A Simple but Effective Way to Identify Persistent Performances Among Actively-managed Mutual Funds

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Abstract

We show the number of stocks contributing to the overall performance of an actively managed mutual fund is related to the persistency of the fund performance. Among the funds that have similar risk-adjusted returns, the funds that rely on a few high return stocks underperform the funds that hold many above-median return stocks. The difference between two groups is as large as 8% annual risk-adjusted return empirically. This result holds throughout our sample period, and is not generated by survivorship bias, look-back bias, or fund expenses.

JEL Code: G11
Keywords: Mutual funds, Luck vs. skill, Performance evaluation, Holdings data

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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 positive risk-adjusted returns. However, there are two difficulties in the task of identifying the managers with true skill. First is that there is a considerable possibility of 'false discoveries'. The stock-picking ability of a mutual fund manager is often measured by the risk-controlled performance of his portfolio. Typically, a factor regression using Fama French (1993) 3-factors or Carhart (1997) 4-factors is used to measure a fund's performance, namely alpha. Like all other statistical measures, this method contains a probability to falsely identify a non-skilled manager as a skilled one. Fama and French (2010) and Barras, Scaillet, and Wermers (2010) find those factor models tend to falsely identify a lucky manager as a skilled one.

The other difficulty is that younger mutual funds or managers tend to have low signal-to-noise ratio because they have little track record. 'Star' managers may be the managers with true skills, but by the time they are identified, their funds may have become too large to grow further, too many other investors are replicating the fund, or the managers may be preparing for retirement. If investors can identify talented managers earlier, they would have better opportunities to get good investment returns.

In this paper, we test if the information in mutual fund holdings data can increase the accuracy of identifying the managers with true stock picking ability. We focus on the holdings data because it has potential to reduce the two problems stated above – false discoveries and late discoveries. Cohen, Coval, and Pastor (2005) or Baker, Litov, Wachter, Wurgler (2010) show that holdings data, a cross sectional distribution of individual stock performances inside a mutual fund, may contain additional information about fund manager ability that time-series data of overall fund returns cannot easily identify. The question is: What kind of indicator from holdings data would contain information about stock picking ability of a manager?

We start from the idea that a mutual fund holding can be thought as repeated draws to achieve higher risk-adjusted returns. In the large universe of stocks, fund managers pick the stocks that would increase the risk-adjusted returns of their portfolios. If a manager has no skill, his pick would be like random choices – some picked stocks would have positive risk-adjusted returns and other have negative ones. When we count the *number* of good performing stocks in such holdings data, about half of the stocks will be performing above market-median and others will be not. Meanwhile, if there is a manager who picks many positive risk-adjusted return stocks, it would be hard to achieve that status by chance. It is similar to having a series of coin flipping that has too many Heads. Thus, the number of stocks that does better than market in a mutual fund has a potential to work as an indicator of skill. One may question whether overall fund return already captures that difference. A counter-example would be a mutual fund that has overall good risk-adjusted returns because a manager picked single super-performing stock, while all other stocks in the portfolio are mediocre performing stocks. The counting method from holdings data would tell that the *number* of better performing stocks is only about half of total stocks in the portfolio, which is not a special performance.[1] A fund return is an average of individual stock returns in a fund, while we are using a method similar to the median of individual stock returns. Unless the two measures are perfectly correlated, we can use two dimensions of measures to identify a skilled manager more accurately. It is an empirical question of course whether this multi-dimension approach gives better results.

[1] Some funds like venture capital intentionally aim for this type of return distribution. However, our purpose is to develop a fund performance measure that works on average, instead of accounting for all the possible strategies to achieve better performances.

Using the framework of “Sign Test”, which is a nonparametric test used to check the significance of a median, we show that the number of above-median performance stocks in a portfolio can be an indicator of manager’s stock selection skill. We construct a fund performance measure from this logic; First we count the number of stocks in a portfolio that did better than market-wide median performance, controlling for each stock’s risk characteristics. Next, we include additional controls to the first method. We add the magnitude of stock performances, dispersion of performances inside a fund, and dollar amount invested to each stock. We call this measures as ‘consistency’ measure, because it captures how consistently a manager picked above-median performing stocks.

In our empirical section, we test how this measure performs. We use all actively managed mutual funds in Thomson Reuter’s Database and CRSP Mutual Fund Database from Sept 1, 2000 to Dec 31, 2009. We find that our consistency measure predicts future fund performances very well. Among the funds that had similar risk-adjusted performances in the past, the funds with higher consistency measure generate 0.79% additional Carhart 4-factor alpha. We also show that the quality of a mutual fund holding is much better in those high consistency fund groups. We measure 1 year risk-adjusted return of each mutual fund holding, after controlling for the current performances. We find that high consistency funds outperform low consistency funds, and the difference is as large as 8.65% annual return, risk-adjusted by Daniel, Grinblatt, Titman, and Wermers (1997) method. This result shows that only high consistency funds continue their superior performances, while low consistency funds do not show outstanding future returns even if their current performances are good. We further find the larger returns of high consistency funds is generated by active portfolio management.

We find that our measure makes difference in the funds that did well in the past. This result is not surprising because the funds without current good performances would not have many skilled managers to identify, and their signal-to-noise ratios would be already too low to acquire additional difference in future performances. This result also tells that survivorship bias is not an issue in our test, because the bias would affect mostly the funds with low performances.

We check the robustness of our results. First, we test whether mutual funds create a look-back bias in their holdings data by intentionally delaying the release of the data. If there is some lag between the effective holdings date and data release date, managers may be tempted to window-dress their holdings data. We find the outperformance of high consistency funds is actually stronger for the funds that do not delay. Next, we test if our result holds in different time periods. We divide our sample period into three periods and see whether our result holds in each time period. We show the outperformance of high consistency funds is not a one-time phenomenon. Lastly, we find the differences in mutual fund fees are negligible in most cases, and high consistency funds sometimes have lower fees than low consistency funds.

The main contribution of the paper is showing that additional information from mutual fund holdings data, albeit simple, can vastly improve the prediction power for future fund performances. Our finding would be useful to those who wants to identify the funds to perform better in the future and to those who need to develop a more precise measure of fund manager skills. Our paper is related to a growing literature that seeks additional indicators of managerial skill to supplement traditional factor analysis. Especially, Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Cohen, Coval, and Pastor (2005), Kacperczyk and Seru (2007), Kacperczyk, Sialm, and Zheng (2008), and Elton, Gruber, and Blake (2011) show different aspects of holdings data can be used to extract additional information about managers' skill.

Another contribution of this paper is showing that luck-driven performances can be separated from skill-driven performances using additional statistics from holdings data. 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 measure also differentiates a temporary good performance from a continuous good performance. However, unlike other papers' conclusion that most of the good fund performances are driven by luck, we find some good performances do continue. The persistency of some fund performances indicates that actively managed mutual funds have value, and investors can benefit from the funds when they a method to identify the skilled fund managers.

Rest of this paper is organized as follows. Section I describes the statistical theory that supports our consistency measures. 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 actively managed mutual funds since we assume actively managed mutual funds in general operate under this objective function.[2]

From the universe of stocks, managers pick stocks to be included in /excluded from their fund. If a manager includes many good performing stocks, the fund performance will become better. We can view a fund holdings snapshot as a realized result of this picking process.

Now we define the term, "Stock picking ability".

Definition: A fund manager without stock picking skill is the manager who has 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 similar to selecting a stock randomly. 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 a probability significantly higher than 50%. Such manager will consistently pick and include higher risk-adjusted return stocks in his portfolio.

We can think a current fund holdings snapshot as the result of repeated picks of the fund manager. Using our definition of 'skilled manager', we construct a statistical test 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.

[2] 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.

H0: 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:

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

where

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

Equation (1) has the largest value when *k = n/2*. The value gets smaller when *k* gets closer to *n* or zero. For an 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 (H0: 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 (H0: 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 lower probability that an unskilled fund manager achieved it by chance. Therefore, we arrive to the conclusion that a manager who picks more above-median risk-adjusted returns stocks out of his whole portfolio has low probability that the manager is not a skilled one. Since we are only interested in identifying a fund manager with stock picking ability, 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 first indicator is k/n, acquired from holdings data.

$$\mathrm{m}_1 = k/n \qquad (2)$$

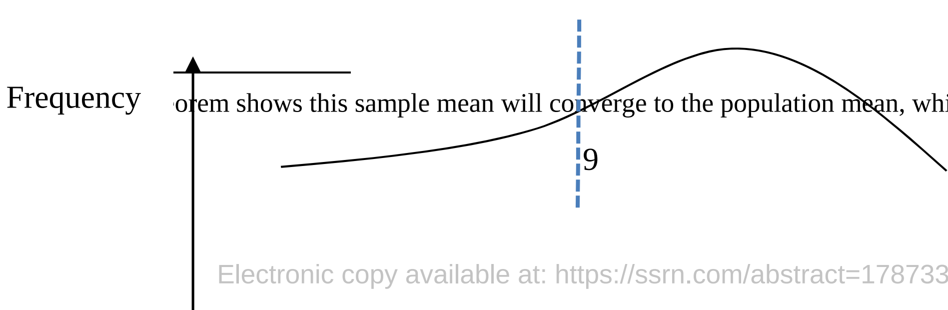
where k is the number of stocks with above-median risk-adjusted returns and n is the number of stocks in a fund holding.

We admit that this indicator is a very simple one with many limitations. This measure only counts the number of stocks that are better than market median. We therefore expand m_1 measure by incorporating additional controls. We add the magnitude of performance first. We can rank all individual stock performances in stock market into, say 100 ranks. Rank 50 then becomes market-median. From holdings data, we can see the distribution of these rankings within a mutual fund. Suppose a fund has two stocks with 40 rank, one stock with 80 rank, and one stock with 95 rank. Our first measure m_1, the counting, will tell that 2 out of 4 stocks are above market-median. We add the information that 80 or 95 is much better than median (rank 50), while 40 is not very below the median. We also want to control for the amount of rank dispersion within a fund, i.e. standard deviation of rankings. Small funds or the funds that intentionally aim for a few big returns may have high dispersion of rankings inside their holdings. Mutual funds typically do not put the same weights to all the stocks, so we should control for the weights on each stock. We divide the whole measure by the number of stocks n to normalize the fund size. Lastly, we also include that the size of each stock holding is not equal inside a fund. With these controls, we acquire the following statistic:

$$m_2 = -\frac{n}{(n-1)\cdot(n-2)} \cdot \sum w_i^{3/2} \cdot ((x_i - \bar{x})/\hat{\sigma})^3 \qquad (3)$$

where n is the number of stocks in the fund, w_i is the weight of the stock i, x_i is the ranking of stock i, $\bar{x}$ is the mean of the ranks in a mutual fund holding, and σ is the standard deviation of the rankings in the fund.

We call this measure m_2. This statistic captures how many of the individual stock ranks are above sample mean $\bar{x}$, which converges to market-median (rank 50).[3] The statistic also controls for the number of stocks in a fund (n), the standard deviation of rankings, and weights to each stock. This statistic is actually the sample skewness statistic with a minus sign in front. The statistic basically captures the number of stocks performing better than market-median, with some controls included. To see why a skewness statistic of rankings is equivalent to a counting method, we use histograms. The funds that have many above-median rank stocks will have the following holdings pattern when we put ranks in x-axis and frequency in y-axis:



[3] (orem shows this sample mean will converge to the population mean, which is rank 50 by design.

Figure 1: Funds with many above-median performing stocks

In contrast, the funds that have many below-median rank stocks will have the following holdings pattern:

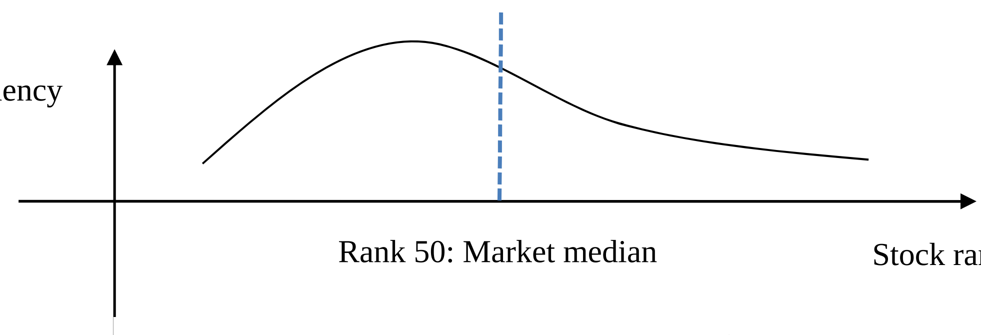


Figure 2: Funds with many below-median performing stocks

When this skewness of these *rankings* is calculated, funds with figure 1 type holdings would have negative skewnesses (left-skewed or longer left tail) and the funds with figure 2 type holdings would have positive skewnesses (right-skewed or longer right tail). Thus, the skewness of rankings measures how many stocks in a fund performed above median, controlling for the dispersion of ranks and difference in weights. We put negative sign in front so that bigger m_2 means more stocks with rankings above market-median. When we calculate the correlation statistic between two measures m_1 and m_2, we get 83%, which means two measures are capturing similar information. The high correlation may indicate that the importance of the additional controls in m_2 is not as large as expected. We will use m_2 in our empirical section. We also did the same empirical tests using m_1 method, and not surprisingly, we acquire qualitatively similar results.

Note that m_2 measure has nothing to do with time-series skewness of stock returns in asset pricing literature. The skewness of stock returns in asset pricing is related to tail risk in returns – a stock return showing a sudden jump (or crash). The statistic in this paper is calculated from the *rankings* of stocks at the time when holdings data is reported. It is a characteristic of a fund holding (snapshot), rather than the past series of stock returns (time-series).

While fund alpha is a mean of individual stock alphas in a fund, our indicators are similar to the median of alphas, in the sense that they are less vulnerable to outliers. When two different statistics (mean and median) are used together, it could uncover the information that is not easily captured by one statistic. We will test if our indicators increase the prediction power of mutual fund performances when used with the fund alpha variable. Specifically, we want to see whether our indicators can tell difference in future fund performances among the funds that had similar Carhart 4-factor fund alphas in the past.

II. Data and Methodology

We use the Thomson Financials Mutual Fund Stock Holdings Data for September 1, 2000 through Dec 31, 2009, and identify the stocks included in different mutual funds. Our sample period does not start until September 2000 because we require sample funds to be also in the CRSP mutual fund daily return database and in the Mutual Fund Link database. We use the Mutual Fund Link Data to merge the Thomson Holdings data with the CRSP mutual fund database. We only use the actively-managed equity mutual funds defined by the Thomson

Holdings Data. The actively managed equity mutual funds are the funds that have "Investment Objective Code" of 2 and 3.[4] The Objective Code 2 stands for aggressive growth and 3 stands for growth. In addition, we require the funds to have a non-zero asset. We have a total of 1,380 equity mutual funds in our sample, and each fund has on average 23 holdings reports. We estimate stock alphas for each holdings report date. For example, if a fund has a holdings report effective June 30, 2004, for each stock in that fund we use the previous 125 business days of returns to estimate the alphas of individual stocks in the fund. Most of the funds report their holdings on a quarterly basis, and therefore we estimate the performance of individual stocks every two report cycles.[5] Table I reports some summary statistics of the funds in our sample.

(Table I Goes About Here)

For each holdings snapshot, we see how each of the stocks in the holdings report performed relatively better to market-wide median performance. A risk-adjusted performance of a stock is estimated using the Carhart 4-factor model. The risk-adjusted performance of a stock is measured by the intercept (alpha) of the following 4-factor model:

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

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 Center for Research in Security Prices (CRSP) of the University of Chicago 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

[4] We do not include international equity funds (Code 1) because the daily stock return data for international stocks are not easily available. We also exclude growth and income funds (Code 4) because these funds may have a goal to obtain a stable income rather than outperforming others by good stock-picking.
[5] The regulatory requirement is to report holdings semi-annually, so some of the quarterly holdings reports are from voluntary disclosures. We will deal with this issue in the later part of the paper.

stocks in the CRSP database using a 125-business-day estimation period, which is approximately a half year.[6]

In order to see which stocks performed better than market median, we rank the alphas of all CRSP individual stocks into 100 groups within the same estimation period. The groups above 50 are above-median-performing stocks, and the others are below-median-performing stocks. For each holdings report, we collect the rankings of each stock in the portfolio. We calculate our performance measure m_2 from the rankings. m_2 is weighted sample skewness statistic of *rankings* in each holdings report. For the weight in m_2, we use market value of each stock at the time of holding. When m_2 is high, we call the fund as a 'high consistency' fund, indicating that the manager consistently picked many above-median performing stocks.

Our goal is to test whether our consistency measure captures additional information that is traditional fund performance measures cannot easily detect. So we control for current risk-adjusted performance of a fund using Carhart 4-factor alpha, and then see what difference our consistency measures can tell among the funds with similar alphas. A fund's alpha is calculated as the weighted average of individual stock alphas. This calculation should give the same alpha as the one calculated from regressing daily fund returns with Carhart 4-factors. Kacperczyk, Sialm, and Zheng (2008) shows the lag between quarterly holdings report and daily fund return can make the two measures slightly different. We use the alpha from holdings data because we are basically measuring the quality of a fund holding. We also find daily stock return data could be more accurate than daily fund return data in CRSP. CRSP mutual fund data contains huge outliers such as 200% daily return. Additional to these outliers, the CRSP return data has to be

[6] 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 use half-year data to balance two factors. Note that Bollen and Busse (2004) uses quarterly data to estimate fund alphas.

merged to holdings data, and during this process, additional noise can enter into the data. Consistent with this observation, Elton, Gruber, and Blake (2011) find that the alpha from holdings data contains more information about future fund performances than the alpha from time-series fund return data.

We rank each holdings report by its fund alpha to control for the current performance of the fund. When we rank a fund performance, we minimize look-back bias by comparing the alpha with all the fund performances during a 1-year period prior to the release date. If a holdings report is released on July 31, 2005, for example, we compare the fund alpha with all other fund alphas available during July 31, 2004 ~ July 31, 2005 period. We call this comparison period as 'rolling year' period. The comparison sample size in the rolling year period may vary over time, especially when fund holdings release dates are concentrated in particular calendar months. We also tried a cruder sort such as sorting by every calendar year, and it does make much difference. Alpha already captures a large degree of time-series variation in market-wide returns, so the difference is not large anyway. We sort fund alphas into quintiles. Within each fund alpha quintile, we sort again into quintiles by our consistency measure m_2. This gives us 5 x 5 = 25 sorted groups. We measure the future performances of funds in each group.

III. Results

A. Predictive Power of Our Consistency Measure

Our first test is to see whether a consistency measure in the past is related to current fund performance. We sort all fund holdings reports into the 5x5 matrix – sort first by current performance and then one of our consistency measures. Then we evaluate the risk-adjusted performance of the 4th holdings data of that fund released after that point. 4-periods gap is equivalent to 1 year or more since most of the funds report their holdings every quarter.[7] So we are comparing the quality of a holdings report after controlling for the past year's risk-adjusted performance and our consistency measure. Since our alphas are estimated using 125 business days (about half-year data), there is no overlapping between estimation period and prediction period. We are allowing some additional gap between two alpha estimation points, so that fund managers may have changed a significant portion of their portfolios. Table II reports the average size of monthly Carhart 4-factor alpha values by our consistency measure.

(Table II Goes About Here)

We find the funds with high consistency measures outperform the funds with low consistency measures, after controlling for their current performances. When we are using our measure m_1, this result can be simply stated that a fund with many stocks contributing to its current performance has better future performance compared to a fund relying on a few high return stocks. We see this difference only exists for past performance rank 5 (Best). Among the good performing funds, the funds with high consistency measure generated additional 79 basis points of monthly alpha compared to the funds with low consistency measure. We also find similar results when we vary the gap between initial point and future performance measurement point to 3-periods or 5-periods.

This result shows the persistency of a mutual fund performance is limited to the funds that continue to pick many above-median performing stocks. We see some of the persistency across current performance ranks – funds that did well in the past continues to do so in the past. In mutual fund literature, studies find the persistency of performances exists for a short period, as in Bollen and Busse (2004) , Avramov and Wermers (2006), and Kosowski, or Timmerman, and

[7] We checked the data to make sure the gap between two holdings data is at least 1 year.

Wermers, and White (2006). Elton, Gruber, and Blake (2011) specifically finds persistency in 4-factor alphas measured from holdings reports. Our finding complements these papers by showing that the persistency is mostly a phenomenon among the funds with high consistency measure.

If the persistency of mutual fund performance is an indicator of true stock picking ability of a fund, it is actually not surprising to see that our measure works for only well-performed funds. Suppose we group fund managers into two categories: the managers without stock-picking ability and the managers with stock-picking ability. This simple setting reflects that no manager would intentionally pick poor performing stocks. If a manager does not have stock-picking ability, his stock selection would not be different from a random selection of stocks. The manager would have 50% probability to pick an above-median performing stock. Ex post, the random selection can end up with extremely good performances or really bad performances, but the average fund performances of these managers would be similar to that of passive investment strategies (e.g., index funds). On the other hand, the managers with stock-picking ability will pick above-median performing stocks more frequently, and their fund performances will be consistently good.

Now suppose an investor observes overall fund performances without knowing the stock-picking ability of fund managers. She only knows that there are two types of managers—one with true ability and the other without. Then the funds with currently bad performances would be mostly the ones managed by the managers without ability and with bad luck. The matter is more complicated for the funds currently with good performances, because the two types of managers are mixed in this category. The investor knows that good performances can be a result of actual ability or a result of good luck. Therefore, if a fund performance measure successfully identifies the managers with true stock-picking ability, it should be more informative for the funds that are currently performing well.

This result also shows that our test result is not driven by survivorship bias. Such a bias would apply mostly to the poor-performing funds because these funds are more likely to vanish. As a result, the performance of the poor-performing funds is likely to be exaggerated, instead of the well-performing funds.

Next, we use fund performance measure suggested by Daniel, Grinblatt, Titman, and Wermers (1997). They suggest ‘CS measure’, which shows a fund’s return after controlling for the risk characteristics of stocks. They argue that the CS measure is better in estimating the quality of fund holdings compared to Carhart 4-factor model or Fama French 3-factor model. CS measure is the difference between the return of a mutual fund holdings and the return of the benchmark portfolio. The benchmark portfolio is constructed from the stocks with similar size, book-to-market, and momentum. See Daniel, Grinblatt, Titman, and Wermers (1997) for the details of the CS measure.

From each holdings report, we calculate 1 year CS return of each stock in the holdings report and aggregate them by the weights to the stocks in the report. We sort each holdings report into the 5x5 matrix and then pick the 4^{th} holdings report released after the group formation date. The gap between the group formation date and the 4^{th} holdings report is at least 1 year. We report annualized CS returns in Table III.

(Table III Goes About Here)

Table III shows that CS return result is similar to the Carhart 4-factor alpha result in Table II. The difference in CS returns is the largest in performance rank 5 (Best). The difference in CS returns is estimated as 8.65% per year. Other performance ranks show much smaller differences in returns.

We also check serial correlation in fund holdings. If a portfolio performances are serially correlated, a manager who once achieved a high return may continue to do so by just maintaining his current holdings. We cannot claim our consistency measure as a measure of managerial stock picking ability in such a case.

We classify all holdings reports to our 5 x 5 groups by first sorting with fund alpha and then our consistency measure. We restrict the sample to the funds that are included in our earlier analyses. Then we calculate the 1-year *future CS return of the holdings report* we used to form the 5 x 5 groups. This method is equivalent to an investment strategy mimicking a fund portfolio holdings report. After observing a holdings report, an investor constructs the same portfolio and waits for another year. If our earlier results are due to serial correlation in portfolio performances, this mimicking method should also yield a risk-adjusted return similar to our earlier results.

(Table IV Goes About Here)

Table IV shows the mimicking method works better for the funds that have high consistency measures. Our consistency measure makes significant difference in current performance quintile 3 (Mediocre), 4, and 5 (Best). The difference between high consistency funds and low consistency funds is 1.65%, in the best performance quintile. This result indicates that the quality of a portfolio is much better (longer persistency) if there are many stocks contributing to its overall return. Therefore, our consistency measure can be also used for this mimicking investment strategy.

While our consistency measure predicts future performances, the mimicking method does not yield better returns if traditional 4-factor alpha is used alone. There is actually a considerable amount of mean-reversion in returns, especially if fund consistency is low. The return from the mimicking portfolio is much smaller than what we observe in Table III (1.65% vs. 8.65%). The superior return of high consistency funds in Table II and Table III is therefore not driven by serial correlation in portfolio returns. There seems to be a considerable amount of portfolio rebalancing, and this interim trading is generating the large outperformance of high consistency funds. This result confirms that our consistency measure captures managerial stock picking ability.

B. Robustness

In this subsection, we test whether some of the possible biases in holdings reports are driving our results. We first seek the possibility of look-back bias in holdings data. As in Table I, there are some holdings reports released much after the effective holdings date. For holdings data, only semi-annual report is mandatory and the reports between the required ones are voluntary disclosures.[8] Mutual funds may not be in a rush to prepare the voluntary disclosures. Also, there can be a correction of holdings data after it was initially released. If there is a considerable gap between effective holdings date and data publish date, fund managers may want to window-dress the holdings data by first observing stock performances and then create a holdings report. Table V reports summary statistics on the gap between the effective date of the holdings and the actual filing date. It shows that the median gap between the two dates is zero, indicating that most of

[8] This requirement changed several times; Elton, Gruber, and Blake (2011) documents that the requirement was quarterly disclosure once, changed to semi-annual disclosure, and then changed back to quarterly disclosure.

funds file their effective holdings data on the same day. Still, there is on average a 35-day gap between the effective holdings date and the actual filing date.

(Table V Goes About Here)

We redo our test in Table II, using the sub-sample of reports that have little gap between effective holdings date and data release date. Since these reports are not subject to look-back bias, we expect the result from this subsample to be less subject to look-back bias. In Table VI, we report the results when we allow only 5-day gap between effective date and release date. We allow 5 days because there are cases that an effective date is a weekend and the release date is the next business day. The results are similar when we allow absolutely no gap.

(Table VI Goes About Here)

The results in Table VI is almost the same as the results in Table II. Therefore, our consistency measure is not picking up look-back bias, and investors can actually use the measures to achieve higher risk-adjusted return from mutual fund holdings data.

Another possible bias is that our result may be a time-specific phenomenon. One can also ask whether the superior performance of the high consistency funds comes from taking high market beta during the bull markets. If a fund manager has true stock-picking ability, he would engage in market timing and change the beta of his portfolio to increase fund returns. Successful market timing would make funds perform better not only in good times but also in bad times.

We divide our sample period into 3, approximately every 3 years. The first period is from Sept 1, 2000 to Dec 31, 2003. This period is mostly a bear market period after the burst of High-tech bubble. Next period is from Jan 1, 2004 to Dec 31, 2006, which is a bull market period. The last period is from Jan 1, 2007 to Dec 31, 2009, when financial crisis hit the US stock market. In Table VII, we do our fund alpha analysis by sub-sample period. We measure current fund performance and consistency at one point, and then measure the fund alpha of the 4th report released after the initial point.

(Table VII Goes About Here)

We find the previous result in Table II holds in this sub-sample analysis as well. Among the funds that currently have good performances, high consistency funds significantly outperformed low consistency funds in every sub-sample. The magnitude of the outperformance and statistical significance is similar across different time periods as well. This result shows that the outperformance of high consistency funds is robust to different market conditions, and the funds manager seems to have ability to time the market. We see some temporary underperformance of high consistency funds, but the result is restricted to the funds that currently have mediocre or worst performances, and the magnitude of the difference is much smaller.

The subsample analysis also confirms that survivorship bias is not driving our result. The better performance of high consistency funds exists in both bull market and bear market. Survivorship bias would be larger in bear markets and smaller in bull markets, but we do not observe any correlation between market condition and the ourperformance of high consistency funds.

C. Fund Fees and Our Consistency Measure

If investors are informed that a fund manager has good stock-picking ability, the mutual fund seller may charge investors higher fees. The fund seller can extract some rent from investors if investors are continuously lured by the ability (or reputation) of the fund manager. In an extreme case, the seller may increase the fees such that the net return of a renowned fund is the same as the net returns of other funds.[9] Here, we test the relationship between our consistency measure and mutual fund fees. We use the expense ratio and management fee of the CRSP mutual fund database to measure the size of the fees. Since our expense ratio data are annual data, we take an annual average of our consistency measure and merge them with the expense ratio data.

Similar to previous tables, we create a 5 x 5 matrix by current performance and the consistency ranking. Table VIII reports the expense ratios and management fees in each group. We see little variation in mutual fund fees. There is some tendency that funds with better current performances have higher expense ratios, but the differences by consistency rankings do not show a certain pattern. The differences are mostly insignificant and they are not large enough to justify the additional risk-adjusted returns achieved by high consistency funds. This result suggests that fees are not adjusted properly according to our measure of fund manager's stock-picking ability. Our results are consistent with Bailey, Kumar, and Ng (2011) who find that fund investors have substantial behavioral biases, but are not consistent with the rational expectation model of Berk and Green (2004). Perhaps financial institutions do not charge differential fees when investors cannot easily distinguish luck from actual stock-picking ability.

(Table VIII Goes About Here)

IV. Summary and Conclusion

This paper shows that investors can learn more about a fund manager's stock-picking ability by analyzing the distribution of the individual stock performances inside a fund. We use a

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

simple framework of "Sign Test" to measure the probability to consistently pick many above-median performing stocks. The intuition is that it is difficult to have a large number of above-median performing stocks in a portfolio by chance. We develop the measures of fund performance consistency using the number of above-median stocks in a portfolio as an indicator of managerial skill.

We find that our consistency measures predict future fund performances surprisingly well. Mutual funds with higher consistency measure earned higher risk adjusted returns measured by Carhart 4-factor model or characteristic based model (CS measure). Also, our measure is particularly useful in identifying the source of a good mutual fund performance. Among the funds that currently have good performances, the funds with high consistency measures continue their good performance, while the funds with low consistency do not. This result can be stated that the number of stocks contributing to overall fund performance is related to the persistency of the fund performance. We further find that high consistency funds have better portfolio quality, and investors can even earn extra returns by mimicking high consistency fund portfolios.

Survivorship bias, look-back bias, or fees do not explain the better returns of high consistency funds. We find our results hold throughout the sample period, indicating that the results are not a time specific phenomenon. Our measure does not require a long series of past performance data, making it an ample method to identify talented managers in their early career stage. Overall, our measure would be a useful tool to gauge the stock-picking ability of a fund manager, providing strong implications for choosing mutual funds or deciding compensations for fund managers.

A few words of caution are warranted. In this study, we develop a relatively simple but intuitive performance measure that can differentiate luck-driven performances from ability-driven performances, using publicly available data. Our measure, however, does not identify all possible types of managerial skills, as is the case for all statistical tests. For example, low cross-sectional consistency funds can be managed by 'sluggers', who achieve good fund performance by picking only one super-performing stock (Such as Google in 2000s). If sluggers persistently produce superior returns, they are not an accidental success, but probably practice a different valuable skill. Nonetheless, 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 defined by the Thomson Financials Mutual Fund Stock Holdings Data for Sept 1, 2000 to Dec 31, 2009. The number of mutual funds in our sample is 1,380.

	Mean	Median	Standard Deviation
Number of holdings report per mutual fund	25.9 reports	30 reports	11.4 reports
Number of days between two holdings reports	91 days	91 days	46 days
Number of stocks in a fund	138 stocks	73 stocks	290 stocks
Percentage of stock holdings	84%	88%	16%
Fund total assets (million $)	$1,473 mil.	$319 mil.	$5,250 mil.

Table II
Size of Carhart 4-factor alpha by our consistency measure

Alpha (α) represents the excess return achieved by the fund over and above what is the predicted return of the Carhart's (1997) 4-factor model. We acquire Carhart 4-factor alpha of a holdings data by taking the weighted average of individual stock return alphas, using the holdings as the weight. The individual stock alphas are estimated using prior 125 business days' returns. We sort the fund alpha into quintiles every rolling year, and then within each performance quintile, we sort by one of our consistency measures. This gives us 5 x 5 = 25 groups. The number of observation per group is around 1000. Then we report equal-weighted average fund alphas of each group acquired from the 4th holdings report released after the date of initial group formation. The time difference between consistency measure calculation and alpha calculation is approximately 1 year. We convert the acquired alpha values to monthly scale. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of the table. Significant differences in 5% level are marked with *.

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best current Performance)
Consistency Rank 5 (Highest Consistency)	-0.60%	-0.54%	-0.30%	0.01%	1.22%
Consistency Rank 4	-0.64%	-0.55%	-0.26%	0.06%	0.74%
Consistency Rank 3	-0.67%	-0.53%	-0.30%	-0.04%	0.53%
Consistency Rank 2	-0.64%	-0.50%	-0.34%	-0.05%	0.49%
Consistency Rank 1 (Lowest Consistency)	-0.56%	-0.49%	-0.35%	0.01%	0.33%
Difference between Consistency 5 and Consistency 1 (High – Low)	-0.04% (0.06%)	-0.05% (0.04%)	0.05% (0.05%)	0.00% (0.06%)	0.79%* (0.08%)

Table III
Daniel, Grinblatt, Titman, and Wermers (DGTW) performance measure (CS measure)

We calculate 1 year CS returns for each holdings report. We sort mutual funds by current performances measured by alpha, and then sort by our consistency measure. We report the CS returns of the 4th holdings report released from the date of consistency measurement. CS measure is acquired by comparing the monthly returns of mutual fund holdings to the monthly returns of the benchmark portfolio. CS measure represents a manager's stock picking ability after controlling for the characteristics of stocks. The details of constructing and interpreting DGTW measure can be found in Daniel, Grinblatt, Titman, and Wermers (1997). We report annualized CS return by sorted group. The number of observation per sorted group is around 1,000. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of the table. Significant differences in 5% level are marked with *, and standard errors of the differences are in the parentheses.

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best current Performance)
Consistency Rank 5 (Highest Consistency)	-4.67%	-3.43%	-1.92%	0.64%	11.17%
Consistency Rank 4	-5.21%	-3.32%	-2.07%	1.23%	8.40%
Consistency Rank 3	-4.61%	-3.11%	-1.45%	0.26%	5.93%
Consistency Rank 2	-5.52%	-2.82%	-2.19%	0.53%	3.39%
Consistency Rank 1 (Lowest Consistency)	-5.47%	-3.26%	-2.44%	0.42%	2.52%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.80% (0.41%)	0.17% (0.38%)	0.52% (0.41%)	0.22% (0.54%)	8.65%* (0.81%)

Table IV
DGTW performance measure of a mimicking portfolio

We report the CS returns of a mimicking portfolio that holds the same stocks in a mutual fund holdings report. We first sort mutual funds by current performances measured by alpha, and then sort by our consistency measure. From that point, we track monthly CS returns of the fund holdings for the next 1 year. CS measure is acquired by comparing the monthly returns of mutual fund holdings to the monthly returns of the benchmark portfolio. We report annualized CS return by sorted group. The number of observation per sorted group is around 1,000. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of the table. Significant differences in 5% level are marked with *, and standard errors of the differences are in the parentheses.

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best current Performance)
Consistency Rank 5 (Highest Consistency)	0.27%	1.12%	1.02%	1.27%	0.23%
Consistency Rank 4	0.39%	0.51%	0.58%	0.47%	-0.26%
Consistency Rank 3	0.39%	1.30%	0.11%	-0.52%	-0.52%
Consistency Rank 2	-0.71%	0.83%	-0.01%	-0.63%	-1.92%
Consistency Rank 1 (Lowest Consistency)	-0.81%	0.70%	0.24%	0.18%	-1.42%
Difference between Consistency 5 and Consistency 1 (High – Low)	1.08% (0.56%)	0.42% (0.37%)	0.78%* (0.39%)	1.09%* (0.45%)	1.65%* (0.61%)

Table V
Gap between the effective holdings date and the actual filing date

Our sample includes domestic, actively-managed equity mutual funds defined by the Thomson Financials Mutual Fund Stock Holdings Data for Sept 1, 2000 to July 31, 2009. The number of mutual funds in our sample is 1,380. We compute the time span from the report date to the filing date for our sample equity mutual funds. The report date is the effective date of the stock holdings of a mutual fund. If the report date is June 30, 2001, for example, the stock holdings of the mutual fund are effective as of that date. The filing date is the date when the holdings report is actually filed and becomes publicly available.

	Mean	Standard Deviation	25%	50% (Median)	75%
Gap between the report date and the filing date	35.5 days	46.2 days	0 days	0 days	90 days

Table VI
Performances of the sub-sample of funds that report their holdings promptly

In this table, we only use the holdings data that is released within 5 days after the effective holdings date. We first sort mutual funds by current performances measured by alpha, and then sort by our consistency measure. Carhart 4-factor alpha is the alpha of the 4^{th} holdings report released from the initial group formation date. We report monthly alpha by sorted group. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of the table. Significant differences in 5% level are marked with *, and standard errors of the differences are in the parentheses.

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best current Performance)
Consistency Rank 5 (Highest Consistency)	-0.60%	-0.56%	-0.23%	0.06%	1.32%
Consistency Rank 4	-0.61%	-0.54%	-0.28%	0.11%	0.88%
Consistency Rank 3	-0.69%	-0.51%	-0.30%	0.02%	0.51%
Consistency Rank 2	-0.66%	-0.45%	-0.33%	0.01%	0.61%
Consistency Rank 1 (Lowest Consistency)	-0.49%	-0.48%	-0.28%	0.13%	0.40%
Difference between Consistency 5 and Consistency 1 (High – Low)	-0.11% (0.06%)	-0.08% (0.05%)	0.05% (0.07%)	-0.07% (0.07%)	0.92%* (0.11%)

Table VII
Fund performances by our consistency measure during different periods (Alpha)

We separate our sample into three periods; Sept 1, 2000 ~ Dec 31, 2003, Jan 1, 2004 ~ Dec 31, 2006, and Jan 1, 2007 ~ Dec 31, 2009. We acquire Carhart 4-factor alpha of a holdings data by taking the weighted average of individual stock return alphas, using the holdings as the weight. The individual stock alphas are estimated using prior 125 business days' returns. We sort the fund alpha into quintiles every rolling year, and then within each performance quintile, we sort by one of our consistency measures. This gives us 5 x 5 = 25 groups. Within each sub-sample, we report equal-weighted average fund alphas of each group acquired from the 4th holdings report released after the date of initial group formation. The time difference between consistency measure calculation and alpha calculation is approximately 1 year. We convert the acquired alpha values to monthly scale. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of the table. Significant differences in 5% level are marked with *.

Sub-sample 1: Sept 1, 2000 to Dec 31, 2003

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Consistency Rank 1 (Highest Consistency)	-0.63%	-0.51%	-0.30%	0.20%	1.50%
Consistency Rank 2	-0.63%	-0.45%	-0.20%	0.24%	1.20%
Consistency Rank 3	-0.53%	-0.44%	-0.29%	0.13%	0.77%
Consistency Rank 4	-0.66%	-0.38%	-0.25%	0.12%	0.98%
Consistency Rank 5 (Lowest Consistency)	-0.44%	-0.32%	-0.22%	0.28%	0.77%
Difference between Consistency 5 and Consistency 1 (High – Low)	-0.19% (0.10%)	-0.18%* (0.07%)	-0.08% (0.08%)	-0.08% (0.12%)	0.73%* (0.20%)

(Table VII continues on the next page.)

(Table VII continues.)

Sub-sample 2: Jan 1, 2004 to Dec 31, 2006

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Consistency Rank 1 (Highest Consistency)	-0.88%	-0.77%	-0.61%	-0.29%	1.06%
Consistency Rank 2	-0.81%	-0.78%	-0.48%	-0.24%	0.50%
Consistency Rank 3	-0.83%	-0.64%	-0.45%	-0.25%	0.41%
Consistency Rank 4	-0.80%	-0.66%	-0.49%	-0.25%	0.27%
Consistency Rank 5 (Lowest Consistency)	-0.75%	-0.69%	-0.57%	-0.27%	0.16%
Difference between Consistency 5 and Consistency 1 (High – Low)	-0.13%* (0.06%)	-0.08% (0.05%)	-0.04% (0.07%)	-0.02% (0.06%)	0.90%* (0.12%)

Sub-sample 3: Jan 1, 2007 to Dec 31, 2009

	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Consistency Rank 1 (Highest Consistency)	-0.24%	-0.23%	0.05%	0.21%	1.26%
Consistency Rank 2	-0.41%	-0.34%	-0.07%	0.26%	0.76%
Consistency Rank 3	-0.53%	-0.44%	-0.14%	0.05%	0.52%
Consistency Rank 4	-0.41%	-0.36%	-0.25%	0.00%	0.43%
Consistency Rank 5 (Lowest Consistency)	-0.39%	-0.46%	-0.25%	0.06%	0.27%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.17% (0.14%)	0.23%* (0.10%)	0.30%* (0.09%)	0.15% (0.11%)	0.99%* (0.14%)

Table VIII
Mutual fund expense ratios and fees

Our sample includes domestic equity mutual funds defined by the Thomson Financials Mutual Fund Stock Holdings Data for Sept 1, 2000 to Dec 31, 2009. We first rank funds into quintiles by their current fund performances (Carhart 4-factor alpha) each rolling year and then rank them by our consistency measure m_1. This process produces a 5 x 5 matrix. For each group, we report the average expense ratio and management fees acquired from CSRP Mutual Fund Data. The difference between the highest consistency rank and the lowest consistency rank is reported at the bottom of each panel. Significant differences in 5% level are marked with *.

Panel A: Expense Ratios					
	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Consistency Rank 1 (Highest Consistency)	1.34%	1.23%	1.25%	1.31%	1.57%
Consistency Rank 2	1.38%	1.25%	1.30%	1.33%	1.49%
Consistency Rank 3	1.34%	1.20%	1.28%	1.30%	1.49%
Consistency Rank 4	1.35%	1.23%	1.32%	1.35%	1.55%
Consistency Rank 5 (Lowest Consistency)	1.55%	1.24%	1.31%	1.42%	1.80%
Difference between Consistency 5 and Consistency 1 (High – Low)	-0.19%* (0.07%)	-0.01% (0.03%)	-0.06%* (0.02%)	-0.09%* (0.03%)	-0.23% (0.13%)

(Table VIII continues on the next page.)

(Table VIII continues.)

Panel B: Management Fees					
	Performance Rank 1 (Worst Current Performance)	Performance Rank 2	Performance Rank 3	Performance Rank 4	Performance Rank 5 (Best Current Performance)
Consistency Rank 1 (Highest Consistency)	0.73%	0.68%	0.69%	0.72%	0.87%
Consistency Rank 2	0.64%	0.68%	0.75%	0.76%	0.82%
Consistency Rank 3	0.72%	0.63%	0.69%	0.76%	0.81%
Consistency Rank 4	0.73%	0.67%	0.75%	0.78%	0.80%
Consistency Rank 5 (Lowest Consistency)	0.70%	0.68%	0.73%	0.76%	0.80%
Difference between Consistency 5 and Consistency 1 (High – Low)	0.03% (0.03%)	0.00% (0.02%)	-0.04%* (0.02%)	-0.04%* (0.02%)	0.07%* (0.03%)