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The win–loss ratio as an ability signal of mutual fund managers: a measure that is less influenced by luck

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Abstract To better identify skilled mutual fund managers, we develop a mutual fund performance predictor that is less influenced by luck. We posit that it is unlikely for a fund manager to consistently hold numerous above median performing stocks unless he has stock-picking ability. Using the number of above median performing stocks as a fund performance predictor (win–loss ratio), we find that a higher win–loss ratio in 1 year is associated with 2–4 % additional risk-adjusted return in the next. The ratio also has an economically and statistically significant predictive power after controlling for other fund performance predictors in the literature.

Keywords Mutual funds · Luck vs. skill · Win–loss ratio · Performance evaluation · Holdings data

JEL Classification G11

Are there truly talented mutual fund managers who consistently generate additional risk-adjusted returns? If so, how can we identify those skilled managers? Avramov and Wermers (2006) find that among the three investment strategies they form, predictability of manager skills is the dominant source of mutual fund investment profitability. Identifying skilled managers from observed performances is not a simple task, as past records contain a significant amount of randomness or noise. The literature addressing mutual fund performance persistence (Hendricks et al. 1993) focuses on two major

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sources: (1) true skill or (2) luck. A lucky fund manager may have achieved better performance by chance and investors cannot easily differentiate the lucky manager from a skilled one. Recent studies, such as Barras et al. (2010) and Fama and French (2010), argue that most of the majority performance persistence is due to luck. A measure that can provide additional information regarding managerial skill would be a useful tool for investors.

In this paper, we use fund holdings data to calculate the number of stocks that generate above median risk-adjusted performances. We hypothesize that a fund manager cannot consistently have a large number of above median performing stocks in his holdings by chance unless he has stock-picking ability. A mutual fund holding can be thought of as repeated draws of stocks to achieve higher risk-adjusted fund returns. From the large universe of stocks, a fund manager selects those stocks that he believes would increase the risk-adjusted returns of his portfolio. If the manager has no skill, his selection would be akin to random choices. Some of the stocks would have risk-adjusted returns that are higher than the median, while others would have returns lower than the median. A totally random draw will select approximately one-half above median performing stocks and the other half would consist of below median performing stocks. However, if a fund consistently holds a large number of above median performing stocks, we can conjecture that the fund manager has the skill to select these stocks. It is like having a series of coin tosses with significantly more heads than the tails.

One may assume that information obtained from the fund returns data is the same as information from the holdings report, as the average of the component stock returns in the holdings is the fund return. There is a significant difference, as can be illustrated in the following example. Suppose a fund manager has achieved a 0.5 % risk-adjusted return for a 3-month period. From this information, investors cannot tell whether the manager has achieved this performance through his skill or by chance. However, if the holdings data of the fund reveal that all ten of his component stocks in the fund holdings have achieved a 0.5 % risk-adjusted return, investors may assume that this outcome is unlikely to be driven by luck. Similarly, Cornell (1979), Copeland and Mayers (1982), Grinblatt and Titman (1993), and Ferson and Khang (2002) demonstrate that information from the holdings data may improve the evaluation of portfolio performance.

We measure the risk-adjusted returns of each stock in the Center for Research in Security Prices (CRSP) database by regressing daily stock returns on Carhart's (1997) four factors and estimating its intercept (alpha). We estimate the alpha for each stock using 250 daily returns representing approximately 1 year. We compare each stock's alpha with the median alpha for the entire universe of stocks in the CRSP database during the same estimation period and determine whether the stock's alpha is above or below the median. We then calculate the number of stocks in a mutual fund holding that have alphas above the median, normalizing them by the total number of stocks held in the fund. We call this percentage the "win–loss ratio" as it measures how many above median performing stocks (winner stocks) the fund manager has selected out of the total number of stocks held in the fund.

We find that this win–loss ratio is a good predictor of mutual fund performance. High win–loss ratio funds generate approximately 2–4 % additional risk-adjusted returns in the subsequent year. This evidence is robust after accounting for fund size, the number of stocks held in the fund, past fund performance, the sample period, and mutual fund fees. In addition, the win–loss ratio maintains an economically and statistically significant predictive power even after controlling for other fund performance predictors. This robustness demonstrates that our win–loss ratio is not driven by fund size or the number of stocks. These results indicate that our findings would be useful to those who attempt to identify outperforming funds and to others who try to develop a more precise measure of a fund manager's stock-picking ability.

Our work is related to a growing literature that seeks additional indicators of managerial skills from holdings data. For example, Cohen et al. (2005), Kacperczyk et al. (2005), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), and Petajisto (2013) find that some aspects of the holdings data can be used to extract additional information concerning a manager's skill. All of the previous research with holdings data, however, focuses on particular aspects of fund holdings, implicitly assuming that better performance would only be achieved through certain investment strategies. Kacperczyk et al. (2005) focus on the fund's industry concentration, while Kacperczyk and Seru (2007) examine a fund's use of public information. Cremers and Petajisto (2009) study the ratio of component stocks that are not included in major stock indices, and Huang et al. (2011) examine the fund's risk shifting behavior. If there is a fund manager who can consistently achieve better performance without those particular investment strategies, he would be falsely identified as unskilled. Our win–loss ratio measure is less affected by these issues as it only examines whether an individual stock performance is above the market median. In addition, the results strongly indicate that our measure provides a substantially better prediction of risk-adjusted fund performance and adds significant predictive power even after controlling for other performance indicators suggested in the literature.

Our method also contributes to the growing literature that investigates the role of luck or measurement error in observed fund performance. Fund performance has been typically measured from the time series returns of a fund, but this measure is vulnerable to the effect of randomness. Kosowski et al. (2006), Barras et al. (2010), and Fama and French (2010) use time series statistical techniques and determine that a considerable number of good fund performances are achieved by chance. Barras et al. (2010) and Fama and French (2010) also determine that information obtained from the time series returns of a fund is often insufficient in determining whether its manager has true stock picking ability or has achieved fund performance simply by chance. A remedy for this low signal-to-noise problem is to increase the number of observations. However, implementing such a remedy is difficult in practice. Fund return data are available only on a monthly basis prior to the year 2000. The sample would be limited to those funds that have long historical records. Alternatively, the holdings data are reported every quarter or half year and contain information on 83 component stocks, on average. Since our win–loss ratio measure is based on each component stock's risk-adjusted performance, the large number of cross-sectional observations in the holdings data available every 3 or 6 months increases the likelihood of successfully differentiating luck-driven performances from performance driven by actual skill. Thus, our work provides an additional venue for fund performance evaluation using statistics from the holdings data to identify good performance that is not likely driven by luck.

The rest of this paper is organized as follows. Section 1 describes the statistical theory that supports our win–loss ratio measure. Section 2 explains the data and our empirical methodologies, while Sect. 3 presents our results. Section 4 provides a summary and our conclusions.

1 Our win–loss ratio measure

We begin with a simple assumption that the objective function of mutual fund managers is to increase the risk-adjusted returns of their funds. Note, however, that some funds may have different objective functions, such as generating a more stable income. Our focus in this paper is on actively managed mutual funds whose objective is to grow the value of the fund after controlling for risk.[1]

From the large universe of stocks, fund managers select stocks to be included in their funds. We define a "skilled fund manager" as the one who has more than a 50 % probability of picking stocks whose risk-adjusted returns are above the market median risk-adjusted return. Our intuition is as follows. If a fund manager has no stock picking ability, his selection will be a random one. There is 50 % probability that a selected stock has a risk-adjusted return higher than the market median risk-adjusted return. Alternatively, a manager with true stock-picking ability should achieve a probability significantly higher than 50 %. This manager will consistently select stocks with risk-adjusted returns higher than the market median risk-adjusted return for his portfolio.

Investors have information asymmetry. They cannot observe whether a manager is a skilled one (with more than a 50 % probability to select better stocks) or not. They need to identify the hidden probability using the past selection record of a manager. Investors can use the current fund holding as the result of a fund manager's repeated picks. Using the definition of a skilled manager, investors can conduct a statistical test of fund holdings to determine whether a fund manager has true stock-picking ability. We set the null hypothesis that a fund manager has a 50 % chance to select a stock with a risk-adjusted return higher than a market median risk-adjusted return:

$$H_0 : p = 0.5$$

Under the null, we use binomial distribution to compute the probability of acquiring currently realized stock picks (i.e., current holdings). Out of n stocks, the probability of having k stocks with risk-adjusted returns above the market median risk-adjusted return is:

$$\Pr(K = k) = \binom{n}{k} \cdot p^k (1-p)^{n-k} = \binom{n}{k} \cdot \frac{1}{2}^k \left(\frac{1}{2}\right)^{n-k} = \binom{n}{k} \cdot \left(\frac{1}{2}\right)^n, \quad (1)$$

where:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

[1] Fund managers may also try to maximize their own personal objective functions. This agency problem is beyond the scope of this paper. We still assume that agency problems for actively managed funds are not substantially different from those of other fund types.

Note that k is the number of stocks with above median risk-adjusted returns and n is the number of stocks held in the fund.

Equation (1) has the largest value when $k = n/2$. The value gets smaller when k is closer to n or zero. For example, suppose there is a fund manager who has 50 stocks in his portfolio. If 30 of those stocks have risk-adjusted returns above the market median, the probability that this fund manager is an unskilled one ($H_0 : P = 0.5$) is:

$$\Pr(K = 30) = \binom{50}{30} \cdot \left(\frac{1}{2}\right)^{50} = 4.19\,\%$$

If all 50 stocks have risk-adjusted returns above the market median, the probability that this fund manager is an unskilled one ($H_0 : P = 0.5$) is:

$$\Pr(K = 50) = \binom{50}{50} \cdot \left(\frac{1}{2}\right)^{50} \approx 0.00\,\%$$

In Eq. (1), if a fund manager has a larger number of stocks with risk-adjusted returns higher than the market median, there is a lower probability that this manager achieved this outperformance by chance. Since the probability q decreases as k increases, uninformed investors should seek a manager whose portfolio has a high k value. In other words, non-skilled managers cannot easily mimic the signal of high k. Therefore, we surmise that investors may use a number of above median performing stocks to identify skilled managers.

As such, we calculate the number of stocks in a portfolio with above median risk-adjusted returns (k) and normalize it by the total number of stocks (n) in the portfolio. Our indicator is k/n, which can be acquired from the holdings data.

$$m_1 = k/n \tag{2}$$

We admit that this indicator is a very simple one with limitations. This measure only calculates the number of stocks that have better risk-adjusted performance than the market median. We can modify m_1 by incorporating additional controls. For example, we can add different weights to each stock. We can also redefine the skilled fund manager as one who has more than a 90 %, instead of a 50 %, probability to select those stocks whose risk-adjusted returns are above the market median risk-adjusted return. We find that this measure(s) with additional control(s) has over an 80 % Pearson correlation(s) with m_1, suggesting that additional controls would not significantly change the empirical results.[2] In fact, for measures with additional controls, we acquire qualitatively similar results. Consequently, we use m_1 for most of our empirical tests as our win–loss ratio measure.

[2] The weight seems to be of little importance as fund managers are typically not allowed to invest too heavily in just a few stocks. Informal interviews with fund managers have indicated that normally the fund's risk management department requires fund managers to distribute investments broadly across component stocks. These interviews also taught us that fund managers try to pick seemingly good stocks, but they usually do not attempt to guess how good the performance of individual stocks will be. The outcomes of these interviews strongly support the use of our measure of managerial skill, m_1, for our empirical tests.

Unless the fund manager changes component stocks for a portfolio right before releasing a holdings report, the win–loss ratio from its past holdings report contains information as to how many above median performing stocks the manager has selected in the past.[3] If a manager has selected several above median performing stocks due to his superior skill, it is likely that the fund performance will continue to be good.

2 Data and methodology

We use Thomson Financials Mutual Fund Stock Holdings Data from January 1, 1982 to December 31, 2008. To measure the subsequent 1-year returns from the point of holdings data release, we acquire monthly fund returns data from the CRSP Mutual Fund Data and daily stock returns from the CRSP Stock Returns Data from January 1, 1983 to December 31, 2009. We use Mutual Fund Link Data (MFLINK) to merge the Thomson Data with the CRSP Mutual Fund Data. We examine only actively managed equity mutual funds whose main goal is to maximize risk-adjusted return. In the Thomson Data, we select those funds with an Investment Objective Code of 2 or 3. The Objective Code 2 stands for aggressive growth, while Objective Code 3 represents growth. Likewise, we use fund information in the CRSP data to remove those funds that are not actively managed or not equity-based, such as index funds, money market funds, or bond funds. We also follow the criteria in Kacperczyk et al. (2008) to filter out actively managed mutual funds. After this filtering, we have a total of 1530 actively managed equity mutual funds in our sample. Each fund has, on average, 24 holdings reports during the sample period.

First, we run the Carhart (1997) four-factor model to estimate the risk-adjusted performance of individual stocks. The risk-adjusted performance of a stock is measured by the intercept (alpha) of the following four-factor model:

$$r_i - r_\mathrm{f} = \alpha_i + \beta \cdot (r_\mathrm{m} - r_\mathrm{f}) + \delta \cdot \mathrm{SMB} + \phi \cdot \mathrm{HML} + \gamma \cdot \mathrm{UMD} + \varepsilon, \tag{3}$$

where r_i is the return on stock i, r_f is the risk-free interest rate, r_m is the return on the stock market, SMB is the small-minus-big size factor, HML is the high-minus-low book-to-market factor, and UMD is the up-minus-down momentum factor. All of the observations are on a daily basis. The CRSP Stock Returns Data provide the daily returns of stocks listed in major US stock exchanges. Daily asset pricing factors are acquired from the data library website of Ken French. We estimate the alphas of all of the stocks in the CRSP database using a rolling 250 business day estimation period, which is approximately one full year.[4]

[3] Kacperczyk et al. (2008) find returns from the holdings report are not much different from those from actual fund holdings, suggesting that holdings data can serve as a fair record of the overall past performance of a fund manager.

[4] Note that we obtain similar results with different estimation periods. When the estimation period is longer, the alpha becomes more accurate, but there can be considerable overlapping between the alpha estimation period and the prediction period. We also estimate alphas using monthly returns, but due to the small number of observations per year (12), the estimated alpha is not reliable.

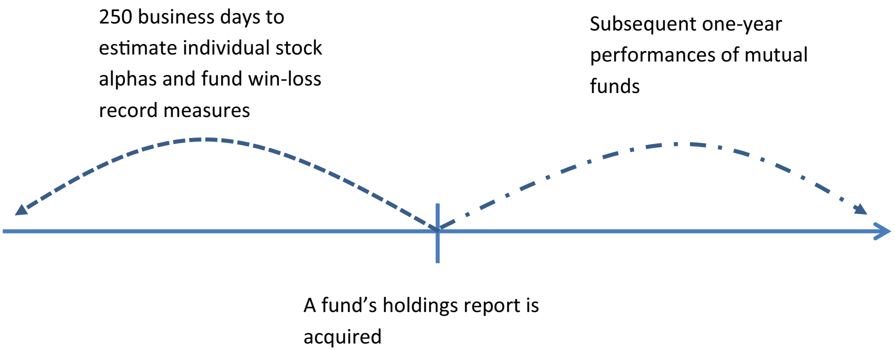

Fig. 1 Estimation of fund win–loss ratio and subsequent performance

After we acquire the alpha of each individual stock, we determine whether the stock's alpha is higher than the median alpha of all of the stocks in the CRSP Stock Returns Data during the same estimation period (previous 250 business days). The stocks that have alphas above the median alpha are above median performing (winner) stocks, and the others are below median performing (loser) stocks. We calculate our performance measure of a fund holding, m_1, with the number of above median performing stocks divided by the total number of stocks in the fund. When m_1 is high, we label this fund as a "high win–loss ratio" fund as high m_1 indicates that the manager has selected many above median performing stocks. Figure 1 illustrates our estimation period and prediction period.

Since the average value of m_1 for the entire sample of mutual funds changes over time, we compare a fund's win–loss measure (m_1) with those of other actively managed equity mutual funds. We track back 1 year from a mutual fund holdings report and rank the m_1 of a fund by comparing it with other funds' win–loss ratios. If a holdings report is reported on July 31, 2005, for example, we compare the win–loss ratio of the fund with the win–loss ratios of other funds from July 31, 2004 to July 31, 2005. We then rank the win–loss ratios into quintiles. One drawback of this method is that the sample size used for the comparison may vary over time, especially when the reports of fund holdings are clustered in particular calendar months. We also tried a cruder sorting, such as ranking by every calendar year, and actually got stronger results. However, sorting by calendar year creates a look-back bias. Comparing a holdings report acquired in March with a holdings report acquired in June of the same year is not realistic. We examine whether investors can use our win–loss ratio measure to achieve significantly higher risk-adjusted returns. Sorting by calendar year would not allow us to do so. Figure 2 illustrates this comparison process.

Next, subsequent 1-year fund returns from the release of a holdings report are measured in four different ways. First, we calculate fund alphas using the Carhart (1997) four-factor model. There are only 12 observations per year if we use monthly fund returns data. As such, the estimation would be subject to large errors. In contrast, including more past time series observations will create an overlap between the win–loss ratio calculation period and the performance measurement period. For these

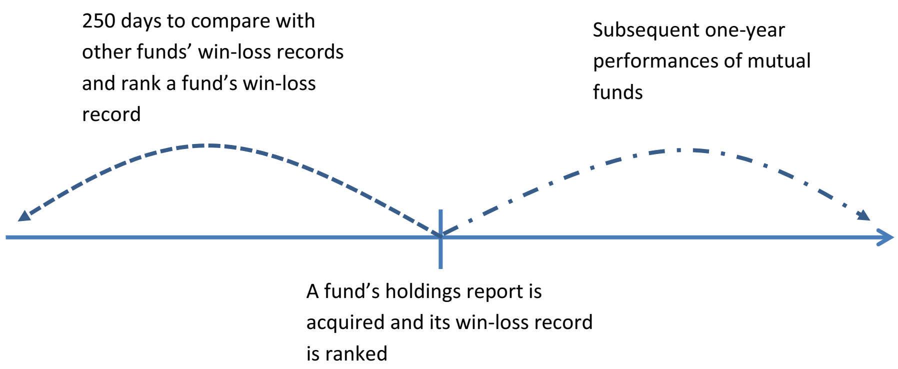

Fig. 2 Ranking of funds by win–loss ratio and their subsequent performance

reasons, we employ the daily returns of the stocks in the holdings data and use the weighted averages of these returns every day, using immediate past holdings as their weights. This process is equivalent to mimicking a fund return with the use of the holdings data. Kacperczyk et al. (2008) find that these replicated returns are very similar to the fund returns in the CRSP mutual fund database (e.g., with only one basis point difference in the monthly returns on average). We track 1-year subsequent daily fund returns from the point of a holding report, and estimate the Carhart (1997) four-factor alpha from this daily return series.[5] In unreported results, we measure fund performances with the conditional alpha of Ferson and Schadt (1996). We find the conditional alpha generates similar implications in our analysis.

In addition, we calculate the benchmark-adjusted return of each stock. Every month, Daniel et al. (1997) risk-adjusted return is calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is again the weighted average of individual stocks' benchmark-adjusted returns (see Daniel et al. 1997 or Wermers 2004 for details of this measure).[6] While the fund alphas are calculated from daily returns, the Daniel et al. (1997) benchmark-adjusted returns are calculated from monthly returns. If both of the performance measures have the same implication, the result is not driven by the differences between daily and monthly returns.[7]

Moreover, following the method outlined in Kacperczyk et al. (2008), we construct the monthly holdings-based return, which tracks stock returns based on the latest fund holdings. Finally, we report monthly, fee-adjusted returns from the CRSP mutual fund

5 We also tried another aggregation method, estimating stock alphas separately and aggregating them by holdings data. Elton et al. (2011) find that this method is equivalent to estimating alphas from portfolio returns. We obtain qualitatively similar results from this alternative method.

6 Daniel et al. (1997) benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

7 Frequency of data may influence the results. For example, Bollen and Busse (2005) find fund performance persistence is stronger if measured by daily returns.

database. Note that among the four measures, the first two return measures are adjusted for risk, while the last two measures are not.

Table 1 reports the summary statistics of our sample. Panel A presents the pooled sample summary statistics, while panel B provides the summary statistics by win–loss ratio quintiles. Panel B indicates that win–loss quintile 3, the middle group, has a win–loss ratio of about 50 %. Win–loss quintile 5, the highest win–loss ratio group, has an average win–loss ratio of 75.8 %. Unskilled fund managers would not achieve such a high win–loss ratio by chance. In contrast, win–loss quintile 1, the lowest win–loss ratio group, has an average win–loss ratio of 28.5 %.

3 Results

3.1 Predictive power of our win–loss ratio measure

We first determine whether our win–loss ratio measure can predict additional risk-adjusted fund returns. In this section, we calculate subsequent fund returns for our win–loss ratio ranks to determine whether there is a significant difference across those ranks. Table 2 reports 1-year subsequent returns from win–loss ratio ranking formation. We employ the average of the returns in the subsequent years and all of the average returns are in the monthly scale. We calculate the equal-weighted average within a win–loss ratio quintile, but our results do not change by switching to the value-weighted average.[8]

Table 2 indicates that high win–loss ratio funds produce better returns in the subsequent year. The differences in the risk-adjusted returns (alpha and Daniel et al. 1997 benchmark-adjusted returns) are 0.19 and 0.36 % per month, respectively, which are equivalent to about 2 and 4 % per year.[9] The difference is primarily driven by particularly high risk-adjusted returns for the highest win–loss ratio rank (win–loss quintile 5). This result is consistent with the statistical intuition we rely on. According to the binomial probability structure presented in Sect. 1, the probability of having k above median performing stocks out of n total stocks is:

$$\Pr(K = k) = \binom{n}{k} \cdot p^k (1-p)^{n-k} = \binom{n}{k} \cdot \frac{1}{2}^k \left(\frac{1}{2}\right)^{n-k} = \binom{n}{k} \cdot \left(\frac{1}{2}\right)^n. \quad (4)$$

Note that the probability in Eq. (1) does not linearly increase or decrease because the term:

$$\binom{n}{k} = \frac{n!}{k!\,(n-k)!}$$

[8] For visual convenience, we center the returns to zero by subtracting the average return of the whole sample. As such, the centered returns have a zero mean.

[9] We tried pooling by fund managers. We employ the average of the win–loss ratios of our sample funds managed by the same manager before we assign the average into a quintile. We obtain qualitatively similar results that are available upon request.

Table 1 Summary statistics

Panel A: All funds in the sample			
	Mean	Median	Standard deviation
Number of holdings reports available per fund	24.5 reports	24 reports	14.3 reports
Number of stocks in a fund holding	83 stocks	60 stocks	90 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	99 %	100 %	6 %
Fund total assets at the end of quarter (million $)	$1138 mil.	$228 mil.	$4466 mil.
Win–loss ratio (number of above median performing stocks/total number of stocks held)	52.9 %	52.4 %	18.0 %
Panel B: Funds by our win–loss ratio quintiles			
Win–loss quintile 1 (lowest)	Mean	Median	Standard deviation
Number of holdings reports available per fund	23.8 reports	23 reports	14.9 reports
Number of stocks in a fund holding	64 stocks	46 stocks	70 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	98 %	100 %	8 %
Fund total assets at the end of quarter (million $)	$870 mil.	$171 mil.	$3305 mil.
Previous 12-month realized fund return after fees (monthly average return)	0.95 %	1.07 %	1.46 %
Win–loss ratio (number of above median performing stocks/total number of stocks held)	28.5 %	28.6 %	9.1 %
Win–loss quintile 2 (low)	Mean	Median	Standard deviation
Number of holdings reports available per fund	24.2 reports	24 reports	14.5 reports
Number of stocks in a fund holding	88 stocks	60 stocks	100 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	99 %	100 %	6 %
Fund total assets at the end of quarter (million $)	$1278 mil.	$248 mil.	$5107 mil.
Previous 12-month realized fund return after fees (monthly average return)	0.95 %	1.08 %	1.59 %
Win–loss ratio (number of above median performing stocks/total number of stocks held)	41.5 %	41.5 %	7.7 %

Table 1 continued

Win–loss quintile 3 (mid)	Mean	Median	Standard deviation
Number of holdings reports available per fund	24.5 reports	24 reports	14.1 reports
Number of stocks in a fund holding	97 stocks	64 stocks	119 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	99 %	100 %	6 %
Fund total assets at the end of quarter (million $)	$1340 mil.	$258 mil.	$5780 mil.
Previous 12-month realized fund return after fees (monthly average return)	0.85 %	1.02 %	1.66 %
Win–loss ratio (number of above median performing stocks/total number of stocks held)	50.6 %	50.0 %	7.8 %
Win–loss quintile 4 (high)	**Mean**	**Median**	**Standard deviation**
Number of holdings reports available per fund	24.6 reports	24 reports	14.1 reports
Number of stocks in a fund holding	89 stocks	64 stocks	89 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	99 %	100 %	5 %
Fund total assets at the end of quarter (million $)	$1212 mil.	$257 mil.	$4089 mil.
Previous 12-month realized fund return after fees (monthly average return)	0.93 %	1.04 %	1.78 %
Win–loss ratio (number of above median performing stocks/total number of stocks held)	60.1 %	59.7 %	7.7 %
Win–loss quintile 5 (highest)	**Mean**	**Median**	**Standard deviation**
Number of holdings reports available per fund	25.4 reports	25 reports	14.2 reports
Number of stocks in a fund holding	74 stocks	62 stocks	52 stocks
Percentage of stock holdings (individual stock's market value aggregated/end of quarter assets)	99 %	100 %	6 %
Fund total assets at the end of quarter (million $)	$962 mil.	$210 mil.	$3504 mil.
Previous 12-month realized fund return after fees (monthly average return)	1.15 %	1.10 %	2.26 %

Table 1 continued

Win–loss quintile 5 (highest)	Mean	Median	Standard deviation
Win–loss ratio (number of above median performing stocks/total number of stocks held)	75.8 %	75.3 %	9.8 %

Our sample includes domestic equity mutual funds in the Thomson Financials Mutual Fund Stock Holdings Data from January 1, 1982 to December 31, 2008. We include only actively managed equity mutual funds, following the definition of Kacperczyk et al. (2008). The total number of mutual funds in our sample is 1530. Panel A reports the summary statistics of all of the pooled observations, while panel B presents the summary statistics by our win–loss ratio quintile

Table 2 Subsequent year performances of sample mutual funds sorted by our win–loss ratio measure

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 5 (highest win–loss ratio)	0.10* (0.01 %)	0.27* (0.04 %)	0.15* (0.03 %)	0.16* (0.03 %)
Win–loss quintile 4	0.02 (0.01 %)	0.00 (0.03 %)	−0.07* (0.02 %)	−0.05 (0.02 %)
Win–loss quintile 3	−0.02 (0.01 %)	−0.07* (0.02 %)	−0.08* (0.02 %)	−0.09* (0.02 %)
Win–loss quintile 2	−0.03* (0.01 %)	−0.09* (0.02 %)	−0.02 (0.02 %)	−0.03 (0.02 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.09* (0.01 %)	−0.09* (0.02 %)	0.05 (0.02 %)	0.03 (0.02 %)
Difference between quintile 5 and quintile 1 (high–low)	0.19* (0.01 %)	0.36* (0.04 %)	0.10* (0.03 %)	0.13* (0.03 %)

We calculate our win–loss ratio for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. We rank sample mutual funds to quintiles by comparing with other holdings reports released during the same 1-year period. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. All returns are in monthly scale. Standard errors are in parentheses. The coefficients and differences significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series, using the Carhart (1997) four-factor model. In addition, we compute the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database

increases or decreases exponentially with a change in k. In other words, the probabilities are not very different from each other when k is near $n/2$, but the probability quickly reaches near zero as k approaches n. Thus, it is relatively easy for luck-driven funds to move between quintiles 2 and 4, but it is very difficult to be in quintile 5 (highest) by chance. As a result, the highest win–loss ratio quintile contains many of the funds where k is near n, which is a much stronger indication of managerial skill (stock-picking ability).

We find that some of the returns (not risk-adjusted) are higher in win–loss quintile 1 (lowest win–loss ratio quintile) when compared to the middle ranks. These raw returns may be higher as there may be some funds in quintile 1 that intentionally aim at one or two seemingly big return stocks. Funds that act like venture capitals may look for one or two "home run" stocks instead of trying to fill their portfolios with many above median performing stocks. If those "sluggers" persistently produce superior returns, the fund's performance is not an accidental success, but the manager probably practices a different, but valuable skill. Admittedly, our win–loss ratio measure would not be able to capture this type of skill. Nonetheless, quintile 1's risk-adjusted returns are the lowest on average, suggesting that there are not that many funds in this group that enjoy sufficient rewards for their risk.

3.2 Other fund characteristics and our win–loss ratio measure

In this section, we investigate whether our win–loss ratio provides additional information to the known, traditional measures of fund performance predictors. We control the effect of:

1. fund size/number of stocks in a fund,
2. past fund returns,
3. momentum trading,
4. time-specific phenomenon, and
5. standard deviation of stock performances in a fund.

3.2.1 Fund size/number of stocks in a fund

It can be relatively easier for smaller funds to have higher win–loss ratios as the measure's denominator is the total number of stocks in a fund. The Law of Large Numbers indicates that an unskilled manager with a larger number of stocks should have a win/loss ratio closer to 0.5. An unskilled manager with a smaller number of stocks is more likely to exhibit an extreme win/loss ratio by sheer luck. Thus, one can argue that our results may be simply stating that smaller funds are performing better than larger funds. However, it is not necessarily true that the number of stocks is monotonically increasing with fund size. When a certain degree of diversification is reached, managers may restrict the number of stocks to a level they can manage. The number of stocks may also vary by fund characteristic. A fund benchmarking the S&P100 index may be larger in size, but may hold a fewer number of stocks when compared to a fund benchmarking the Russell 3000.

We complete a double-sorting, ranking by fund asset-size quintiles and then by win–loss ratio quintiles to determine whether our win–loss ratio measure only captures the size effect. This yields 25 (5×5) clusters. Equal-weighted, subsequent 1-year returns are calculated for each cluster.

Table 3 indicates that high win–loss ratio funds generate higher risk-adjusted returns regardless of the fund size. We do not observe particularly better results in the smallest

Table 3 Subsequent year performances of sample mutual funds double sorted by fund size and our win–loss ratio measure

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Size quintile 1 (*smallest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.09* (0.03 %)	0.15 (0.07 %)	0.24 (0.09 %)	0.32* (0.08 %)
Win–loss quintile 4	0.01 (0.02 %)	−0.08 (0.06 %)	−0.10 (0.07 %)	−0.13 (0.07 %)
Win–loss quintile 3	−0.01 (0.02 %)	0.02 (0.05 %)	0.04 (0.06 %)	−0.01 (0.06 %)
Win–loss quintile 2	0.00 (0.02 %)	−0.06 (0.05 %)	−0.05 (0.06 %)	−0.09 (0.06 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	0.03 (0.06 %)	0.06 (0.06 %)	0.00 (0.06 %)
Difference between quintile 5 and quintile 1 (high–low)	0.16* (0.04 %)	0.12 (0.09 %)	0.18 (0.10 %)	0.32* (0.10 %)
Size quintile 2 (*small*)				
Win–loss quintile 5 (highest win–loss ratio)	0.06 (0.03 %)	0.24* (0.08 %)	0.35* (0.07 %)	0.39* (0.07 %)
Win–loss quintile 4	0.03 (0.02 %)	0.17 (0.07 %)	0.12 (0.06 %)	0.14 (0.05 %)
Win–loss quintile 3	0.01 (0.02 %)	−0.03 (0.04 %)	0.01 (0.05 %)	−0.02 (0.04 %)
Win–loss quintile 2	−0.05 (0.02 %)	−0.03 (0.04 %)	0.09 (0.04 %)	0.10 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.11* (0.02 %)	−0.10 (0.04 %)	0.07 (0.04 %)	0.06 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.17* (0.03 %)	0.34* (0.09 %)	0.28* (0.08 %)	0.33* (0.08 %)
Size quintile 3 (*mid*)				
Win–loss quintile 5 (highest win–loss ratio)	0.07* (0.02 %)	0.23 (0.09 %)	0.29* (0.07 %)	0.28* (0.06 %)
Win–loss quintile 4	−0.00 (0.02 %)	−0.02 (0.06 %)	−0.03 (0.05 %)	0.01 (0.05 %)

Table 3 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 3	−0.03 (0.02 %)	−0.10 (0.05 %)	−0.01 (0.05 %)	−0.01 (0.05 %)
Win–loss quintile 2	−0.01 (0.02 %)	−0.10 (0.04 %)	0.02 (0.04 %)	−0.01 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	−0.14* (0.04 %)	0.05 (0.04 %)	0.02 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.14* (0.03 %)	0.37* (0.10 %)	0.24* (0.08 %)	0.26* (0.07 %)
Size quintile 4 (*large*)				
Win–loss quintile 5 (highest win–loss ratio)	0.11* (0.02 %)	0.35* (0.10 %)	0.18* (0.06 %)	0.16 (0.06 %)
Win–loss quintile 4	0.00 (0.02 %)	0.02 (0.06 %)	−0.10 (0.05 %)	−0.06 (0.05 %)
Win–loss quintile 3	−0.03 (0.02 %)	−0.07 (0.04 %)	−0.08 (0.05 %)	−0.08 (0.04 %)
Win–loss quintile 2	−0.05 (0.02 %)	−0.15* (0.04 %)	−0.05 (0.04 %)	−0.05 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	−0.12* (0.03 %)	0.06 (0.04 %)	0.04 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.18* (0.03 %)	0.47* (0.10 %)	0.12 (0.07 %)	0.12 (0.07 %)
Size quintile 5 (*largest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.14* (0.02 %)	0.28* (0.09 %)	−0.15 (0.06 %)	−0.16* (0.05 %)
Win–loss quintile 4	0.04 (0.03 %)	−0.00 (0.07 %)	−0.15* (0.04 %)	−0.16* (0.04 %)

Table 3 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 3	−0.02 (0.01 %)	−0.14 (0.07 %)	−0.14* (0.04 %)	−0.14* (0.04 %)
Win–loss quintile 2	−0.04* (0.01 %)	−0.11* (0.03 %)	−0.13* (0.03 %)	−0.13* (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.11* (0.01 %)	−0.12* (0.03 %)	−0.01 (0.03 %)	−0.01 (0.03 %)
Difference between quintile 5 and quintile 1 (high–low)	0.25* (0.02 %)	0.41* (0.10 %)	−0.14 (0.06 %)	−0.15 (0.06 %)

We first rank mutual funds by asset size (quintiles) and then rank them by our win–loss ratio measure (quintiles). We calculate our win–loss ratio for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. This process results in 25 (5×5) clusters. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. All returns are in monthly scale. Standard errors are in parentheses. The coefficients and differences significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series, using the Carhart (1997) four-factor model. In addition, we calculate the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database size quintile indicating that the fund size is not driving our main results. We also perform another double-sorting, ranking by the number of stocks held in the fund quintiles and then by win–loss ratio quintiles. The results are similar. High win–loss ratio funds generate higher risk-adjusted returns regardless as to the number of stocks held in the fund. The results are available upon request.

3.2.2 Past fund returns

Next, we determine whether our win–loss ratio measure provides additional information to the "traditional" fund performance measure. According to the literature of fund performance persistence (Hendricks et al. 1993), past fund returns predict fund performance. However, many of the recent studies find that this persistence is statistically insignificant (Fama and French 2010; Barras et al. 2010). We use a common measure of past fund performance, namely the Carhart (1997) four-factor alpha. Following Kacperczyk and Seru (2007) and Elton et al. (2011), the fund alpha is estimated from monthly fund returns for the previous 36 months using the Carhart (1997) four-factor model. First, we sort the sample funds by this traditional alpha and then sort by our win–loss ratio. Then, we track the 1-year subsequent returns from the point of sorting. If the explanatory power of our win–loss ratio measure is highly correlated with that of the traditional alpha, we would not observe differences in the risk-adjusted returns after this double sorting. This result would indicate that our measure does not add significantly important information to the traditional fund performance measure.

Table 4 demonstrates that our main results hold across different past performance quintiles. Thus, our measure adds further information regarding future risk-adjusted performance in addition to the traditional fund performance measure. The result is particularly strong for the funds that did the best in the past (performance quintile 5). This evidence confirms that the win–loss ratios of mutual funds are an important indicator of managerial skill.

The implication from this particular evidence is similar to that of the observation of the jump in fund performance for the highest win–loss ratio quintile in Table 2. If a manager has skill, his past performance, measured by the traditional alpha, would likely be higher than that of other managers. This suggests that there would be few skilled managers in the lower past performance quintiles 1–4. It will be difficult to statistically identify skilled managers from these quintiles as the number of skilled managers is small when compared to the number of observations in each quintile resulting in a low signal-to-noise ratio. The situation is different, however, for funds that did very well in the past as there are many skilled managers in this highest past performance quintile. A statistical method would produce significantly stronger results as there would be many skilled fund managers in this quintile resulting in a high signal-to-noise ratio. Thus, if our measure identifies skilled managers, it is not surprising to see the greatest predictive power among those funds that performed the best in the past. As such, our measure should be useful in identifying temporarily good fund performance driven by luck, not skill.

Another important implication from Table 4 is warranted. The strong predictive power of our win–loss ratio measure for the good or better performing funds suggests

Table 4 Subsequent year performances of sample mutual funds double sorted by past fund performance and our win–loss ratio measure

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Past performance quintile 1 (*lowest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.01 (0.03 %)	0.07 (0.07 %)	0.21* (0.07 %)	0.15 (0.07 %)
Win–loss quintile 4	−0.01 (0.02 %)	0.03 (0.05 %)	0.11 (0.06 %)	0.01 (0.06 %)
Win–loss quintile 3	−0.05 (0.02 %)	−0.05 (0.05 %)	0.01 (0.05 %)	0.02 (0.05 %)
Win–loss quintile 2	−0.05 (0.02 %)	−0.09 (0.06 %)	0.00 (0.05 %)	−0.00 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.09* (0.02 %)	−0.14* (0.04 %)	0.04 (0.04 %)	0.01 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.10* (0.03 %)	0.21 (0.08 %)	0.17 (0.08 %)	0.14 (0.08 %)
Past performance quintile 2 (*low*)				
Win–loss quintile 5 (highest win–loss ratio)	0.08* (0.02 %)	0.02 (0.07 %)	0.15 (0.06 %)	0.14 (0.06 %)
Win–loss quintile 4	0.01 (0.02 %)	−0.05 (0.05 %)	−0.06 (0.05 %)	−0.06 (0.05 %)
Win–loss quintile 3	−0.02 (0.02 %)	−0.02 (0.04 %)	−0.02 (0.05 %)	−0.00 (0.05 %)
Win–loss quintile 2	−0.04 (0.02 %)	−0.12* (0.04 %)	−0.05 (0.04 %)	−0.08 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.11* (0.02 %)	−0.09 (0.04 %)	0.04 (0.04 %)	0.01 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.19* (0.03 %)	0.11 (0.08 %)	0.11 (0.07 %)	0.13 (0.07 %)
Past performance quintile 3 (*mid*)				
Win–loss quintile 5 (highest win–loss ratio)	0.08* (0.02 %)	0.12 (0.05 %)	0.04 (0.06 %)	0.03 (0.06 %)
Win–loss quintile 4	−0.01 (0.02 %)	−0.02 (0.04 %)	−0.14 (0.05 %)	−0.11 (0.05 %)

Table 4 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 3	−0.01 (0.02 %)	−0.03 (0.04 %)	−0.08 (0.05 %)	−0.10 (0.05 %)
Win–loss quintile 2	−0.06* (0.01 %)	−0.03 (0.04 %)	−0.01 (0.04 %)	−0.01 (0.05 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.08* (0.02 %)	−0.07 (0.03 %)	0.04 (0.04 %)	0.02 (0.03 %)
Difference between quintile 5 and quintile 1 (high–low)	0.16* (0.03 %)	0.19* (0.06 %)	0.00 (0.07 %)	0.01 (0.07 %)
Past performance quintile 4 (*high*)				
Win–loss quintile 5 (highest win–loss ratio)	0.02 (0.02 %)	0.02 (0.06 %)	−0.14 (0.06 %)	−0.10 (0.06 %)
Win–loss quintile 4	−0.04 (0.02 %)	−0.12 (0.09 %)	−0.17* (0.05 %)	−0.15* (0.05 %)
Win–loss quintile 3	−0.04 (0.02 %)	−0.01 (0.04 %)	−0.16* (0.05 %)	−0.16* (0.05 %)
Win–loss quintile 2	−0.02 (0.02 %)	−0.07 (0.04 %)	−0.04 (0.05 %)	−0.03 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	−0.03 (0.03 %)	0.11 (0.04 %)	0.09 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.09* (0.03 %)	0.05 (0.07 %)	−0.25* (0.07 %)	−0.19 (0.07 %)
Past performance quintile 5 (*highest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.22* (0.03 %)	0.56* (0.14 %)	0.02 (0.08 %)	0.08 (0.08 %)
Win–loss quintile 4	0.09* (0.02 %)	0.28 (0.16 %)	−0.18 (0.07 %)	−0.14 (0.07 %)
Win–loss quintile 3	0.09 (0.02 %)	0.15 (0.09 %)	−0.06 (0.06 %)	−0.03 (0.06 %)

Table 4 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 2	0.02 (0.02 %)	0.01 (0.05 %)	−0.03 (0.05 %)	−0.03 (0.05 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.04 (0.02 %)	−0.05 (0.04 %)	0.03 (0.04 %)	0.04 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.26* (0.03 %)	0.61* (0.14 %)	−0.01 (0.09 %)	0.03 (0.09 %)

First, we rank mutual funds by alphas estimated from the Carhart (1997) four-factor model with their monthly fund returns during the previous 36 months and then rank by our win–loss ratio measure. We calculate our win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. This process results in 25 (5 × 5) clusters. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. All returns are in monthly scale. Standard errors are in parentheses. The coefficients and differences significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series using the Carhart (1997) four-factor model. In addition, we compute the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database that our earlier results in Table 2 are not driven by survivorship bias. This bias would primarily apply to poorly performing funds as these funds are more likely to vanish.

3.2.3 Momentum trading

Our win–loss measure may look like a type of momentum trading, as it is capturing whether a fund did well in the individual stock level in the past. Our win–loss ratio is not a momentum trading as we are controlling the momentum factor in measuring individual stock performances, i.e., funds cannot achieve high win–loss ratio by momentum trading. Further, Carhart (1997) shows that the inclusion of momentum factor eliminates the difference in fund performances due to momentum trading. Still, to cope with the possibility that some of the momentum-trading effect may not be fully controlled, we impose further restrictions. We regress the previous 36 months of fund returns with Carhart (1997) four-factor model to identify the funds that rely heavily on momentum trading. We sort funds by the coefficient on the momentum factor and then sort by our win–loss ratio. Then, we track the 1-year subsequent returns from the point of sorting. If the explanatory power of our win–loss ratio measure is highly correlated with that of momentum trading, we would not observe differences in the risk-adjusted returns after this double sorting.

Table 5 verifies that our main results are robust to momentum factor loadings. Thus, we reject the hypothesis that our win–loss ratio is a type of momentum trading strategy.

3.2.4 Time-specific phenomenon

We divide our sample period into two and examine whether our results are related to a time-specific phenomenon. The first sample period is from January 1982 to December 1994 and the second sample period is from January 1995 to December 2008.

Table 6 indicates that in both subsample periods, high win–loss ratio funds produced better risk-adjusted returns. This table confirms that our earlier results are not a time-specific phenomenon. Note that for the more recent subsample period, we find that some of the non-risk-adjusted returns are high in win–loss quintile 1 (the lowest win–loss ratio). This may be the result of some funds that achieved very high fund returns by successfully investing in one or two home run stocks (i.e., Google in the 1990s). When analyzing only the portfolio returns of these funds, the portfolio returns look better than the others as one or two home run stocks pushed up the mean dramatically. However, it is difficult to statistically distinguish whether a manager selected the home run stock(s) due to his skill or by chance. From an investor's point of view, when there is little information about each fund manager, it is risky to choose a fund from the low win–loss ratio group, even though its raw return looks high, as there is a greater chance of false discovery; that is, identifying an unskilled manager as a skilled one. Fama and French (2010) and Barras et al. (2010) find that this false discovery problem is quite severe in mutual fund selection. Moreover, the overall risk-adjusted return of this group is low, indicating that it is, on average, a better idea for investors to select from high win–loss ratio funds.

Table 5 Subsequent year performances of sample mutual funds double sorted by momentum factor loading and our win–loss ratio measure

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Momentum factor loading quintile 1 (*lowest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.08 (0.03 %)	0.27 (0.13 %)	−0.02 (0.06 %)	−0.03 (0.06 %)
Win–loss quintile 4	0.03 (0.02 %)	−0.05 (0.07 %)	−0.04 (0.05 %)	−0.05 (0.05 %)
Win–loss quintile 3	0.04 (0.02 %)	−0.04 (0.04 %)	0.01 (0.05 %)	−0.02 (0.05 %)
Win–loss quintile 2	−0.05 (0.02 %)	−0.13* (0.04 %)	0.02 (0.05 %)	0.01 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.13* (0.02 %)	−0.14* (0.04 %)	−0.01 (0.04 %)	−0.03 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.21* (0.04 %)	0.41* (0.13 %)	−0.01 (0.07 %)	0.00 (0.07 %)
Momentum factor loading quintile 2 (*low*)				
Win–loss quintile 5 (highest win–loss ratio)	0.02 (0.02 %)	0.06 (0.07 %)	−0.08 (0.06 %)	−0.08 (0.06 %)
Win–loss quintile 4	−0.01 (0.02 %)	−0.02 (0.04 %)	−0.13 (0.05 %)	−0.13 (0.05 %)
Win–loss quintile 3	−0.02 (0.02 %)	−0.10 (0.04 %)	−0.09 (0.05 %)	−0.10 (0.05 %)
Win–loss quintile 2	−0.06* (0.02 %)	−0.08 (0.04 %)	0.01 (0.04 %)	−0.00 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	−0.05 (0.03 %)	0.10 (0.04 %)	0.06 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.09* (0.03 %)	0.11 (0.08 %)	−0.18 (0.07 %)	−0.14 (0.07 %)
Momentum factor loading quintile 3 (*mid*)				
Win–loss quintile 5 (highest win–loss ratio)	0.02 (0.02 %)	−0.01 (0.07 %)	−0.08 (0.06 %)	−0.05 (0.06 %)
Win–loss quintile 4	−0.01 (0.02 %)	−0.08 (0.04 %)	−0.15* (0.05 %)	−0.15* (0.05 %)

Table 5 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 3	−0.03 (0.02 %)	−0.11 (0.04 %)	−0.13 (0.05 %)	−0.11 (0.05 %)
Win–loss quintile 2	−0.05 (0.02 %)	−0.04 (0.04 %)	−0.01 (0.04 %)	0.02 (0.05 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.09* (0.02 %)	−0.08 (0.04 %)	0.04 (0.04 %)	0.01 (0.04 %)
Difference between quintile 5 and quintile 1 (high–Low)	0.11* (0.03 %)	0.07 (0.08 %)	−0.12 (0.07 %)	−0.06 (0.07 %)
Momentum factor loading quintile 4 (*high*)				
Win–loss quintile 5 (highest win–loss ratio)	0.07* (0.02 %)	0.05 (0.09 %)	−0.13 (0.06 %)	−0.10 (0.06 %)
Win–loss quintile 4	−0.01 (0.02 %)	0.01 (0.05 %)	−0.12 (0.06 %)	−0.10 (0.06 %)
Win–loss quintile 3	0.01 (0.02 %)	0.02 (0.04 %)	−0.04 (0.06 %)	−0.02 (0.06 %)
Win–loss quintile 2	−0.02 (0.02 %)	−0.02 (0.05 %)	0.03 (0.05 %)	0.02 (0.04 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.02 %)	−0.04 (0.04 %)	−0.00 (0.04 %)	−0.02 (0.04 %)
Difference between quintile 5 and quintile 1 (high–low)	0.14* (0.03 %)	0.09 (0.10 %)	−0.13 (0.07 %)	−0.08 (0.07 %)
Momentum factor loading quintile 5 (*highest*)				
Win–loss quintile 5 (highest win–loss ratio)	0.13* (0.03 %)	0.30* (0.08 %)	0.32* (0.08 %)	0.27* (0.07 %)
Win–loss quintile 4	0.10* (0.02 %)	0.35* (0.10 %)	0.05 (0.07 %)	0.07 (0.07 %)
Win–loss quintile 3	0.02 (0.02 %)	0.10 (0.08 %)	−0.04 (0.07 %)	0.01 (0.06 %)

Table 5 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 2	0.02 (0.02 %)	0.07 (0.13 %)	0.12 (0.06 %)	0.15 (0.06 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.05 (0.02 %)	0.01 (0.07 %)	0.03 (0.05 %)	0.05 (0.05 %)
Difference between quintile 5 and quintile 1 (high–low)	0.18* (0.04 %)	0.29 (0.11 %)	0.29* (0.09 %)	0.22 (0.09 %)

First, we rank mutual funds by the coefficient on the monthly momentum factor, estimated from the Carhart (1997) four-factor model with their monthly fund returns during the previous 36 months. Then, the funds are ranked by our win–loss ratio measure. We calculate our win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. This process results in 25 (5×5) clusters. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. All returns are in monthly scale. Standard errors are in parentheses. The coefficients and differences significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series using the Carhart (1997) four-factor model. In addition, we compute the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database

Table 6 Subsequent year performances of sample mutual funds sorted by our win–loss ratio measure: analysis of two subsample periods

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Panel A: Subsample period of January 1, 1983 *to December* 31, 1995				
Win–loss quintile 5 (highest win–loss ratio)	0.03 (0.02 %)	−0.04 (0.05 %)	0.32* (0.04 %)	0.27* (0.03 %)
Win–loss quintile 4	−0.03 (0.01 %)	−0.12* (0.03 %)	0.12* (0.03 %)	0.12* (0.03 %)
Win–loss quintile 3	−0.04* (0.01 %)	−0.16* (0.03 %)	0.09* (0.03 %)	0.08 (0.03 %)
Win–loss quintile 2	−0.04* (0.01 %)	−0.34* (0.03 %)	−0.02 (0.03 %)	−0.03 (0.02 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.07* (0.01 %)	−0.44* (0.03 %)	−0.10* (0.03 %)	−0.12* (0.03 %)
Difference between quintile 5 and quintile 1 (high–low)	0.10* (0.02 %)	0.40* (0.06 %)	0.42* (0.04 %)	0.39* (0.04 %)
Panel B: Subsample period of January 1, 1996 *to December* 31, 2009				
Win–loss quintile 5 (highest win–loss ratio)	0.12* (0.01 %)	0.36* (0.05 %)	0.10 (0.04 %)	0.12* (0.04 %)
Win–loss quintile 4	0.03* (0.01 %)	0.04 (0.04 %)	−0.14* (0.03 %)	−0.11 (0.03 %)
Win–loss quintile 3	−0.01 (0.01 %)	−0.04 (0.03 %)	−0.15* (0.03 %)	−0.15* (0.03 %)

Table 6 continued

	Alpha (four-factor model) (%)	DGTW benchmark-adjusted return (%)	Holdings-based return (%)	Realized return (after fees) (%)
Win–loss quintile 2	−0.02 (0.01 %)	0.00 (0.02 %)	−0.02 (0.02 %)	−0.02 (0.02 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.10* (0.01 %)	0.06* (0.02 %)	0.11* (0.02 %)	0.09* (0.02 %)
Difference between quintile 5 and quintile 1 (high–low)	0.22* (0.02 %)	0.30* (0.05 %)	−0.01 (0.04 %)	0.03 (0.04 %)

We calculate our win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. We rank sample mutual funds into quintiles by comparing with other holdings reports released during the same 1-year period. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. We divide our sample into two subsample periods. All returns are in monthly scale. Standard errors of the difference between returns for the highest win–loss quintile and for the lowest win–loss quintile are in parentheses. The differences in coefficients significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series using the Carhart (1997) four-factor model. In addition, we compute the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database

3.2.5 Standard deviation of stock performances in a fund

Another method of controlling for the number of stocks in a fund or fund size is to use the standard deviation of stock performance in a fund. Small funds may have a high standard deviation of stock performance in their holdings, and our win–loss ratio may be influenced by such volatility. In addition, Brown et al. (1992) argue that dividing performance measures by standard deviation is a sufficient "back of the envelope" method of correcting for survivorship bias.

We divide our win–loss ratio by the standard deviation of the win–loss indicator (1 or 0) in a fund.[10] Here, we modify our measure to form a "win–loss ratio Z-score." This Z-score measure yields similar results to our original win–loss ratio, indicating that the effect of standard deviation is not large enough to change the original results. The results with the Z-score measure are available upon request.

3.3 Alternative measures of the win–loss ratio

Thus far, we have used the above median performance as the criterion of good performance, but the line does not have to be drawn at the 50th percentile. Recall that holdings data may be thought of as repeated draws of stocks, and the line can be drawn at other, higher percentiles. It is also difficult for a manager to hold many stocks above the higher percentile simply by chance. In contrast, if our measure is merely capturing a specific (unknown) factor related to the median, a change in the percentile as the criteria would eliminate the prediction power of the win–loss ratio measure. In this section, we use the upper 75th percentile as the bar and calculate the number of stocks above this bar. There is a trade-off in raising the bar too high, such as to the 99th percentile, as there would not be as many stocks in each fund that are above such an extremely high bar.

We compute the number of stocks that are above 75th percentile in each fund and normalize them by the total number of stocks in the fund. Then, we rank them by this alternative win–loss ratio measure quintile and report 1-year subsequent returns. The results are reported in Table 7.

We observe a similar pattern as in the earlier results using the 50th percentile as the criteria. High win–loss ratio funds, measured by the 75th percentile cutoff point, have higher risk-adjusted returns. The magnitude of the differences from the low win–loss ratio funds is also similar to that in Table 2, which uses the 50th percentile or median as the cutoff criteria. Thus, our empirical results are not sensitive to the cutoff point for the win–loss ratio measure.

3.4 Fund expenses/fees and our win–loss ratio measure

If investors believe that some fund managers have good stock-picking ability, the fund sellers may charge higher fees to investors. In other words, a fund seller can extract

[10] Dividing by the standard deviation of returns is not a feasible option, as the numerator is a binomial number. The scale and the distribution of the numerator and the denominator would be different, yielding results dependent upon the numerator or the denominator alone.

Table 7 Subsequent year performances of sample mutual funds sorted by an alternative win–loss ratio measure

	Alpha (four-factor model)	DGTW benchmark-adjusted return	Holdings-based return	Realized return (after fees)
Win–loss quintile 5 (highest win–loss ratio)	0.08* (0.01 %)	0.19* (0.05 %)	0.12* (0.03 %)	0.15* (0.03 %)
Win–loss quintile 4	0.03* (0.01 %)	0.02 (0.02 %)	0.01 (0.02 %)	0.02 (0.02 %)
Win–loss quintile 3	−0.01 (0.01 %)	−0.03 (0.02 %)	−0.03 (0.02 %)	−0.05 (0.02 %)
Win–loss quintile 2	−0.05* (0.01 %)	−0.06* (0.02 %)	−0.04 (0.02 %)	−0.05 (0.02 %)
Win–loss quintile 1 (lowest win–loss ratio)	−0.09* (0.01 %)	−0.10* (0.02 %)	−0.05 (0.02 %)	−0.07* (0.02 %)
Difference between quintile 5 and quintile 1 (high–low)	0.17* (0.01 %)	0.29* (0.05 %)	0.17* (0.04 %)	0.22* (0.03 %)

We calculate an alternative win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above-upper 75th percentile risk-adjusted returns by the total number of stocks held in the fund. We rank sample mutual funds to quintiles by comparing with other holdings reports released during the same 1-year period. Then, we track subsequent 1-year returns from the day of the holdings release. Since our sample of the holdings data is from January 1, 1982 to December 31, 2008, subsequent 1-year fund returns data are from January 1, 1983 to December 31, 2009. All returns are in monthly scale. Standard errors of the difference between returns for the highest win–loss quintile and for the lowest win–loss quintile are in parentheses. The differences in coefficients significant at the 1 % level are marked with *. Note that we measure subsequent 1-year fund returns in four different ways. First, we calculate fund alphas from the daily return series using the Carhart (1997) four-factor model. In addition, we compute the benchmark-adjusted return of each stock every month. Daniel et al. (1997) benchmark-adjusted returns are calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock's return. A fund's benchmark-adjusted return is the weighted average of individual stocks' benchmark-adjusted returns. Moreover, we construct the monthly holdings-based returns that track stock returns based on the latest fund holdings. See Kacperczyk et al. (2008) for details. Finally, we obtain monthly, fee-adjusted returns from the CRSP mutual fund database

Table 8 Expense ratios and management fees for sample mutual funds sorted by our win–loss ratio measure

	Expense ratios (annual) (%)	Management fees (annual) (%)
Win–loss quintile 5 (highest win–loss ratio)	1.50	0.83
Win–loss quintile 4	1.37	0.79
Win–loss quintile 3	1.32	0.78
Win–loss quintile 2	1.33	0.77
Win–loss quintile 1 (lowest win–loss ratio)	1.38	0.78
Difference between quintile 5 and quintile 1 (high–low)	0.12* (0.02 %)	0.05* (0.01 %)

We calculate our win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. We rank sample mutual funds to quintiles by comparing with other holdings reports released during the same 1-year period. For each win–loss quintile, we report the average expense ratio and management fee acquired from the CSRP Mutual Fund Data. Note that expense ratios and fees are annualized. Our sample of the holdings data is from January 1, 1982 to December 31, 2008. Standard errors of the difference between ratios/fees for the highest win–loss quintile and for the lowest win–loss quintile are in parentheses. The differences in coefficients significant at the 1 % level are marked with *

rent from investors when investors are lured by some signals (such as reputation) from the fund manager. In an extreme case, the seller may increase the fees to a level such that the net return of a renowned fund is the same as the net returns of other funds.[11] In this subsection, we examine the relationship between our win–loss ratio measure and mutual fund fees. To measure the size of the fees, we use the expense ratio and management fees acquired from the CRSP mutual fund database. Since expense ratio data are annual data, we employ an annual average of our win–loss ratios and merge them with the fund fees data.

Table 8 reports the expense ratios and management fees by win–loss ratio quintiles. These fees are on an annual basis as a percentage of the fund assets. We see a slight increase in mutual fund fees as we move toward higher win–loss ratio funds. However, the difference is about 0.1 % per year, which is a fraction of the additional risk-adjusted returns generated by high win–loss ratio funds. Note that we observe approximately 2–4 % additional annual risk-adjusted returns in Table 2 for high win–loss ratio funds. This result suggests that fees in practice are not adjusted for our measure of fund manager's stock-picking ability. We also examine whether the after-fee fund returns from the CRSP mutual fund database differ from the returns before fees. The two returns share almost identical variations, as documented in Kacperczyk et al. (2008). Our results are also consistent with Bailey et al. (2011) who find that fund investors have substantial behavioral biases in fund selections. These results are not consistent, however, with the rational expectation model of Berk and Green (2004). It may be

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

that funds do not charge differential fees when investors cannot easily distinguish luck from actual stock-picking ability.

3.5 Other fund performance predictors and our win–loss ratio measure

In this subsection, we compare our win–loss ratio measure with other mutual fund performance predictors suggested in the literature. We select mutual fund performance indicators that can be readily derived from our sample. Kacperczyk et al. (2005) find that the high industry concentration of a fund is a predictor of future performance. They measure the concentration of a fund on a specific industry and develop a measure called the Industry Concentration Index (ICI). Cremers and Petajisto (2009) and Petajisto (2013) define the Active Shares Ratio, which measures the deviation of a fund holding from various stock market indices. They find that a higher Active Shares Ratio is linked to better performance. Kacperczyk et al. (2008) introduce the Return Gap, which is the variation in the difference between realized fund returns and holdings-based returns. They demonstrate that the Return Gap is positively correlated with future performance.

The ICI measure can be calculated from the Thomson Mutual Fund Holdings Data, and we follow the industry definitions in Kacperczyk et al. (2005). The Active Share Ratio data are directly downloaded from Antti Petajisto's website: http://www.petajisto.net/data.html. The Return Gap is obtained by subtracting holding-based returns from realized returns, which we use in earlier tables in this paper.

First, we calculate the Pearson correlations among those three performance indicators and our win–loss ratio measure. Next, we sort our funds by our win–loss ratio quintiles, and then compute the averages of other performance indicators for each quintile. Table 9 reports the results.

Panel A of Table 9 indicates that our win–loss ratio measure has a correlation of 6.08 % with the ICI, 8.46 % with the Active Share Ratio, and 3.35 % with the Return Gap, respectively. These are all significant at the 1 % level, but are not unexpectedly high given our large sample size (between 22,782 and 31,361). Note that the ICI and the Active Share Ratio have the highest correlation of 27.79 %, while the ICI and the Return Gap have the lowest (insignificant) correlation of 0.19 %. Panel B of Table 9 also indicates that our win–loss ratio measure is related to other predictors of fund performance. Win–loss quintile 5, the highest win–loss ratio funds, has the highest ICI, the highest Active Share Ratio, and the highest Return Gap. These positive relationships with other indicators of performance suggest that our win–loss ratio measure may be another way of capturing underlying managerial skill. Still, the relation between other indicators and our measure is not completely monotonic, suggesting that our measure is not a mere reflection of those other indicators. Also, the magnitude of the indicators is rather similar across quintiles 1–4, while there is a considerable jump in quintile 5. As we argue in the previous sections, most of skilled managers would be in this quintile and, as a result, other skill indicators (ICI, Active Share Ratio, and Return Gap) would be most prominent as well.

To further examine whether our win–loss ratio measure adds significant predictive power to those provided by other performance indicators suggested in the literature, we run the univariate and multivariate regressions of fund performance on the performance

Table 9 Other performance predictors for sample mutual funds and our win–loss ratio measure

Panel A: Correlations among performance predictors

Win–loss ratio	Industry Concentration Index	Active Share Ratio	Return Gap
Win–loss ratio	6.08 %*	8.46 %*	3.35 %*
Industry Concentration Index		27.79 %*	0.19 %
Active Share Ratio			3.79 %*
Return Gap			

Panel B: Other performance predictors sorted by our win–loss ratio quintiles

	Industry Concentration Index	Active Share Ratio	Return Gap
Win–loss quintile 5 (highest win–loss ratio)	0.177	0.835	−0.094 %
Win–loss quintile 4	0.134	0.799	−0.119 %
Win–loss quintile 3	0.125	0.795	−0.136 %
Win–loss quintile 2	0.120	0.788	−0.145 %
Win–loss quintile 1 (lowest win–loss ratio)	0.153	0.796	−0.138 %
Difference between quintile 5 and quintile 1 (high–low)	0.024* (0.003)	0.039* (0.003)	0.044 %* (0.010 %)

We calculate our win–loss ratio measure for each mutual fund holdings report by dividing the number of stocks in the fund with above median risk-adjusted returns by the total number of stocks held in the fund. In panel A, we report the Pearson correlation coefficients among various performance predictors in the literature. Those predictors include the Industry Concentration Index (Kacperczyk et al. 2005), the Active Share Ratio (Cremers and Petajisto 2009; Petajisto 2013), the Return Gap (Kacperczyk et al. 2008), and our Win–loss Ratio measure. In panel B, we rank sample mutual funds to quintiles by comparing with other holdings reports released during the same 1-year period. For each win–loss ratio quintile, we calculate averages of the Industry Concentration, the Active Share Ratio, and the Return Gap. Standard errors of the difference between predictors for the highest win–loss quintile and for the lowest win–loss quintile are in parentheses. The coefficients significant at the 1 % level are marked with *

Table 10 Fund performance prediction by performance predictors: a horse race

Panel A: Univariate regression on Carhart's (1997) four-factor alpha

Dependent variable: Carhart four-factor alpha				
Win–loss ratio	0.005* (17.77)			
Industry Concentration Index		0.006* (11.22)		
Active Shares Ratio			0.001 (2.89)	
Return Gap				−0.015 (−1.02)
Observations	31,361	31,361	22,782	29,343

Panel B: Univariate regression on Daniel et al.'s (1997) benchmark-adjusted return

Dependent variable: Daniel et al.'s benchmark-adjusted return				
Win–loss ratio	0.010* (11.66)			
Industry Concentration Index		0.006* (3.70)		
Active Shares Ratio			−0.002 (−2.33)	
Return Gap				0.351* (4.73)
Observations	31,264	31,264	22,758	29,266

Panel C: Multivariate regression on Carhart's (1997) four-factor alpha (1st column) and Daniel et al.'s (1997) benchmark-adjusted return (2nd column)

	Dependent variable: Carhart four-factor alpha	Dependent variable: Daniel et al.'s-adjusted returns
Win–loss ratio	0.005* (14.51)	0.016* (15.14)
Industry Concentration Index	0.005* (6.06)	0.002 (1.05)
Active Shares Ratio	0.001 (0.20)	−0.003* (−3.79)
Return Gap	−0.044 (−2.33)	0.355* (3.65)
Observations	21,640	21,620

We test the explanatory power of various fund performance predictors with the following equation:

$$\begin{aligned}&\text{Fund Performance}_{i,t} = \alpha + \beta_1 \cdot \text{WinLoss\_Record}_{i,t-1}\\&+\beta_2 \cdot \text{Industry\_Concentration\_Index}_{i,t-1} + \beta_3 \cdot \text{Active\_Shares\_Ratio}_{i,t-1}\\&+\beta_4 \cdot \text{Return\_Gap}_{i,t-1} + \varepsilon_{i,t}\end{aligned}$$

We measure the performance predictors for each mutual fund holding i and track 1-year subsequent fund performances from the measurement date. *Fund Performance* is measured with Carhart's (1997) four-factor alpha in panel A and the first column of panel C and with Daniel et al.'s (1997) benchmark-adjusted returns in panel B and in the second column of panel C. Standard errors are corrected for clustering by i and t. t values are in parentheses and coefficients significant at the 1 % level are marked with *

indicators. Panel A of Table 10 reports the results of the univariate regressions for the risk-adjusted fund performance measured by the Carhart (1997) four-factor alpha, while panel B presents the results for the Daniel et al. (1997) benchmark-adjusted return. The results suggest that our win–loss ratio and the ICI (as well as the Return Gap, but only for panel B) in 1 year are significantly correlated with the risk-adjusted fund performance in the next. The t value (17.77 in panel A and 11.66 in panel B) for the coefficient is highest for our win–loss ratio, suggesting that our measure in 1 year has the strongest correlation with the risk-adjusted fund performance in the next. The ICI has the next strongest correlation with a t value of 11.22 in panel A and 3.70 in panel B. Panel C provides the results for the multivariate regression. We regress the subsequent year's fund performance on the previous year measures of the win–loss ratio, the ICI, the Active Shares Ratio, and the Return Gap. Again, our win–loss ratio measure is the winner. Its t values are the highest with 14.51 for the Carhart (1997) four-factor alpha and 15.14 for the Daniel et al. (1997) benchmark-adjusted return. The t-value for the ICI is the next highest with 6.06 for the Carhart (1997) four-factor alpha, but interestingly its t value is only 1.05 and is insignificant for the Daniel et al. (1997) benchmark-adjusted return. Instead, the Return Gap has a significant t value (3.65) for the Daniel et al. (1997) benchmark-adjusted return, while the Active Share Ratio has a significant, but negative t value (−3.79). Both the Return Gap and the Active Ratio are not significant for the Carhart (1997) four-factor alpha.

The coefficients for the win–loss ratio are also economically significant. Panel C in Table 10 indicates that a 1 % higher win–loss ratio is related to a 0.005 % higher monthly (0.06 % annual) Carhart (1997) four-factor alpha and a 0.016 % higher monthly (0.19 % annual) Daniel et al. (1997) return. Note that in Table 1, the highest win–loss ratio quintile has an average ratio of 76 %, but the lowest win–loss ratio quintile has an average ratio of 29 %. The difference (47 %) between two quintiles would then be related to a 0.235 % (0.005 % × 47) monthly (2.82 % annual) difference in the Carhart (1997) four-factor alpha and a 0.752 % (0.016 % × 47) monthly (9.024 % annual) difference in the Daniel et al. (1997) returns. In sum, our win–loss ratio measure provides a consistently stronger prediction of the risk-adjusted performance of actively managed equity mutual funds, and provides significant predictive power even after controlling for other performance indicators suggested in the literature.

We also investigate whether our win–loss measure is related to the recent findings of Amihud and Goyenko (2013). They find that the R^2 of fund returns to asset pricing factors is an indicator of future performance. The R^2 measure is derived from the past 24-month fund returns and predicts the next month's return. We confirm that including this R^2 variable in the regression does not change our results in Table 10. The results are available upon request.

4 Conclusion

We develop a win–loss ratio measure of fund manager skill by calculating the number of above median performing stocks in each mutual fund holdings report. Our logic is that a fund holding can be thought of as repeated draws of stocks to achieve higher risk-adjusted returns in the portfolio level, and it is not likely for fund managers to select many above median performing stocks in the fund holdings by chance.

We find that our win–loss ratio measure predicts future fund performance very well. Mutual funds with higher win–loss ratios earn higher risk-adjusted returns, measured by the Carhart (1997) four-factor model alpha or the Daniel et al. (1997) benchmark-adjusted return. Our measure is free from look-back bias. As such, a relatively uninformed investor can use our measure to identify skilled fund managers.

Our results are not driven by fund size, the number of stocks in a fund, or survivorship bias, and our win–loss ratio measure predicts variations in future risk-adjusted fund returns that are not fully captured by traditional fund performance measures. We also find that our results hold throughout the sample period, indicating that the results are not a time-specific phenomenon. We determine that our measure is correlated with other indicators of future fund performance suggested in the literature. Our results strongly indicate, however, that our win–loss ratio measure provides a better prediction of the risk-adjusted fund performance, and has significant predictive power even after controlling for other performance indicators.

In addition to its predictive power, one advantage of our measure is that it is based on a different type of information when compared to the traditionally used, past fund returns data. Fama and French (2010), and Barras et al. (2010) confirm that even with a long series of fund returns data, it is difficult to identify skilled fund managers. Cross-sectional data, such as holdings reports, can provide important information missing in the past fund returns data. Thus, our research hopes to shed additional light on the noisy process of detecting the true stock-picking ability of mutual fund managers. French (2008), for example, finds that investors spend 0.67 % of the aggregate value of the market each year searching for superior returns.

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