Distribution of Individual Stock Performances in a Mutual Fund and the Fund Manager's Stock Picking Ability

Abstract

We find that the performance distribution of the individual stocks inside a mutual fund can toss out additional information about the fund manager's stock picking ability. When a mutual fund contains mostly mediocre-performing stocks but one super-performer, it is likely that the overall fund performance, albeit good, would be due to luck. On the other hand, a fund that has a larger number of above-average performing stocks may have a good fund performance due to its manager's true ability. With this intuition in mind, we develop a measure of fund manager ability from the distribution of the individual stock performances inside the fund. Our measure predicts fund performances for up to two years. An investment strategy based on our measure can generate an extra 9% annual return. Our measure has the strongest explanatory power for currently well-performing mutual funds, suggesting that it would be very useful to tell whether the current good performance is due to luck or true ability of the fund manager.

1. Introduction

The stock picking ability of a mutual fund manager is often measured by the overall performance of his portfolio. However, because the overall portfolio performance is an average, the measure is sensitive to outliers. A fund manager, who does not have much of stock picking ability, can pick up a stock or two with large positive alphas by chance.[1] These stocks, such as Google in 2005 or Microsoft in 1986, can boost up the portfolio performance without significantly changing the risk characteristics of the portfolio. In a case like this, overall fund performance measure would falsely suggest that the fund manager has stock picking ability. This type of error seems to be quite common in the mutual fund industry. For example, Barras, Sacillet, and Wermers (2010) and Fama and French (2010) find that most of superior mutual fund performances are the result of luck, rather than the manager's stock picking ability.

We hypothesize that the distribution of individual stock performances inside a fund tosses out additional information about a fund manager's stock picking ability. A fund manager nowadays typically picks 70 or more stocks. If we measure the performances of those stocks individually, we would be able to see the distribution of the performances inside a fund. The shape of the performance distribution can tell whether a fund manager picked mostly the stocks with above-average performances, or just a few super-performing stocks. Suppose there are two managers with good fund performances. One manager could have achieved the good performance by picking a lot of above-average performing stocks. The other manager could have achieved a similar performance by picking mostly mediocre-performing stocks but one super-performing

[1] Alpha represents the excess return over and above what is expected by a benchmark or predicted return of an asset pricing model.

stock. Who would more likely to continue the good performance? We conjecture that, if a fund manager has true stock picking ability, he would pick relatively better-performing stocks consistently. Such consistency can be measured by analyzing the shape of the individual stock performance distribution inside a fund, such as the skewness of the distribution. We develop our measure of stock picking ability with this intuition in mind, and test whether our measure can indeed predict the future performance of mutual funds managed by the same managers.

The existing literature on mutual fund performance has not focused on the distribution of the performances inside funds. The main reason is that the stock holdings of mutual funds were not available to the public until early 2000s. Wermers (2000) is one of the early papers that analyzes the holdings data of mutual funds. Kacperczyk and Seru (2007) and Kacperczyk, Sialm, and Zheng (2008) also point out that the holdings data were not clean enough to be linked to the mutual fund performance data. A paper that uses the holdings data to measure the manager's stock picking ability is Cohen, Coval, and Pastor (2005). They examine the similarity among fund managers' stock holdings, and demonstrate that managers who make similar portfolio decisions to those of renowned fund managers tend to produce good performances in the future. In this paper, we study whether the holdings data can give additional information about the fund manager's stock picking ability. Our work is also related to the newly-emerging literature that studies the correlation between luck and mutual fund performance. Koswski, Timmerman, Wermers, and White (2006) and Fama and French (2010) use bootstrapping techniques to filter out luck from stock picking ability. Barras, Scaillet, and Wermers (2010) use the False Discovery Rate approach by Storey (2002) to identify luck from performance. These methods are still based on the overall fund performance, instead of using the performance distributions of individual stocks inside the fund. Our measure of stock picking ability would be useful as it more precisely differentiates luck-driven performances from ability-driven performances.

To examine the distribution of the performances inside a fund, we estimate individual stock alphas inside equity mutual funds, using the Carhart (1997) 4-factor model. We then calculate the moments of the individual stock alphas. Note that the traditional fund performance measure regresses a fund's net-asset-value (NAV) on the Carhart 4-factors. Technically, two approaches should yield the same estimated coefficients, because a linear transformation of a sample corresponds to the same linear transformation of the coefficients. The weighted average of individually estimated alphas, for example, would be equal to the alpha of the fund. However, our method enables us to see the distribution of individual stock performances inside a fund. From the distribution, we can measure which manager consistently picked the stocks with above-average performances. If a manager consistently picked above-average performing stocks, the individual stock performance distribution inside the fund would be left-skewed. Thus, we develop a performance measure based on the skewness of the performance distributions inside mutual funds.

We find that our skewness-based measure predicts future fund performances fairly well. A fund that contains a larger number of above-average performing stocks continues to have a better performance for the next 8 holdings reports. That is equivalent to predicting the fund performance for the next 2 years. We also find that our stock picking ability measure works especially well for the best-performing mutual funds.

Therefore, our measure would be very useful in telling whether a superior performance of a mutual fund is due to the manager's stock picking ability or luck.

Next, we construct a feasible investment strategy based on our skewness measure. We find that the strategy that uses our measure can make significant differences in future returns. The difference is the largest for the funds that currently have good performances. Among the funds that currently have the best overall performances, the funds with the most left-skewness generate an average of 27.6% 12-month cumulative return, while the funds with the most right-skewness generate an average of 18.3%. Overall, our measure can toss out additional information on a fund manager's stock picking ability, and provides strong implications for choosing mutual funds or deciding compensations for fund managers.

This paper is organized as follows. Section 2 describes the data and our methodologies. Section 3 presents our results. Section 4 summarizes and concludes the paper.

2. Data and Methodology

We first run the Carhart 4-factor model to estimate the performance of a stock. The performance of a stock is measured by the intercept (alpha) of the following 4-factor model:

$$r_i = \alpha_i + \beta \cdot r_m + \delta \cdot SMB + \phi \cdot HML + \gamma \cdot MOM + \varepsilon$$

where r_i is the return on stock i, r_m is the daily return on the stock market, SMB is the small-minus-big size factor, HML is the high-minus-low book-to-market factor, and MOM is the winners-minus-losers momentum factor. All observations are in daily basis.

The Center for Research in Security Prices (CRSP) of the University of Chicago provides daily returns of stocks listed in major US stock exchanges. We regress these daily returns on daily asset pricing factors, acquired from the data library website of Ken French. We estimate the alphas of all stocks in the CRSP database using 125 business day estimation period, which is approximately a half year.[2] The Arbitrage Pricing Theory (APT)-based estimations such as the Carhart 4-factor model are appropriate for portfolio returns, but in this paper, we estimate the performance of individual stocks using the Carhart 4-factor model and then aggregate the individual estimations to the portfolio level. Technically, there should be little difference between two estimation methods. If we denote the weight of each stock in a portfolio as *w*, a portfolio that contains *n* stocks should have the return equal to the weighted average of individual stock returns:

$$r_p = \sum_{j=1}^{n} w_j \cdot r_j$$

If we take individual estimates of the Carhart 4-factor model and get weighted averages, it will be the same as running one model for the overall fund return.

$$\begin{aligned}
w_1 \cdot r_1 &= w_1 \cdot \alpha_1 + w_1 \cdot \beta_1 \cdot r_m + w_1 \cdot \delta_1 \cdot SMB + w_1 \cdot \phi_1 \cdot HML + w_1 \cdot \gamma_1 \cdot MOM + w_1 \cdot \varepsilon \\
+ w_2 \cdot r_i &= w_2 \cdot \alpha_2 + w_2 \cdot \beta_2 \cdot r_m + w_2 \cdot \delta_2 \cdot SMB + w_2 \cdot \phi_2 \cdot HML + w_2 \cdot \gamma_2 \cdot MOM + w_2 \cdot \varepsilon \\
+ \cdots &= \cdots \\
+ w_n \cdot r_n &= w_n \cdot \alpha_n + w_n \cdot \beta_n \cdot r_m + w_n \cdot \delta_n \cdot SMB + w_n \cdot \phi_n \cdot HML + w_n \cdot \gamma_n \cdot MOM + w_n \cdot \varepsilon \\
\hline
r_p &= \alpha_p + \beta_p \cdot r_m + \delta_p \cdot SMB + \phi_p \cdot HML + \gamma_p \cdot MOM + \varepsilon
\end{aligned}$$

[2] Note that we obtain similar results with the 60- or 90-day estimation periods.

An estimated parameter from a portfolio return should be the same as the weighted average of the parameters estimated from the individual stock returns inside the portfolio. So the portfolio alpha should equal to the weighted average of individually-estimated alphas of the stocks for the portfolio.

$$\alpha_p = \sum_{j=1}^{n} w_j \cdot \alpha_j$$

An advantage of our approach is that we can see the distribution of individual stock performances inside a fund. We conjecture that a fund manager who consistently picks above-average performing stocks has true stock picking ability. Suppose there are twenty stocks in a fund. If a fund manager has no true stock picking ability, the twenty stocks would be random twenty draws from the universe of stocks. On average, the manager would have ten above-average performers and ten below-average performers. There may be still a lucky fund manager who picked one super-performing stock. Then the overall performance of the fund will be above-average, but the number of above-average performing stocks inside the fund would be still ten (or eleven). When a fund manager has true ability, however, would tend to pick a larger number of above-average performing stocks. He may end up with, for example, fifteen above-average performing stocks and five below-average performing stocks. Whether a fund manager picks a larger number of above-average stocks can be examined by studying the distribution of individual stock performances.

In order to see which stocks performed better than others, we rank the alphas of individual stocks into 100 groups within the same estimation period. The groups above 50 are above-average performing stocks and the others are below-average performing stocks during our 125-day estimation period. For example, if a fund holds only two stocks, A and B, and their alpha rankings were the 14th and the 36th, respectively, we can tell that the fund has two below-average performing stocks. Without the rankings, we cannot compare the alphas estimated for the different time periods because the overall alpha level of the stock market may vary over time. Koswski, Timmerman, Wermers, and White (2006) point out that the noise in fund performance estimates varies by fund and by time, and argue that a ranking process can control for such differences across funds.

We use the Thomson Financials Mutual Fund Stock Holdings Data for July 31st 2002 through Feb 28th, 2006, and identify the stocks included in different mutual funds. We only use the equity mutual funds defined by the Thomson Financials Data. The equity mutual funds are the funds that have "Investment Objective Code" of 2 to 4. The Objective Code 2 stands for aggressive growth, 3 stands for growth, and 4 stands for growth and income. In addition, we require the funds to have a non-zero asset. We have 1,604 equity mutual funds in our sample and each equity fund has on average 11 holdings reports. We estimate stock alphas for each holdings report date. For example, if a fund has a holdings report effective as of June 30th, 2004, for each stock in that fund, we use the previous 125 business days of returns to estimate the alphas of individual stocks in the fund. Most of the funds report their holdings on semi-annual or quarterly basis, and therefore we estimate the approximate performance of individual stocks every one or two report cycle. Table 1 reports some summary statistics of the funds in our dataset.

We calculate the weighted skewness of the alpha rankings to see which fund has a higher tendency to hold above-average performing stocks. Skewness is a measure whether a distribution is clustered away from the mean. If the distribution is clustered above the mean, it is called left-skewed distribution because it has longer tail on the left. Applying this concept to the individual stock performance distribution inside a fund, a manager with true stock picking ability would pick more above-average performing stocks, and so the distribution inside the fund would show left-skewness. We use weighted skewness because a manager can adjust his performance by changing the weights of each stock. A manager with stock picking ability may choose to put a heavy weight to several stocks with good perspectives to increase the fund's future performance instead of searching for additional stocks. The weight is the market value of a stock holding compared to the total market value of the fund. The weighted skewness of a fund can be calculated as:

$$s = \frac{n}{(n-1)\cdot(n-2)} \cdot \sum w_i^{3/2} \cdot ((x_i - \bar{x}) / \hat{\sigma})^3$$

where n is the number of stocks in the fund, w_i is the weight of the stock i, x_i is the alpha ranking of stock i, and σ is the standard deviation of the alpha rankings in the fund.

If our measure really captures the stock picking ability of a fund manager, we should see the fund with more negative skewness measure continues to show good performances in the future. We test if the current period's skewness measure can predict the fund performance, by estimating the following model.

$$mean(\alpha)_{i,t+j} = \lambda_0 + \lambda_1 \cdot skew^*(\alpha)_{i,t} + \varepsilon \qquad (1)$$

The skewness in the equation has * sign because it is derived from rankings. If the skewness has the prediction power, current skewness measure of fund i at period t should be negatively and significantly correlated with future fund performance at period $t+j$. This means the coefficient λ_1 should be negative and significant. We use OLS estimation with an error structure that corrects for heteroscedasticity and for clustered errors. We fix clustering by fund and year. Petersen (2009) shows that an OLS model with such correction yields a consistent estimation of the coefficients.

3. Results

3.1. Predictive Power of Our Skewness Measure

Table 2 shows that our skewness measure is negatively and significantly correlated with future fund performances. The significant prediction power is not just for the next report, but continues for eight consecutive report periods. The t-statistics range from -6 to -22, indicating that our finding is highly significant. Adjusted R-squares of the estimated model range from 7% to 17%. Note that the adjusted R-squares are the highest for the next period (t+1) and gradually decrease afterwards, suggesting that power would be lower for longer-term prediction as is intuitively the case. Results indicate that our measure is useful in capturing the actual stock picking ability of a fund manager. A manager who consistently picks above-average performing stocks continues to show good fund performance for up to two years. If the current performance of a fund is driven by luck, there would be little chance that the performance will continue for a long period of time. Our result is consistent with Bollen and Busse (2004), Avramov and Wermers (2006) and Kosowski, Timmerman, and Wermers, and White (2006), who find persistency in mutual fund performances.

3.2. Results Stratified by Current Performance

Next, we stratify mutual funds by their current performances. The predictive power of our skewness measure can be different by the current performance level. Suppose we classify fund managers into two categories: the managers without stock picking ability and the managers with stock picking ability. This simple setting reflects that no manager would intentionally pick below-average performing stocks. If a manager does not have stock picking ability, his stock selection would not be different from a random selection of stocks. Ex post, the random selection can end up with extremely good performances or really bad performances, but the average fund performances of these managers would be similar to that of passive investment strategies (e.g., index funds). On the other hand, the managers with stock picking ability will have a left-skewed distribution of individual stock performances, and their fund performances will be above average.

Now suppose an investor observes overall fund performances without knowing the stock picking ability of fund managers. She only knows that there are two types of managers – one with true ability and the other without. Then the funds currently with the worst performances would be mostly the ones managed by the managers without ability and with bad luck. The matter is more complicated for the funds currently with the best performances, because two types of managers are mixed in this category. The investor knows that the best performances can be a result of actual ability or a result of good luck. Therefore, if a fund performance measure successfully identifies the managers with true stock picking ability, it should be more informative for the funds that are currently performing the best. Koswski, Timmerman, Wermers, and White (2006), Barras, Scaillet, and Wermers (2010), and Fama and French (2010) attempt to filter out luck from actual ability by using the overall fund performances. Here, we test whether our skewness measure, which is based on performances of individual stocks, is more informative for the funds with the best performances. Our goal is to examine whether the source of the best performances is luck or actual stock picking ability.

Our test can also control for the effect of survivorship bias. Such a bias would apply mostly to the poor-performing funds because these funds are more likely to vanish than other funds. As a result, the performance of the poor performing funds is likely to be exaggerated. If this effect was the main driver of our earlier result, we would be able to observe the pattern in the performance-stratified result. With this in mind, we rank current fund performances into quintiles and run the regression equation (1) by quintile.

Table 3 shows that the negative correlation between future performance of a fund and our skewness measure is stronger as we move toward better performance categories. The correlation is indeed the strongest for the best performance quintile. It appears that the survivor ship bias, if there is any, does not affect our results, because those funds are the ones least affected by the survivorship bias. Also, adjusted R-squares are the largest for the best performance quintile (e.g., 8.2% for t+1 and 6.0% for t+7). Meanwhile, the adjusted R-squares of the other performance quintiles are 1% or less. We can now see that our earlier result in Table 2 are mostly driven by the funds that currently have good performances. Thus, our stratification test further indicates that our method is particularly useful in identifying luck-driven good performances from ability-driven good performances.

3.3. Investment Strategy with our Skewness Measure

We then test whether investors can use our measure to make significant profits. If our positive consistency is an indicator of fund manager ability, investors should buy the fund whose manager has actual stock picking ability. Let’s assume that an investor buys mutual funds after their holdings reports are filed. The filing date is when the holdings report is publicly available. Some mutual funds file their holdings data several months after the effective holdings date. For example, "Investco Mid-Cap Growth Fund" filed its holdings report 151 days after the effective holdings date. The holdings data of Oct 31st, 2001 is filed on March 31st, 2002. Table 4 reports summary statistics on the differences between the effective date of the holdings and the filing date. It shows that the median difference between the two dates is zero, indicating that most of funds file their effective holdings data on the same day. Still, there is on average 31 day difference between the effective holdings date and actual file date. Even if investors want to use our skewness data to select mutual funds, they have to wait until the holdings report is publicly available. So we measure cumulative returns of mutual funds after the holdings report is available (or filed). This restriction allows a lag between the effective holdings date and the execution of actual investment.

We track the daily return of the funds using their net-asset-value (NAV) data from the date that a holdings report is filed. We first rank funds into quintiles by our skewness measure. For each quintile, we calculate 3-month (62 business days), 6-month (125 business days), 9-month (187 business days), and 12-month (250 business days) cumulative returns. The net-asset-value (NAV) data are acquired from the CRSP mutual fund database. We merge the daily returns data with our holdings dataset. We use the Mutual Fund Link Data (MF links) created by Russ Wermers to merge two databases. Wermers (2000) show the effectiveness of this link data. While the Thomson database classifies mutual funds only by the managers and holdings, the CRSP database has more detailed classification. The CRSP database classifies funds by its manager, holdings, and share classes. One mutual fund may have share classes A and B, which are the same fund but differs in fees and distributions. We aggregate the returns of different share classes in the CRSP database by taking the weighted average of returns. The weight is the latest total net-asset-value of each share class. After the matching, we have 3,373 observations of fund filing dates.

Table 5 shows that the funds with more negative skewness measures have higher cumulative returns. The difference between the highest and the lowest quintiles is 9.6% annually. If investors bought mutual funds with the most negative skewness measures, they could earn a 9.6% additional annual return compared to the mutual funds with the most positive skewness. Thus, our skewness measure can be useful for actual investment purposes. Also, the difference between the two quintiles is more noticeable as we use longer period returns. The pattern shows that our measure is capturing the differences in long term fund performances that would be less influenced by luck. Overall, the result shows that investors can use our measure to learn the true stock picking ability of a manager rather than being lured by simple overall fund performances. Financial institutions can use our measure to construct a proper incentive structure for their fund managers. The size of return difference between the two quintiles also confirms that survivorship bias is not a factor that drives our result. Linnainmaa (2010) shows the degree of survivorship bias is around 1% per year.

We also report more stratified results. We rank the current performances of mutual funds into quintiles and then rank the quintiles by our skewness measure. The process gives us a 5x5 matrix. As we show in Table 3, our skewness measure is particularly useful to identify the source of current good performance. Table 6 shows that the funds with more negative skewness measures tend to do better than the funds with positive skewness measures. The difference is accentuated for the funds that currently have the best performances. In Panel D of Table 5, for example, among the funds that currently have the best performances, the funds that have negative skewness show 27.6% cumulative 12-month returns, but the funds that have positive skewness show only 18.3% cumulative 12-month returns. Even if the current fund performances are the same, the future performances can vastly differ by our skewness measure. This result confirms that our skewness measure well represents the true stock picking ability of a fund manager.

3.4. Fund Fees and Our Skewness Measure

If investors know that a fund manager has good stock picking ability, the mutual fund seller may charge investors higher fees. The fund seller can extract some rent from investors if investors are continuously lured by the ability (or reputation) of the fund manager. In an extreme case, the seller may increase the fees such that the net return of a renowned fund is the same as the net returns of other funds.[3] Here, we test the relationship between our skewness measure and mutual fund fees. We use the expense ratio of the CRSP mutual fund database to measure the size of the fees. Since our expense ratio data are annual data, we take annual average of our skewness measures and merge them with the expense ratio data.

Similar to Table 6, we create a 5x5 matrix. We rank the funds by current performances and then rank by our skewness measure. Table 7 reports the expense ratios. The expense ratios are on average 1% to 2%. The size of the expense ratios is not large enough to explain the differences in future returns by our skewness measure. Moreover,

[3] This type of rent-seeking behavior would be stronger for hedge funds, which are not regulated and face less competition from each other.

there is a tendency that the funds with more positive skewness charge higher fees to investors (about 0.5% higher). This result indicates that fees are not adjusted properly according to the fund manager's stock picking ability. Perhaps financial institutions have little room to change the fees due to competition in the mutual fund industry, especially when it is hard to identify luck from actual stock picking ability in practice.

4. Summary and Conclusion

This paper shows that investors can learn about a fund manager's stock picking ability by analyzing the distribution of the stock performances inside a fund. A lucky manager may buy one or two super-performing stocks by chance, and those stocks would boost up the average fund performance. On the other hand, if a fund manager has true stock picking ability, the manager will consistently pick the above-average performing stocks. With this intuition in mind, we develop a measure based on the skewness of the individual stock performance distributions inside a fund. If a manager picks a larger number of above-average performing stocks, the distribution would be more left-skewed.

We find that our skewness measure predicts future fund performances fairly well. Our measure can predict the performances of mutual funds for up to two years. Our measure is particularly useful in identifying the source of a good mutual fund performance. Among the funds that currently have good performances, the funds with left-skewness continue their good performances, while the funds with right-skewness do not. This result indicates that our skewness measure can tell whether current good performances are driven by luck or true stock picking ability.

Our skewness measure can yield actual differences in mutual fund investments as well. We construct a feasible investment strategy that assumes an investor buys a fund after its holdings report is released. We find that an investor who uses our skewness measure can earn significant additional return after controlling for the fees. Our skewness measure can explain as much as a 9.3% difference in 12-month cumulative returns for current best-performers. Overall, our skewness measure would be a useful tool to gauge the true stock picking ability of a fund manager, providing strong implications for choosing mutual funds or deciding compensations for fund managers.

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Table 1: Summary Statistics.

We report the summary statistics of our mutual fund sample. Our sample includes equity mutual funds defined by the Thomson Financials Mutual Fund Stock Holdings Data during July 31st, 2002 to Feb 28th, 2006. The number of mutual funds in our sample is 1,604.

	Mean	Median	Standard Deviation
Number of holdings report per mutual fund	10.8 reports	12 reports	3.3 reports
Number of days between two holdings reports	92 days	92 days	44 days
Number of stocks in a fund	137 stocks	74 stocks	286 stocks
Percentage of stock holdings	86%	91%	18%
Fund total assets (million $)	$1,716 mil.	$343 mil.	$5,742 mil.

Table 2: Our Skewness Measure and Future Fund Performances

We test if the current period's skewness measure for a fund can predict the fund performance for the following periods. The hypothesis is tested using the following regression equation:

$$mean(\alpha)_{i,t+1} = \lambda_0 + \lambda_1 \cdot skew^*(\alpha)_{i,t} + \varepsilon \quad (1)$$

where *skew* represents the weighted skewness of the alpha rankings of individual stocks inside a find. It has * sign because it is derived from rankings. α represents the excess return over and above what is predicted return of the Carhart's (1997) 4-factor model.

We use OLS estimation with corrections for heteroscedasticity and clustered errors. We fix clustering by fund and year. We report t-values in the parentheses under coefficients for λ_1. For visual convenience, the coefficients are multiplied by 10^3. The coefficients significant at the 1%, 5%, and 10% levels are marked with small a, b, and c, respectively.

	Fund performance after one period *(t+1)*	Fund performance after two periods *(t+2)*	Fund performance after three periods *(t+3)*	Fund performance after four periods *(t+4)*
λ_1	-0.465[a] (-22.57)	-0.323[a] (-14.65)	-0.313[a] (-11.99)	-0.313[a] (-11.72)
Observations	15,597	14,051	12,518	11,021
Adjusted Rsq.	17.1%	8.4%	8.0%	8.2%

	Fund performance after five periods *(t+5)*	Fund performance after six periods *(t+6)*	Fund performance after seven periods *(t+7)*	Fund performance after eight periods *(t+8)*
λ_1	-0.315[a] (-8.57)	-0.306[a] (-6.01)	-0.282[a] (-6.10)	-0.274[a] (-7.65)
Observations	9,541	8,098	6,675	5,295
Adjusted Rsq.	8.5%	8.7%	7.3%	6.8%

Table 3: Our Skewness Measure and Future Fund Performances: Stratified by the Fund's Current Performance

We rank our sample funds into into quintiles by their current performance. We then test if the current period's skewness measure for a fund can predict the fund performance for the following periods. The hypothesis is tested using the following regression equation:

$$mean(\alpha)_{i,t+1} = \lambda_0 + \lambda_1 \cdot skew^*(\alpha)_{i,t} + \varepsilon \qquad (1)$$

where *skew* represents the weighted skewness of the alpha rankings of individual stocks inside a find. It has * sign because it is derived from rankings. α represents the excess return over and above what is predicted return of the Carhart's (1997) 4-factor model.

We use OLS estimation with corrections for heteroscedasticity and clustered errors. We fix clustering by fund and year. We report t-values in the parentheses under coefficients for λ_1. For visual convenience, the coefficients are multiplied by 10^3. The coefficients significant at the 1%, 5%, and 10% levels are marked with small a, b, and c, respectively. We report the cases of t+1, t+3, t+5, and t+7 periods afterwards.

Current Performance Quintile 1 (Worst)				
	Fund performance after one period *(t+1)*	Fund performance after three periods *(t+3)*	Fund performance after five periods *(t+5)*	Fund performance after seven periods *(t+7)*
λ_1	-0.545[a] (-4.28)	0.010 (0.57)	0.007 (0.16)	0.043 (1.20)
Observations	3,228	2,725	1,840	1,195
Adjusted Rsq.	1.2%	0.0%	0.0%	0.4%
Current Performance Quintile 2				
	Fund performance after one period *(t+1)*	Fund performance after three periods *(t+3)*	Fund performance after five periods *(t+5)*	Fund performance after seven periods *(t+7)*
λ_1	-0.003 (-1.35)	-0.002 (-0.77)	-0.000 (-0.14)	0.000 (0.22)
Observations	3,272	2,787	2,072	1,415
Adjusted Rsq.	0.1%	0.0%	0.0%	0.0%
Current Performance Quintile 3				
	Fund performance after one period *(t+1)*	Fund performance after three periods *(t+3)*	Fund performance after five periods *(t+5)*	Fund performance after seven periods *(t+7)*
λ_1	-0.009[a] (-3.55)	-0.000 (-0.33)	-0.008[a] (-2.83)	-0.006 (-1.54)
Observations	3,169	2,486	1,934	1,402
Adjusted Rsq.	0.4%	0.0%	0.4%	0.2%

Current Performance Quintile 4				
	Fund performance after one period *(t+1)*	Fund performance after three periods *(t+3)*	Fund performance after five periods *(t+5)*	Fund performance after seven periods *(t+7)*
λ_1	-0.020[a] (-5.16)	-0.016[a] (-3.97)	-0.009[b] (-2.04)	-0.018[a] (-2.69)
Observations	3,056	2,306	1,894	1,368
Adjusted Rsq.	0.8%	0.6%	0.2%	1.0%

Current Performance Quintile 5 (Best)				
	Fund performance after one period *(t+1)*	Fund performance after three periods *(t+3)*	Fund performance after five periods *(t+5)*	Fund performance after seven periods *(t+7)*
λ_1	-0.361[a] (-8.48)	-0.242[a] (-5.35)	-0.279[a] (-4.12)	-0.000[a] (-2.92)
Observations	2,872	2,214	1,801	1,295
Adjusted Rsq.	8.4%	4.5%	6.3%	6.0%

Table 4: Difference between Effective Holdings Date and Actual Filing Date

We compute the difference between the report date and the filing date for our sample equity mutual funds. The report date is the effective date of the stock holdings data. If the report date is June 30th, 2001, the holdings data is valid as of that date. The filing date is when the holdings report is actually filed and becomes publicly available.

	Mean	Standard Deviation	Minimum	Maximum	25%	50% (Median)	75%
Difference between the report date and the filing date	31 days	49 days	0 days	519 days	0 days	0 days	61 days

Table 5: An Investment Strategy based on Our Skewness Measure

We track the daily return of the funds using their net-asset-value (NAV) data from the date when a holdings report is filed. We first rank funds into quintiles by our skewness measure. For each quintile, we calculate 3-month (62 business days), 6-month (125 business days), 9-month (187 business days), and 12-month (250 business days) cumulative returns.

	3-month cumulative return	6-month cumulative return	9-month cumulative return	12-month cumulative return	Observations
Skewness Rank 1 (Most negative skewness)	-2.23%	7.69%	12.68%	22.46%	674
Skewness Rank 2	-1.28%	5.73%	8.98%	18.39%	675
Skewness Rank 3	-0.73%	5.02%	6.79%	15.84%	675
Skewness Rank 4	0.27%	3.69%	4.68%	13.52%	675
Skewness Rank 5 (Most positive skewness)	0.02%	3.31%	4.56%	12.87%	674

Table 6: An Investment Strategy based on Our Skewness Measure: Stratified by Fund's Current Performance and Our Skewness Measure

We track the daily return of the fund using its net-asset-value (NAV) data from the date when a holdings report is filed. We first rank funds into quintiles by their current fund performance and then rank by their skewness of alpha rankings of individual stocks inside the funds. This process produces a 5x5 matrix. For each class, we calculate 3-month (62 business days), 6-month (125 business days), 9-month (187 business days), and 12-month (250 business days) cumulative returns.

Panel A: 3-month cumulative return

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Skewness Rank 1 (Most negative skewness)	-1.30%	-1.56%	-2.46%	-1.92%	-2.58%
Skewness Rank 2	-0.48%	-1.49%	-0.89%	-1.14%	-1.93%
Skewness Rank 3	0.18%	0.54%	-0.36%	-1.00%	-2.19%
Skewness Rank 4	0.35%	0.74%	0.16%	-0.79%	-1.53%
Skewness Rank 5 (Most positive skewness)	-0.02%	-0.17%	-0.08%	0.15%	0.05%

Panel B: 6-month cumulative return

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Skewness Rank 1 (Most negative skewness)	2.56%	2.22%	6.09%	5.90%	10.58%
Skewness Rank 2	2.65%	3.42%	7.77%	6.59%	10.18%
Skewness Rank 3	2.71%	3.35%	7.26%	7.29%	9.94%
Skewness Rank 4	2.08%	2.99%	5.77%	5.22%	7.77%
Skewness Rank 5 (Most positive skewness)	2.29%	2.91%	5.63%	6.78%	6.12%

Panel C: 9-month cumulative return

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Skewness Rank 1 (Most negative skewness)	4.42%	4.84%	6.09%	10.39%	17.32%
Skewness Rank 2	3.57%	5.52%	7.77%	10.78%	16.00%
Skewness Rank 3	3.05%	3.75%	7.26%	11.33%	14.86%
Skewness Rank 4	3.01%	3.22%	5.77%	7.07%	12.12%
Skewness Rank 5 (Most positive skewness)	2.77%	3.74%	5.63%	10.29%	7.77%

Panel D: 12-month cumulative return

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Skewness Rank 1 (Most negative skewness)	11.08%	10.58%	13.26%	19.31%	27.63%
Skewness Rank 2	11.46%	13.69%	18.01%	21.19%	27.29%
Skewness Rank 3	10.75%	12.80%	16.80%	20.99%	27.37%
Skewness Rank 4	11.50%	11.74%	15.21%	16.40%	23.48%
Skewness Rank 5 (Most positive skewness)	11.12%	11.08%	14.08%	20.24%	18.26%

Table 7: Mutual Fund Expense Ratios.

We first rank funds into quintiles by their current fund performances and then rank them by their skewness of alpha rankings of individual stocks inside the funds. This process produces a 5x5 matrix. For each class, we report the average expense ratio.

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Skewness Rank 1 (Most negative skewness)	1.17%	0.96%	1.21%	1.31%	1.66%
Skewness Rank 2	1.27%	1.17%	1.22%	1.39%	1.53%
Skewness Rank 3	1.40%	1.17%	1.30%	1.34%	1.52%
Skewness Rank 4	1.31%	1.21%	1.30%	1.39%	1.47%
Skewness Rank 5 (Most positive skewness)	1.67%	1.27%	1.34%	1.42%	2.00%