

Opening the Box on the Stock Selection Skills of US Mutual Funds

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Abstract: This paper uses the hit rate, the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon, as a proxy for stock selection skill. We find that the average fund in our sample would have achieved a higher hit rate by holding the stocks of the benchmark portfolio, and that many of the active investment decisions made by fund managers actually decrease their realised hit rate. We find that the hit rate is closely related to contemporaneous fund performance, and has some predictive power of future fund performance.

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As at August 2014, the total amount invested in US equity mutual funds was in excess of \$8 trillion, with more than \$5 trillion of this figure invested in actively managed funds. Furthermore, the amount invested in active funds continues to grow, with these funds receiving an inflow approaching \$100 billion in 2013¹. Based on the fact that the fees associated with investing in an active fund are roughly 100 basis points per year, compared to passive funds with fees of roughly 20 basis points per year, it would appear that investors in US equities pay around \$40 billion a year in the hope of beating the market².

The reason why so many investors are motivated to invest in actively managed US equity mutual funds is puzzling, given that the bulk of evidence in the literature suggests that these funds cannot outperform the market, especially after account is taken of their fees³. Another puzzling feature of the fund management industry is that a great deal of this annual fee income of \$40 billion ends up in the pocket of those who are employed to deliver this seemingly disappointing performance to their clients. The focus of this paper is on whether there is any evidence to suggest that such handsomely rewarded fund managers have any skill.

There are two important aspects of the equity investment process; (i) stock selection and (ii) portfolio construction. Of these, stock selection is by far the major focus of active fund manager activity, yet it has been the subject of relatively little academic analysis, with attention being largely focussed on portfolio returns. Of the studies that do examine the stock selection skill of managers, there is evidence to suggest that this is an area in which fund managers do have skill. For example, Wermers (2000) finds that the stock selection skill of the average active mutual fund manager accounts for outperformance of the fund's characteristic benchmark by 70 basis points per year. Kosowski et al. (2006) find that while the average active manager does not select stocks well enough to cover their fees, there are a minority of managers with superior stock selection skill who are able to add value after accounting for fees. More recently, Cohen, Polk and Silli (2010) and Yeung et al. (2012) find that the stocks in which fund managers display the highest conviction do realise significant outperformance.

In this paper, we attempt to lift the lid on the stock selection skill of US equity mutual fund managers. We employ a measure that is widely used in the mutual fund industry, the manager's hit rate, as a measure of stock selection skill. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. Given that the aim of the fund is to outperform its benchmark, it is obvious that this can only be achieved if the fund's portfolio includes stocks that yield a rate of return greater than would be realised by purchasing all the stocks in the fund's benchmark portfolio. For example, if all the stocks in the fund's portfolio underperform the return of the fund's benchmark index, then the

¹ Data from Investment Company Institute August 2014.

² Data from Investment Company Institute 2014.

³ Studies which examine active fund performance are discussed in the literature review in Section I.

portfolio must underperform the benchmark portfolio, irrespective of the weights assigned to each stock. The greater the percentage of stocks that outperform, i.e. the higher the hit rate, the more likely it is that the fund's portfolio will outperform the benchmark index. Hence, the importance of a manager's stock selection skill as measured by their hit rate in facilitating the fund outperforming its benchmark.

We examine the hit rates of actively managed US equity mutual funds from 1995 to 2012, and find that the average hit rate of the samples varied between 47.0% and 49.6%, depending on the time horizon over which the hit rate was calculated. These average hit rates are interesting and somewhat surprising as they are less than 50%, which is the hit rate that it is tempting to assume would be realised if stocks were selected randomly i.e. in the absence of stock selection skill. We also calculate the hit rates achieved by the benchmark indices, and find that on average these are also less than 50%. This demonstrates that a hit rate of 50% is not the appropriate hurdle against which to judge a manager's stock selection skill, as on average over half of the stocks included in the benchmark index underperform the benchmark return. Rather, to examine whether the active decisions made by the funds in the sample increase or decrease hit rates, we also calculate each fund's excess hit rate, the hit rate of the fund minus the hit rate of the fund's benchmark index. We find that only 42.45% of managers achieve a higher hit rate than their benchmark, with the typical manager underperforming by 1.76%. This is bad news for the stock selection skill of managers, as it suggests that the average fund in the sample would have achieved a higher hit rate by simply holding all of the stocks of the benchmark portfolio. However, the excess hit rates realised by managers do vary by the style and size objective of the fund, with small cap and value funds achieving higher excess hit rates than large cap and growth funds.

Of course, a high hit rate does not necessarily translate into a higher return, as the stocks which underperform the benchmark index may be weighted heavily in the fund's portfolio, therefore undoing the benefits of a high hit rate. In order to examine the relationship between hit rates and fund performance, we calculate both the contemporaneous and future performance of portfolios formed based on hit rate ranking. We find a strong contemporaneous relationship between hit rates and portfolio performance, evidenced by the fact that the funds ranked in the top quartile portfolio by their hit rates outperform those ranked in the bottom quartile portfolio by 10.8% annually. We also find that there is a relationship between hit rates and future fund performance, with the portfolio with the highest hit rates outperforming the portfolio with the lowest hit rates by 1.7% to 2.5% annually, depending on the number of portfolios formed.

Finally we use regression analysis to examine the impact that many of the active investment decisions made by fund managers have on their hit rates. We turn to the recent literature that has identified a number of active decisions that are highly correlated with fund performance. We include measures of these active decisions along with a number of control variables in a model to explain fund hit rates. We find that these variables have significant explanatory power over empirical hit rates and interestingly, our findings suggest that many of the active decisions made by managers actually decrease their realised

hit rate. This is consistent with our finding that the average manager in our sample would have achieved a higher hit rate by holding the stocks of the benchmark portfolio. When we examine the difference in the impact of the active decisions on hit rates in strong market years compared to weak market years, we find that the active decisions made by managers tend to impact their hit rates more negatively during weak markets. Overall, we find that the active investment decisions which increase hit rates in both strong and weak market years are a higher incidence of the *active weight* of Doshi, Elkamhi and Simutin (2014), *selectivity* of Amihud and Goyenko (2013), and both *positive* and *negative book-to-market (BTM) tilt* of Bird, Pellizzari and Yeung (2014). The active decisions which decrease hit rates in both strong and weak market years are a higher incidence of the *active share* of Cremers and Petajisto (2009), and both *positive* and *negative size tilt* of Bird, Pellizzari and Yeung (2014), as well as a lower incidence of *herding* of (Jiang and Verardo (2013).

The remainder of the paper is structured as follows. Section I contains the background and literature review to our study, Section II describes the data and methodology used in the paper, Section III contains our empirical results, while Section IV concludes.

I. Background and Literature Review

The debate on whether actively managed mutual funds add value over passively managed funds begun in the 1960s with the introduction of risk-adjusted performance measures⁴. Probably the most widely quoted and referenced paper in this area, Jensen (1968) finds that mutual funds do not outperform the market, concluding that both average fund performance and individual fund performance is no better than random. Later literature on the performance of mutual funds has been extensive and somewhat mixed, but the literature has tended to arrive at the same conclusion: on average after fees, active funds do not outperform their benchmarks. To quote just a few examples⁵; Gruber (1996) found that from 1985 to 1994, the return of the average actively managed mutual fund underperformed passive market indices by approximately 65 basis points per year. A year later, Carhart (1997) demonstrated that a fund's net returns are negatively correlated with the fund's expense ratio, which are in general higher for actively managed funds than passive funds. More recently, Barras, Scaillet and Wermers (2010) demonstrate that net of expense fees, the average mutual fund exhibits zero alpha, while Fama and French (2010) use bootstrap simulations to show that the net returns of the average mutual fund underperform CAPM, three factor and four factor benchmarks by approximately the amount equal to the expense fee of the fund.

Of course, the finding that actively managed funds as a group underperform their benchmarks does not rule out the possibility that there are individual funds that consistently

⁴ See Jensen (1968) Sharpe (1966) Treynor (1965)

⁵ Other studies include: Grinblatt and Titman (1989); Elton et al. (1993); Hendricks, Patel and Zeckhauser (1993); Brown and Goetzmann (1995); Malkiel (1995); Ferson and Schadt (1996); Daniel et al. (1997); Zheng (1999); Baks, Metrick and Wachter (2001); Carhart et al. (2002); Kosowski et al. (2006). This list is not exhaustive; rather it includes some of the other widely referenced studies on the performance of mutual funds.

outperform the market. Studies on performance persistence focus on whether the past performance of individual funds can be used to predict their future performance. In summary, the majority of these studies now conclude that there is not sufficient evidence of long-term performance persistence in mutual funds. While initial studies from the early 1990s found signs of persistence in fund performance, for example Grinblatt and Titman (1992); Hendricks, Patel and Zeckhauser (1993); Goetzmann and Ibbotson (1994); Elton, Gruber and Blake (1995); Brown and Goetzmann (1995) and Gruber (1996), later papers find that the evidence is weak for long-term persistence, and that most signs of persistence found in the earlier studies can be explained by survivorship bias and momentum strategies (see Daniel et al. (1997); Wermers (1997); Carhart (1997); Bollen and Busse (2005) and Busse, Goyal and Wahal (2010)).

The empirical evidence that the average active fund underperforms its benchmark, and that individual funds do not consistently outperform, suggests that investors in mutual funds would be well advised to delegate their funds to passively managed mutual funds. As mentioned in the introduction, what is puzzling is that investors have not withdrawn their investments from active funds, and in fact continue to invest despite these disappointing findings. One of the strangest aspects of this active management puzzle is that the fund managers in charge of active funds are highly paid despite the fact that the funds which they manage do not outperform passively managed funds. As Berk (2005) points out; 'in a competitive market, people can earn economic rents only if they have a skill that is in short supply'. In this light, to justify the fees paid to active fund managers, it is necessary that these managers have skill. There has been some evidence of manager skill in the literature, for example Fama and French (2010) find that although the average actively managed fund underperforms, there are a small proportion of funds which have sufficient skill to cover their costs, while stronger evidence is found by Berk and Van Binsbergen (2012), who conclude that the average mutual fund manager has skill and that this skill persists.

Studies which directly examine whether fund managers exhibit stock selection skill are mixed in concluding whether the average active manager demonstrates stock selection skill; however, overall most studies find evidence that there are at least some managers with superior stock selection skill (Wermers, 2000; Kosowski et al., 2006; Cohen, Polk and Silli, 2010; Yeung et al., 2012). Daniel et al. (1997) develop characteristic-based benchmarks to evaluate mutual fund performance, and find that the average mutual fund has enough stock selection skill to outperform the fund's benchmark by approximately the expense fee of the fund. Examining mutual fund trades, Chen, Jegadeesh and Wermers (2000) find that for the year following the trade, stocks bought by active funds achieve returns of around 200 basis points higher than the stocks they sell. In a similar spirit, Baker et al. (2010) study the trades made by mutual funds before earnings announcements and find that the stocks recently bought by the fund outperform the stocks recently sold around the next earnings announcement.

The other area of literature relevant to our study is the recent work which examines the relationship between the active investment decisions made by fund managers and fund

performance. The papers in this area have developed variables which capture the active decisions made by funds, and these decisions have been found to be closely related to fund performance. The variables capture active decisions by calculating deviation from a benchmark portfolio or common factors (Cremers and Petajisto (2009); Doshi, Elkamhi and Simutin (2014); Amihud and Goyenko (2013)), the concentration of a fund's portfolio across industries (Kacperczyk, Sialm and Zheng (2005)), the unobserved skill of manager trading (Dyakov (2012)), the tendency to follow trading decisions (Jiang and Verardo (2013)) and the style tilt of the fund's portfolio (Bird, Pellizzari and Yeung (2014)). The background to these studies and the calculation of the variables are outlined in further detail in the Appendix. In our analysis, we examine how these active decisions, the majority of which have been found to increase fund performance, relate to the hit rate. The active decisions which have been found to actually decrease fund performance are a number of the style tilts in Bird, Pellizzari and Yeung (2014); namely *positive BTM tilt*, *negative momentum tilt*, *negative size tilt* and *positive size tilt*. Several instances have been found where the relationship of the active decision to fund performance changes with either management style and / or the state of the market. For example, the *active share* of Cremers and Petajisto (2009) is typically positively related to fund performance, however this becomes negative for growth managers during periods when markets are weak (Bird, Pellizzari and Yeung (2014)).

II. Data and Methodology

A. Data

Our sample includes all active, long only US equity mutual funds from 1995 to 2013. We derive most of the fund information from the CRSP (Centre for Research in Security Prices) Survivor-Bias-Free US Mutual Fund Database, with the exception of the quarterly fund holdings data, which is obtained from Thomson Reuters S12 Mutual Fund Holdings. We make use of MFLINKS to combine information from these two databases. For stock level information, we utilise both the CRSP and CRSP/Compustat Merged Database (CCM) for returns and accounting information respectively. The quarterly fund holdings data gives us a snapshot of the stocks in each fund's portfolio every quarter, allowing us to calculate the hit rate of each fund. The data on the 18 benchmark index constituents is obtained from Russell and Standard and Poors, in order to determine the value-weighted return of the benchmark index.

One of the key areas of our study is to examine how the active investment decisions of fund managers impact on their hit rates. To this end we calculate the 12 active investment decisions that are described in the Appendix, which have been shown to be positively related to fund performance. The additional data required to calculate these 12 variables comes from a number of sources. To calculate the *industry concentration* measure of Kacperczyk, Sialm and Zheng (2005), we obtain industry classification data from CRSP. We make use of the CDA/Spectrum institutional holdings database, which collects the 13F filings by institutional investors, to replicate the *herding* measure of Jiang and Verardo (2013). Finally, we obtain the data for the ten benchmark factors used to calculate the *selectivity* measure of Amihud and Goyenko (2013) from DataStream and the Kenneth

French data library. Our final dataset includes 158,800 observations from a total of 4,156 funds.

B. Methodology

The methodology followed in this paper is conducted in three steps; we (i) calculate empirical hit rates, (ii) investigate the relationship between hit rates and fund performance and (iii) examine the impact which the active decisions made by managers have on the hit rate.

B.1. Assigning each Fund a Benchmark Index

Our measure of stock selection skill, the hit rate, is calculated as the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. By definition, an essential step prior to calculating hit rates is to assign an appropriate benchmark index to each fund in our sample.

We follow the method of Cremers and Petajisto (2009), which was refined by Yeung et al. (2012). The method assigns one of 18 benchmark indices to each fund in the sample on the basis of it being the index which most closely resembles the holdings of the fund's portfolio over the sample period. This method is based on the measure *active share*, one of the active decisions we examine in the regression analysis. Each quarter, we determine which of the 18 benchmark indexes produces the lowest *active share* (i.e. the index whose constituents are closest to the holdings of the fund). Then, for the whole sample period, the benchmark index is assigned which produces the lowest *active share* in the greatest number of quarters⁶.

This method has the advantage of assigning the index closest to the fund's holdings over the sample period, while at the same time maintaining a single benchmark index over the life of the fund. We have not used the benchmark index which is self-declared by each fund, as this may lead to a bias, an issue discussed in Sensoy (2009) who remarks "almost one-third of actively managed, diversified U.S. equity mutual funds specify a size and value/growth benchmark index in the fund prospectus that does not match the fund's actual style." This issue is also discussed in Chan, Chen and Lakonishok (2002). In Table I we list the 18 benchmark indices and provide some statistical details on each.

⁶ For more details on the approach used to assign a benchmark index, see Yeung et al. (2012)

Table I
Benchmark Indices Descriptive Statistics

This table outlines descriptive statistics for the 18 indices used as benchmark portfolios for the funds in our sample. Following Yeung et al. (2012), each fund in the sample is assigned the benchmark index which produces the smallest *active share* in the greatest number of quarters. Columns one to four report details on the return and the hit rate of each index. Column five and column six report the size and style objective of each index, respectively. No. of observations refers to the number of fund quarters with the benchmark index.

Index Name	Average Monthly Return	Standard Deviation of Monthly Return	Average Index 12 Month Hit Rate	Standard Deviation of Index Hit Rate	Size Objective	Style Objective	No. of Observations
Russell 1000	0.76%	4.61%	49.00%	10.31%	Large	Neutral	1083
Russell 1000 Growth	0.69%	5.35%	48.80%	10.40%	Large	Growth	8248
Russell 1000 Value	0.81%	4.48%	49.30%	9.12%	Large	Value	3925
Russell 2000	0.76%	5.86%	45.70%	7.20%	Small	Neutral	1250
Russell 2000 Growth	0.62%	7.12%	46.30%	9.93%	Small	Growth	23636
Russell 2000 Value	0.88%	5.08%	44.50%	4.34%	Small	Value	17642
Russell Midcap	0.93%	5.06%	46.00%	6.90%	Middle	Neutral	505
Russell Midcap Growth	0.85%	6.62%	46.70%	7.84%	Middle	Growth	14097
Russell Midcap Value	0.96%	4.79%	45.50%	4.78%	Middle	Value	6360
S&P 400	1.07%	5.22%	45.70%	8.35%	Middle	Neutral	2790
S&P 400 Growth	1.34%	6.36%	43.80%	9.11%	Middle	Growth	6213
S&P 400 Value	0.99%	5.28%	46.90%	6.00%	Middle	Value	4444
S&P 500	0.75%	4.55%	49.80%	11.62%	Large	Neutral	27711
S&P 500 Growth	0.76%	4.77%	48.30%	10.17%	Large	Growth	11478
S&P 500 Value	0.74%	4.75%	51.10%	11.41%	Large	Value	5808
S&P 600	0.94%	5.60%	44.70%	5.47%	Small	Neutral	2894
S&P 600 Growth	0.88%	6.13%	45.60%	7.89%	Small	Growth	12850
S&P 600 Value	0.95%	5.45%	43.80%	5.60%	Small	Value	7866

B.2. Calculating the Hit Rate

The hit rate is calculated as the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over the specified time horizon. For example, if a fund holds ten stocks in its portfolio, and six of these stocks outperform the return of the benchmark index over the time horizon, then the hit rate is 0.60, or 60%. We calculate each fund's hit rate over four different time horizons – one month, three month, six month and 12 month, in order to examine the impact of the time horizon on the distribution of hit rates.

Hit rates are calculated as follows. For each stock in the fund's portfolio at the release of the quarterly holdings, the return of the stock over the next X months (where X is the time horizon the hit rate is calculated over) is compared to the value-weighted return of the benchmark index over the same period. If the return of the stock is greater than the return of the benchmark index, then the stock outperformed the benchmark and a one is assigned to

that stock. On the other hand, if the stock return is less than the benchmark index return, a zero is assigned to the stock. This is done for each stock in the fund's portfolio. The hit rate is then calculated as the average number of one's (hits) divided by the total number of stocks (hits plus misses).

A particular advantage of using the hit rate as a measure of stock selection skill is that it is calculated looking forward, as the return of the stock and the return of the benchmark index are calculated over the time horizon following the release of the quarterly holdings. It cannot be manipulated by the fund selling the stocks which have achieved a low return just prior to the release of the quarterly fund holdings in order to increase their hit rate.

B.3. Relationship between Hit Rates and Fund Performance

Our second area of analysis examines the relationship between hit rates and fund performance. We measure the contemporaneous performance of portfolios formed based on hit rate ranks. Abnormal performance measures fund performance, and is calculated as follows;

$$\text{Abnormal Performance}_{i,t} = \text{Fund Return}_{i,t} - \text{Return of Fund's Benchmark Index}_{i,t} \quad (1)$$

To examine if the funds which achieve the highest hit rates also achieve the highest performance in the same quarter, we calculate the contemporaneous performance of portfolios formed based on hit rate ranks. At the beginning of each quarter we rank all funds in the sample by their 12 month hit rates and form four quintile portfolios based on these rankings. We then calculate the equally weighted contemporaneous abnormal performance achieved by each of the four portfolios. We anticipate that the portfolios with the highest hit rates will achieve the highest abnormal returns.

B.4. Regression Analysis: the Impact of Active Investment Decisions on Hit Rates

Our third area of analysis uses regression analysis to examine the impact that the active investment decisions made by fund managers have on their hit rates. A number of studies have developed variables which capture these active decisions, and they have been found to be closely related to fund performance. The reason that we use these variables is to determine which active decisions positively impact hit rates, and which of the decisions actually decrease hit rates. We run regressions where we use each fund's hit rate as the dependent variable against which we regress the 12 active investment decisions that we have identified and discussed in detail in the Appendix: *active share, active weight, selectivity, industry concentration, return gap, herding, negative BTM tilt, positive BTM tilt, negative momentum tilt, positive momentum tilt, negative size tilt and positive size tilt.*

The relationship between these 12 variables and the hit rate has not been previously examined, and therefore the impact that the active decisions have on the hit rate is uncertain. There is no reason why the sign of the relationship found between these variables and performance will be maintained when we examine their impact on the hit rate. In theory, the stocks bought by funds which deviate from the benchmark portfolio should be bought on the belief that the stock will earn a return higher than the return of the benchmark. In line with this theory, all active decisions made by managers should increase the hit rate of the fund. Our intuition is therefore that each of the variables will have a positive impact on hit rates. In Section III we see that many of the active decisions in fact decrease hit rates.

We include as control variables a number of fund characteristics which have been found to be associated with fund performance: *turnover*, *fees*, *size*, *age*, *past fund flows*, *past returns* and *benchmark return*⁷. These controls are the same as those used in the analysis in Yeung et al. (2012). By including these variables in the regressions, we control for the cross-sectional differences between funds that may be related to the hit rate.

A quarterly time fixed effect dummy is included for each quarter (besides one of the quarters to avoid multicollinearity). Including time fixed effects controls for unobserved heterogeneity over time, which may be correlated to the explanatory variables of the model. Our basic regression for multivariate analysis is as follows:

$$\text{Hit Rate}_{i,t} = \alpha_i + \sum_{j=1}^{12} b_j \text{Active Decision}_{i,j,t-1} + \sum_{j=13}^{20} c_j \text{Control Variable}_{i,j,t-1} + \text{Quarterly Fixed Effects} + e_{i,t} \quad (2)$$

Hit Rate_{*i,t*} is the hit rate for fund *i* at time *t*

Active Decision_{*i,j,t-1*} is the value for active decision *j* for fund *i* at time *t* – 1

Control Variable_{*i,j,t-1*} is the value for control variable *j* for fund *i* at time *t* – 1

There is evidence in the literature that active funds are best able to add value during periods of weak market performance (Moskowitz (2000), Kosowski (2006) and Glode (2011)), which suggests that the success of the active decisions made by managers may vary throughout the market cycle. We investigate if this true in our study by examining whether the relationship between the active decisions and hit rates are different in strong market years compared to weak market years. We do this by running a separate regression, equation (3), which includes an interaction term between each of the 12 active decisions and a dummy variable *bad year*, which indicates whether the observation comes from a year in which the market performed poorly. We define a ‘bad year’ as a year when the return of the S&P 500 was less than the annualised return of the three month Treasury bill. Over the sample period 1995 to 2012, there are a total of 40 strong market quarters and 32 weak

⁷ *Turnover* is the turnover for fund *i* at time *t*, *fees* is the expense ratio of fund *i* at time *t*, *size* is the natural log of the fund’s net tangible assets at time *t*, *age* is the age in years of fund *i* at time *t*, *past fund flows* is the quarterly inflow of fund *i* in the six months prior to time *t*, *past returns* is the excess return of fund *i* in the half year prior to time *t*, *benchmark return* is the benchmark index return of fund *i* at time *t*.

market quarters. If the coefficient of the active decision is different in strong market years than in weak market years, then the decision has a different average effect on hit rates in years when the market performs well compared to years when the market performs poorly. The regression is as follows;

$$\text{Hit Rate}_{i,t} = \alpha_i + \sum_{j=1}^{12} b_j \text{Active Decision}_{i,j,t-1} + \sum_{j=1}^{12} d_j \text{Active Decision}_{i,j,t-1} * \text{Bad Year Dummy}_t + \sum_{j=13}^{20} c_j \text{Control Variable}_{i,j,t-1} + \text{Quarterly Fixed Effects} + e_{i,t} \quad (3)$$

The coefficient of each active decision in strong market years is the standalone coefficient of the decision, b_j . The coefficient of each active decision in weak market years is the stand alone coefficient b_j , plus the coefficient d_j of the interaction term between the *bad year* dummy variable and the active decision.

III. Results

In this section, we present the empirical results of our study. First, we calculate and examine the distribution of the empirical hit rates of our sample. We then examine the relationship between hit rates and fund performance. Finally, we examine the impact which the active decisions made by managers have on their realised hit rates.

A. Empirical Hit Rates

In this subsection, we calculate and examine the distribution of the empirical hit rates of the sample. We then calculate the hit rates of the 18 benchmark indices and subsequently the excess hit rates of each fund. Finally, we examine the differences in the hit rates achieved by the style and size objective subsets of the sample, and the differences in hit rates during strong and weak market years.

A.1. Hit Rates of the Sample

In Table II we present the descriptive statistics for the hit rates achieved by the sample, which provides insight into the distribution of the hit rates over the four time horizons. We find that the average hit rate decreases, and the standard deviation of hit rates increase, as the time horizon which the hit rate is calculated over increases. The average one month hit rates are 49.63%, and decrease to 47.02% over a 12 month time horizon. A key take away from this table is that the average hit of the sample, for all time horizons, is less than 50%. At first glance, this is somewhat surprising as it is tempting to believe that if a fund selected stocks completely at random, in the absence of any stock selection skill, half of the stocks would by chance achieve a hit rate greater than the return of the benchmark index, and the fund would realise a hit rate of 50%. We will shortly see that this presumption is wrong and 50% is not an appropriate benchmark to use when assessing a manager's stock selection skills.

Table II
Descriptive Statistics: Hit Rates

This table presents descriptive statistics for the hit rates achieved by the sample. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. The sample includes all long only active US equity Mutual funds from 1995 to 2012. The sample includes 158,800 observations. All numbers reported are percentages.

	Mean	Median	Standard Deviation
1 month (%)	49.63	49.69	8.45
3 month (%)	49.35	49.33	8.73
6 month (%)	48.45	48.40	9.10
12 month (%)	47.02	46.88	9.72

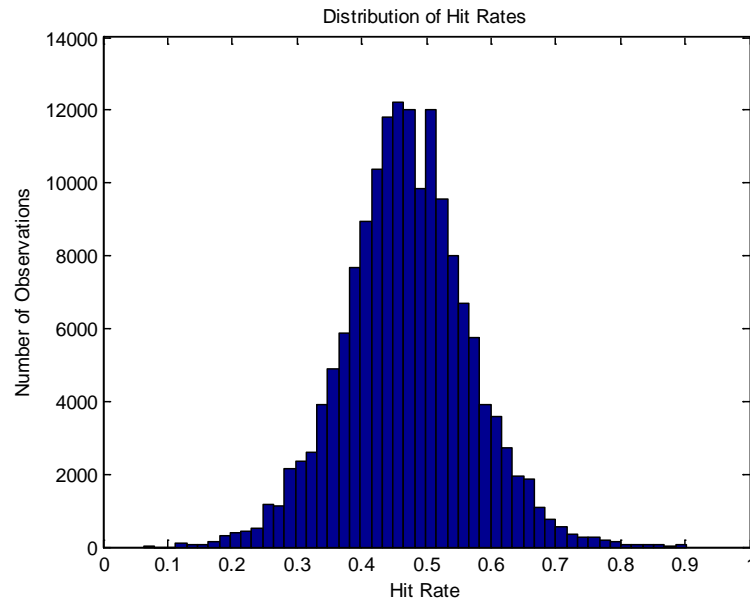
We have calculated the empirical hit rates of the sample over four time horizons; one month, three month, six month and 12 month. The average fund turnover of the sample is 0.98, which makes the average holding period over the sample of funds 1.02 years. As a result, the 12 month hit rate is measured over the time horizon which is closest to the typical holding period of the funds in the sample. Hit rates calculated over the funds' holding period should be the best measure of fund manager stock selection skill, as funds select stocks they expect to outperform over the period that the fund holds the stock in its portfolio. As a consequence, for the remainder of the paper, we will concentrate our attention on analysing the hit rates calculated for a 12 month holding period⁸. Figure 1 displays a histogram of the hit rates achieved by the sample over a 12 month time horizon, illustrating the dispersion in the hit rates achieved by the sample⁹. The average hit rate for each quarter of the sample period is not reported. However, we examine if there was an increase or a decrease in hit rates from 1995 to 2012, and find that there is no trend in the fluctuation of hit rates through time.

⁸ We have also undertaken the analysis for the hit rates over the other three time horizons, and the results are consistent with those reported in the paper.

⁹ Applying the Lilliefors test, we found the distribution of hit rates to be non-normal.

Figure 1
Distribution of Hit Rates

This figure displays the distribution of the 12 month hit rates of the sample. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. The sample includes all long only active equity US mutual funds from 1995 to 2012. The mean of the distribution is 47.02%, standard deviation is 9.72%, the skewness is 0.1084 and the kurtosis is 3.6623. The sample includes 158,800 observations.



A.2. Hit Rates of the Benchmark Indices and Excess Hit Rates

We next examine whether the active stock selection decisions made by managers in deviating from the holdings of the benchmark portfolio tend to increase or decrease the hit rates that they achieve. In order to arrive at a conclusion on this issue it is necessary to determine what the hit rates of the sample would have been if the funds had not made active stock selection decisions, and instead simply held the stocks in the benchmark portfolio. To do this, we calculate the hit rates of the 18 benchmark indices, and then calculate the excess hit rates of the sample: the hit rate achieved by the fund minus the hit rate of the fund's benchmark index. This is valid for two reasons. Firstly, the constituents of the benchmark index are formed based on an objective rules, and so do not include active decisions. Second, active stock selection involves excluding stocks from the fund's portfolio that are included in the benchmark portfolio, or including stocks in the fund's portfolio that are not included in the benchmark portfolio. By comparing the hit rate of the fund's portfolio with that of the benchmark portfolio, we are able to gauge the ability of the manager to identify stocks that outperform the benchmark portfolio. Of course, the absence of active stock selection decisions does not preclude a manager changing the weights of the stocks and so making active portfolio construction decisions.

The hit rate of each benchmark index is calculated using the same method as the calculation of the hit rate for each fund; the return of each stock in the benchmark portfolio

is compared to the overall value-weighted return of the benchmark portfolio. The average hit rate of each benchmark index is reported in column three of table I. What is interesting is that the average hit rate of each benchmark index, except the S&P 500, is less than 50%. This means that on average, fewer than half of the stocks in the benchmark index achieved a return greater than the return of the benchmark portfolio. We have already seen that the hit rate distribution is positively skewed and so this finding reflects that the average stock return exceeds the median return. However, it is more complicated than that as the index portfolios are market value weighted and so the finding might reflect that the larger cap stocks outperform the smaller cap stocks.

The reason behind the finding aside, what we are able to conclude is that 50% is not the appropriate hurdle to evaluate the absolute hit rate of a fund against; as if a fund randomly includes a stock from the benchmark index in its portfolio, the probability of the stock obtaining a return greater than that of the benchmark portfolio is less than 50%¹⁰. Rather, the appropriate hurdle is the hit rate of the benchmark portfolio, which is the hit rate that a manager would achieve if they simply held the stocks in the benchmark index. Thus, the excess hit rate for each fund is then calculated as follows;

$$\text{Excess Hit Rate}_{i,t} = \text{Fund Absolute Hit Rate}_{i,t} - \text{Fund's Benchmark Index Hit Rate}_{i,t} \quad (4)$$

Table III
Descriptive Statistics: Excess Hit Rates

This table reports descriptive statistics for the 12 month excess hit rates of the sample. The excess hit rate is calculated as the hit rate the fund achieved, minus the hit rate achieved by the fund's benchmark over the same time horizon. % Positive reports the percentage of excess hit rates which are greater than 0. The sample includes all long only active US equity Mutual funds from 1995 to 2012. The sample includes 158,800 observations. All numbers reported are percentages.

	Mean	Median	Standard Deviation	% Positive
Excess Hit Rate	-1.76	-1.30	8.73	42.45

Table III reports that the average excess hit rate is negative; the typical fund achieves a hit rate which is 1.76% lower than the hit rate of the respective benchmark index¹¹. This is not good news for the stock selection skill of actively managed funds, as it demonstrates that the average fund in our sample would have achieved a higher absolute hit rate without making any active stock selection decisions and simply holding the stocks in the benchmark portfolio. Consequently, this finding suggests that the active stock selection decisions made by managers, on average, decrease the hit rate realised by the fund. Of course, this is not true for all funds, as we find that 42.45% of funds achieve a hit rate greater than that of their

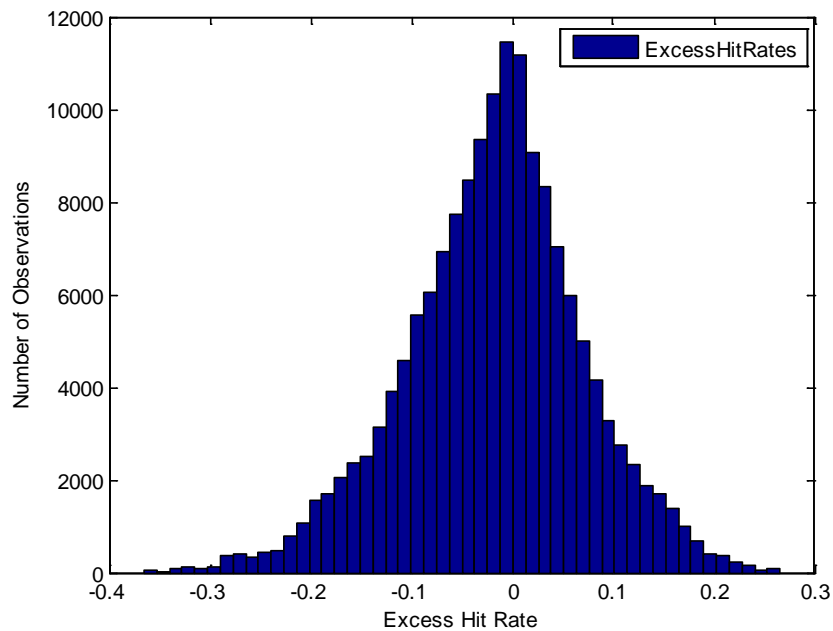
¹⁰ Absolute hit rate refers to the hit rates of the sample calculated in Table II.

¹¹ Whilst we report excess hit rates as percentages, the average excess hit rate of 1.76% should be interpreted as the average fund hit rate being 0.0176 lower than the hit rate of the benchmark index, not 1.76% lower than the benchmark index.

benchmark index. Figure 2 displays the distribution of the excess hit rates of the sample, which we see is slightly negatively skewed¹². Again the Lilliefors test rejects the null hypothesis that excess hit rates come from a normal distribution, however observing Figure 2 we see that as with hit rates, the excess hit rates generally follow a bell-shaped distribution.

Figure 2
Distribution of Excess Hit Rates

This figure displays the distribution of the 12 month excess hit rates of the sample. The excess hit rate for each fund is calculated as the hit rate the fund achieved, minus the hit rate achieved by the fund's benchmark over the same time horizon. The mean is -1.76%, the standard deviation is 8.86%, the skewness is -0.1579 and the kurtosis is 3.2474. The sample includes 158,800 observations.



A.3. Hit Rates by Style and Size Objective

We next examine the extent to which the hit rates achieved by the sample are related to the investment style objective and capitalisation focus of each fund. To do this we sort the sample of funds by both their investment style and size objective, based on the characteristics of their benchmark index, which are reported in column five and six of Table I. For example, the subsample of growth funds contains all funds which have a growth benchmark index (Russell 1000 Growth, Russell 2000 Growth, Russell Midcap Growth, S&P 400 Growth, S&P 500 Growth, S&P 600 Growth). The results are presented in Table IV.

¹² Applying the Lilliefors test, we find the distribution of excess hit rates to be non-normal.

Table IV**Descriptive Statistics: Size and Style Objective Subsamples**

This table reports descriptive statistics for the hit rate and excess hit rate of the size and style objective subsets of the sample. Each fund in the sample is assigned to both a style and a size objective based on the size and style objective of the fund's benchmark index. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. The excess hit rate is the hit rate achieved by the fund minus the hit rate achieved by the fund's benchmark over the same time horizon. % positive reports the percentage of excess hit rates which are greater than zero. Number of observations refers to the number of fund level observations included in the subsample.

Objective	Absolute Hit Rate	Excess Hit Rate	% Positive	No. of Obs
Whole Sample	47.02%	-1.76%	42.49%	158,800
Growth Style	45.87%	-2.15%	41.04%	76,363
Neutral Style	48.74%	-1.93%	40.41%	36,582
Value Style	47.57%	-0.98%	46.44%	45,855
Small Cap	44.38%	-0.07%	52.08%	36,863
Medium Cap	44.82%	-1.82%	40.93%	34,090
Large Cap	49.00%	-2.45%	39.01%	87,847

There are two key takeaways from Table IV: (i) there are significant differences in both the absolute hit rates and the excess hit rates achieved across the style and size objectives of the sample. We test the significance of the difference in the means of each of the subsets, and each is statistically different from the others at the 1% level, for both hit rates and excess hit rates. (ii) The subsets which achieve absolute high hit rates are not the same as the subsets which achieve high excess hit rates. If we rank the hit rates achieved by the subsets, these rankings are different for absolute and excess hit rates.

The information contained in the first column of Table IV suggests that the best stock selectors are those who pursue style neutral and / or large capitalisation portfolios. Before jumping to this conclusion, it is instructive to examine the hit rates of the 18 benchmark portfolios reported in column three of Table I. These display large variation ranging from 43.8% (S&P 400 Growth) and 51.1% (S&P 500). Hence a fund achieving the average hit rate of 47.02% represents quite a good outcome if it is a mid-cap growth fund, but a bad outcome if it is a large cap value fund. This emphasises the need to also examine the excess hit rate when making judgements about the stock selection skill of individual funds or groups of funds.

Figure 3

Distribution of Hit Rates based on Style Objective

This figure displays the distribution of absolute hit rates and excess hit rates for subsets of the sample. The whole sample has been divided into value, growth and neutral style objectives based on the style objective of the fund's benchmark. Growth style objective includes 76,363 observations, value style objective includes 45,855 observations and neutral style objective includes 36,582 observations.

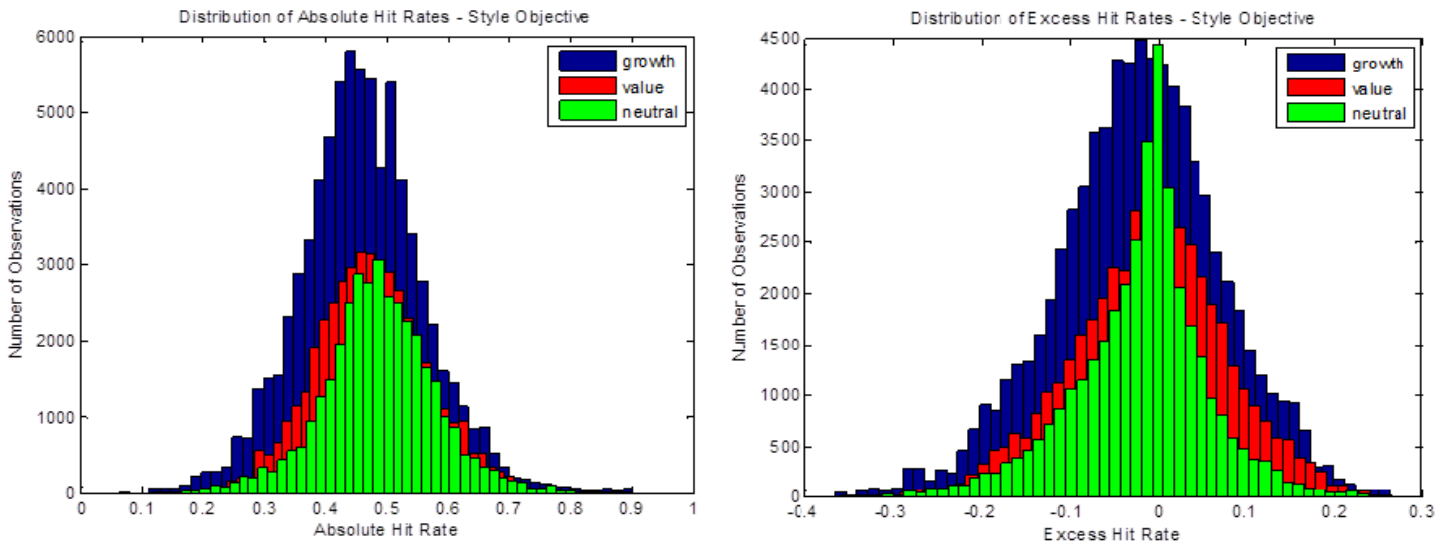
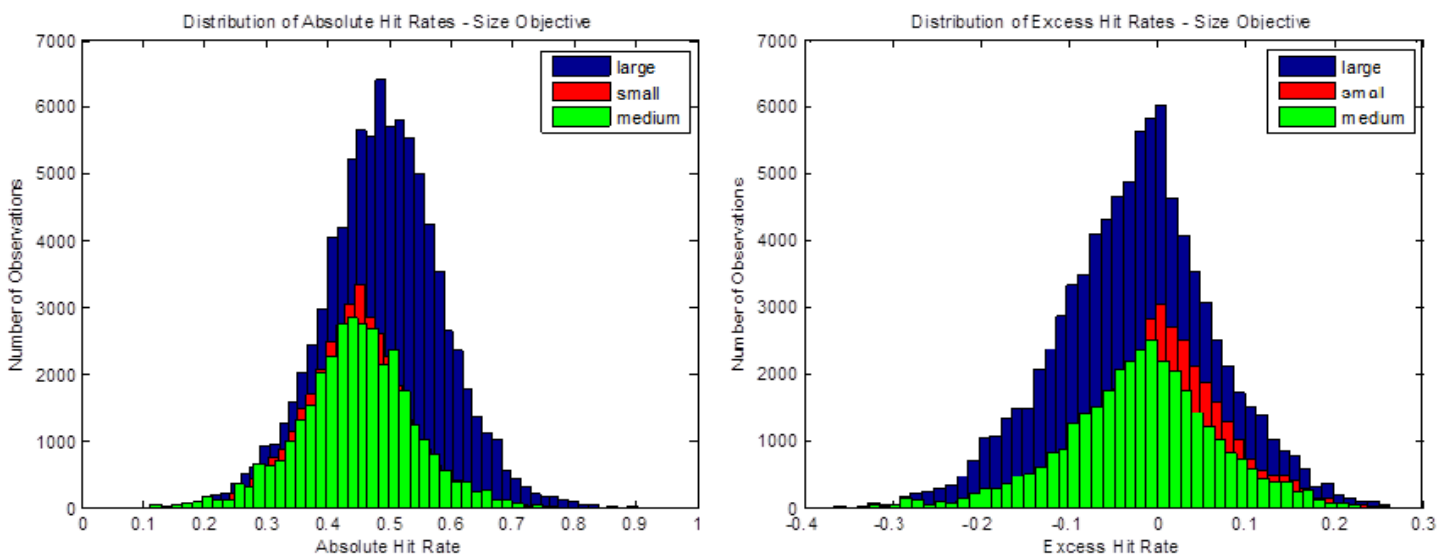


Figure 4

Distribution of Hit Rates based on Size Objective

This figure displays the distribution of absolute hit rates and excess hit rates for subsets of the sample. The whole sample has been divided into small, middle and large size objectives based on the size objective of the fund's benchmark. Large style objective includes 87,847 observations, medium style objective includes 34,090 observations and small style objective includes 36,863 observations.



We see in column two of Table IV that the funds that achieve the best excess hit rates are the small cap funds, where approximately 52% of funds achieve a hit rate better than

their benchmark. At the other end of the scale we have the large cap funds, whose average hit rate is 2.45% less than their benchmark and where only approximately 39% of the funds outperform their benchmark. In between, we have the medium cap managers who achieve an excess hit rate of -1.82% with only 41% of funds achieving a positive excess hit rate. Hence, the small cap managers display far superior stock selection skills as evidenced by their hit rates than the other managers. When it comes to investment style, it is the value managers who display the superior stock selection skills with an average excess hit rate of -0.98% with in excess of 46% of value managers having a positive excess hit rate. This is a somewhat impressive outcome for the value managers as their investment universe consists of stocks that on average outperform the rest of the stock universe. The distributions of hit rates by fund style and size objectives are presented in Figures 3 and 4.

A.4. Hit Rates during Strong Markets and Weak Markets

As previously mentioned, the literature has found evidence that active managers add the most value during periods when the market performs poorly (Moskowitz (2000), Kosowski (2006) and Glode (2011)). To investigate whether this finding is consistent with the results of our study, we examine the difference in the average absolute hit rates and excess hit rates of our sample in years when the market performs strongly, compared to years when the market performs poorly. The results are presented in Table V.

Table V
Hit Rates in Strong Market and Weak Market Years

This table reports the differences in hit rates achieved in years in which the market performed well compared to years that the market performed poorly. Weak market years include observations from years when the return on the S&P 500 was less than the return on a three month treasury bill. Strong market years include observations which are not from weak market years. Columns one and two report the average absolute hit rates in strong market years and weak market years. Columns three and four report the average excess hit rates in strong market years and weak market years. All numbers reported are percentages.

	Hit Rate		Excess Hit Rate	
	Strong Market Years	Weak Market Years	Strong Market Years	Weak Market Years
Whole Sample	45.34	48.46	-1.39	-2.11
Growth Objective	44.27	47.19	-1.89	-2.44
Neutral Objective	46.46	50.77	-1.21	-2.64
Value Objective	46.18	48.73	-0.71	-1.23
Small Objective	43.29	44.40	1.22	-1.28
Middle Objective	42.99	45.12	-1.30	-2.31
Large Objective	47.13	49.64	-2.55	-2.41

Column one and two of Table V demonstrate that for all style and size subsets, the absolute hit rates are significantly higher in weak market years than in strong market years.

We tested the difference between the two means for the whole sample, as well as the subsets of the whole sample, which confirms that the difference is significant at the 1%. In isolation, this finding suggests that the stock selection of active mutual funds is superior during which markets are weak which is consistent with previous findings which suggest that these are the periods when the funds achieve their best relative performance. However, an examination of columns three and four of Table V indicate that for all style and size subsets, with the exception of funds with a large size objective, excess hit rates are actually significantly better (in most cases, less bad) in strong market years than in weak market years. Again we test the significance of the difference in the means, which confirms that they are significantly different at the 1% level for all subsets of the sample. Therefore, absolute hit rates are higher in weak market years, whereas excess hit rates are higher in strong market years. This must reflect that the hit rates of the benchmark indices are also higher in weak market years by an amount greater than the increase in the hit rates of the funds in the sample. We calculated the benchmark hit rates in strong market years and weak market years, and found that the hit rate of the benchmark indices are around 15% higher in weak markets. Overall these findings suggest that the relatively better performance of the funds during periods when markets are weak is not a result of the managers displaying superior stocks picking skills during such periods.

B. The Relationship between Hit Rates and Fund Performance

This subsection contains results for our second area of analysis, in which we examine the relationship between hit rates and fund performance. If hit rates and fund performance are highly correlated, this emphasises the importance of managers having strong stock selection skill. We first examine the contemporaneous relationship between hit rates and fund performance, in order to determine if the funds which achieve the highest hit rates in a given period also achieve the highest performance in the same period. It seems intuitive that this would be the case; however, there is no guarantee of this, as the benefits of a high hit rate may be undone by poor portfolio construction decisions. For example, the fund may heavily weight the stocks in its portfolio which do underperform the benchmark. After we examine the contemporaneous relationship between hit rates and fund performance, we then go on to examine whether a good hit rate is indicative of good future fund performance which would suggest that there is some persistence in a fund's hit rate through time and so whether they have some predictive power of future performance.

In the methodology section of the paper, we explained how we formed portfolios based on the realised hit rates of funds and in Table VI we report the performance of these portfolios. On average, funds which achieve the highest hit rates also achieve the highest fund performance when both are measured over the same time horizon. The difference in the abnormal return achieved between the top and bottom quartile is greater when funds are ranked on their absolute hit rates, 10.8%, than when the funds are ranked on excess hit rates, 8.8%. Overall, these results suggest that the portfolio construction process of the funds which achieve the highest hit rates is not unwinding the gains to be made from superior stock selection. This reinforces our interest in examining the hit rate, as indeed hit rates are closely related to fund performance. Of course, due to problems of causality, we cannot conclude that achieving a higher hit rate causes higher abnormal performance. We are only able to conclude that high hit rates and high abnormal performance are highly associated. For

example, the strong relationship between hit rates and fund performance could arise because funds with increased stock selection skill are also more skilled at portfolio construction.

Table VI
Hit Rates and Contemporaneous Fund Performance

This table reports the returns of portfolios formed on the basis of the ranks of fund hit rates. Each quarter funds are ranked based on their hit rates calculated with a 12 month time horizon. Four quartile portfolios are then formed based on these rankings. Quartile 1 is the portfolio with the highest hit rates. Quartile 4 is the portfolio with the lowest hit rates. The returns reported are the average contemporaneous annual abnormal returns of each of the four portfolios. Column one and two present returns and the standard deviation of returns for portfolios formed on absolute hit rate rankings. Column three and four present returns and the standard deviation of returns for portfolios formed on excess hit rate rankings. All numbers reported are percentages.

Portfolios	Formed on basis of Absolute Hit Rates		Formed on basis of Excess Hit Rates	
	Average Return (%pa)	Standard Deviation of Returns (%pa)	Average Return (%pa)	Standard Deviation of Returns (%pa)
Quartile 1 (high)	4.7	5.4	4.0	5.4
Quartile 2	0.9	3.1	0.4	3.1
Quartile 3	-1.1	2.3	-1.1	2.0
Quartile 4 (low)	-6.1	3.7	-4.8	3.1

We also examine the relationship between the past hit rate of a fund and its future performance. We calculate the average hit rate of each fund over the past four quarters and form portfolios based on these rankings¹³. We then calculate the average excess return of the portfolios over the next quarter. When quartile portfolios are formed, there is a difference of 1.7%pa between the top and bottom quartile portfolios. When we form decile portfolios, the annual difference between the top and bottom decile portfolio is 2.5%. In both cases, the relationship between hit rates and portfolio performance is strictly monotonic. In summary, we find that the hit rate is closely related to contemporaneous fund performance, and that it also has some predictive power on future fund performance.

C. The Impact of Active Investment Decisions on Hit Rates

In this subsection, we examine which of the active investment decisions made by fund managers increase their hit rates, and which active decisions actually decrease their hit rates. In Subsection A we found that the average manager in our sample would have achieved a higher hit rate by simply holding the stocks in the benchmark portfolio. We therefore expect that some of the active decisions made by managers actually decrease the fund's realised hit rate. Our findings may provide some insights into how to identify the managers with better stock picking skills, those who are likely to achieve the highest hit rates.

¹³ Using the hit rate over the past four quarters to form portfolios allows us to rank the funds based on the hit rates they consistently achieved, compared to using only the most recent quarter.

Table VII
Correlation Structure

This table reports the correlation structure between the variables used throughout this paper. Panel A reports the correlation structure between hit rates over different time horizons; one month, three month, six month and 12 month. Panel B reports the correlation structure between the hit rate over a 12 month time horizon and the 12 active investment decisions used as explanatory variables in the regressions. The calculation of the 12 active decisions is explained in the Appendix.

Panel A: Correlation Structure Between Hit Rates													
Variables	1 Month			3 Month			6 Month			12 Month			
1 Month	1.00												
3 Month	0.56***			1.00									
6 Month	0.38***			0.63***			1.00						
12 Month	0.23***			0.37***			0.56***			1.00			

Panel B: Correlation Structure Between Variables													
Variables	12 Month	Active Share	Active Weight	Selectivity	Ind. Con	Return Gap	1 Minus Herding	Neg. BTM Tilt	Pos. BTM Tilt	Neg. Mom Tilt	Pos Mom Tilt	Neg Size Tilt	Pos Size Tilt
12 Month	1.00												
Active Share	-0.11***	1.00											
Active Weight	0.04***	0.32***	1.00										
Selectivity	0.03***	-0.13***	0.04***	1.00									
Ind. Con	-0.05***	0.39***	0.21***	-0.03***	1.00								
Return Gap	-0.04***	0.01***	-0.02***	0.04***	-0.01***	1.00							
1 Minus Herding	0.00	-0.05***	-0.02***	0.00	0.00	-0.06***	1.00						
Neg. BTM Tilt	0.04***	-0.25***	-0.02***	0.16***	-0.13***	-0.01***	0.02***	1.00					
Pos. BTM Tilt	0.07***	0.19***	0.22***	-0.12***	0.03***	0.00	-0.01***	0.38***	1.00				
Neg. Mom Tilt	0.01***	-0.22***	-0.07***	0.02***	-0.11***	-0.02***	0.01***	-0.05***	-0.17***	1.00			
Pos. Mom Tilt	-0.01***	0.11***	0.16***	0.01***	0.13***	-0.04***	-0.01**	-0.11***	-0.07***	0.43***	1.00		
Neg. Size Tilt	0.07***	-0.35***	-0.23***	-0.02***	-0.23***	0.00	0.01***	0.03***	-0.09***	0.09***	-0.05***	1.00	
Pos. Size Tilt	-0.06***	0.24***	-0.21***	-0.12***	0.04***	0.01***	0.00	-0.13***	-0.09***	-0.01***	-0.03***	0.21***	1.00

***1% significance, **5% significance, *10% significance

C.1. Correlation Structure between Variables

Prior to undertaking the regression analysis, we consider the correlation structure between the hit rates and that the various active decisions that we use in the regressions. It is of particular importance to consider the correlation structure between the 12 active decisions, as these are used as the explanatory variables when we conduct multivariate analysis. If these active decisions are too highly correlated, multicollinearity may be present; which is problematic as it makes regression results less reliable by increasing the standard errors of the coefficients.

The correlation structure is reported in Table VII. Panel A demonstrates that the hit rates over different time horizons are highly correlated; however, as only one hit rate time horizon is used as the dependent variable at any one time when we run the regressions in equation (2) and (3), this is not problematic. In panel B, most of the correlations between the active decisions are significantly different from zero at the 1% level. Importantly however, the correlations between the active decisions are not high enough for multicollinearity to present problems.

C.2. Univariate Regressions

Before examining the combined impact of the 12 active decisions into a single multivariate regression, we undertake a univariate analysis on each of the active decisions. This is done by running the regressions in equation (2) and equation (3), however instead of including all 12 active decisions, only one active decision is included at a time. We therefore run 12 separate regressions of equation (2), and 12 regressions of equation (3). This identifies the impact of each individual active decision on the dependent variable, the hit rate. Table VIII displays the results of the univariate analysis with the coefficients of the control variables not being reported at this stage.¹⁴

A key finding of Table VIII is that almost all of the active decisions made by the managers have a significant impact on the level of their hit rates. All of the active decisions are significant at the 1% level in all three columns, with the exception of *negative momentum tilt* for the whole sample and *herding* during periods of weak markets, both of which are not statistically significantly different from zero at the conventional levels. Perhaps a more surprising finding is that the impact of the active decisions is negative in the majority of cases, suggesting that the majority of these decisions are associated with the managers achieving lower hit rates. This is consistent with our finding that the average fund in our

¹⁴ To make the table simpler to interpret, the sign on the three negative tilt variables have been reversed. This has been done as a negative coefficient for a negative tilt means that the variable has a positive impact on hit rates. The sign has been reversed in each of the three columns for both univariate and multivariate analysis.

sample would have achieved a higher hit rate in the absence of making any active stock selection decisions.

Another interesting finding from Table VIII is that many of the active decisions have a different relationship with hit rates in strong market years compared to the relationship they have in weak market years. With the exception of the *negative BTM tilt* and *negative momentum tilt*, the coefficient attached to each active decision takes on a significantly different value in strong markets than it does in weak markets. These findings are interesting and overall bad news for the stock selection skill of active managers, however as our primary interest is in examining the results of the multivariate analysis, we save most of the interpretation of these results for the next section.

Table VIII
Univariate Analysis

This table reports results from the univariate analysis. The dependent variable is the 12 month hit rate. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. The 12 active decisions are calculated following the method of the respective papers, and are described in the Appendix. Each active decision is run in a separate regression, that of equation (2) for column one, and equation (3) for column two and three. Weak market years include observations from years when the return on the S&P 500 was less than the return on a three month treasury bill. Strong market years include observations that are not from weak market years. The sample includes 158,800 observations.

	Whole Sample	Strong Market Years	Weak Market Years
Active Share	-0.0605***	-0.0855***	-0.0407***
Active Weight	0.0551***	0.0290***	0.0797***
Selectivity	0.1400***	-0.0543***	0.3529***
Industry Concentration	-0.1603***	-0.1193***	-0.1956***
Return Gap	0.0969***	0.2349***	-0.1133***
1 Minus Herding	-0.0508***	-0.0876***	0.0001
Negative BTM Tilt	-0.0143***	-0.0156***	-0.0136***
Positive BTM Tilt	0.0245***	0.0142***	0.0309***
Negative Momentum Tilt	-0.0007	-0.0164***	0.0101***
Positive Momentum Tilt	-0.0080***	0.0044***	-0.0186***
Negative Size Tilt	-0.0282***	-0.0319***	-0.0251***
Positive Size Tilt	-0.0604***	-0.0498***	-0.0686***

***1% significance, **5% significance, *10% significance

C.3. Multivariate Regressions

In reality, managers tend to have a large number of active bets running at any point in time. Therefore, examining the impact of the active decisions in a multivariate context is more likely to be relevant, as it will provide a better insight into the incremental impact of each of the decisions. Due to the correlation structure between the variables, the sign and significance of the coefficients may differ from the univariate analysis.

Table IX

Multivariate Analysis

This table reports the results of the multivariate analysis. The dependent variable is the 12 month hit rate. The hit rate is the percentage of stocks in a fund's portfolio which achieve a return greater than the return of the fund's benchmark index over a specified time horizon. The 12 active decisions are calculated following the method of the respective papers, which are explained in the Appendix. Weak market years include observations from years when the return on the S&P 500 was less than the return on a three month treasury bill. Strong market years include observations that are not from weak market years. The sample includes 158,800 observations.

	Whole Sample	Strong Market Years	Weak Market Years
C	0.5291***	0.5394***	0.5394***
Active Share	-0.0678***	-0.0948***	-0.0510***
Active Weight	0.0627***	0.0993***	0.0271***
Selectivity	0.1087***	0.0237***	0.3216***
Industry Concentration	-0.0471***	0.0428***	-0.0764***
Return Gap	0.1140***	0.2322***	-0.0814***
1 Minus Herding	-0.0678***	-0.1085***	-0.004
Negative BTM Tilt	0.0134***	0.0130***	0.0042***
Positive BTM Tilt	0.0336***	0.0289***	0.0341***
Negative Momentum Tilt	0.002	0.0016	0.0043**
Positive Momentum Tilt	-0.0033***	0.0110***	-0.0066***
Negative Size Tilt	-0.0179***	-0.0132***	-0.0118***
Positive Size Tilt	-0.0173***	0.0043	-0.0293***
Turnover	-0.0030***		-0.0023***
Fees	-0.1999***		-0.1746***
Size	-0.0014***		-0.0002
Age	0.0003***		0.0001***
Past Fund Flows	0.0000		0.0000
Past Returns	-0.0789***		-0.0985***
Benchmark Returns	0.0553***		0.0649***
N	160,565		160,565
Quarterly Fixed Effects	Yes		Yes
R ²	0.2167		0.2609

***1% significance, **5% significance, *10% significance

Table IX reports the results of the multivariate analysis. As a first observation, almost all the signs and the level of significance of the 12 active decisions are consistent with those of the univariate analysis in Table VIII. As the multivariate analysis isolates the marginal predictive power of each variable, this consistency in both the univariate and multivariate

analysis demonstrates that the impact of each active decision is not incorporated by the other decisions. That is, each of the active decisions captures a different dimension of information about the hit rate.

The results of Table IX indicate that many of the active decisions made by managers actually decrease their realised hit rates. This is consistent with our finding in Subsection A that the average manager in our sample would have achieved a higher hit rate by holding the stocks in the benchmark portfolio. Although the impact of each active decision on the hit rate has not been previously explored, this finding might come as a surprise, as our intuition was that in deviating from the holdings of the benchmark index, managers would include stocks in their portfolio that they expect to realise a return greater than the return of the benchmark index, and thus achieve a higher hit rate. This is clearly not the case as in column one, which reports the impact of the decision over the whole sample period, half of the 12 active decisions have a significant negative impact on the realised hit rate. These six active decisions are *active share*, *industry concentration*, *herding*, *positive momentum tilt*, *negative size tilt* and *positive size tilt*¹⁵.

As all of our active decisions with the possible exception of some of the style tilts (especially the negative momentum tilt) have been found to be positively associated with fund performance, it is surprising to find that only half of them have the same impact on hit rates as they do on fund performance. For example, *active share*, which was found in Cremers and Petajisto (2009) to be positively associated with fund returns, is found to have a negative impact on hit rates. Funds with a large *active share* are those that are taking large positions in stocks relative to the stock's weighting in the benchmark index. What we are able to conclude from this is that the positive relationship between these active decisions and fund performance is not due to the impact of the active decisions on hit rates. The difference between the impact of the decision on fund performance and the impact on hit rates must lie in portfolio construction, that is, in the size of the bets that managers take in deviating from the benchmark portfolio. The stocks on which managers take the larger bets must be behaving in accordance with expectations and achieving high returns, as the outperformance these funds achieve is not a result of their hit rates, which tend to be lower. What is also interesting is that despite the similarity in the idea behind the variables, *active share*, *selectivity* and *active weight* do not all have the same impact on hit rates. *Active Share* has a negative coefficient, whereas *selectivity* and *active weight* both have a positive coefficient.

When we examine the differences in the impact of the active decisions in strong market years and weak market years, again we find that some of the active decisions have a different impact on hit rates depending on the performance of the market. We see that more of the active decisions (seven) have a negative impact in years in which the market performs

¹⁵ As the variable we calculate is one minus herding, this means that funds which exhibit less *herding* realise lower hit rates.

poorly than in years which the market performs well (three). The momentum tilts are a good example of this; tilts towards winners (*positive momentum tilt*) have a positive impact on hit rates in strong markets, but a negative impact in weak markets. This suggests that favouring winning stocks performs well in good market years when stocks continue to perform well for an extended period, but the opposite tends to be the case in weak markets when stocks tend to reverse more quickly.

Overall, when we examine the results of all three columns, the results show that four of the active decisions increase hit rates in all three columns (*active weight, selectivity, positive BTM tilt* and *negative BTM tilt*), whereas four of the variables decrease hit rates in all three columns (*active share, herding, negative size tilt* and *positive size tilt*). As for the other variables, three of the variables (*industry concentration, return gap* and *positive momentum tilt*) have a different impact on hit rates depending on how the market is performing, whereas *negative momentum tilt* only has a significant impact on hit rates in weak market years. As noted previously, in the case of some active decisions there is the same positive relationship with both performance and hit rates (e.g. the active weight of Doshi, Elkamhi and Simutin, 2014) whereas for other active decisions the impact on hit rate is at variance with that on performance (e.g. the active shares of Cremers and Petajisto, 2009).

The reason that the coefficient for the intercept and the control variables, as well as the R^2 , are the same in columns two and three of table IX is that they come from the same regression, that of equation (3). It is also worth briefly commenting on the relationship between the control variables and the hit rate, which gives us insight into how certain fund characteristics relate to the hit rate. *Turnover* and *fees* both have the same negative impact on hit rates as they do on fund performance. Interestingly, we find that older funds have superior hit rates but larger funds have inferior hit rate, which is consistent with it being more difficult to identify mispriced stocks as one's assets grow. Previous studies have found some persistence in fund performance over relatively short periods of time but our findings suggest that good previous investment performance translates into lower future hit rates.

In summary, what we have found from the results of the multivariate analysis is that the active decisions made by managers are related significantly to the hit rate, and that many of these active decisions actually tend to decrease the hit rate realised by the fund, particularly during periods when market are performing poorly. Overall, these results are consistent with the finding that the average fund in our sample would have achieved a higher hit rate over the sample period by holding the stocks in the benchmark portfolio.

IV. Conclusion

In this paper we examine the stock selection skill of US mutual funds. Specifically, we use the hit rate as a proxy for stock selection skill. We find that hit rates are a useful measure, as they are closely related to contemporaneous fund performance. Unfortunately, our findings indicate that many of the active investment decisions made by the funds in our

sample actually decrease the hit rate realised by the fund. In our sample period from 1995 to 2012, we find that the average active US equity mutual fund would have actually achieved a higher hit rate in the absence of active stock selection decisions, by simply holding the stocks in the benchmark portfolio. The question for investors therefore becomes one of how to identify those managers who are likely to achieve a high hit rate.

We examined the impact on hit rates of active decisions which had previously been found to be positively correlated with performance. We found that while some of these active decisions increase hit rates, the majority of them in fact decrease the hit rate the fund achieves. Managers that realise high hit rates tend to be those with high *active weight*, and *selectivity*, and *who actively pursue style tilts*. We find that the impact of many of the active decisions on the hit rate depends on whether the market is performing well or not.

Our study which is the first to use fund hit rates as a proxy for manager stock selection skills is best placed in the literature with previous studies that have examined the stock selection skills of active funds. Our findings are inconsistent with those of Wermers (2000) and Daniel et al. (1997) as we do not find evidence that the average manager exhibits stock selection skill. We do however show that there are managers that are able to achieve a high hit rate when deviating from the holdings of the benchmark portfolio, suggesting that there are a minority of managers with superior stock selection skill (Kosowski et al., 2006; Fama and French, 2010). Overall, our findings add to the evidence from studies on fund performance which bring into question the ability of the average fund manager, as well as fuelling the debate as to why these managers are in such heavy demand from investors and so well remunerated.

Given our findings, there are two natural avenues for future research. First, we have presented some evidence in this paper that the past hit rates of a fund do provide some useful information when trying to predict future fund performance. Therefore, a logical consequence for a future study is the further development of a model which will help identify managers with superior stock selection skill. Second, evidence in Cohen, Polk and Silli (2010) and Yeung et al. (2012) suggest that fund managers do have stock selection skill, but that this skill is limited to identifying a limited number of mispriced stocks (Yeung et al. (2012)). However, managers are encouraged to take full advantages of the diversified benefits associated with holding large portfolios. The average (median) number of stocks held by the funds in our sample are 141 (81) stocks. This raises the possibility that managers are able to identify a small number of stocks that outperform their benchmark but these are swamped but have to hold many underperforming stocks to populate large portfolios. This suggests a finer examination of the stock holdings of the funds in order to identify whether the managers can achieve a high hit rates on their more preferred stocks

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Appendix

Definition and Calculation of Active Decisions

This appendix discusses the findings and calculation of the 12 active decisions which we examine in our regression analysis. The first six variables are from six separate papers. The remaining six variables are measures of style tilt, developed in Bird, Pellizzari and Yeung (2014). We calculated each of the variables by replicating the method of the relevant papers. Brief descriptions of the calculation of variables are included below. For more detailed explanations of how the variables are calculated, see the relevant papers. The first three variables, *active share*, *active weight* and *selectivity*, are similar in spirit in that they each directly measure a fund's activeness. Although the idea of the variables is similar, each variable is calculated differently and captures different information on fund activeness.

Active Share: Cremers and Petajisto (2009) measure fund activeness by comparing the portfolio weights of the stocks held by a fund to the portfolio weights of the stocks in the fund's benchmark index. The study develops a method of assigning a benchmark index to each fund in the sample. The paper finds that the funds with the highest *active share* tend to outperform their benchmarks. This supports the view that skilled managers tend to underweight or overweight certain stocks relative to the weights of those stocks in the fund's benchmark portfolio, and indeed the paper concludes that funds with a high *active share* appear to have stock selection ability. *Active share* is calculated as;

$$\text{Active Share} = \frac{1}{2} \sum_{i=1}^N |\omega_{fund,i} - \omega_{index,i}| \quad (\text{A1})$$

$\omega_{fund,i}$ is the weight of stock i in the fund's portfolio and $\omega_{index,i}$ is the weight of stock i in the portfolio of the fund's benchmark index.

Active Weight: Doshi, Elkamhi and Simutin (2014) measure a fund's activeness as the proportion of a fund's holdings that differs from the value-weighted index of these holdings. Unlike the calculation of *active share*, calculation of *active weight* does not require assigning each fund a benchmark. The paper finds that the most active funds, those with the highest *active weight*, tend to outperform funds with low *active weight* and that part of the outperformance is due to the superior stock selection skill of funds with high *active weight*. *Active weight* is calculated as;

$$\text{Active Weight} = \frac{1}{2} \sum_j |\omega_{it}^j - \omega_{it}^{jm}| \quad (\text{A2})$$

ω_{it}^j is the weight of the stock in the fund's portfolio and ω_{it}^{jm} is the weight of the stock in a market capitalisation weighted portfolio.

Selectivity: Amihud and Goyenko (2013) measure fund activeness as the deviation of the fund's portfolio from common factors. The deviation is measured by obtaining the *r-squared* from a regression of fund performance on a multifactor benchmark model of ten common factors. The paper suggests that funds with a lower *r-squared* are more active, as this indicates greater deviation of the fund's return from that of common factors, and finds that these funds with lower *r-squared* achieve greater future performance. Ferson (2012) finds consistent evidence that funds with lower *r-squared* achieve better performance. The paper calculates $1 - R^2$, and terms this *selectivity*, which is the variable which we use. Therefore, an increase in *selectivity* indicates a higher level of activeness.

$$\text{Selectivity} = 1 - R^2 \quad (\text{A3})$$

Portfolio Industry Concentration: Kacperczyk, Sialm and Zheng (2005) measure how concentrated a fund's holdings are across different industries. They find that fund managers that concentrate a high proportion of holdings within a few industries, those with a high *industry concentration index*, achieve increased fund performance. The paper concludes that this is a result of skilled managers identifying underpriced stocks within industries in which they have informational advantages, and suggests that this is primarily due to their stock selection skill. This finding is consistent with Desai, Liang and Singh (2000) and Mikhail et al. (2006) who examine the stock selection skill of analysts, and find that the best analysts are those who focus on a single or fewer industries.

To calculate *industry concentration*, the market is split into ten industries and each stock is assigned to one of these ten industries. The variable is then calculated as:

$$\text{Industry Concentration Index}_t = \sum_{j=1}^{10} (\omega_{j,t} - \bar{\omega}_{j,t})^2 \quad (\text{A4})$$

$\omega_{j,t}$ is the value weight for industry j held by the mutual fund and $\bar{\omega}_{j,t}$ is the industry weights of the total stock market.

Return Gap: Dyakov (2012) finds that an increased *return gap*, the difference between the return the fund would have achieved based on their reported holdings and the fund's actual return, infers higher fund manager skill. The variable captures the increase in fund performance due to the unobserved trading of skilled managers. The paper finds that the *return gap* contains information about future fund performance, and that increased *return gap* increases funds flow. The variable is calculated as follows;

$$\text{ReturnGap}_{i,t} = \text{Return}_{i,t} - (\text{HoldingsReturn}_{i,t} - \text{ExpenseRatio}_{i,t}) \quad (\text{A5})$$

Return_{*i,t*} is the fund's actual return

HoldingsReturn_{*i,t*} is the return on the disclosed holdings

ExpenseRatio_{*i,t*} is the most recently available expense ratio for each quarter.

Herding: Jiang and Verardo (2013) develop the *herding* measure, which captures a fund's tendency to follow the past trading decisions of other funds. The paper finds that a higher incidence of *herding* has a negative impact on fund performance, and concludes that following the collective trading decisions of other investors is an indication of a lack of skill. This is consistent with the herding effect found in analyst recommendations, where superior analysts tend to issue their recommendations before their peers in Desai, Liang and Singh (2000) and Mikhail et al. (2006).

The *herding* variable is based on the correlation between a fund's trades, and is calculated in two steps. Firstly the following regression is run;

$$\text{Trade}_{i,j,t} = \alpha_{j,t} + \beta_{j,t}\Delta\text{IO}_{i,t-1} + \gamma_{j,t}\text{Mom}_{i,t-1} + \delta_{1,j,t}\text{MC}_{i,t-1} + \delta_{2,j,t}\text{BM}_{i,t-1} + \varepsilon_{i,j,t} \quad (\text{A6})$$

Trade_{*i,j,t*} is the % change in the holdings of stock *i* in fund *j*'s portfolio during quarter *t*

ΔIO_{*i,t-1*} is change in aggregate institutional ownership of stock *i* during the quarter *t* – 1

Mom_{*i,t-1*} is the return on stock *i* measured during quarter *t* – *i*

MC_{*i,t-1*} is the logarithm of the market capitalisation of stock *i* at the end of quarter *t* – 1

BM_{*i,t-1*} is the stock's log book to market ratio at the end of the previous quarter

The coefficient $\beta_{j,t}$ forms the basis of the herding variable. A smoothed measure of $\beta_{j,t}$, $FH_{j,t}$ is then constructed to capture the average herding tendency of the fund. Recent observations are weighted more heavily. This smoothed measure is the variable that we use in this paper. The variable we report in our analysis is one minus $FH_{j,t}$, so that an increase in the variable actually means that the fund exhibits less herding.

$$FH_{j,t} = \frac{\sum_{h=1}^t \frac{1}{h} \beta_{j,t-h+1}}{\sum_{h=1}^t \frac{1}{h}} \quad (\text{A7})$$

Style Tilt: Bird, Pellizzari and Yeung (2014) develop six variables to capture the style tilt of a fund, by measuring the difference in style between the fund's holdings and the

holdings of the fund's benchmark portfolio. The six variables are the positive and negative values of three style tilt measures; value/growth, momentum and size. The paper finds that four of the six style tilts made by active funds actually decrease performance; *positive BTM tilt*, *negative momentum tilt*, and both *positive* and *negative size tilt*.

Value/growth is measured by the stock's book to market (BTM) ratio, momentum is measured by the stock's return over the past six months and size is measured by the market value of the firm's equity. Each quarter, each stock is ranked on the three factors and assigned a score from one to five for the quintile of the stock's rank. A rank of one is given for the bottom quintile, ascending to a rank of five for the top quintile. The style tilt for each of the three variables is calculated as follows;

$$\text{Style Tilt in dimension } l = \sum_{j=1}^N (\omega_j^a C_j^l - \omega_j^b C_j^l) \quad (\text{A8})$$

ω_j^a is the weight of stock j in the fund's portfolio

ω_j^b is the weight of stock j in the fund's benchmark portfolio

C_j^l is stock j 's score in dimension l