight portfolio. Performance-evaluation regressions demonstrate that Chinese stock mutual funds outperformance passive market indices and common risk benchmarks and offer good investment opportunities. Viewed as a whole, Chinese stock mutual funds have a bias towards small-cap and growth stocks, and tend to chase past winners in our sample period.

Existing works on Chinese mutual funds have demonstrated some persistence in the performance of individual funds. For example, Chi and Qiao (2022) show that funds' past 12-month returns or CAPM alphas are indicative of their future performance. While informative, raw returns or CAPM alphas provide an incomplete adjustment for risk factors, so it is possible that the return persistence observed under these measures may be due to omitted risk factors (Carhart, 1997). We use the six models described earlier to evaluate the risk-adjusted performance of individual mutual funds, and we rank funds based on their past risk-adjusted performance. Performance persistence remains after controlling for additional risk factors: A portfolio of the top 25% of funds, ranked by lagged 12-month alpha relative to the Fama-French three-factor model and rebalanced monthly, has an equal-weight (value-weight) average monthly return of 1.16% (1.06%), compared to 0.84% (0.73%) for the portfolio of all funds. Moreover, the high average returns of this top-25% portfolio cannot be explained by its factor exposure, as its factor model alphas are also higher compared to the portfolio of all funds. Risk-adjusted performance persistence is robust to different specifications. A portfolio of the top 25% of funds formed using the models of Carhart (1997) or Liu et al. (2019) also significantly outperform a portfolio of all funds, earning similar rates of average returns compared to the portfolio formed using the Fama-French three-factor model.

Although a portfolio of the top 25% of funds can provide investors with high average returns, it is exposed to periodic large losses. A top-25% portfolio formed using the Fama-French three-factor model exhibits a maximum drawdown of -56.59%, on the same scale but somewhat less extreme as the maximum drawdowns of the CSI300 Index (-70.47%) and the CSI500 Index (-69.13%). Furthermore, the top-25% portfolio returns show large and positive correlations with the indices: 0.87 with the CSI300 and 0.92 with the CSI500. Evidently, the top-25% portfolio is exposed to market risk, which can be rather volatile in the A-share market. An investor may further improve her risk-return tradeoff if she were able to remove the influence of market risk from a selection of the top-performing funds. In theory, the investor may want to rank funds on their expected performance, take long positions in the top funds and short positions in the bottom funds. However, constructing a position that offers the return of shorting mutual funds is difficult. Instead, we explore hedged portfolio strategies that seek to achieve market neutrality while selecting the top-performing funds. We combine the top-25% portfolio with index futures traded on the CSI300 and CSI500 indices, exploring both static hedging that maintain a constant hedge ratio against the indices, as well as dynamic hedging that adjust the hedge ratio each month. In the absence of hedging, a value-weight portfolio of the top 25% of funds has an annual average return of 12.70%, a volatility of 25.63%, and a maximum drawdown of -56.59%. With a static hedge ratio, these figures become 7.53%, 9.41%, and -13.10%. With dynamic hedging, the hedged portfolio shows an average return of 9.45%, a volatility of 8.03%, and a maximum drawdown of -13.55%. Dynamic hedging also substantially improves the Sharpe ratio of the portfolio from 0.42 to 0.93.

Our results can be summarized into three key findings. First, actively managed stock mutual funds in the Chinese A-share market offer good investment opportunities for investors. In aggregate, this group of funds outperforms market indices. Second, individual funds exhibit performance persistence robust to measurement using different factor model specifications. Third, performance persistence can be captured through a portfolio of the top-performing funds, which offers an improved investment opportunity compared to a portfolio of all funds. The top-fund portfolio can be further improved by hedging out market risk. All in all, these findings indicate that in a young and emerging stock market, mutual funds offer professional guidance that add value for investors. Individual fund performance shows a wide dispersion; the best funds offer economically large risk-adjusted returns that persist over time.

Our results in the A-share market are inconsistent with the prevailing wisdom for the U.S. markets. The key findings in the U.S. markets – mutual funds do not outperform the stock market in aggregate, and past performance of individual funds does not persist into the future – do not appear to generalize to the Chinese A-share market.

A large literature, mostly based on U.S. markets, study the aggregate performance of mutual funds. The overall message of this literature is that mutual funds do not outperform the stock market (Jensen, 1968; Elton et al., 1993; Baks et al., 2001; Fama and French, 2010; Jones and Wermers, 2011; Pastor and Stambaugh, 2012; Pastor et al., 2015). In fact, after fees, the aggregate set of mutual funds has a tendency to underperform the aggregate stock market. Our finding that Chinese stock mutual funds, in aggregate, outperform the stock market diverge from the above studies. Even net of fees, Chinese funds handily beat the CSI300 and CSI500 indices. The contrast between Chinese and U.S. funds may be attributable to the dissimilar levels of maturity – in market structure, regulation, and market participants – between these markets. In particular, the high degree of saturation of institutional investors in the U.S. markets may be associated with more efficient prices and lower likelihoods of profiting against an uninformed retail investor.

Our paper is also related to the literature on performance persistence in mutual funds. Some studies suggest that although funds on average underperform the market, relative performance persists (Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Grinblatt and Keloharju, 2000; Avramov and Wermers, 2006). We find that not only does relative performance persist for raw returns, but also for risk-adjusted performance. Other studies reject the idea that mutual fund performance exhibits persistence, especially after controlling for common risk factors. Carhart (1997) demonstrates that portfolios ranked by past returns show large differences in average returns, but the spread becomes insignificant controlling for the momentum factor. In comparison, we find that in the A-share market, risk-adjusted returns, even after controlling for momentum, continue to persist for individual funds.

The remainder of our paper is organized as follows. Section 2 describes the dataset. Section 3 evaluates the performance of aggregate stock mutual funds using six benchmark models. Section 4 studies a portfolio of the top-performing funds. Section 5 explores the possibility of performance improvements after hedging out the market exposure. Section 6 concludes.

## 2. Data description

Our data source is Wind Information® (WIND). WIND is a leading Chinese financial data provider. Founded in 1994, WIND serves more than 90% of the domestic financial enterprises. We use a sample of actively managed stock mutual funds, for a sample period between August 2006 to June 2020. For much of our analysis, we require 12 months to estimate risk exposures of fund returns. Therefore, our results are based on the period from August 2007 to June 2020.

To qualify as an actively managed stock mutual fund, we require the fund to meet the following criteria. First, the fund must not be not passively indexing. Second, the fund must invest primarily in the Chinese A-share stock market. Third, the fund must invest at least 60% of total net assets into stocks. As a result of these filters, we arrive at a total of 1,038 stock mutual funds in our sample. It is worth noting that the Chinese actively managed stock mutual funds in aggregate exhibit significant skills to beat the market (Chen and Chi, 2018). Using 535 funds from 2003 to 2015, the authors find an alpha relative to the CAPM of 6.7% per year for an equal-weight portfolio of funds, and an alpha of 5.2% for a value-weight portfolio of funds. By investing in actively managed stock mutual funds in China, an investor not only obtains the passive market exposure (beta), but also has the opportunity to harvest superior returns (alpha) in excess of the market returns.

Figure 1 shows the number and assets under management (AUM) of actively managed stock mutual funds in the Chinese A-share market from 2006 to 2020. During our sample period, we witnessed a steady growth from fewer than 100 funds in 2006 to nearly 1,200 funds in 2020. The number of funds in existence increased nearly every year in this period. In Figure 1b, we observe that the total AUM of the Chinese stock mutual funds has grown from ¥209 billion (US$26 billion) in 2006 to ¥2,062 billion (US$299 billion) in 2020. The robust growth in the mutual fund space has been accompanied by the growth of the Chinese A-share stock market. In November 2014[6], the Chinese A-share market overtook the Japanese stock market and became the second largest stock market with a total market capitalization exceeding $5 trillion.

We show in Figure 2 that there are large cross-sectional differences in the average monthly returns of stock mutual funds. With a mean of 1.9% and a standard deviation of also 1.9%, if average returns were normally distributed, we would expect 95% of funds to fall within -1.9% and 5.7% per month. Instead, there is a large range of average returns that spans from -3% to nearly 20% per month. Moreover, we observe a skewness of 3.46 and a kurtosis of 21.2, indicating that the fund-level average monthly returns are positively skewed and have fat tails.

## 3. Performance evaluation with factor models

To better understand the behavior of Chinese mutual fund returns, we apply six factor models to evaluate the aggregate performance of stock mutual funds. We begin with the celebrated Capital Asset Pricing Model, which makes a connection between average returns and market risk. We consider two proxies for market returns: the CSI300 Index, a value-weighted index that tracks the performance of the top 300 stocks traded on the

[6] https://www.bloomberg.com/news/articles/2014-11-27/china-surpasses-japan-as-world-s-second-biggest-equity-market

Shanghai Stock Exchange and the Shenzhen Stock Exchange – the Chinese counterpart to the S&P 500, and a second proxy in the total value-weighted A-share stock market index. The first CAPM model is as follows:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{CSI300,t} - R_{ft}) + \varepsilon_t \tag{1}$$

where $R_{mf,t}$ is the value-weighted aggregate returns for all actively-managed stock mutual funds at time $t$. Each month, we compute the aggregate return using each fund's last available total net assets as the weight. Fund TNA data are available at the end of each quarter. For months between quarters, we infer the month-end TNA by the last available TNA multiplied by the total return of the fund since the last quarter end[7].

$R_{ft}$ is the risk-free rate proxied by the three-month Chinese household savings deposit rate. Since this rate is reported as an annual figure, we divide it by 12 to get a monthly rate. $R_{CSI300,t}$ is the return on the CSI300 Index. $b_{mf}$ is the market beta of the aggregate set of mutual funds, and $\alpha_{mf}$ measures whether CAPM is able to explain the average returns of the left-hand variable. A large and positive $\alpha_{mf}$ indicates that the CAPM cannot fully explain the average returns. Our second model is CAPM with the value-weight A-share market index:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{m,t} - R_{ft}) + \varepsilon_t \tag{2}$$

where $R_{m,t}$ is the value-weight A-share market return. We include two different market proxies because the CSI300 Index is a widely tracked index that many stock mutual funds declare as their performance benchmark, whereas the value-weight market index better represents the performance of the overall A-share market.

Our third model is the Fama-French three-factor model (FF3F), which augments the CAPM with two additional risk factors. Following Fama and French (1993), the universe of stocks

[7] Our approach is not able to take into account the effects of creations and redemptions in mutual funds.

is divided into six value-weight portfolios by market capitalization and the book-to-market ratio. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios (Fama and French, 1993), whereas HML (High Minus Low) is the average return on the two value portfolios minus the average returns on the two growth portfolios.

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{m,t} - R_{ft}) + s_{mf}SMB_t + h_{mf}HML_t + \varepsilon_t \quad (3)$$

where we continue to use the value-weight A-share market return, $R_{m,t}$, as the market proxy. $SMB_t$ and $HML_t$ are the size and value factors. Carhart (1997) demonstrates that accounting for momentum (Jegadeesh and Titman, 1993) is important in capturing the return behavior of the U.S. mutual funds. In the same spirit, we explore FF3F plus a momentum factor (MOM):

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{m,t} - R_{ft}) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_t \quad (4)$$

where $MOM_t$ is constructed as the average return on the two high prior-return portfolios minus the average return on the two low prior-return portfolios, in a set of six value-weight portfolios formed on size and prior 12-month returns.

While the Fama-French and Carhart models are widely used in performance attribution in the U.S. markets, some researchers argue for alternative models specialized for the Chinese A-share market. Liu, Stambaugh, and Yuan (2019), LSY, construct a size factor, also called *SMB*, that excludes the smallest 30% of firms, as well as a value factor *VMG* (Value Minus Growth) based on the earnings-price ratio. The market factor in LSY also excludes the smallest 30% of firms. We consider the LSY 3-factor model as a competing model to the ones above:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{m,t} - R_{ft}) + s_{mf}SMB_{LSY,t} + v_{mf}VMG_{LSY,t} + \varepsilon_t \quad (5)$$

where $SMB_{LSY,t}$ and $VMG_{LSY,t}$ are size and value factors of LSY. Liu et al. (2019) also propose a fourth factor, $PMO$ (Pessimistic Minus Optimistic), which takes long positions in low-turnover stocks thought to reflect investor pessimism and short positions in high-turnover stocks thought to reflect investor optimism. The LSY 4-factor models is then:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(R_{m,t} - R_{ft}) + s_{mf} SMB_{LSY,t} + v_{mf} VMG_{LSY,t} + p_{mf} PMO_{LSY,t} + \varepsilon_t \qquad (6)$$

Table 1 reports the average monthly returns of the FF3F, MOM, and LSY factors. In our sample period, the Fama-French size factor earned an average monthly return of 0.87%, statistically significant at the 5% level. HML did not earn a positive average return in this period, whereas momentum earned an economically large 0.50% per month. The LSY size factor, with an average monthly return of 0.68%, is statistically significant at the 10% level. The LSY VMG and PMO factors are both significant at the 1% level, earning 0.95% and 0.84% per month, respectively. The CSI300 index exhibits an average monthly return of 0.45% in our sample period. In comparison, the CSI500 Index, an index of medium and small stocks of good liquidity and representativeness from the Shanghai and Shenzhen exchanges, shows an average return of 0.67% per month.

Table 2 reports the outcomes of the performance-evaluation regressions of the aggregate returns of stock mutual funds on various benchmarks. Panels A and B report results based on the net returns, the returns that mutual fund investors earn. For a complete picture, Panels C and D report results based on the gross returns[8]. On average, Chinese actively managed stock mutual funds charge around 1.75% in fees per year: 1.5% in management fee and 0.25% in custodian fee, or between 14 and 15 basis points per month. Consequently, the average equal-weight net return reported in Panel A (0.84%) is roughly 14 basis points lower than the average equal-weight gross return reported in Panel C

[8] An investor in Chinese mutual funds is subject to a management fee and a custodian fee. A management fee is paid directly to the fund. A smaller custodian fee is paid to a third party, typically a bank or a trust, who holds the invested assets of mutual funds. We do not account for front load or back load fees which may vary based on investor types, investment amount, and holding periods. Adding back front or back load fees would further inflate gross returns and amplify the outperformance relative to benchmark models.

(0.98%). Similarly, the average value-weight net return in Panel B (0.73%) is about 15 basis points lower than the average value-weight gross return in Panel D (0.88%). We see a similar spread in the alphas under various factor models. Net returns are what matter to the fund investors as those are the returns they actually earn from their investments. Nonetheless, the gross returns are useful in the performance evaluation process because it measures fund returns in a fair manner against benchmark factors.

Let us start our analysis with gross returns. Panel C shows that an equal-weight portfolio of all mutual funds earns 0.98% per month before fees. A CAPM with the CSI300 Index as the market proxy shows a market beta of 0.77 and a monthly alpha of 0.71%. A CAPM with the A-share value-weight market shows a market beta of 0.84 and an alpha of 0.65%. Under the Fama-French three-factor model or the Carhart four-factor model, we observe alphas of 0.51% and 0.38% per month, respectively. Under the LSY 3-factor model, the monthly alpha is 0.87%, and for the LSY 4-factor model, the alpha is 0.82%. The alphas relative to benchmark models are all statistically significant at the 5% level, and some are significant at the 1% level.

The risk-adjusted outperformance of aggregate mutual funds remains robust for the value-weight portfolio. In Panel D, the value-weight portfolio of all funds earns 0.88% per month before fees. We continue to observe economically and statistically large alphas relative to the six benchmark factor models, ranging between 0.29% and 0.76% per month. As a whole, Chinese stock mutual funds are able to beat the market and various risk benchmarks before fees.

Across the six factor models in Panel C, the R-squareds range from 78% to 94%, indicating that these models capture much of the return variation in the equal-weight portfolio of all funds and serve as relevant benchmarks. Multifactor models are associated with the highest explanatory power: FF3F achieves an R-squared of 92%, similar to those observed for the LSY models. It is interesting to see that the LSY models register significantly larger alphas than FF3F and FF3F+MOM. It seems the Fama-French three-factor and Carhart four-factor models are better able at explaining the performance of Chinese mutual funds, despite the fact Liu et al. (2019) construct their models specifically for the Chinese A-share market.

Judging by the FF3F+MOM model coefficients, we see that the Chinese stock mutual funds tend to have a market beta around 0.8, an SMB coefficient around 0.1, an HML coefficient around -0.5, and an MOM coefficient around 0.2. The market beta of 0.8 is consistent with the practice that most Chinese stock mutual funds do not fully invest fund assets into stocks all the time. In our sample construction, a fund is included as long as it meets the minimum threshold of 60% of total net assets invested in stocks. It is common for a Chinese mutual fund to invest a part of fund assets in cash instruments such as Chinese government bonds. The positive SMB coefficient, negative HML coefficient, and positive MOM coefficient suggest that Chinese stock mutual funds on average have a tilt towards small-cap and growth stocks, and tend to chase past winner stocks in our sample period[9]. Under the LSY models, we observe a positive SMB coefficient, and a negative coefficient on their value factor VMG, similar to those observed under the FF3F+MOM model. We observe a statistically insignificant coefficient on the turnover factor PMO.

Even after fees, we still see in the majority of our models a statistically significant alpha. For example, in Panel A, CAPM(CSI300) alpha is 0.57% per month (t=2.06), FF3F alpha is 0.36% per month (t=2.18), and LSY 3-factor alpha is 0.72% per month (t=3.93). The outperformance of Chinese stock mutual funds stands in sharp contrast to what we observe in the U.S. markets. Fama and French (2010) document that the U.S. stock mutual funds are not able to beat the market benchmark. We interpret this difference as evidence for different developmental stages of the two markets. 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.

[9] In Chen and Chi (2018) that covers an earlier sample period, a negative SMB coefficient is documented. We verify in our data that we find similar factor loadings with data based on the same sample period as in Chen and Chi (2018). This is consistent with the expanding stock universe that mutual funds invest in, which tend to include more small-cap stocks from the China Growth Enterprise Market after its inception in 2009.

In the Chinese A-share stock market, where less sophisticated retail investors dominate the trading volume, it may be relatively less difficult for professional money managers to outperform.

## 4. The top-performing fund portfolio

The previous section demonstrates that in aggregate, Chinese stock mutual funds outperform A-share market returns and other common risk benchmarks. In this section, we explore the cross-sectional variation in the Chinese stock mutual fund performance. Figure 2 illustrates a large cross-sectional variation in stock mutual funds' average monthly returns: the best and worst funds' average monthly returns differ by more than 20%. An investor may construct a superior portfolio if she had some ability to select funds that tend to outperform and avoid funds that underperform. The task of consistently picking outperforming funds relies on the notion of performance persistence. That is, there must be some continuation in fund returns such that past outperformance can provide some signal for future performance.

Chi and Qiao (2022) document that past fund returns as well as CAPM alphas serve as useful forecasting signals for future fund performance. Raw returns do not adjust for risk, and CAPM alpha may not sufficiently adjust for risk as there are other known risk factors associated with average returns, such as size and value. We extend the previous work that measures performance persistence in A-share mutual funds by using multifactor alphas. To the extent these alphas measure the latent skill fund managers may possess, a more precise measure of outperformance in factor alphas can lead to better identification of managerial skill.

We form a top-fund portfolio using FF3F alphas and test whether their outperformance persists into the next month. At the beginning of each month, we sort all available funds[10] in our sample by their past 12-month FF3F alphas. We then select the top 25% of funds to

[10] Because we require 12 months to estimate factor loadings and alphas, we do not consider young funds with a history shorter than 12 months.

form our top-fund portfolio. Because the information we use are all available at the time of portfolio formation, our strategy is implementable in real time. If risk-adjusted performance exhibits persistence, we would expect the top-fund portfolio to continue to perform relatively well.

In Table 3, we report the performance-evaluation outcomes for the top-fund portfolio. First, we show that the top-fund portfolio exhibits substantially higher average returns than the portfolio of all funds. An equal-weight portfolio of the top 25% of funds has an average return of 1.16% per month, compared to 0.84% for an equal-weight portfolio of all funds. A value-weight portfolio of the top funds shows an average return of 1.06% per month versus 0.73% for a portfolio of all funds.

Second, we conduct the same six performance-evaluation regressions as in Table 2 to the top-fund portfolio. Adjusting for common risk factors, we observe larger alphas under various factor models for the top-fund portfolio. For example, an equal-weight (value-weight) portfolio of the top funds has an alpha of 0.69% (0.63%) against the Fama-French three-factor model, significantly larger compared to the 0.36% (0.28%) alpha for all funds. We observe economically large and statistically significant alphas for net returns across the six factor models, under both the equal-weight and value-weight specifications. Monthly risk-adjusted performance ranges from 0.55% to 1.16% for the equal-weight top-fund portfolio, and from 0.48% to 1.07% for the value-weight top-fund portfolio. In comparison, the portfolio of all funds exhibits smaller point estimates for alphas, ranging from 0.23% to 0.72% for the equal-weight portfolio, and 0.15% to 0.62% for the value-weight portfolio.

The R-squareds in the top-fund portfolio regressions are generally lower than those of the all-fund portfolio. For example, the R-squareds for the top-fund portfolio regressions range from 76.21% to 90.68% under the equal-weight specifications, and from 77.61% to 90.73% under the value-weight specifications. In comparison, the R-squareds for a portfolio of all funds regressions range from 77.72% to 93.77% under the equal-weight specifications, and from 78.35% to 93.88% under the value-weight specifications. Lower R-squareds indicate that the top 25% of funds are more actively deviating away from the benchmark indices. In doing so, the fund managers not only generate more tracking error, but also produce higher average returns.

Table 4 compares the performance of the top-fund portfolio against broad market indices CSI300 and CSI500. CSI300 represents the 300 largest stocks in the Chinese A-share stock market. CSI500 represents the 500 most liquid stocks other than the CSI300 component stocks. These two indices are widely tracked by investment products, and many passive stock mutual funds and exchange-traded funds use these indices as benchmarks. Compared to the CSI300 and CSI500 indices, the top-25% fund portfolio has higher average returns, lower volatilities, smaller maximum drawdowns, and higher Sharpe ratios. For example, the equal-weight portfolio of the top 25% of funds earns 13.89% per annum with a Sharpe ratio of 0.48, compared to CSI300's (CSI500) 5.43% (8.06%) return per annum and 0.12 (0.19) Sharpe ratio. Though maximum drawdowns are smaller for the equal-weight and value-weight top-fund portfolios, it is rather large at -56.35%.

In Figure 3, we plot the cumulative returns of the top-25% fund portfolios (both equal-weight and value-weight), CSI300 and CSI500 indices. Over the 13 years from 2007 to 2020, the top-25% equal-weight fund portfolio has grown from 1 to 3.43, whereas the CSI300 Index remained virtually unchanged at 0.99 and the CSI500 Index grew to 1.33. Clearly, the top-25% fund portfolio dominated in performance relative to these two market indices.

As a robustness check, instead of the FF3F model, we also employ the CAPM (with aggregate A-share market return as benchmark), FF3F+MOM, LSY 3-factor, and LSY 4-factor models to compute the funds' past 12-month alpha. We sort funds by these alternative alphas and form the top-25% fund portfolios. In Figure 4, we plot the cumulative returns of these alternative equal-weight top-fund portfolios, as well as our original FF3F version. We show that despite the differences amongst these various portfolios, they all have grown from 1 in 2007 to values higher than 2.75 in 2020. All of these various top-fund portfolios substantially outperform the passive benchmarks of

CSI300 and CSI500, that have grown from 1 in 2007 to 0.99 and 1.33 in 2020, respectively. Our results suggest that there is a strong pattern of performance persistence amongst Chinese stock mutual funds, robust to the specification of the performance-attribution model.

## 5. Hedged portfolio strategies

Although a portfolio of the best 25% of funds offer high average returns, it is not immune to tail risk. The maximum drawdown of the top-fund portfolio is still a whopping -56.35%. Indeed, the top-performing funds are still subject to the market risk, which can be very volatile in the Chinese A-share market. The CSI300 and CSI500 indices have annual volatilities of 28.68% and 31.41%, respectively, and maximum drawdowns of -70.47% and -69.13%. Some investors may find such large volatility and tail risk to be undesirable, and a portfolio that can hedge out the market risk as a more appealing alternative. In this section, we explore portfolios strategies that take long positions in the top-performing funds while hedging out market risk. We hedge using the CSI300 and CSI500 indices, which have active futures markets that can be readily used to alter market risk exposure.

Table 5 presents the pairwise correlations among the portfolios of top funds, portfolios of all funds, and the market indices. Value-weight and equal-weight portfolios of funds, whether including only the top 25% or all funds, are all highly correlated with values ranging between 0.991 and 0.999. Portfolios of funds are also positively correlated with the two indices, although the strength of the relations is lower. For example, a value-weight portfolio of the top 25% of funds is 0.881 correlated with the CSI300 and 0.907 correlated with the CSI500. Although these values are large, they show that the top-fund portfolio does not perfectly comove with the stock market. We interpret the less-than-perfect correlations as evidence for the active nature of Chinese stock mutual funds. These funds have to actively deviate from the passive market benchmarks in order to generate outperformance. These correlations corroborate our findings in performance attribution regressions (Tables 2 and 3), where we observed market betas around 0.8 instead of 1.

We consider two methods of hedging out market risk, static and dynamic. For the static approach, we keep a constant hedge ratio against market indices. We examine two types of static hedges. Against the CSI300, we apply a hedge ratio of 0.8 – the unconditional market exposure of the top-fund portfolio from the attribution regressions – we short 0.8 unit of the CSI300 Index for each unit of our long position in the top mutual funds. If we hedge against the CSI300 and CSI500 concurrently, we apply a 0.35 hedge ratio against the CSI300 and 0.45 against the CSI500. For each unit of our long position in the top mutual funds, we short 0.35 unit of the CSI300 Index and 0.45 unit of the CSI500 Index.

For the dynamic hedging approach, we also explore two types of hedges, against the CSI300 only and against both the CSI300 and CSI500 indices. We adjust the hedge ratio against the market indices by estimating the exposure of our portfolio every month. Against the CSI300, we estimate each fund's 12-month beta against the CSI300 Index, then we compute the value-weight average of all CSI300-betas to be the hedge ratio for the portfolio. If we were to hedge against both the CSI300 and CSI500, we first estimate each fund's 12-month betas against the two indices in a multivariate regression involving both indices, then we compute the value-weight averages of all CSI300-betas and CSI500-betas to be the hedge ratios for the indices.

Table 6 provides a comparison of the performance statistics of various hedged strategies against the unhedged strategy. Panel A shows that a value-weight portfolio of the top 25% of funds, selected using the Fama-French three-factor model and rebalanced monthly, earns an average return of 12.70% per year with a volatility of 25.63%. It has a maximum drawdown of -56.59%. A constant hedge against the CSI300 reduces the average return and risk to 8.36% and 12.11%, for an improved Sharpe ratio of 0.53 and reduced maximum drawdown of -21.92%. A constant hedge against both the CSI300 and CSI500 indices further improves the strategy's Sharpe ratio to 0.59 and reduces the maximum drawdown to -13.10%. The hedging scheme that provides the most improvement to the unhedged strategy appears to be dynamic hedging against both the CSI300 and CSI500, which has a Sharpe ratio of 0.93 and a maximum drawdown of -13.55%. Its annualized volatility of 8.03% is the lowest among all strategies.

Panel B of Table 6 shows that hedging out market risk from an equal-weight portfolio of the top 25% of funds makes similar improvements to the risk-return tradeoff. An unhedged equal-weight portfolio earns 13.89% per year with a volatility of 25.11% for a Sharpe ratio of 0.48. It also has a rather large maximum drawdown of -56.35%. Constant hedging against the CSI300 and CSI500 indices lowers the expected return to 8.71%, but also reduces the volatility to just 9.00% for a Sharpe ratio of 0.75. The maximum drawdown is also reduced to just -11.14%. Dynamic hedging against the CSI300 and CSI500 reduces the annualized volatility to 7.97% and improves the Sharpe ratio to 1.16. The maximum drawdown is also limited to smaller than -10%.

Figure 5 plots the cumulative portfolio returns of the four hedging schemes – two static, two dynamic – on the same scale. The hedged portfolios all exhibit a significantly smoother wealth accumulation process compared to the unhedged portfolio returns (see Figure 4). The different schemes show different cumulative returns in our sample period, with dynamic hedging against the CSI300 and CSI500 leading the pack. Evidently, allowing for flexible market exposure of the top-fund portfolio delivers a more attractive risk-return tradeoff for the investor. The value of time-varying hedging ratios outweighs the potential estimation errors associated with re-estimating of market betas each month.

## 6. Conclusion

In our paper, we revisit key issues in mutual fund performance evaluation: Do mutual funds outperform markets benchmarks, and is there performance persistence in individual funds? For the Chinese A-share market, we find affirmative answers to both questions. From 2007 to 2020, a value-weight portfolio of all actively managed stock mutual funds in the A-share market outpaced the CSI300 Index by 0.28% per month. Using six different factor models for performance attribution, we find that the aggregate mutual fund portfolio adds additional value beyond the benchmark risk factors. In aggregate, Chinese mutual funds exhibit a bias towards small-cap stocks, growth stocks, and stocks that have recently performed well.

We uncover performance persistence for individual mutual funds. A portfolio of the top 25% of funds, identified by their lagged 12-month Fama-French three-factor alphas, outperforms the portfolio of all funds by 0.32% per month. The high average returns of the top-25% portfolio cannot be explained by its exposure to risk factors, and is robust to different selection methods including the Carhart four-factor model or the three and four-factor models proposed by Liu et al. (2019). The risk-return opportunity offered by the top-25% fund portfolio can be further improved by hedging out market risk. Dynamic hedging using index futures can raise the Sharpe ratio of this portfolio from 0.42 to 0.93.

The focus of our paper is on documenting risk-adjusted returns and performance persistence. As such, we do not provide a specific economic channel that explains our empirical findings. It would be interesting to explore possible explanations consistent with performance persistence, such as superior skill or information. One possible path is to explore fund holdings data, which may shed light on the relation between skill and return persistence. Performance measures derived from holdings data such as industry concentration (Kacperczyk et al., 2005) or holding similarity (Cohen et al., 2005) may prove to be fruitful directions.

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**Figure 1: Number and AUM of Chinese Stock Mutual Funds**

This figure plots the number and total assets under management in billions of RMB (¥) of actively managed stock mutual funds in the Chinese A-share market from 2006 to 2020.

*Figure 1a: The Number of Chinese stock mutual funds*

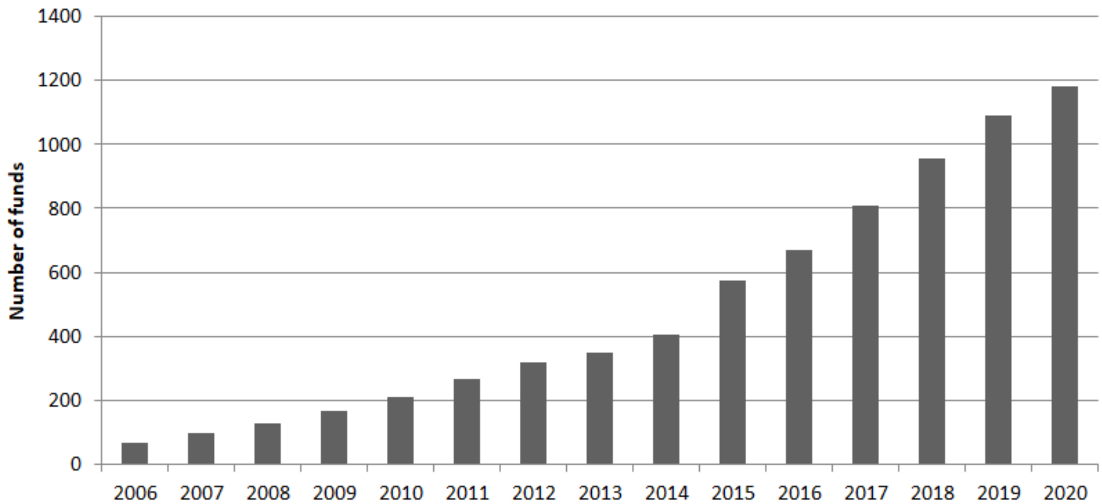



*Figure 1b: AUM (¥billion) of Chinese Stock Mutual Funds*

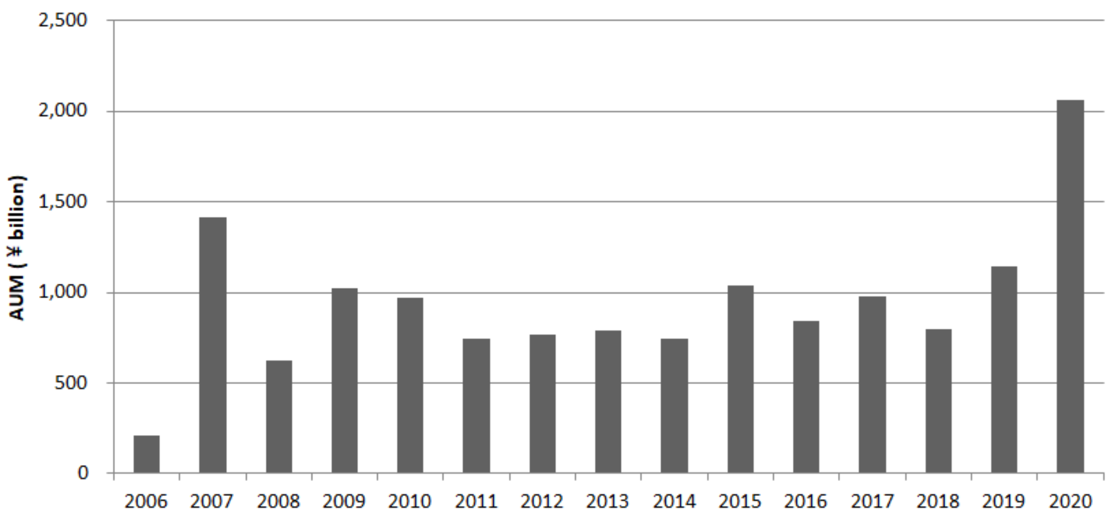


**Figure 2: Average Monthly Returns of Funds**

This figure plots the histogram of the average monthly returns for individual funds. Summary statistics are shown on the top right corner. Our sample consists of 1,038 funds over the sample period from August 2007 to June 2020.

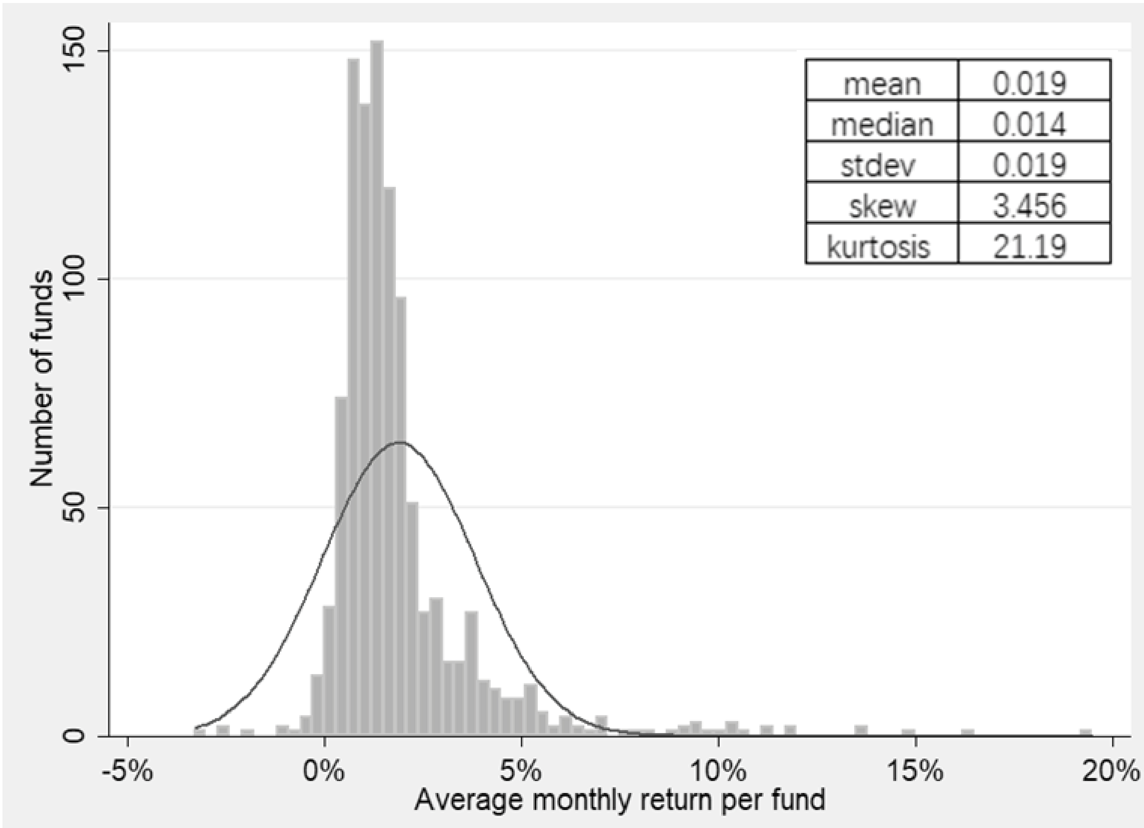
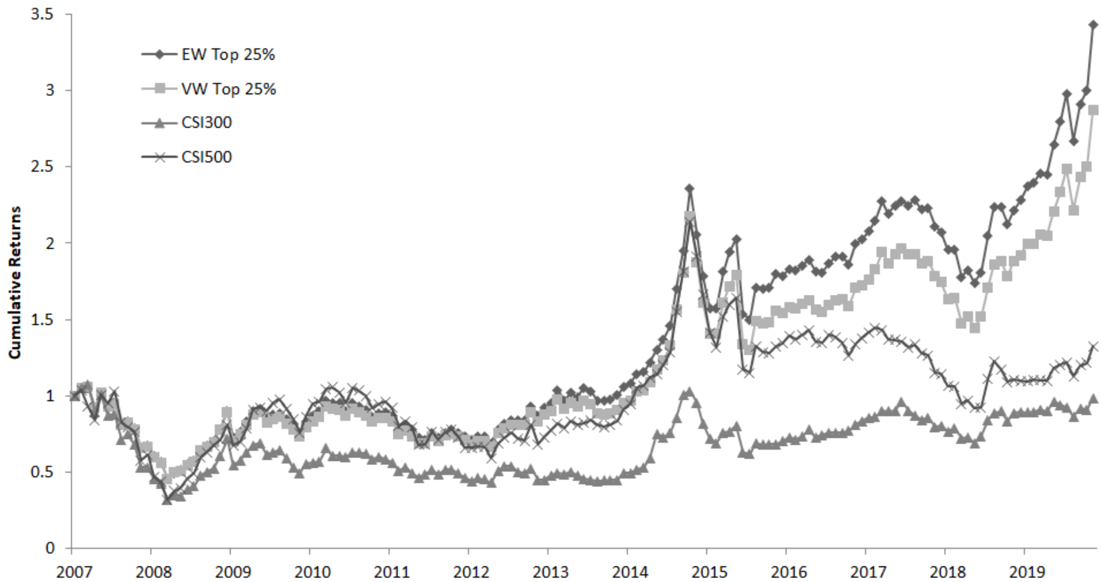


**Figure 3: Performance of the Top-25% Fund Portfolios and Market Indices**

This figure plots the cumulative returns of a portfolio of the top 25% of funds, ranked by their past 12-month alphas relative to the FF3F model. EW indicates equal-weight and VW indicates value-weight. The portfolios are rebalanced monthly. Our sample period is from August 2007 to June 2020.



## Figure 4: Cumulative Returns of Top-Fund Portfolios

This figure plots the cumulative returns of equal-weight portfolios of the top 25% of funds, as measured by alphas relative to different factor models. Our sample period is from August 2007 to June 2020.

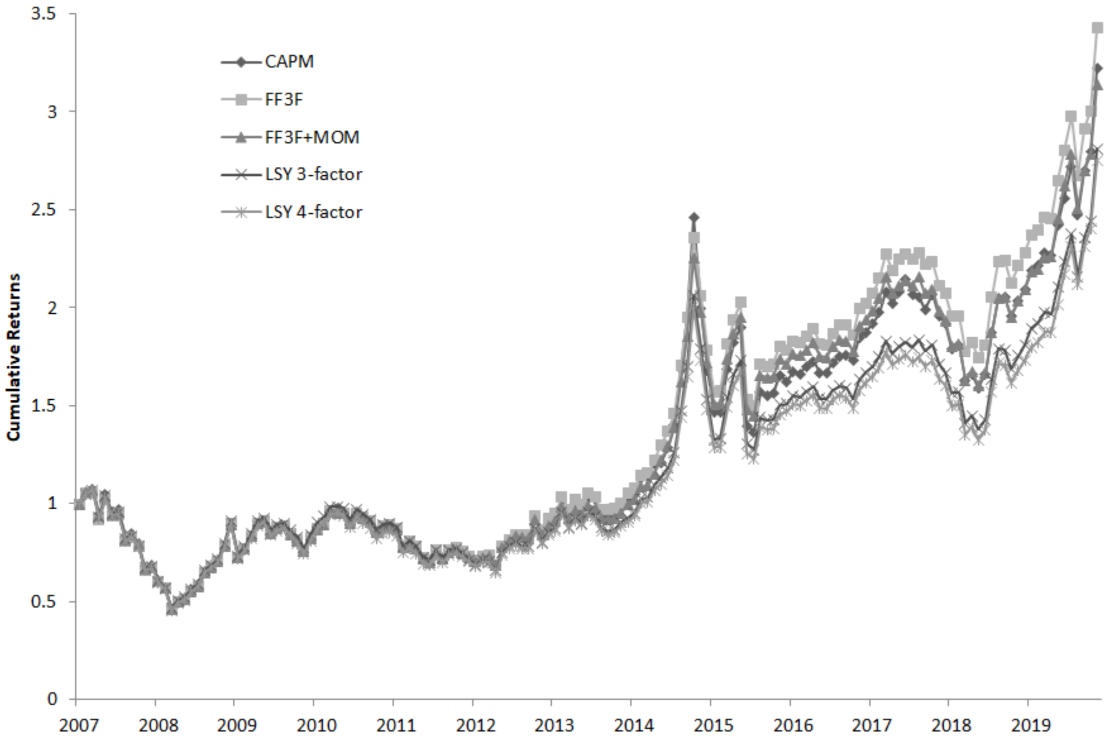
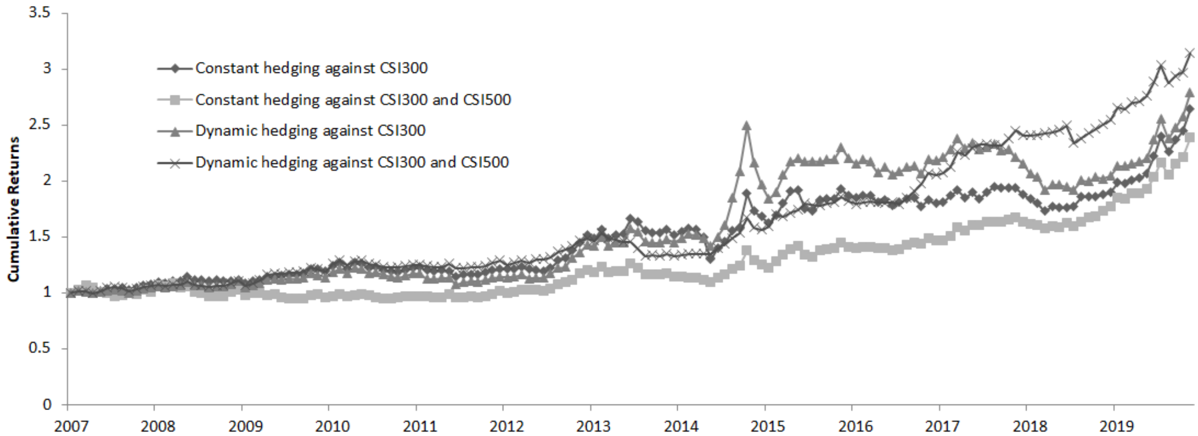


**Figure 5: Cumulative Returns of Market-Neutral Portfolios**

This figure plots the cumulative returns for a top-25% fund portfolio hedged against market indices. The top funds are identified by their past 12-month alphas relative to the FF3F model. All portfolios are value-weight. Our sample period is from August 2007 to June 2020.



## Table 1: Average Monthly Return

This table reports the average monthly returns and t-statistics in parentheses for factors and market indices. *, **, and *** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

| FF3F+MOM Factors | | | | LSY Factors | | | | Stock Indices | |
|---|---|---|---|---|---|---|---|---|---|
| **Rm-Rf** | **SMB** | **HML** | **MOM** | **Rm-Rf** | **SMB** | **VMG** | **PMO** | **CSI300** | **CSI500** |
| 0.20% | 0.87%** | -0.14% | 0.50% | 0.16% | 0.68%* | 0.95%*** | 0.84%*** | 0.45% | 0.67% |
| (0.32) | (2.04) | (-0.51) | (1.22) | (0.26) | (1.81) | (3.21) | (2.79) | (0.68) | (0.92) |

# Table 2: Performance Evaluation of the Aggregate Fund Portfolio

This table reports the performance evaluation regressions of all active stock mutual funds in the market. Equal-weight and value-weight portfolios are reported separately. Panels A and B report results based on net returns, whereas Panels C and D report results based on gross returns. *, **, and *** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

*Panel A: Equal-weight, net returns*

| | **Average return** | **CAPM (CSI300)** | **CAPM (A-share market)** | **FF3F** | **FF3F+MOM** | **LSY 3-factor** | **LSY 4-factor** |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.84% | 0.57%** | 0.50%** | 0.36%** | 0.23% | 0.72%*** | 0.68%*** |
| | | (2.06) | (2.06) | (2.18) | (1.48) | (3.93) | (3.68) |
| **RmRf_CSI300** | | 0.77*** | | | | | |
| | | (15.66) | | | | | |
| **MarkA_prem** | | | 0.84*** | 0.80*** | 0.81*** | | |
| | | | (22.29) | (32.05) | (34.73) | | |
| **SMB** | | | | 0.08 | 0.13** | | |
| | | | | (1.48) | (2.45) | | |
| **HML** | | | | -0.57*** | -0.48*** | | |
| | | | | (-6.95) | (-6.02) | | |
| **MOM** | | | | | 0.19*** | | |
| | | | | | (5.49) | | |
| **MarkA_p_LSY** | | | | | | 0.82*** | 0.83*** |
| | | | | | | (35.97) | (34.02) |
| **SMB_LSY** | | | | | | 0.13* | 0.12* |
| | | | | | | (1.96) | (1.97) |
| **VMG_LSY** | | | | | | -0.28*** | -0.28*** |
| | | | | | | (-3.85) | (-3.88) |
| **PMO_LSY** | | | | | | | 0.06 |
| | | | | | | | (0.92) |
| **R-squared** | | 77.72% | 82.30% | 92.06% | 93.77% | 92.09% | 92.17% |

*Panel B: Value-weight, net returns*

| | **Average return** | **CAPM (CSI300)** | **CAPM (A-share market)** | **FF3F** | **FF3F+MOM** | **LSY 3-factor** | **LSY 4-factor** |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.73% | 0.46%* | 0.40% | 0.28%* | 0.15% | 0.62%*** | 0.55%*** |
| | | (1.68) | (1.63) | (1.67) | (0.94) | (3.25) | (2.90) |
| **RmRf_CSI300** | | 0.78*** | | | | | |
| | | (15.43) | | | | | |
| **MarkA_prem** | | | 0.85*** | 0.80*** | 0.82*** | | |
| | | | (21.70) | (30.55) | (34.53) | | |
| **SMB** | | | | 0.04 | 0.09* | | |
| | | | | (0.71) | (1.72) | | |
| **HML** | | | | -0.60*** | -0.51*** | | |
| | | | | (-7.11) | (-6.32) | | |
| **MOM** | | | | | 0.20*** | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | (6.07) | | |
| **MarkA_p_LSY** | | | | | | 0.83*** | 0.84*** |
| | | | | | | (32.30) | (31.65) |
| **SMB_LSY** | | | | | | 0.10 | 0.09 |
| | | | | | | (1.62) | (1.57) |
| **VMG_LSY** | | | | | | -0.26*** | -0.27*** |
| | | | | | | (-3.53) | (-3.60) |
| **PMO_LSY** | | | | | | | 0.08 |
| | | | | | | | (1.24) |
| **R-squared** | | 78.35% | 82.66% | 92.04% | 93.88% | 91.50% | 91.65% |

*Panel C: Equal-weight, gross returns*

| | **Average return** | **CAPM (CSI300)** | **CAPM (A-share market)** | **FF3F** | **FF3F+MOM** | **LSY 3-factor** | **LSY 4-factor** |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.98% | 0.71%** | 0.65%*** | 0.51%*** | 0.38%** | 0.87%*** | 0.82%*** |
| | | (2.59) | (2.65) | (3.06) | (2.42) | (4.73) | (4.46) |
| **RmRf_CSI300** | | 0.77*** | | | | | |
| | | (15.66) | | | | | |
| **MarkA_prem** | | | 0.84*** | 0.80*** | 0.81*** | | |
| | | | (22.32) | (32.02) | (34.72) | | |
| **SMB** | | | | 0.08 | 0.13** | | |
| | | | | (1.47) | (2.45) | | |
| **HML** | | | | -0.57*** | -0.48*** | | |
| | | | | (-6.95) | (-6.01) | | |
| **MOM** | | | | | 0.20*** | | |
| | | | | | (5.50) | | |
| **MarkA_p_LSY** | | | | | | 0.82*** | 0.83*** |
| | | | | | | (36.02) | (34.09) |
| **SMB_LSY** | | | | | | 0.12* | 0.12* |
| | | | | | | (1.95) | (1.96) |
| **VMG_LSY** | | | | | | -0.28*** | -0.28*** |
| | | | | | | (-3.84) | (-3.87) |
| **PMO_LSY** | | | | | | | 0.06 |
| | | | | | | | (0.94) |
| **R-squared** | | 77.76% | 82.33% | 92.06% | 93.78% | 92.11% | 92.20% |

*Panel D: Value-weight, gross returns*

| | **Average return** | **CAPM (CSI300)** | **CAPM (A-share market)** | **FF3F** | **FF3F+MOM** | **LSY 3-factor** | **LSY 4-factor** |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.88% | 0.60%** | 0.54%** | 0.43%** | 0.29%* | 0.76%*** | 0.70%*** |
| | | (2.22) | (2.23) | (2.54) | (1.89) | (4.03) | (3.67) |
| **RmRf_CSI300** | | 0.78*** | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (15.41) | | | | | |
| **MarkA_prem** | | 0.85*** | 0.80*** | 0.82*** | | |
| | | (21.64) | (30.58) | (34.54) | | |
| **SMB** | | | 0.04 | 0.09* | | |
| | | | (0.72) | (1.72) | | |
| **HML** | | | -0.60*** | -0.51*** | | |
| | | | (-7.13) | (-6.34) | | |
| **MOM** | | | | 0.20*** | | |
| | | | | (6.05) | | |
| **MarkA_p_LSY** | | | | | 0.83*** | 0.84*** |
| | | | | | (32.30) | (31.62) |
| **SMB_LSY** | | | | | 0.10 | 0.09 |
| | | | | | (1.64) | (1.59) |
| **VMG_LSY** | | | | | -0.26*** | -0.27*** |
| | | | | | (-3.54) | (-3.61) |
| **PMO_LSY** | | | | | | 0.08 |
| | | | | | | (1.23) |
| **R-squared** | 78.27% | 82.60% | 92.05% | 93.88% | 91.48% | 91.63% |

## Table 3: Performance Evaluation of the Top-25% Fund Portfolio

This table reports the performance evaluation regressions of the top 25% of funds. Every month, all available stock mutual funds are ranked by their trailing 12-month alphas relative to the FF3F, and a subset of top 25% best-performing funds are selected to form the portfolio we hold for the next month. Equal-weight and value-weight portfolios are reported separately in Panel A and Panel B. *, **, and *** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

*Panel A: Equal-weight, net returns*

| | Average return | CAPM (CSI300) | CAPM (A-share market) | FF3F | FF3F+MOM | LSY 3-factor | LSY 4-factor |
|---|---|---|---|---|---|---|---|
| **Intercept** | 1.16% | 0.89%*** | 0.82%*** | 0.69%*** | 0.55%*** | 1.15%*** | 1.16%*** |
| | | (3.12) | (3.17) | (3.44) | (2.90) | (5.12) | (5.14) |
| **RmRf_CSI300** | | 0.76*** | | | | | |
| | | (16.83) | | | | | |
| **MarkA_prem** | | | 0.83*** | 0.79*** | 0.80*** | | |
| | | | (23.96) | (30.43) | (30.52) | | |
| **SMB** | | | | 0.07 | 0.13* | | |
| | | | | (1.08) | (1.86) | | |
| **HML** | | | | -0.54*** | -0.44*** | | |
| | | | | (-5.50 ) | (-4.56) | | |
| **MOM** | | | | | 0.21*** | | |
| | | | | | (4.45) | | |
| **MarkA_p_LSY** | | | | | | 0.81*** | 0.80*** |
| | | | | | | ( 36.27) | (32.22) |
| **SMB_LSY** | | | | | | 0.07 | 0.07 |
| | | | | | | (0.98) | (1.06) |
| **VMG_LSY** | | | | | | -0.35*** | -0.35*** |
| | | | | | | (-4.22) | (-4.21) |
| **PMO_LSY** | | | | | | | -0.01 |
| | | | | | | | (-0.21) |
| **R-squared** | | 76.21% | 80.07% | 88.72% | 90.68% | 90.07% | 90.07% |

*Panel B: Value-weight, net returns*

| | Average return | CAPM (CSI300) | CAPM (A-share market) | FF3F | FF3F+MOM | LSY 3-factor | LSY 4-factor |
|---|---|---|---|---|---|---|---|
| **Intercept** | 1.06% | 0.78%*** | 0.72%*** | 0.63%*** | 0.48%** | 1.07%*** | 1.07%*** |
| | | (2.78) | (2.77) | (3.00) | (2.41) | (4.58) | (4.53) |
| **RmRf_CSI300** | | 0.79*** | | | | | |
| | | (17.12) | | | | | |
| **MarkA_prem** | | | 0.85*** | 0.81*** | 0.83*** | | |
| | | | (23.48) | (28.20) | (29.66) | | |
| **SMB** | | | | 0.02 | 0.08 | | |
| | | | | (0.31) | (1.15) | | |
| **HML** | | | | -0.57*** | -0.46*** | | |
| | | | | (-5.49) | (-4.62) | | |
| **MOM** | | | | | 0.22*** | | |
| | | | | | (5.04) | | |
| **MarkA_p_LSY** | | | | | | 0.83*** | 0.83*** |
| | | | | | | (32.45) | (29.60) |
| **SMB_LSY** | | | | | | 0.03 | 0.03 |
| | | | | | | (0.38) | (0.41) |
| **VMG_LSY** | | | | | | -0.34*** | -0.34*** |
| | | | | | | (-3.90) | (-3.89) |
| **PMO_LSY** | | | | | | | -0.00 |
| | | | | | | | (-0.01) |
| **R-squared** | | 77.61% | 80.93% | 88.52% | 90.73% | 89.44% | 89.44% |

**Table 4: Performance Statistics of the Top-Fund Portfolio and Market Indices**

This table reports the strategy performance of the top-25% fund portfolio along with the CSI300 and CSI500 indices. Every month, all available stock mutual funds are ranked by their trailing 12-month alphas relative to the FF3F, and a subset of top 25% best-performing funds are selected to form the portfolio we hold for the next month. EW indicates equal-weight and VW indicates value-weight. *, **, and *** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

| | **Annualized Returns** | **Annualized Volatility** | **Sharpe Ratio** | **Maximum Drawdown** |
|---|---|---|---|---|
| **Top25%(EW)** | 13.89% | 25.11% | 0.48 | 56.35% |
| **Top25%(VW)** | 12.70% | 25.63% | 0.42 | 56.59% |
| **CSI300 Index** | 5.43% | 28.68% | 0.12 | 70.47% |
| **CSI500 Index** | 8.06% | 31.41% | 0.19 | 69.13% |

## Table 5: Correlation Matrix of Fund Portfolios and Market Indices

This table shows the correlations among the top-fund portfolio, the portfolio of all funds, and market indices. Every month, all available stock mutual funds are ranked by their trailing 12-month alphas relative to the FF3F, and a subset of top 25% best-performing funds are selected to form the portfolio we hold for the next month. EW indicates equal-weight and VW indicates value-weight. *, **, and *** mark statistical significance at the 10%, 5%, and 1% levels, respectively.

| | **Top 25%(EW)** | **Top 25%(VW)** | **All Funds(EW)** | **All Funds(VW)** | **CSI300** | **CSI500** |
|---|---|---|---|---|---|---|
| **Top 25%(EW)** | 1 | | | | | |
| **Top 25%(VW)** | 0.997*** | 1 | | | | |
| **All Funds(EW)** | 0.993*** | 0.992*** | 1 | | | |
| **All Funds(VW)** | 0.991*** | 0.992*** | 0.999*** | 1 | | |
| **CSI300** | 0.873*** | 0.881*** | 0.881*** | 0.885*** | 1 | |
| **CSI500** | 0.918*** | 0.907*** | 0.928*** | 0.920*** | 0.853*** | 1 |

## Table 6: Performance Statistics of Hedged Portfolios

This table reports the annualized returns, annualized volatility, Sharpe ratio, and maximum drawdown for the top-fund portfolio, with and without hedging. Every month, all available stock mutual funds are ranked by their trailing 12-month alphas relative to the FF3F, and a subset of top 25% best-performing funds are selected to form the portfolio we hold for the next month. Panel A reports results for the value-weight portfolio. Panel B reports results for the equal-weight portfolio. Our sample period is from August 2007 to June 2020. Please refer to the main text for details of hedging.

*Panel A: Value-weight*

| | Annualized Returns | Annualized Volatility | Sharpe Ratio | Maximum Drawdown |
|---|---|---|---|---|
| **No hedging** | 12.70% | 25.63% | 0.42 | 56.59% |
| **Constant hedging against CSI300** | 8.36% | 12.11% | 0.53 | 21.92% |
| **Constant hedging against CSI300 and CSI500** | 7.53% | 9.41% | 0.59 | 13.10% |
| **Dynamic hedging against CSI300** | 9.10% | 13.65% | 0.52 | 26.42% |
| **Dynamic hedging against CSI300and CSI500** | 9.45% | 8.03% | 0.93 | 13.55% |
| **CSI300 Index** | 5.43% | 28.68% | 0.12 | 70.47% |
| **CSI500 Index** | 8.06% | 31.41% | 0.19 | 69.13% |

*Panel B: Equal-weight*

| | Annualized Returns | Annualized Volatility | Sharpe Ratio | Maximum Drawdown |
|---|---|---|---|---|
| **No hedging** | 13.89% | 25.11% | 0.48 | 56.35% |
| **Constant hedging against CSI300** | 9.54% | 12.26% | 0.62 | 20.26% |
| **Constant hedging against CSI300 and CSI500** | 8.71% | 9.00% | 0.75 | 11.14% |
| **Dynamic hedging against CSI300** | 10.79% | 13.77% | 0.64 | 24.52% |
| **Dynamic hedging against CSI300and CSI500** | 11.23% | 7.97% | 1.16 | 9.97% |
| **CSI300 Index** | 5.43% | 28.68% | 0.12 | 70.47% |
| **CSI500 Index** | 8.06% | 31.41% | 0.19 | 69.13% |