

Law of Large Numbers in Mutual Funds: A Simple but Effective Way to Identify Persistent Performances Among Actively-managed Mutual Funds

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Abstract

We show that it is low in probability to have many above-median performing stocks in a fund simultaneously if the manager does not have stock picking ability. Empirically, we find the number of stocks contributing to the overall risk-adjusted performance of an actively managed mutual fund predicts the fund performance. A fund that currently holds larger number of above-median performance stocks generates more than 2% additional risk-adjusted return in the subsequent year.

JEL Code: G11

Keywords: Mutual funds, Luck vs. skill, Performance evaluation, Holdings data

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We show that it is low in probability to have many above-median performing stocks in a fund simultaneously if the manager does not have stock picking ability. Empirically, we find the number of stocks contributing to the overall risk-adjusted performance of an actively managed mutual fund predicts the fund performance. A fund that currently holds larger number of above-median performance stocks generates more than 2% additional risk-adjusted return in the subsequent year.

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Although mutual funds may generate little additional value on average (French 2008), there can be still some talented mutual fund managers who consistently generate additional risk-adjusted returns. How to identify those managers is an important question, as Avramov and Wermers (2006) show predictability in manager skills to be the dominant source of mutual fund investment profitability. In this paper, we use fund holdings data to count the number of stocks that have above-median risk-adjusted performances. The intuition is that a fund manager cannot have a large number of above-median performing stocks by chance. We start from the idea that a mutual fund holding can be thought as repeated draws of stocks to achieve higher risk-adjusted returns. In the large universe of stocks, a fund manager picks the stocks that would increase the risk-adjusted returns of his portfolio. If the manager has no skill, his pick would be like random choices – some picked stocks would have higher than median risk-adjusted returns and others would have lower than median returns. A totally random draw will pick approximately half of above-median performance stocks and half of below-median performance stocks. If a fund, however, contains a large number of above-median stocks in its holdings, we can conjecture that the fund manager has ability to pick stocks. It is like having a series of coin flipping with too many heads.

We measure risk-adjusted returns of each stock in Center for Research in Security Prices (CRSP) database by regressing daily stock returns on Carhart 4-factors and estimating its intercept – alpha. We estimate the alpha of each stock using 250 days of past returns which is approximately 1 year. We compare this alpha with the median alpha during the same estimation period and check if a stock's alpha is above or below the median. Then we count the number of

stocks in a mutual fund that have alphas above the median, normalizing for the total number of stocks in the fund. We call this measure as our ‘consistency measure’ because it measures how consistently a manager picked above-median performance stocks.

This consistency measure well predicts mutual fund performances. We find that high consistency funds generate more than 2% additional risk-adjusted returns in the subsequent year. This phenomenon holds after accounting for fund size, past fund performances, sample period, and mutual fund fees.

The main contribution of the paper is showing that additional information from mutual fund holdings data, albeit simple, can improve the prediction power for future fund performances. Our finding would be useful to those who wants to identify the funds that may perform better in the future and to those who need to develop a more precise measure of fund manager skills.

Our paper is also related to a growing literature that seeks additional indicators of managerial skill from holdings data to supplement traditional factor analysis on mutual fund returns. For example, Cohen, Coval, and Pastor (2005), Kacperczyk, Sialm, and Zheng (2005), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), and Petajisto (2010) show different aspects of holdings data can be used to extract additional information about managers’ skill. In the empirical section, we find these measures are also correlated with our consistency measure, indicating that there are more than a few signals of skilled fund managers.

Another stand of literature differentiates lucky managers from skilled managers using statistical techniques. Koswski, Timmerman, Wermers, and White (2006), Fama and French (2010), and Barras, Scaillet, and Wermers (2010) use time-series statistical techniques to identify lucky managers from skilled managers. Our paper adds to this literature by using a statistics from holdings data, which is cross-sectional, to differentiate a good performance not likely to be

driven by luck. Fund performance is typically measured from the time-series returns of a fund and because fund returns are on monthly basis before 2000s, a researcher has at most 36 observations by using 3-year past data. A holdings data is reported every quarter or half year and it typically contains information on more than 60 stocks. The large number of cross-sectional observation could reduce the possibility of luck distorting a fund performance measure.

Rest of this paper is organized as follows. Section I describes the statistical theory that supports our consistency measure. Section II explains the data and our empirical methodologies, Section III presents our results, and Section IV summarizes and concludes the paper.

I. Our Consistency Measure

We begin with a simple assumption that mutual fund managers try to increase the risk-adjusted returns of their funds.

Assumption: The objective function of mutual fund managers is to increase the fund's risk-adjusted return.

Some funds may have different objective functions such as generating most stable income. Our focus is therefore on the actively managed mutual funds whose objective is to grow the value of the fund.¹

¹ Agency problems, such as fund managers maximizing their personal objective functions may exist. The agency problem is beyond the scope of this paper and we assume agency problem in actively managed mutual funds are not substantially different from other fund types.

From the universe of stocks, managers pick stocks to be included or excluded from their fund. If a manager includes many good performing stocks, the fund performance will become better as a result. Now we define the term, “Stock picking ability”.

Definition: A fund manager with stock picking skill is the manager who has more than 50% probability to pick the stocks with risk-adjusted returns above market median risk-adjusted returns.

Explanation: If a fund manager has no stock picking ability, his pick will be a random selection. Then there is 50% probability that a selected stock has a risk-adjusted return higher than market median. On the contrary, a manager with true ability should have the probability significantly higher than 50%. Such manager will consistently pick many higher risk-adjusted return stocks in his portfolio.

We can think current a fund holding as a snapshot of the fund manager’s repeated picks. Using our definition of ‘skilled manager’, we construct a statistical test of this snapshot whether the fund manager has true stock picking ability. We set the null hypothesis that a fund manager’s pick has 50% chance to select one stock with a risk-adjusted return higher than market median.

$H_0: p = 0.5$

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

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

where

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

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

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

Equation (1) shows that if a fund manager has larger number of stocks with risk-adjusted returns higher than market median, there is low probability that an unskilled fund manager

achieved it by chance. Therefore, we arrive to the conclusion that when a manager picks more above-median risk-adjusted returns stocks, there is low probability that the manager is not a skilled one. Since we are only interested in identifying a fund manager with stock picking ability (probability higher than 50%), the test boils down to counting how many stocks out of n have risk-adjusted return above market median (how close is k to n).

We count 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. Thus, our indicator is k/n , acquired from holdings data.

$$m_1 = k/n \quad (2)$$

where k is the number of stocks with above-median risk-adjusted returns and n is the number of stocks in a fund holding.

We admit that this indicator is a very simple one with many limitations. This measure only counts the number of stocks that have better risk-adjusted performances than market median. We may expand m_1 measure by incorporating additional controls. We can add different weights to each stock and we can also control for the amount above-median performance such as 99 percentile performance is better than 51 percentile performance, etc. However, measures with these additional controls show over 80% Pearson correlation with m_1 , suggesting that the additional controls are not very important.² We will use m_1 in our empirical section as a result,

² The weight seems to have little effect on the measure because fund managers are typically not allowed to invest too much of his position in one or two stocks. Informal interviews with fund managers revealed us that normally risk management departments require fund managers to distribute his funds evenly to multiple stocks. These interviews also gave us indication that fund managers try to pick good stocks, but they only have vague ideas about how good the performance of individual stock will be. This point would explain why difference in individual stock performances is not very important compared to the number of stocks above median.

and when we did the same empirical tests with a measure with additional controls, we acquire qualitatively similar results. We call m_l as our consistency measure.

Unless a fund manager changed entire portfolio right before releasing a holdings report, the consistency measure from a past holdings report contains information on how many above-median stocks the manager picked in the past.³ If a manager consistently picked many above-median stocks because of superior skill, it is likely that the fund performance will continue to be good in the future.

II. Data and Methodology

We use Thomson Financials Mutual Fund Stock Holdings Data for the period from Jan 1, 1982 to Dec 31, 2008. To measure the subsequent one year returns from the point of holdings data release, we acquire monthly fund returns data from CRSP Mutual Fund Data and daily stock returns data from CRSP Stock Returns Data for the period from Jan 1, 1983 to Dec 31, 2009. We use the Mutual Fund Link Data to merge the Thomson data with the CRSP mutual fund data. As outlined by the assumption in the previous section, we only use the actively managed equity mutual funds whose focus is to grow the value of the fund. In Thomson Data we select the funds that have Investment Objective Code of 2 and 3. The Objective Code 2 stands for Aggressive Growth and 3 stands for Growth. In addition, we use fund information in CRSP data to take out the funds that are not actively managed or non-equity based; such as index funds, money market funds, or bond funds. We follow criteria in Kacperczyk, Sialm, and Zheng (2008) to filter out

³ Kacperczyk, Sialm, and Zheng (2008) shows returns from holdings is not much different from actual fund holdings, indicating that holdings data can serve as a fair record on the overall past performance of a fund manager.

actively managed mutual funds. We have a total of 1,530 actively managed equity mutual funds in our sample, and each fund has on average 24 holdings reports.

A risk-adjusted performance of a stock at a particular period is estimated using Carhart 4-factor model. The risk-adjusted performance of a stock is measured by the intercept (alpha) of the following 4-factor model:

$$r_i - r_f = \alpha_i + \beta \cdot (r_m - r_f) + \delta \cdot SMB + \phi \cdot HML + \gamma \cdot MOM + \varepsilon, \quad (4)$$

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 MOM is the winners-minus-losers momentum factor. All observations are on a daily basis. The CRSP Stock Returns Data provides daily returns of stocks listed in major U.S. stock exchanges. Daily asset-pricing factors are acquired from the data library website of Professor Ken French. We estimate the alphas of all stocks in the CRSP database using a 250-business-day estimation period, which is approximately a full year.⁴

After we acquire alphas of each individual stock, we check whether a stock's alpha is higher than the median alpha of the same estimation period (250 days). The stocks above median are above-median-performing stocks, and the others are below-median-performing stocks. We calculate our performance measure of a fund m_i by the number of above-median-performing stocks divided by the total number of stocks in the fund. When m_i is high, we call the fund as a 'high consistency' fund, because it indicates that the manager consistently picked many above-median performing stocks. Figure 1 illustrates our estimation period and prediction period.

(Figure 1 Goes About Here)

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

Since the average value of m_I may change over time depending on the overall performances of mutual funds, we compare a fund's consistency measure with that of other actively managed equity mutual funds. We track back one year from a mutual fund holdings report and rank the m_I of a fund by comparing it with other funds' consistency measures. If a holdings report is reported on July 31, 2005, for example, we compare the consistency measure of a fund with other consistency figures available during July 31, 2004 ~ July 31, 2005 period. We rank the consistency measure into quintiles. A 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 sort such as ranking by every calendar year, and it actually gives stronger results. However, sorting by calendar year creates a look-back bias – comparing a holding data acquired in March with the data acquired in the same year June is not realistic. We want to ensure that an actual investment strategy can be created from our measure. Figure 2 shows this process.

(Figure 2 Goes About Here)

Subsequent 1-year fund returns from a holdings report are measured in 4 different ways. First, we calculate fund alphas using Carhart 4-factor model. There are only 12 observations per year if we use monthly fund returns data and the estimation would include too much error. On the other hand, including more of past time-series observations will create an overlap between consistency calculation period and performance measurement period. Thus we use daily returns of the stocks in the holdings data and take weighted averages of these returns every day, using past holdings as its weight. This process is equivalent to mimicking a fund return by following

the holdings data. Kacperczyk, Sialm, and Zheng (2008) show this replicated return is very similar to monthly fund returns in CRSP mutual fund database (about 1 basis point difference in monthly returns). We track 1-year subsequent daily portfolio returns from the point of a holding report, and we estimate Carhart 4-factor alpha from this daily return series.⁵

Second, we calculate benchmark adjusted returns of each stock. Every month, Daniel, Grinblatt, Titman, and Wermers (1997) risk-adjusted return is calculated by subtracting size, book-to-market, and momentum benchmark returns from a stock return. A fund's benchmark adjusted return is again the weighted average of individual stocks' benchmark adjusted returns. See Daniel, Grinblatt, Titman, and Wermers (1997) or Wermers (2004) for the details of this measure.⁶ We will call this return as DGTW benchmark adjusted return.

Third, we acquire holdings based return, which tracks stock returns based on the latest fund holdings. We follow the method outlined in Kacperczyk, Sialm, and Zheng (2008) to construct the holdings based return. Kacperczyk, Sialm, and Zheng (2008) form monthly fund returns from fund holdings report and so we also calculate monthly holdings return as well. Lastly, we report monthly, fee-adjusted returns from CRSP mutual fund database. The former two return measures are corrected for risk and the latter two are not.

Table 1 shows a summary statistic of our sample.

(Table 1 Goes About Here)

Panel A shows whole summary statistics and panel B shows summary statistics by consistency measure quintiles. Panel A shows the average of our consistency measure is 51%,

⁵ We also tried other aggregation method such as estimating each stock alpha separately and aggregating them by holdings data. Elton, Gruber, and Blake (2011) documents that this method is equivalent to estimating alphas from portfolio returns. We obtain qualitatively similar results from this alternative method.

⁶ The DGTW benchmarks are available via <http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm>

which is slightly above 50%. Overall fund returns are in general positive in our sample. These results may indicate that overall performance of mutual fund was not bad, but our purpose is to see whether our consistency measure can predict additional risk-adjusted fund returns. We will report fund returns by our consistency ranks and see if there is significant difference across ranks.

III. Results

A. Predictive Power of Our Consistency Measure

Table 2 reports one year subsequent return from the point of consistency ranking formation. We take the average of returns in the subsequent year and all average returns are in monthly scale. We take equal weighted average within a consistency quintile and our results do not change by switching to value weighted average.⁷

(Table 2 Goes About Here)

Table 2 shows that the highest consistency funds indeed gain better returns in the future. The difference in risk-adjusted returns (alpha and DGTW adjusted return) is 0.19% (alpha) or 0.36% (DGTW adjusted return) per month, equivalent to 2% or 4% per year. The difference is mostly driven by particularly high returns in the highest consistency ranks (consistency rank 5). This result is consistent to the statistical intuition we are using. According to the binomial probability structure in the previous section, probability to have k above-median stocks out of n total stocks is:

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

⁷ For visual convenience we centered the returns to zero by subtracting the average return of the whole sample. The centered returns thus have zero mean if we take the average of all the returns in the sample.

The function does not linearly increase or decrease because the following term,

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

increases or decreases exponentially by a change in k . In other words, the probability is 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 in probability to move between rank 2 ~ 4 but it is very difficult to be in rank 5 (highest). The highest quintile funds contain many of the funds that have k near n , which is a much stronger indication of managerial skill compared to those of other funds.

We observe some of the returns (not risk-adjusted) are higher in rank 1 (lowest) compared to middle ranks. The raw return may be higher because there can be some funds in rank 1 that intentionally aim for one or two big return stocks. Funds that are acting like venture capitals may look for one or two homerun stocks instead of trying to fill their portfolio with many above-median stocks. If some managers can successfully pick those homerun stock consistently over time, that could be regarded as another type of stock picking ability. Admittedly, our method would not be able to capture such type of skill. Still, the group's risk-adjusted returns are the lowest on average, which means that there are not that many funds in this group who gain sufficient reward for their risk.

B. Other Fund Characteristics and Consistency

It can be relatively easier for small funds to have higher consistency measure, because its denominator is the total number of stocks in a fund. Then our result may be simply telling that small funds are performing better than large funds. However, it is not necessarily true that the

number of stocks is monotonically increasing in fund size. When certain degree of diversification is reached, managers may restrict the number of stocks to the level they can manage. Number of stocks can also vary by fund characteristic: a fund benchmarking S&P100 may be larger in size, but may hold less number of stocks compared to a fund benchmarking Russell 3000.

We do a double sort by fund size and then consistency measure to see if our consistency measure only captures size effect. We rank first by fund asset size quintiles and then by consistency measure. This yields $5 \times 5 = 25$ clusters. Equal weighted, subsequent 1 year return is calculated for each cluster.

(Table 3 Goes About Here)

Table 3 shows high consistency funds generates higher risk-adjusted returns regardless of fund size. We don't see particularly better result in the smallest size quintile. This result indicates that fund size is not driving our result.

Next, we check if our consistency measure provides additional information to the 'traditional' fund performance measure. Following Kacperczyk and Seru (2007) or Elton, Gruber, and Blake (2011), fund alpha at one point is estimated from monthly fund returns during the past 36 months (3 years). We use Carhart 4-factor model to estimate the alpha. Then we sort by this traditional alpha first and then sort by our consistency measure. We track 1 year subsequent returns from the point of sorting. If the explanatory power of our consistency measure is highly correlated with traditional alpha, we will not observe differences in risk-adjusted returns after this double sort, and such result would indicate that our measure does not add information to the traditional fund performance measure.

(Table 4 Goes About Here)

Table 4 demonstrates that our earlier results hold across different past performance quintiles. Thus, our measure adds more information about future risk-adjusted performances on top of traditional fund performance measure. The result is particularly strong for the funds that did well, i.e. performance quintile 5 – highest. This phenomenon actually supports our argument that high consistency is an indicator of managerial skill.

The logic is similar to the one explaining the jump of fund performance in highest consistency quintile. If a manager has skill, her past performance measured by traditional alpha would likely to be also higher than others. This means that in the lower past performance quintiles 1~4, there would not be many skilled managers in the first place. It will be difficult to statistically identify skilled managers from these quintiles, because the number of skilled managers is small compared to the number of observations in each quintile, which results to a low signal-to-noise ratio. The matter is different for the funds that did very well in the past, because there are many skilled managers in this category. A statistical method would produce stronger results because there are fairly many of skilled fund managers to be identified (high signal-to-noise ratio). Therefore, if our method identifies skilled managers, it is natural to have the greatest prediction power among the funds that performed well in the past.

The predictability in the good ~ best performing funds also shows that our earlier results are not driven by survivorship bias. Such a bias would apply mostly to the poor-performing funds because these funds are more likely to vanish.

Lastly, we divide our sample period into two and see if our result is a time-specific phenomenon. The first sample period is from Jan 1982 to Dec 1994 and the second sample period is from Jan 1995 to Dec 2008.

(Table 5 Goes About Here)

Table 5 shows that, in both periods, high consistency funds produced better risk-adjusted returns. This confirms that our earlier results are not a time-specific phenomenon. In the more recent period, we observe that some of the non-risk-adjusted returns are high in the consistency rank 1 (lowest). This result may be caused by some funds that achieved very high fund returns by successfully investing in one or two homerun stocks (Google in 90s, for example). When only the portfolio returns of these funds are analyzed, the portfolio returns would look better than others because this one stock pushed up the whole mean (portfolio return) dramatically. But if we use the logic behind our consistency measure, it is difficult to distinguish statistically whether a manager picked the homerun stock because of her skill or by chance. From an investor's point of view who does not know much about each fund manager, it is risky to choose from that group, because there is higher chance of false discovery – identifying an unskilled manager as a skilled one. Fama and French (2010) and Barras, Scaillet, and Wermers (2010) shows this false discovery problem is severe in mutual fund selection. Moreover, overall risk-adjusted return of this group is low, indicating that it is on average a better choice to select from high consistency funds.

C. Alternative Measures of Consistency

We have used above-median as the criterion of good performance so far, but this line does not have to be drawn at 50 percentile. Our assumption is that a holdings data can be thought as repeated draws of stocks, and if the assumption is correct, the line can be drawn at other higher percentiles because it is also difficult for a manager to have many stocks above that

percentile by chance. On the other hand, if our measure is merely capturing a specific factor related to median, the change of the percentile will eliminate the prediction power. In this section, we use upper 75 percentile as the bar and count the number of stocks above this bar. There is a trade-off in raising the bar too high such as to 99 percentile, because there will not be many stocks in each fund that are above the bar.

We count the number of stocks that are above 75 percentile in each fund and normalize it by the total number of stocks in the fund. Then we rank by this alternative measure quintile and report 1 year subsequent returns. Results are in Table 6.

(Table 6 Goes About Here)

We observe a similar pattern to the previous results. High consistency funds, measured from the 75 percentile cutoff point, have higher risk-adjusted returns. The magnitude of the differences is also similar to Table 2, which uses 50 percentile or median. Thus our consistency measure is not sensitive to the cutoff point. This result also suggests that the overall cross sectional distribution of stock performances in a fund contains information about future fund performances; the shape of the distribution itself can serve as a signal of fund manager skill.

D. Fund Fees

If investors believe that a fund manager has good stock-picking ability, and the mutual fund seller knows this, the seller may charge higher fees to investors. In other words, a fund seller can extract 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.⁸

Indicators of managerial skill therefore have to be relatively unknown to public, if investors want to profit from the signal. Here, we test the relationship between our consistency measure and mutual fund fees. To measure the size of the fees, we use the expense ratio and management fee acquired from CRSP mutual fund database. Since expense ratio data are annual data, we take an annual average of our consistency measure and merge them with the expense ratio data.

(Table 7 Goes About Here)

Similar to the previous tables, we rank by consistency rank quintiles and then report average fund fees. Table 7 reports the expense ratios and management fees by consistency rank. These fees are in annual basis, in percentage of fund assets. We see slight increase in mutual fund fees as we move toward higher consistency funds. But the difference is about 0.1% per year, which is a fraction of additional risk-adjusted returns generated by high consistency funds. Note that we observe approximately 2% or 4% additional annual risk-adjusted returns in Table 2. This result suggests that fees are not fully adjusted according to our measure of fund manager's stock-picking ability. We also checked if after-fee returns from CRSP mutual fund database differ from returns before fees. The two returns shared almost identical variations, and this similarity is also documented in Kacperczyk, Sialm, and Zheng (2008). The irrelevance of fees can be related to Bailey, Kumar, and Ng (2011) who find that fund investors have substantial behavioral biases in fund selections. The result is not consistent, however, with the rational expectation model of Berk and Green (2004). Perhaps financial institutions do not charge highly differential fees when investors cannot easily distinguish luck from actual stock-picking ability.

⁸ This type of rent-seeking behavior would be stronger for hedge funds, which are not regulated and face less competition from each other.

G. Other Fund Performance Predictors

In this section, we compare our consistency measure with other mutual fund performance predictors. There can be more than one way to identify skilled managers, because the skill can affect various other characteristics of a fund. The signals of managerial skill therefore can take multiple forms. There are several skill indicators discovered by researchers, and if our measure actually captures the underlying factor – fund manager skill – it could be also related to the other indicators of skill.

We select mutual fund performance indicators that can be readily derived from our sample. Kacperczyk, Sialm, and Zheng (2005) find high industry concentration of a fund is a predictor of the future performance. They measure how concentrated a fund is to an industry and develop a measure called Industry Concentration Index (ICI). Cremers and Petajisto (2009) and Petajisto (2010) define Active Shares Ratio, which measures the deviation of a fund holding from various stock market indices. They show High Active Shares Ratio is linked to better performances. Kacperczyk, Sialm, and Zheng (2008) introduce Return Gap, which is the difference between realized fund returns and holdings based return. They demonstrate that Return Gap is positively correlated with future performances.

ICI measure can be calculated from Thomson Mutual Fund Holdings Data we have, and we follow the industry definitions in Kacperczyk, Sialm, and Zheng (2005). Active Share Ratio data is directly downloaded from Professor Petajisto's website: www.petajisto.net/data/html. Return Gap is obtained by subtracting holding based returns from realized return, which we already have been using in our previous analyses. We sort our funds according to our consistency

measure quintile, and then report averages of other performance indicators. Table 8 shows the result.

(Table 8 Goes About Here)

Quintile 5, the highest consistency funds, has the highest ICI, highest Active Shares, and lowest Return Gap. This correlation with other indicators demonstrates that our consistency measure is another method of capturing managerial skill. Still, the relation between other indicators and our consistency measure is not completely monotonic, suggesting that our measure is not a mere reflection of these indicators. The magnitude of the indicators is rather similar across the 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 Shares, Return Gap) would be the most prominent as well.

IV. Summary and Conclusion

We count the number of above-median performance stocks in each mutual fund and use it as a measure of managerial skill. Our logic is that a fund holding can be thought as repeated draws of stocks to achieve higher risk-adjusted returns in the portfolio level, and it is difficult to pick many above-median performance stocks simultaneously by chance.

We find that our consistency measures predict future fund performances very well. Mutual funds with highest consistency earned higher risk adjusted returns measured by Carhart 4-factor model alpha or Daniel, Grinblatt, Titman, and Wermers (1997) benchmark adjusted returns. Our method is free from look-back bias and a relatively uninformed investor can use our

measure to estimate future fund returns. Our result is not driven by fund size or survivorship bias, and our consistency method predicts variations in future fund returns not captured by traditional fund performance measure. We find our results hold throughout the sample period, indicating that the results are not a time specific phenomenon.

In addition to its prediction capability, an advantage of our measure is that the method does not require a long series of past performance data, because it is derived from a holdings data and 1-year stock return data. Fund performances have been typically measured from time-series return data, and this method often requires considerable length of data to ensure accuracy. Fama and French (2010), and Barras, Scaillet, and Wermers (2010) show even with a long series of data, the performance estimation may not be very informative. Our consistency variable can improve accuracy in fund performance measurement by adding important information from holdings data. Our measure is correlated with other indicators of future fund performances, demonstrating that it is another type of signal that skilled managers may generate. Overall, our approach can shed additional light on the noisy process of detecting the true stock-picking ability of mutual fund managers. French (2008), for example, shows that investors spend 0.67% of the aggregate value of the market each year searching for superior returns.

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Table I
Summary statistics

We report the summary statistics of our mutual fund sample. Our sample includes domestic equity mutual funds in Thomson Financials Mutual Fund Stock Holdings Data in the period from Jan 1, 1982 to Dec 31, 2008. We include only actively managed equity mutual funds, following the definition of Kacperczyk, Sialm, and Zheng (2008). The total number of mutual funds in our sample is 1,530. Panel A reports the summary statistics of all pooled observations and panel B reports the summary statistics by our consistency measure quintile.

Panel A: All funds, pooled observations

	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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 \$)	\$1,138 mil.	\$228 mil.	\$4,466 mil.
Consistency Measure (Number of above median performance stocks / Total number of stocks)	52.9%	52.4%	18.0%

Panel B: Funds by our consistency measure quintiles

Consistency Rank 1 (Lowest)	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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.	\$3,305 mil.
Previous 12-month realized fund return, after fees (monthly average return)	0.95%	1.07%	1.46%

Consistency Rank 2 (Low)	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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 \$)	\$1,278 mil.	\$248 mil.	\$5,107 mil.
Previous 12-month realized fund return, after fees (monthly average return)	0.95%	1.08%	1.59%

Consistency Rank 3 (Mid)	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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 \$)	\$1,340 mil.	\$258 mil.	\$5,780 mil.
Previous 12-month realized fund return, after fees (monthly average return)	0.85%	1.02%	1.66%

Consistency Rank 4 (High)	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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 \$)	\$1,212 mil.	\$257 mil.	\$4,089 mil.
Previous 12-month realized fund return, after fees (monthly average return)	0.93%	1.04%	1.78%

Consistency Rank 5 (Highest)	Mean	Median	Standard Deviation
Number of holdings report available per mutual 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.	\$3,504 mil.
Previous 12-month realized fund return, after fees (monthly average return)	1.15%	1.10%	2.26%

Table II
Next year performances of mutual funds: Sorted by the consistency measure

We calculate the consistency measure of each mutual fund holdings report. The consistency measure is ranked to quintiles by comparing with other holdings reports released in the previous 1 year period. Then we track 1 year future returns from the point of the holdings data. Since our holdings data has the sample period between Jan 1, 1982 ~ Dec 31, 2008, mutual fund returns data has the period between Jan 1, 1983 ~ Dec 31, 2009. All returns are in monthly scale. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.10%	0.27%	0.15%	0.16%
Consistency Rank 4	0.02%	0.00%	-0.07%	-0.05%
Consistency Rank 3	-0.02%	-0.07%	-0.08%	-0.09%
Consistency Rank 2	-0.03%	-0.09%	-0.02%	-0.03%
Consistency Rank 1 (Lowest Consistency)	-0.09%	-0.09%	0.05%	0.03%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.19%* (0.01%)	0.36%* (0.04%)	0.10%* (0.03%)	0.13%* (0.03%)

Table III
Double Sort 1: Fund size and then consistency measure

We first rank mutual fund by its asset size (quintiles) and then rank by our consistency measure (quintiles). This process gives $5 \times 5 = 25$ clusters. Then we track 1 year future returns from the point of the holdings data. Since our holdings data has the sample period between Jan 1, 1982 ~ Dec 31, 2008, mutual fund returns data has the period between Jan 1, 1983 ~ Dec 31, 2009. All returns are in monthly scale. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

Size quintile 1 (Smallest)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.09%	0.15%	0.24%	0.32%
Consistency Rank 4	0.01%	-0.08%	-0.10%	-0.13%
Consistency Rank 3	-0.14%	0.02%	0.04%	-0.01%
Consistency Rank 2	0.00%	-0.06%	-0.05%	-0.09%
Consistency Rank 1 (Lowest Consistency)	-0.07%	0.03%	0.06%	0.00%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.16%* (0.04%)	0.12% (0.09%)	0.18% (0.10%)	0.32%* (0.10%)

Size quintile 2 (Small)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.06%	0.24%	0.35%	0.39%
Consistency Rank 4	0.03%	0.17%	0.12%	0.14%
Consistency Rank 3	0.01%	-0.03%	0.01%	-0.02%
Consistency Rank 2	-0.05%	-0.03%	0.09%	0.10%
Consistency Rank 1 (Lowest Consistency)	-0.11%	-0.10%	0.07%	0.06%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.17%* (0.03%)	0.34%* (0.09%)	0.28%* (0.08%)	0.33%* (0.08%)

Size quintile 3 (Mid)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.07%	0.23%	0.29%	0.28%
Consistency Rank 4	-0.00%	-0.02%	-0.03%	0.01%
Consistency Rank 3	-0.03%	-0.10%	-0.01%	-0.01%
Consistency Rank 2	-0.01%	-0.10%	0.02%	-0.01%
Consistency Rank 1 (Lowest Consistency)	-0.07%	-0.14%	0.05%	0.02%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.14%* (0.03%)	0.37%* (0.10%)	0.24%* (0.08%)	0.26%* (0.07%)

Size quintile 4 (Large)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.11%	0.35%	0.18%	0.16%
Consistency Rank 4	0.00%	0.02%	-0.10%	-0.06%
Consistency Rank 3	-0.03%	-0.07%	-0.08%	-0.08%
Consistency Rank 2	-0.05%	-0.15%	-0.05%	-0.05%
Consistency Rank 1 (Lowest Consistency)	-0.07%	-0.12%	0.06%	0.04%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.18%* (0.03%)	0.47%* (0.10%)	0.12% (0.07%)	0.12% (0.07%)

Size quintile 5 (Largest)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.14%	0.28%	-0.15%	-0.16%
Consistency Rank 4	0.04%	-0.00%	-0.15%	-0.16%
Consistency Rank 3	-0.02%	-0.14%	-0.14%	-0.14%
Consistency Rank 2	-0.04%	-0.11%	-0.13%	-0.13%
Consistency Rank 1 (Lowest Consistency)	-0.11%	-0.12%	-0.01%	-0.01%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.25%* (0.02%)	0.41%* (0.10%)	-0.14% (0.06%)	-0.15% (0.06%)

Table IV**Double Sort 2: Past fund performance and then consistency measure**

We first rank mutual fund by its past performance (quintiles) and then rank by our consistency measure (quintiles). This process gives $5 \times 5 = 25$ clusters. Past performances of funds are measured by estimating 4-factor alpha using 36-month of past monthly fund returns. Then we track 1 year future returns from the point of the holdings data. Since our holdings data has the sample period between Jan 1, 1982 ~ Dec 31, 2008, mutual fund returns data has the period between Jan 1, 1983 ~ Dec 31, 2009. All returns are in monthly scale. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

Past performance quintile 1 (Lowest)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.01%	0.07%	0.21%	0.15%
Consistency Rank 4	-0.01%	0.03%	0.11%	0.01%
Consistency Rank 3	-0.05%	-0.05%	0.01%	0.02%
Consistency Rank 2	-0.05%	-0.09%	0.00%	-0.00%
Consistency Rank 1 (Lowest Consistency)	-0.09%	-0.14%	0.04%	0.01%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.10%* (0.03%)	0.21% (0.08%)	0.17% (0.08%)	0.14% (0.08%)

Past performance quintile 2 (Low)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.08%	0.02%	0.15%	0.14%
Consistency Rank 4	0.01%	-0.05%	-0.06%	-0.06%
Consistency Rank 3	-0.02%	-0.02%	-0.02%	-0.00%
Consistency Rank 2	-0.04%	-0.12%	-0.05%	-0.08%
Consistency Rank 1 (Lowest Consistency)	-0.11%	-0.09%	0.04%	0.01%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.19%* (0.03%)	0.11% (0.08%)	0.11% (0.07%)	0.13% (0.07%)

Past performance quintile 3 (Mid)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.08%	0.12%	0.04%	0.03%
Consistency Rank 4	-0.01%	-0.02%	-0.14%	-0.11%
Consistency Rank 3	-0.01%	-0.03%	-0.08%	-0.10%
Consistency Rank 2	-0.06%	-0.03%	-0.01%	-0.01%
Consistency Rank 1 (Lowest Consistency)	-0.08%	-0.07%	0.04%	0.02%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.16%* (0.03%)	0.19%* (0.06%)	0.00% (0.07%)	0.01% (0.07%)

Past performance quintile 4 (High)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.02%	0.02%	-0.14%	-0.10%
Consistency Rank 4	-0.04%	-0.12%	-0.17%	-0.15%
Consistency Rank 3	-0.04%	-0.01%	-0.16%	-0.16%
Consistency Rank 2	-0.02%	-0.07%	-0.04%	-0.03%
Consistency Rank 1 (Lowest Consistency)	-0.07%	-0.03%	0.11%	0.09%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.09%* (0.03%)	0.05% (0.07%)	-0.25%* (0.07%)	-0.19% (0.07%)

Past performance quintile 5 (Highest)

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.22%	0.56%	0.02%	0.08%
Consistency Rank 4	0.09%	0.28%	-0.18%	-0.14%
Consistency Rank 3	0.09%	0.15%	-0.06%	-0.03%
Consistency Rank 2	0.02%	0.01%	-0.03%	-0.03%
Consistency Rank 1 (Lowest Consistency)	-0.04%	-0.05%	0.03%	0.04%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.26%* (0.03%)	0.61%* (0.14%)	-0.01% (0.09%)	0.03% (0.09%)

Table V
Sub-period analysis

We separate our sample into two parts and report 1 year future returns by our consistency measure. The first period contains mutual fund returns from Jan 1, 1983 to Dec 31, 1995 and the second period contains mutual fund returns from Jan 1, 1996 to Dec 31, 2009. All returns are in monthly scale. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

Mutual fund returns from 1983 to 1995

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.03%	-0.04%	0.32%	0.27%
Consistency Rank 4	-0.03%	-0.12%	0.12%	0.12%
Consistency Rank 3	-0.04%	-0.16%	0.09%	0.08%
Consistency Rank 2	-0.04%	-0.34%	-0.02%	-0.03%
Consistency Rank 1 (Lowest Consistency)	-0.07%	-0.44%	-0.10%	-0.12%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.10%* (0.02%)	0.40%* (0.06%)	0.42%* (0.04%)	0.39%* (0.04%)

Mutual fund returns from 1996 to 2009

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.12%	0.36%	0.10%	0.12%
Consistency Rank 4	0.03%	0.04%	-0.14%	-0.11%
Consistency Rank 3	-0.01%	-0.04%	-0.15%	-0.15%
Consistency Rank 2	-0.02%	0.00%	-0.02%	-0.02%
Consistency Rank 1 (Lowest Consistency)	-0.10%	0.06%	0.11%	0.09%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.22%* (0.02%)	0.30%* (0.05%)	-0.01% (0.04%)	0.03% (0.04%)

Table VI**Alternative consistency measure (Number of 75% upper percentile stocks)**

We use an alternative consistency measure which counts the number of stocks that performed better than upper 75% percentile. After ranking by this measure, we track 1 year future returns from the point of the holdings data. Since our holdings data has the sample period between Jan 1, 1982 ~ Dec 31, 2008, mutual fund returns data has the period between Jan 1, 1983 ~ Dec 31, 2009. All returns are in monthly scale. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

	Alphas (4-factor)	DGTW Benchmark Adjusted Return	Holdings Based Return	Realized Return (after fees)
Consistency Rank 5 (Highest Consistency)	0.08%	0.19%	0.12%	0.15%
Consistency Rank 4	0.03%	0.02%	0.01%	0.02%
Consistency Rank 3	-0.01%	-0.03%	-0.03%	-0.05%
Consistency Rank 2	-0.04%	-0.05%	-0.04%	-0.05%
Consistency Rank 1 (Lowest Consistency)	-0.09%	-0.10%	-0.05%	-0.07%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.17%* (0.01%)	0.29%* (0.05%)	0.17%* (0.04%)	0.22%* (0.03%)

Table VII
Mutual fund expense ratios and fees

For each consistency group, we report the average expense ratio and management fees acquired from CSR Mutual Fund Data. The fees are based on annual scale. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of each panel. Significant differences in 1% level are marked with *.

	Expense Ratios (Annual)	Management Fee (Annual)
Consistency Rank 5 (Highest Consistency)	1.50%	0.83%
Consistency Rank 4	1.37%	0.79%
Consistency Rank 3	1.32%	0.78%
Consistency Rank 2	1.33%	0.77%
Consistency Rank 1 (Lowest Consistency)	1.38%	0.78%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.12%* (0.02%)	0.05%* (0.01%)

Table VIII**Other mutual fund performance predictors**

We calculate averages of Industry Concentration (Kacperczyk, Sialm, and Zheng 2005), Active Shares (Cremers and Petajisto 2009, Petajisto 2010), and Return gap (Kacperczyk, Sialm, and Zheng, 2008). We report those measures to the third decimals for visual convenience. Standard error of the difference between highest consistency rank and lowest consistency rank is in parentheses. Significant differences in 1% level are marked with *.

	Industry Concentration	Active Shares	Return Gap
Consistency Rank 5 (Highest Consistency)	0.177	0.835	-0.094%
Consistency Rank 4	0.134	0.799	-0.119%
Consistency Rank 3	0.125	0.795	-0.136%
Consistency Rank 2	0.120	0.788	-0.145%
Consistency Rank 1 (Lowest Consistency)	0.153	0.796	-0.138%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.024* (0.003)	0.039* (0.003)	0.044%* (0.010%)

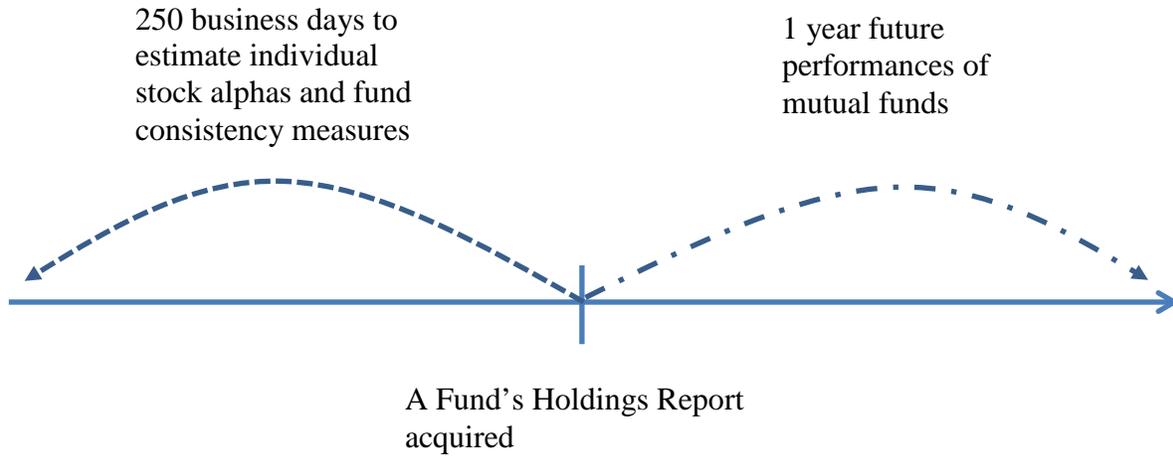


Figure 1. Estimation of fund consistency measure

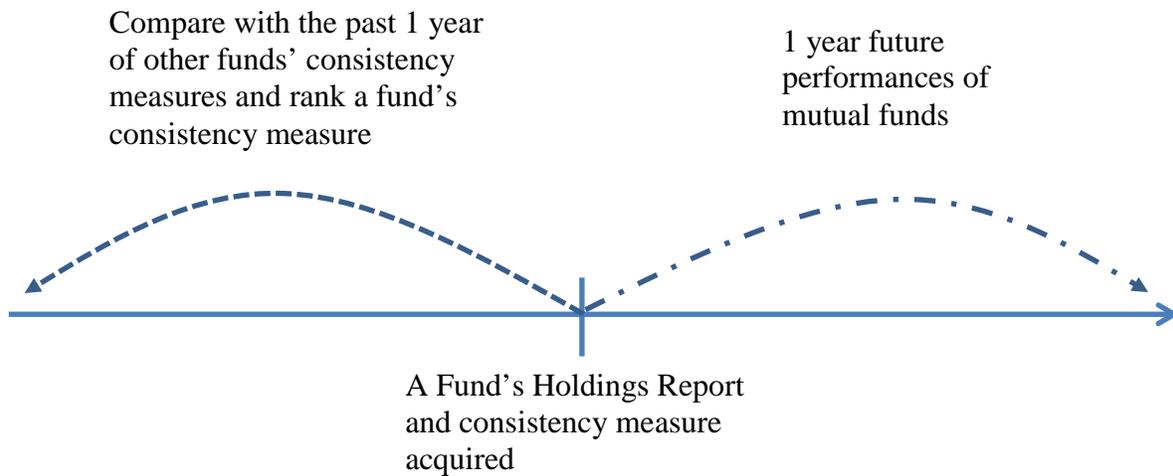


Figure 2. Ranking of consistency measure