Comments welcome

# Window Dressing in Mutual Funds

Vikas Agarwal
Georgia State University

Gerald D. Gay
Georgia State University

and

Leng Ling
Georgia College & State University

First Version: March 31, 2011
This version: November 10, 2011

*JEL Classification:* G11; G20

*Keywords*: Mutual funds; Window dressing; Portfolio disclosure; Fund flows

---

Vikas Agarwal is from Georgia State University, Robinson College of Business, 35 Broad Street, Suite 1207, Atlanta GA 30303, USA. E-mail: vagarwal@gsu.edu. Tel: +1-404-413-7326. Fax: +1-404-413-7312. Vikas Agarwal is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Gerald D. Gay is from Georgia State University, Robinson College of Business, 35 Broad Street, Suite 1203, Atlanta GA 30303, USA. E-mail: ggay@gsu.edu. Tel: +1-404-413-7321. Fax: +1-404-413-7312. Leng Ling is from Bunting College of Business, Georgia College & State University (GCSU), Milledgeville, GA 31061, USA. E-mail: leng.ling@gcsu.edu Tel: 478-445-2587 Fax: 478-445-1535 and also acknowledges research grant support from GCSU. We thank Mark Chen, Conrad Ciccotello, Jesse Ellis, Wayne Ferson, Jason Greene, Zhishan Guo, Marcin Kacperczyk, Jayant Kale, Omesh Kini, Bing Liang, Reza Mahani, David Musto, Tiago Pinheiro, Chip Ryan, Thomas Schneeweis, Vijay Singal, and Tao Shu for their helpful comments and constructive suggestions. We are grateful to the seminar participants at the Bank of Canada, University of Alabama, University of Georgia, University of Massachusetts Amherst, and Wuhan University for their comments. We acknowledge the research assistance of Sujuan Ma and Haibei Zhao. We also thank Linlin Ma and Yuehua Tang for sharing data.

# Window Dressing in Mutual Funds


## Abstract

This paper introduces two measures to investigate potential window-dressing behavior among mutual fund managers. We show that unskilled managers that perform poorly are more likely to window dress by strategically buying winner stocks and selling loser stocks near quarter ends. Further, funds with higher expense ratios and greater portfolio turnover are associated with more window dressing. We also find that funds involved in window dressing perform poorly in the following quarter. Given these adverse effects, we demonstrate how window dressing can exist in equilibrium. Current reporting requirements allow managers up to 60 days' delay to report end of quarter portfolio holdings. We show how window-dressing managers can benefit from incrementally higher fund flows if good performance is realized during the delay period. However, we find that poor performance results in incrementally lower flows than that observed for non-window dressing managers.

# Window Dressing in Mutual Funds

There is growing evidence in the academic literature that investors use quarterly portfolio holdings of mutual funds to determine managerial ability.[1] Although portfolio disclosure by fund managers can provide useful information to investors, it can also create perverse incentives for managers to engage in window dressing. In particular, prior to scheduled reporting dates, managers can purchase or increase their holdings in stocks that have shown good recent performance (winners) and sell or reduce holdings in poor performers (losers) to appear better to current and potential investors.[2] The underlying premise to window dress is that investors base their investment decisions in part on observed portfolio holdings, in addition to other information such as fund performance. We later provide evidence supporting this premise.

Despite some evidence in the mutual fund literature consistent with managerial window-dressing behavior (see, for example, Lakonishok, Shleifer, Thaler, and Vishny, 1991, Sias and Starks, 1997, He, Ng, and Wang, 2004, Ng and Wang, 2004, and Meier and Schaumburg, 2004), there is limited understanding of the detection and measurement of window dressing, the implications of window-dressing behavior for fund performance, and the incentives of portfolio managers to engage in window dressing. Our paper attempts to fill this void by addressing three research questions: (1) which fund characteristics are associated with window dressing?; (2) how

[1] See for example, Grinblatt and Titman (1989, 1993), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (1999, 2000), Chen, Jegadeesh, and Wermers (2000), Gompers and Metrick (2001), Cohen, Coval, and Pastor (2005), Kacperczyk, Sialm, and Zheng (2005, 2008), Sias, Starks, and Titman (2006), Alexander, Cici, and Gibson (2007), Jiang, Yao, and Yu (2007), Kacperczyk and Seru (2007), Huang and Kale (2009), and Baker, Litov, Wachter, and Wurgler (2010).

[2] We note the possibility of other forms of window dressing: (1) managers may decrease their holdings in high-risk securities prior to the reporting date in order to make their portfolios appear less risky (see Musto, 1997 and 1999, and Morey and O'Neal, 2006); (2) at quarter-ends, managers may purchase stocks already held to drive up stock prices and thereby fund values, a practice known as "portfolio pumping", "leaning for the tape", or "marking up" (Carhart, Kaniel, Musto, and Reed, 2002); (3) Managers may invest in securities that deviate from their stated fund objectives and eliminate those assets prior to the reporting date (Meier and Schaumburg, 2004), and (4) managers may invest in stocks covered in the media to influence investors' flows (Solomon, Soltes, and Sosyura, 2011). Our focus is on performance-based window dressing (i.e., buying winners and selling losers).

does window dressing affect future fund performance?; and (3) how do investors react to managers' window-dressing behavior in terms of altering their capital flows and, importantly, what characterizes the equilibrium of this behavior?

A main challenge in any study of window-dressing behavior has to do with the identification and measurement of window dressing. It is difficult to establish with certainty if a mutual fund manager has engaged in window dressing. We attempt to overcome this challenge by developing two measures of window dressing that proxy for the propensity to window dress.

Our first measure is the 'rank gap measure' that identifies the discrepancy in the performance-based ranking of a fund and a ranking based on the proportion of winner stocks and loser stocks held by the fund during a quarter. The intuition underlying this measure is that, on average, a poorly performing fund should have a higher percentage of its assets invested in loser stocks and a lower percentage invested in winners than that observed of a better performing fund. Thus, observing a poorly performing fund with a high percentage of reported holdings in winners and a low percentage in losers suggests a greater likelihood of window dressing. Since this measure is based on ranking a fund's performance as well as winner and loser proportions relative to other funds, it can be viewed as a *relative* measure of window dressing.

Our second measure of window dressing is motivated by the work of Kacperczyk, Sialm, and Zheng (2008) (henceforth, KSZ), who compare the actual fund performance (using the net asset values) with the performance of the fund's prior quarter-end portfolio assuming it to be held for the current quarter. They refer to the difference between the two performance figures as 'return gap' and attribute it to manager skill. Since we are interested in examining the window-dressing behavior of mutual fund managers, instead of using the prior quarter-end portfolio as in their study, we use the current quarter-end portfolio and assume that the manager held it throughout the current quarter. The underlying intuition behind our approach is that a manager upon observing winner and loser stocks towards the quarter end will tilt portfolio holdings towards winner stocks and away from loser stocks to give investors a false impression of stock selection ability. Hence, the window dressing measure in this setting can be inferred from the difference between the returns of the quarter-end portfolio (and assuming that the manager held this same portfolio at the beginning of the quarter) and the fund's actual quarterly return. We refer to this second measure of window dressing as the "backward holding return gap" (BHRG) measure. In contrast to rank gap measure, which is *relative* as it exploits the inconsistency between the fund's *relative* ranking based on performance and holding winner and loser stocks, the BHRG measure is *absolute* as it compares the performance of holdings with the fund's actual return. Appendix A provides an example that shows how BHRG differs from the KSZ return gap measure, and how the BHRG and return gap measures help to distinguish window dressers from skilled and unskilled managers.

Our study uses the rank gap and BHRG measures to test several hypotheses included within the three main components of our study: (1) the determinants of window dressing, (2) the impact of window dressing on future fund performance, and (3) investors' reaction to window dressing in the form of capital flows. In the first part of our study, we posit that fund managers with lower ability (unskilled) that perform poorly during the quarter are more likely to window dress. The basis for this hypothesis is that there is little incentive for well-performing, higher-ability (skilled) managers to distort their portfolios to mislead investors.[3] In contrast, poorly performing unskilled managers are more likely to window dress with the hope that investors will give them benefit of doubt if the reported portfolio holdings consist of largely winner stocks. We further

[3] We acknowledge that skilled and/or well-performing funds may also distort their disclosed portfolios to avoid revealing their trading strategies and mitigating front-running behavior.

hypothesize that funds with higher expense ratios and greater portfolio turnover are more likely to be associated with window dressing. Higher expense ratios imply greater benefits to the fund managers if investors respond to the window-dressed portfolios in terms of higher flows. Greater turnover can be a result of unnecessary trading activity of buying winners and selling losers at quarter ends due to window dressing. Our results are consistent with these hypotheses. Using the four-factor alpha of Carhart (1997) that controls for momentum trading (which also involves buying winners and selling losers), we find that window dressing is negatively related to fund's past performance and manager skill (using the KSZ return gap measure) and positively related to expense ratio and turnover.  Further, these findings are also economically significant. For example, a one standard deviation decline in alpha is associated with an increase of approximately 6.6% and 18.6% in the average rank gap and BHRG window dressing measures, respectively.  For manager skill, the corresponding increases are 1.4% and 20.6%, respectively.

The second part of our study deals with the impact of window dressing on future fund performance. We posit that managers of funds involved in window dressing should be associated with poor future performance as window dressing is a costly and value-destroying exercise associated with managers attempting to misguide investors by showing portfolios that are not representative of their investment strategies. In particular, churning the portfolio around quarter ends will destroy value for investors in the form of unnecessary transaction costs. Consistent with our hypothesis, we find that future fund performance is indeed negatively related to both rank gap and BHRG, our two window dressing measures.  We find that a one standard deviation increase in the rank gap and BHRG measures is associated with a decline of 32.1% and 39.3%, respectively, in the average values of next quarter's alpha.  In our empirical tests, we are careful to address the argument that our window-dressing measures are not simply capturing the activities of managers engaged in momentum trading first documented by Jegadeesh and Titman (1993). That is, a fund that window dresses and another fund that pursues a momentum strategy could be difficult to distinguish as both could be buying winners and selling losers. Our finding that the two window-dressing measures are negatively correlated with future performance suggests that the managers are not following a momentum-based strategy, which would have resulted in better future performance on average.

The third and last part of our study relates to investors' reaction to managers' window-dressing behavior. Given its adverse effects on future fund performance one would expect investors to punish such managers with reduced fund flows. This in turn leads to an interesting question: why do some managers, especially those of poorly performing funds, nevertheless do it and bear the risks involved? We argue that window-dressing managers potentially benefit from two factors. First, window-dressing activity can be inferred to some extent by the discrepancy between a fund's reported performance and its performance imputed from its disclosed portfolio holdings. Second, SEC rules allow a delay of portfolio disclosure for up to 60 days that provides a window-dressing manager an opportunity to benefit from good performance during the delay period.[4] If a window-dressing manager performs well during the delay period, then the investors are less likely to attribute the discrepancy to window-dressing and more likely to a change in the manager's security selection strategy. In this case, during the period subsequent to the portfolio disclosure, the fund will be rewarded with incrementally higher flows than that justified by the fund's past performance. In contrast, if the performance during the delay period is bad, then

[4] Under the Securities Act of 1933, the Securities Exchange Act of 1934, and the Investment Company Act of 1940, mutual fund managers are required to periodically disclose their holdings. Following a 1985 amendment, funds were required to submit annual and semiannual reports (N-CSR and N-CSRS, respectively); however, a large majority of managers voluntarily continued to disclose their portfolio holdings on a quarterly basis as was previously required. Effective May 10, 2004, the U.S. Securities and Exchange Commission requires investment companies to also file their complete portfolio schedules as of the end of the first and the third fiscal quarters on Form N-Q. Further, schedules must be filed within 60 days following quarter ends. See http://www.sec.gov/rules/final/33-8393.htm#IB for details.

investors are more likely to attribute the discrepancy to window dressing and punish the manager with incrementally lower flows than that justified by past performance.

In essence, we argue that managers that window dress are essentially taking a bet that will pay off if their performance between the quarter end and filing/disclosure date turns out to be good. Investors are more likely to believe that these managers have stock selection ability if they attribute the improved fund performance to the disclosed high (low) proportion of assets invested in winning (losing) stocks. In this scenario, as the signals of managerial ability from both high performance over the delay period and a composition of portfolio holdings tilted towards winners reinforce each other, investors will reward such funds with higher flows. In contrast, if the window-dressing manager experiences continued poor performance during the delay period, then investors will receive conflicting signals and will suspect managers of window-dressing behavior and shun such funds by withdrawing or not investing capital.

Our results are consistent with such an equilibrium. In particular, we find that window dressers receive lower unconditional flows relative to non-window dressers subsequent to the delay period. However, conditional on the state of good performance during the delay period, window dressers benefit from higher flows while conditional on the bad performance state, they incur a cost in terms of lower flows. We also find evidence consistent with window dressers taking a risky bet on fund flows wherein they exhibit greater dispersion in flows across the good and bad performance states. This bet by window dressers has an unconditional mean flow that is lower than that of non-window dressers, but has a non-zero probability of higher conditional mean flows in the good performance state.

In addition to the contribution of our paper to the window-dressing literature discussed before, our paper builds on a broader literature that studies the effects of portfolio disclosure on the investment decisions of money managers (Musto, 1997 and 1999), the consequences of frequent portfolio disclosure such as free riding and front running by other market participants (Wermers, 2001, and Frank, Poterba, Shackelford, and Shoven, 2004), the determinants of portfolio disclosure and its effect on performance and flows (Ge and Zheng, 2006), and the motivation for institutional investors' confidential 13F holdings that allow them to disclose portfolio holdings with a delay (Agarwal, Jiang, Tang, and Yang, 2011).

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops testable hypotheses. Section 3 describes the data and the construction of the main variables used in the study including the two window dressing measures. Section 4 analyzes the determinants of window-dressing behavior of fund managers. Section 5 investigates the effect of window dressing on future fund performance. Section 6 contains the analysis of the effect of window dressing on future fund flows and the description of the equilibrium. Section 7 concludes.

## 2. Related Literature and Testable Hypotheses

One strand of related literature studies the relation between the turn-of-the-year effect and window dressing by institutional investors. Earlier papers in this literature include Haugen and Lakonishok (1988) and Ritter and Chopra (1989) who argue that window dressing can potentially explain the January effect. Sias and Starks (1997), Poterba and Weisbenner (2001), and Chen and Singal (2004) attempt to disentangle tax-loss selling and window-dressing explanations for the turn-of-the-year effect and provide evidence in support of tax-loss selling. Starks, Yong, and Zheng (2006) sharpen the tests in these prior studies by studying municipal bond closed-end funds to provide further support for tax-loss selling driving the January effect.

Another strand of literature studies the trading behavior of institutional investors around quarter ends to find evidence of window dressing. Lakonishok, Shleifer, Thaler, and Vishny (1991) examine the quarterly purchase and sales of equity holdings of pension funds and show that they sell more losers in the fourth quarter compared to the prior three quarters. He, Ng, and Wang (2004) examine the quarterly holdings of different types of institutions to show that the ones who invest on behalf of clients sell more poorly performing stocks during the last quarter than during the first three quarters of the year. Moreover, this trading behavior is more pronounced for institutions whose portfolios have underperformed the market. Ng and Wang (2004) find that institutions sell more extreme losing small stocks in the last quarter of the year, but buy more small winners and small losers in the subsequent quarter, and conclude that this trading pattern is consistent with window dressing. Meier and Schaumburg (2004) analyze window-dressing behavior in equity mutual funds by proposing shape tests for alternative trading patterns and find evidence consistent with window dressing.

Motivated by the insights in these studies, we develop two new measures of window dressing to test a number of hypotheses related to the determinants and consequences of window dressing. To start, we posit that mutual fund managers having lesser skill and achieving poor performance during a quarter are more likely to window dress. The rationale is that these managers choose to window dress as a last resort when they have performed poorly, have limited skill, and therefore little expectation that they will perform better in the future. Further, we expect funds with higher expense ratios to be more associated with window dressing as the managers of these funds stand to gain the most in terms of fees from their investors. Furthermore, we expect that funds involved in window dressing should also exhibit greater turnover resulting from portfolio churning around quarter ends. Our first hypothesis is therefore as follows:

*Hypothesis 1: Window dressing should be negatively related to manager skill and fund performance in the first two months of a quarter, and positively related to fund's expense ratio and portfolio turnover.*

As stated earlier, the main objective of window dressing is to strategically alter the portfolio composition around quarter ends prior to portfolio disclosure so as to appear better to current and potential investors. Therefore, window dressing should invariably be associated with unnecessary trading and portfolio churning that will exacerbate transaction costs without enhancement to fund performance. However, buying winners and/or selling losers towards quarter end can also be consistent with a manager adopting an alternative investment strategy such as momentum. In contrast to window dressing, momentum strategies should be associated with better future performance (see Jegadeesh and Titman, 1993). This distinction provides us with a test to validate our proposed measures of window dressing thus leading to our second hypothesis:

*Hypothesis 2: Window dressing should be associated with lower future fund performance.*

We note that one critical issue missing from the literature on window dressing relates to the incentives of fund managers to engage in window dressing. If investors believe managers to be guilty of misleading them by strategically changing their portfolios around quarter ends, investors will punish the managers by lowering flows into the funds. This poses the question—how do fund managers stand to gain by window dressing?

To better understand the incentives behind window dressing, we make two arguments. Our first argument rests on investors receiving two signals about a manager's ability. The first signal relates to a fund's quarterly performance that is observed immediately upon the quarter end. The second signal relates to the portfolio composition that is received with a delay of up to 60 days following quarter end. These two signals can sometimes conflict with each other. For example, a fund may disclose a high (low) proportion of winner (loser) stocks, but may exhibit poor quarterly performance. Such incongruence between the two signals of managerial ability can be attributable to either window dressing or security selection aimed at superior future performance. Our second argument is that the fund's performance during the delay period helps investors resolve the potential conflict between the two signals. If the performance is good, then investors are more likely to attribute this conflict to improved security selection and reward the fund with higher flows than that justified by past performance. In contrast, if the performance over the delay period is bad, then investors are more likely to attribute the conflict between the two signals to window dressing and punish the fund with lower flows than justified by past performance. These two scenarios together can explain how window dressing can occur in equilibrium, leading us to our third and final hypothesis:

*Hypothesis 3: Relative to non-window dressers, funds whose managers window dress should receive higher (lower) incremental future flows if the fund performance over the reporting delay period is good (bad).*

## 3. Data and Variable Construction

We construct our main data set by merging the survivorship-bias-free mutual fund database from the Center for Research in Security Prices (CRSP) with the Thomson Financial mutual fund holdings database. Since the focus of our study is on actively managed U.S. equity funds, we follow KSZ (2008) to exclude balanced, bond, international, money market and sector funds. The CRSP mutual fund database includes information on mutual funds' monthly returns, total net assets, inception date, fee structure, investment objectives, portfolio turnover ratio, and other attributes. The Thomson Financial mutual fund database provides quarterly or semiannual holdings of mutual funds in our sample. We merge these two databases using the MFLINKS database from Wharton Research Data Services (WRDS).

Since the CRSP mutual fund database provides information at the share-class level, we aggregate the data at the fund level by weighting each share class by its total net assets to obtain value-weighted averages of monthly returns and annual expense ratios. Our final sample comprises of 95,695 quarterly reports from 2,976 equity funds that cover the period January 1984 through December 2008.

*3.1. Measures of window dressing*

As window-dressing behavior cannot be ascertained with certainty from financial data, a main contribution of our paper is to introduce measures of window dressing that use reported fund holdings and returns. In particular, we propose a relative and an absolute measure of window dressing, both measures capturing the inconsistency between fund's performance using net asset value (NAV) information and fund's performance from the reported portfolio holdings.

*3.1.1 Rank Gap: Relative measure of window dressing*

At the end of each fund fiscal quarter we sort in descending order all domestic stocks appearing in the CRSP stock database into quintiles according to their returns over the past three months.[5] The first (fifth) quintile consists of stocks that achieve the highest (lowest) returns. Then, using the reported holdings of each fund, we identify stocks that belong to the various quintiles and calculate the proportion of the fund's assets invested in the first and fifth quintile set of stocks. We refer to these two proportions as the winner and loser proportions, respectively.

[5] As discussed previously, before May 2004, funds were required to report their portfolio holdings every 6 months, although a large number of funds voluntarily disclosed their portfolios every 3 months. In our sample, we include all these funds. As a result, funds that report every 3 month will show up 4 times each year while those that report every 6 months will show up twice.

Next, for each fiscal quarter that has at least 100 funds reporting holdings, we rank the funds in three ways. For the first ranking, we sort all the funds in descending order by their quarterly returns, with funds in the first percentile bin being the best performing funds (and all assigned rank equal to 1) and funds in the 100$^{th}$ percentile being the worst (and all assigned rank equal to 100). For the second ranking, we sort all the funds in *descending* order according to their proportion of winner stock holdings and again assign ranks between 1 and 100 to this statistic, with funds in the first percentile bin having the highest winner proportion and funds in the 100$^{th}$ percentile having the lowest. For the third ranking, we sort all the funds in *ascending* order according to their proportion of loser stock holdings and assign rank similarly. Hence, funds in the first percentile bin have the lowest loser proportion and funds in the 100$^{th}$ percentile have the highest. Note that we switch the sorting order for the loser stocks to make the interpretation of rankings consistent with that for the winner stocks (e.g., a high proportion of winners is analogous to a low proportion of losers).

In the absence of window dressing, a well-performing fund should have a high rank based on fund performance, a high rank of winner proportion, and a high rank of loser proportion. In contrast, a poorly performing fund should have a low rank of fund performance, a low rank of winner proportion, and a low rank of loser proportion. These relations are illustrated in Appendix B. If a fund has a low rank of performance, but relatively high rankings of winner and loser proportions, such inconsistency would hint towards the fund manager being engaged in window dressing. The larger is this rank inconsistency, the higher is the likelihood of window dressing. We thus compute rank inconsistency as

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2},$$

where *PerformanceRank* is the rank of fund performance, *WinnerRank* is the rank of winner proportion, and *LoserRank* is the rank of loser proportion. The theoretical range of rank consistency is [–99, 99]. To help interpret rank inconsistency as a probability measure and lie between 0 and 1, we scale it to obtain our first window dressing measure, Rank Gap:

$$[(PerformanceRank - \frac{WinnerRank + LoserRank}{2}) + 100] / 200,$$

The theoretical bound of the rank gap measure is thus (0.005, 0.995). The higher is the rank gap measure, the greater is the likelihood of window dressing. In Table 1 Panel A, we report summary statistics for the rank gap measure and observe that the mean (median) of this measure in our sample is 0.5 (0.4975).

*3.1.2 Backward Holding Return Gap (BHRG): Absolute measure of window dressing*

Our second measure of window dressing is backward holding-based return gap (BHRG), which is motivated by the KSZ return gap measure. BHRG is defined as the difference between the quarterly return net of expenses of a hypothetical portfolio comprised of the fund's end-of-quarter holdings (assumed to be held throughout the quarter), and the fund's actual quarterly return.[6] Similar to the rank gap measure, the higher is the BHRG, the greater is the likelihood of window dressing. In Table 1 Panel A, we report summary statistics for BHRG and show that the mean (median) is 0.010 (0.004).

Although the KSZ return gap measure and BHRG share some similarities in the way that they are computed, the objectives of these two measures are different. While return gap is intended to capture managerial skill, BHRG attempts to measure window dressing. Appendix A

[6] Quarterly expenses are defined as the annual expense ratio from the CRSP mutual fund database divided by four. Also, for the computation of quarterly returns on the hypothetical portfolio, we adjust the number of shares and the stock prices for stock splits and other share adjustments.

provides an illustration of how both measures are computed, and how BHRG helps identify a window dressing manager while return gap measure is used to identifying a skilled manager.

In our subsequent empirical analysis, we use both window dressing measures (rank gap and BHRG) in their continuous forms. As both measures are intended to capture the propensity to window dress, they do not provide a definitive categorization of funds actually engaged in window dressing and those who are not. Presumably, the percentage of funds engaged in window dressing should be relatively small. Hence, in order to categorize funds as window dressers and non-window dressers, we also construct indicator variables of window dressing based on the top 10% and 20% values of the rank gap and BHRG continuous measures. We repeat our tests using these alternative measures of window dressing.

### *3.2. Other variables: performance, fund flows, portfolio turnover, manager skill, and style*

#### *3.2.1 Performance*

Our measure for fund performance should control for the momentum effect as buying winners and selling losers to window dress is also consistent with momentum trading. Hence, as a performance measure, we compute the monthly alphas using the four-factor model of Carhart (1997). Our monthly alphas are computed "out-of-sample" using 24-month rolling windows ending in the prior month. For example, January alpha is the difference between the fund's return in January minus the sum product of the estimated beta coefficients (from the 24-month window ending in December) and factors returns in January. Finally, we aggregate monthly alphas to obtain quarterly alphas. Table 1, panel B shows that the mean (median) quarterly alpha is −0.28% (−0.29%).

#### *3.2.2 Fund flows*

For each fund, we calculate monthly percentage net fund flows as $\left[TNA_t - TNA_{t-1} \cdot (1+r_t)\right] / TNA_{t-1}$, where $TNA_t$ and $TNA_{t-1}$ are the fund's total net assets at the end of months $t$ and $t-1$, respectively, and $r_t$ is the fund's net-of-fee return during month $t$. For some of our empirical tests, we use quarterly fund flows, which are computed in a manner similar to the monthly fund flows by summing the dollar flows over the three months of the quarter divided by the total net assets at the beginning of the quarter. In Table 1 Panel B we observe that the mean (median) quarterly percentage flows is 3.54% (–0.35%).

*3.2.3 Portfolio Turnover*

Since we relate window dressing to portfolio turnover during a quarter, instead of using the annual turnover ratio reported in the CRSP mutual fund database, we compute the quarterly turnover ratio directly from the holdings data as the minimum of the dollar values of purchases and sales, divided by total net assets at the beginning of the quarter.[7] From Table 1 Panel B, we can see that the mean (median) quarterly portfolio turnover is 12% (10%).

*3.2.4 Manager skill*

For manager skill, we follow KSZ (2008) and use the 12-month moving average of the monthly return gap. They find that higher return gap leads to higher future performance in the following month. The monthly return gap is computed as the difference between a fund's monthly return and the monthly return of a hypothetical portfolio that is assumed to have been invested each month of a quarter in the stock positions disclosed at the beginning of the quarter. In Table 1, Panel B we report that the mean (median) manager skill measure is –0.0003 (–0.0002), similar to the figures in the KSZ (2008) study.

*3.2.5 Style*

[7] We recognize that this "trade volume" does not account for interim trading or trading of securities that do not appear in the holdings either at the beginning or at the end of a quarter.

We use the investment objective code (IOC) field from the Thomson Financial mutual fund holdings database to construct style dummies. We exclude four categories (international, municipal bonds, balanced, and bonds & preferreds) from the nine style categories to classify the funds in our sample into the five remaining categories: Aggressive Growth, Growth, Growth & Income, Metals, and Unclassified. If a fund's IOC is Unclassified, we use the Lipper objective codes (EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE), Strategic Insight objective (AGG, GMC, GRI, GRO, ING, SCG), and Wiesenberger Fund Type code (G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG) to identify if the fund is an actively managed equity fund for including it in our sample.

### *3.3. Correlations*

Table 1, Panel C provides the correlations between the key variables. Of note, it is interesting that the two window dressing measures, rank gap and BHRG, have a positive correlation of 0.50. In addition, we observe a negative correlation between both window dressing measures and fund performance (correlation of –0.37 with the rank gap measure, and –0.08 with BHRG). Furthermore, the two window dressing measures are negatively correlated with manager skill (correlations of –0.13 and –0.19); positively related with expense (both correlations equal to 0.07); and positively related with turnover (correlations of 0.15 and 0.33). Although these correlations are based on contemporaneous values of the different variables, and therefore do not necessarily imply causality, it is interesting to see that the sign of the correlations are consistent with our three hypotheses. We next test our hypotheses formally using multivariate analyses.

## 4. Motivation for and determinants of window dressing

### *4.1. Do investors respond to portfolio characteristics?*

In a world where investors only cared about fund performance in evaluating managerial ability, it is not clear why fund managers would attempt to distort portfolio characteristics, e.g., engage in window dressing, prior to disclosing their holdings. As noted in the introduction, there is growing evidence that investors rely on portfolio characteristics in addition to performance for identifying skilled managers. If this is indeed the case then capital flows from investors should also account for such characteristics. In the context of our study, these characteristics relate to the proportion of reported winners and losers in the disclosed portfolio. Therefore, we examine the relation between fund flows and proportions of winners and losers, after controlling for past performance by estimating the following ordinary least squares (OLS) regression:

$$\begin{aligned}\text{Flows}_{i,t+1} &= \beta_0 + \beta_1 \text{WinnerProp}_{i,t} + \beta_2 \text{LoserProp}_{i,t} + \beta_3 \text{Alpha}_{i,t} + \beta_4 \text{Manager Skill}_{i,t} \\ &+ \beta_5 \text{Expense}_{i,t} + \beta_6 \text{Size}_{i,t} + \beta_7 \text{Turnover}_{i,t} + \beta_8 \text{Load}_{i,t} + \text{Style dummies} + \text{Time dummies} + \psi_{i,t}\end{aligned} \quad \textbf{(1)}$$

where $\text{Flows}_{i,t+1}$ is the quarterly percentage net flow for fund *i* in quarter *t+1*, $\text{WinnerProp}_{i,t}$ ($\text{LoserProp}_{i,t}$) is the proportion of assets of fund *i* invested in the top (bottom) quintile of stocks in quarter *t*, $\text{Alpha}_{i,t}$ is the average risk-adjusted return or alpha of the fund *i* over quarter *t*, $\text{Manager Skill}_{i,t}$ is the 12-month moving average of the monthly return gap measure for fund *i* as of the end of quarter *t*, $\text{Expense}_{i,t}$ is the annual expense ratio of fund *i* during quarter *t*; $\text{Turnover}_{i,t}$ is the portfolio turnover of fund *i* during quarter *t*, $\text{Size}_{i,t}$ is the size of fund *i* measured as the logarithm of total assets at the end of quarter *t*, $\text{Load}_{i,t}$ is an indicator variable that takes a value of 1 if fund *i* has either front-end or back-end load during quarter *t*, and 0 otherwise, and $\psi_{i,t}$ is the error term. Throughout the paper, we cluster the standard errors by fund to account for cross-correlations in our panel data, and also include fixed effects for time and funds' investment styles.

Table 2 reports the results from the regression in equation (1). From the column labeled (1), we observe a positive and highly significant coefficient on the winner proportion (coeff. = 0.0773, p-value = 0.000), and a negative and highly significant coefficient on the loser proportion (coeff. = –0.0628, p-value = 0.000). It is important to note that the observed significant relation between fund flows and certain portfolio characteristics (i.e., winner and loser proportions) is in addition to the flows being driven by past performance (coeff. = 0.3512, p-value = 0.000) as has been documented in the extant literature (e.g., Chevalier and Ellison, 1997 and Sirri and Tufano, 1998). We observe similar findings in column (2) and (3) where we include alternative measures and combinations of manager skill and performance. In addition to the results for our main variables of interest, we observe a positive relation between fund flows and managerial skill and expense ratio, and a negative relation with portfolio turnover and load. Overall, these findings support the underlying premise for window dressing by the fund managers as investors respond to portfolio characteristics over and above the funds' past performance.

### *4.2. Determinants of Window Dressing*

Our first hypothesis is that window dressing is more likely to be associated with (a) relatively unskilled managers and funds performing poorly in the first two months of a quarter, and (b) funds having higher expense ratios and greater portfolio turnover. We test this hypothesis using both sorts on skill and performance as well multivariate regressions. An advantage of the sorting technique is that it does not impose linearity on the relation between window dressing and skill or performance. Also, given that both skill and performance are continuous variables, this method allows us to easily observe and interpret interaction effects. However, the sorting method is limited in the number of variables that one can sort on. To overcome this limitation we also later use multivariate regression techniques.

In Table 3 we present the results of our sorting analysis. Because both skill and performance are likely to influence window dressing, we conduct a conditional double sort where we first sort funds into five Managerial Skill quintiles and then, within each skill quintile, we sort into performance quintiles based on the average monthly four-factor alphas from the first two months of the quarter (2-month 4-factor alpha).[8] Panels A and B report the averages of the two window dressing measures, rank gap and BHRG, respectively for the 25 double-sorted portfolios. In both panels, controlling for managerial skill, in each row as we move from left to right (that is, from lowest to highest performance quintile), the average window dressing measure is monotonically decreasing. Similarly, controlling for performance, in each column as we move from top to bottom (that is, from lowest to highest skill quintile), the average window dressing measure again is monotonically decreasing. In addition to these patterns, the differences in the window dressing measures between the extreme performance quintiles as well as the skill quintiles are all highly significant at the 1% level. Further, we can observe the interactive effects of skill and performance on window dressing. We find (1) that the highest and lowest mean values of window dressing are in cells (1,1) and (5,5) respectively, and (2) that the values decrease monotonically along this diagonal. Together, these findings provide support for our first hypothesis that window dressing is negatively related to manager skill and first two months' performance during the quarter.

[8] In our reported empirical tests throughout the paper, we use the average alpha over the first two months of a quarter assuming that the manager window dresses during the third month. If we assume that the manager waits until the last day of the quarter, we can use the average three-month alpha instead of the average two-month alpha. Our results using this alternative specification are similar.

We next extend this analysis to a multivariate setting where in we estimate two different specifications: (1) OLS regressions based on each of the two window dressing measures (rank gap and BHRG) as the dependent variable, and (2) logistic regressions based on indicator variables of window dressing corresponding to the top 10% or top 20% values of the rank gap and BHRG measures as the dependent variables. Our regressions take the following form:

$$\begin{aligned}\text{WD}_{i,t} &= \lambda_0 + \lambda_1 \text{Two-month Alpha}_{i,t} + \lambda_2 \text{Manager Skill}_{i,t-1} + \lambda_3 \text{Expense}_{i,t} + \lambda_4 \text{Turnover}_{i,t} \\ &+ \lambda_5 \text{Size}_{i,t} + \lambda_6 \text{Load}_{i,t} + \text{Style dummies} + \text{Time dummies} + \xi_{i,t}\end{aligned} \qquad \textbf{(2)}$$

where $\text{WD}_{i,t}$ is the window dressing measure for fund *i* in quarter *t*, specified as a continuous (indicator) variable in the OLS (logistic) specification; $\text{Two-month Alpha}_{i,t}$ is the average risk-adjusted return or alpha of the fund *i* over the first two months of quarter *t*; $\xi_{i,t}$ is the error term, and the other variables are as defined previously.

Table 4, panel A, reports the results from the OLS and logistic regressions. Regardless of the window dressing measure used or its form (continuous or indicator), we observe the estimated coefficients of the performance and manager skill variables to be negative and statistically significant at the 1% level, confirming our findings from the double-sorting analysis. For example, using the continuous form of the rank gap measure (see column 2 of the table), we find that the estimated coefficient on the average two-month alpha variable is −2.1914 and that on the manager skill variable to be −1.9678, both significant at the 1% level. Using the continuous form of the BHRG measure as the dependent variable (column 5), the corresponding estimated coefficients are −0.1261 and −0.6198, respectively, again both significant at the 1% level. Further, these findings are also economically meaningful. To illustrate, a one standard deviation increase in alpha is associated with a decrease of 0.0331 in the rank gap measure, which represents approximately 6.6% of the average rank gap value of 0.5. For manager skill, a one standard deviation increase corresponds to a decrease of 0.0068 in the rank gap measure, which represents a 1.4% decline in the average rank gap value. For BHRG, the corresponding declines for one standard deviation increases in alpha and skill are 0.0019 and 0.0021 (18.6% and 20.6% of the average BHRG value of 0.0102), respectively.

For the regression based on the indicator variable representing the top 10% values of rank gap (see column 3), we find that the estimated coefficients on alpha and skill are –36.1561 and –42.6324, respectively, and significant at the 1% level. The economic significance of these coefficients is that a one standard deviation increase in (a) alpha reduces the probability of window dressing by 3.54% (39.8% of the implied probability of 8.89%); and (b) manager skill reduces the probability of window dressing by 1.12% (12.6% of the implied probability of 8.89%).[9] Using an indicator variable based on the top 10% values of BHRG (see column 6), the estimated coefficients on alpha and skill are –7.9389 and –35.5941, respectively, and statistically significant at the 1% level. In terms of economic significance, a one standard deviation increase in alpha and skill is associated a reduction in the probability of window dressing of 1.38% and 1.41% (or 10.0% and 10.2% of the implied probability of 13.8%), respectively. We find similar results for the top 20% indicator variable specifications (columns 4 and 7). Together, these findings are consistent with our first hypothesis that unskilled managers and funds that have performed poorly in the first two months of a quarter are more likely to window dress.

Our first hypothesis also relates the expense ratio and portfolio turnover to window dressing. In that regard, we find that the estimated coefficients on expense ratio are uniformly positive and statistically significant at the 1% level in all but one specification where it is significant at the 10% level. This finding is consistent with managers of funds with higher fees having greater

[9] We compute the implied probability of window dressing by keeping all the continuous independent variables at their mean values and the indicator load variable at 0.

incentive to engage in window dressing. Further, we find that the estimated coefficients on quarterly turnover are positive and statistically significant at the 1% level across all six specifications. Again, this finding is consistent with our first hypothesis that greater turnover can be a result of unnecessary trading activity of buying winners and selling losers.

In addition to the fund characteristics included as independent variables in equation (2), there can potentially be others that can influence the decision to window dress. We consider three such characteristics: (1) whether the fund is team managed or has a single manager (with the rationale being that window dressing may be less likely in a team environment as it requires coordination and agreement among multiple individuals); (2) the extent to which the fund's investors are institutional investors (with the rationale being that institutional investors are more likely than retail investors to detect and penalize window dressing behavior); and (3) whether the fund is currently closed to new investment (with the rationale being that a manager of such a fund has less ability to affect fund inflows through window dressing). We augment equation (2) by including measures to capture these three characteristics: $Team_{i,t}$, an indicator variable that takes a value of 1 if fund *i* is team managed during quarter *t*, and 0 otherwise; $InstProp_{i,t}$, defined as the proportion of fund *i*'s assets during quarter *t* that are held in institutional share classes; and $OpenProp_{i,t}$, defined as the proportion of fund *i*'s assets in share classes during quarter *t* that are open to new investment.

As the number of observations decreases significantly after adding these variables, we separately report the results from estimating augmented equation (2) in Table 4, panel B.[10] We find insignificant coefficients on the team managed and institutional ownership variables. In contrast we find weak evidence that window dressing is positively related to a fund being open to

[10] The drop in observations is due to team management information beginning in 1993 while information on the institutional share classes and open to new investment variables begins in 1999.

new investment (see columns 1 and 4 when we use the continuous forms of window dressing measures).[11]

Overall our findings in Table 4 support our first hypothesis that window dressing is negatively related to recent performance and manager skill, and is positively related to a fund's expense ratio and portfolio turnover. In the next section, we examine how window dressing affects future fund performance.

## 5. Window dressing and future performance

Building on the results in the previous section, we hypothesize that window dressing, as a value-destroying activity involving unnecessary portfolio turnover, should be associated with lower future performance. Since momentum-based trading also shares the characteristic with window dressing of buying winners and selling losers, but unlike window dressing should be associated with better rather than worse future performance (see Jegadeesh and Titman, 1993). Nonetheless, we are careful to control for any potential momentum trading in our empirical tests by computing performance based on the four-factor model of Carhart (1997).

We first conduct single sorts of funds into deciles each quarter according to values of rank gap and BHRG, respectively. We then compute and report in Table 5 mean four-factor alphas estimated over the subsequent quarter for each rank gap decile (panel A) and each BHRG decile (panel B). For each window-dressing measure, we observe that the alphas exhibit a monotonically *decreasing* pattern as we go from the lowest to the highest decile. This pattern

[11] Related to this finding, unlike open-end funds that may have incentives to window dress in order to influence flows, such incentives are less likely to exist for closed-end funds. Hence, for robustness we compute BHRG for 88 closed-end equity funds over the same time period of our analysis and find that their average BHRG (0.0068) is significantly lower than that of open-end funds (0.0102) at the 1% level (note that we do not test the difference in averages using the rank gap measure since it is a relative measure that is bounded between 0 and 1 and has a mean of approximately 0.5).

suggests that higher window dressing is associated with lower subsequent performance. The difference in the mean alphas for the bottom and top window-dressing decile (10–1) is –0.33% for rank gap and –0.30% for BHRG, both of which are statistically significant at the 1% level. Further, these spreads or differences in mean alphas are of similar order of magnitude as the average quarterly alpha of –0.28% reported earlier in Table 1, panel B.

As mentioned earlier, buying winners and selling losers can also be attributed to momentum trading. Hence, along with alphas, we also report raw returns and momentum betas for each decile. We continue to observe a monotonically decreasing pattern of raw returns for funds sorted by rank gap, and with a statistically significant spread between the extreme deciles of –0.99%. However, the pattern is less pronounced when funds are sorted by BHRG and the spread of –0.26% is statistically insignificant. Interestingly, the momentum betas estimated from the four-factor model show a monotonically *increasing* pattern, ranging from 0.002 (–0.054) for the lowest decile to 0.126 (0.200) for the highest decile of funds sorted by rank gap (BHRG). Furthermore, the spreads between the two deciles are both statistically significant at the 1% level. Taken together, these findings underscore that the spreads in the mean alphas are significant, despite the concurrent evidence of a momentum effect in the sorted deciles.

Next, we explore the effect of manager skill in conjunction with window dressing. We double sort the funds each quarter into 25 portfolios by first sorting on manager skill and then on window dressing. Table 6 reports the means of the next quarter four-factor alphas for the 25 portfolios (rank gap results are reported in panel A and BHRG results are in panel B). Controlling for manager skill, in each row of panels A and B as we move from left to right (lowest to highest value of window dressing), the average alphas generally decrease. This pattern corroborates our prior finding using single sorts in Table 5 that greater window dressing is associated with subsequent worse performance. The last column labeled (5−1) shows that differences in average alphas between the 5th (highest window dressing) and 1st (lowest window dressing) quintiles are significant at the 10% level or lower in most cases.

The bottom rows of panels A and B of Table 6 show the differences in the average alphas across manager skill after controlling for window dressing. Consistent with KSZ (2008), we observe that the performance of the 5th quintile (highest manager skill) is significantly greater than the performance of the 1st quintile (lowest manager skill) in all five cases for rank gap (panel A) and four out of the five cases for BHRG (panel B). Also of note, in both panels, the worst performing funds are in the upper right hand corner, e.g., funds with the highest window dressing and the lowest skill.

Our results so far indicate that window dressing appears to adversely affect subsequent fund performance. To further verify if these results hold in a multivariate setting, we estimate the following regression:

$$\begin{aligned}\text{Alpha}_{i,t+1} &= \vartheta_0 + \vartheta_1\text{WD}_{i,t} + \vartheta_2\text{Manager Skill}_{i,t} + \vartheta_3\text{Expense}_{i,t} + \vartheta_4\text{Turnover}_{i,t} \\ &+ \vartheta_5\text{Size}_{i,t} + \vartheta_6\text{Load}_{i,t} + \vartheta_7\text{Flow}_{i,t} + \text{Style dummies} + \text{Time dummies} + \varepsilon_{i,t}\end{aligned} \quad \textbf{(3)}$$

where all variables are as defined previously.

Results using the continuous window-dressing measures are reported in panel A of Table 7, while panel B reports results using indicator variables of window dressing. In panel A, findings from three models are reported: in Model 1, rank gap is used as the window dressing measure; in Model 2, BHRG is used; and in Model 3, both measures are included.

For Model 1, we show that the estimated coefficient of rank gap is −0.0087, significant at the 1% level, which indicates that a larger rank gap (i.e., higher window dressing) is associated with lower fund performance in the following quarter. A one standard deviation increase in rank gap is associated with a decrease of 0.09% in quarterly alpha (32.1% of the average alpha value of –0.28%). This evidence is consistent with our second hypothesis that window dressing destroys value and drags down fund performance due to unnecessary trading costs. The estimated coefficient of manager skill is positive (coeff. = 0.3907) and is significant at the 1% level, a finding consistent with KSZ (2008) that greater manager skill is associated with better future performance. Results for the other control variables are also consistent with prior literature. For example, the estimated coefficient on fund size is negative (coeff. = –0.0332) and significant at the 1% level, indicating that bigger funds are associated with worse performance due to decreasing returns to scale (Berk and Green, 2004) that can arise from organizational diseconomies (Chen, Hong, Huang, and Kubik, 2002), among other factors.

In Model 2, we obtain similar results when we replace rank gap with BHRG, our alternative window dressing measure. The estimated coefficient on BHRG is negative (coeff. = –0.0299) and significant at the 1% level. A one standard deviation increase in BHRG is associated with a decrease of 0.11% in quarterly alpha (39.3% of the average alpha value of –0.28%). In Model 3, when we include both rank gap and BHRG, the estimated slope coefficients for both are negative and significant at the 5% level (rank gap coeff. = –0.0056 and BHRG coeff. = –0.0210).

In Table 7 Panel B, we replace the continuous forms of the two window dressing measures with indicator variables corresponding to the top 10% and 20% values of rank gap and BHRG, respectively. In the results reported for Models 4 and 5, using the top 10% indicator variable for each window dressing measure, the estimated coefficients on the measures (rank gap coeff. = –0.0025 and BHRG coeff. = –0.0018) continue to be negative and significant at the 5% level or better. This implies that the performance of window-dressing managers is lower by 0.25% and 0.18%, respectively, which are economically large values in view of the average alpha value of –0.28%. In Model 6, when both measures are included, only the rank gap measure is significantly negative. The results in Models 7-9 when we use the top 20% indicator values are analogous to those in Models 4-6.

Since we control for the manager skill (KSZ 12-month average return gap measure) in all our tests, our results confirm that BHRG measure of window dressing is distinct from the KSZ measure. Also, our finding that lower future performance is associated with greater window dressing is in sharp contrast to momentum trading being typically associated with higher future performance (see, e.g., Jegadeesh and Titman, 1993, Carhart, 1997, and Sias, 2007). Hence, even though both momentum trading and window dressing involve buying winners and selling losers, we show that the strategic quarter-end purchase of winners and sale of losers in case of window dressing leads to worse performance, and therefore cannot be attributed to momentum trading. Further, it is important to note that we use four-factor alphas that control for any momentum effect. Together, these findings are consistent with our second hypothesis that funds involved in window dressing tend to show worse future performance.

If window dressing is harmful for investors as the above results suggest, one would expect investors to rationally respond to this value-destroying activity and withdraw their capital from those funds involved in window dressing. Thus, *prima facie* there appears to be little incentive for a fund manager to window dress. We next shed light on this issue and investigate how window dressing can exist in equilibrium.

## 6. Window dressing and fund flows

Our third hypothesis relies on poorly performing managers potentially benefitting from window dressing as a result of regulatory reporting requirements. As discussed earlier, SEC allows the fund managers to file their portfolio holdings reports up to 60 days following the end of a quarter.

If a manager chooses to window dress and fund performance subsequently improves during the delay period, it may make it difficult for investors to discern if this manager has engaged in window dressing or is exhibiting stock selection skill. Thus, a fund manager who window dresses, but performs well during the delay period, may end up receiving the benefit of doubt from the investors, who may attribute manager's good performance to security selection and not to window dressing. As a result, this manager will receive higher flows between the filing date and the end of the quarter compared to the managers who do not window dress. However, if the window dressing manager fails to achieve good performance during the delay period, he is penalized with lower flows compared to non-window dressers.

To test the above conjecture we collect data on the actual filing dates of funds from their electronic N-Q and N-CSR filings in the SEC EDGAR database available over the period 1994-2008. We then compute the fund flows between the filing date and the end of the quarter using assets under management on the two dates and returns over the period.[12] This number is then normalized by the number of days between the two dates to produce an average daily fund flow measure, which we denote as *DlyFlow*. We then estimate the following regression:

$$\begin{aligned}\text{DlyFlow}_{i,t+1} = {} & \gamma_0 + \gamma_1 \text{WDdummy}_{i,t} + \gamma_2 \text{WDdummy}_{i,t} \times \text{GoodPerfdummy}_{i,t} \\ & + \gamma_3 \text{GoodPerfdummy}_{i,t} + \gamma_4 \text{Perf}_{i,t} + \gamma_5 \text{Manager Skill}_{i,t} + \gamma_6 \text{Expense}_{i,t} \\ & + \gamma_7 \text{Turnover}_{i,t} + \gamma_8 \text{Size}_{i,t} + \gamma_9 \text{Load}_{i,t} + \text{Style dummies} + \text{Time dummies} + \omega_{i,t}\end{aligned} \quad \textbf{(4)}$$

where $\text{DlyFlow}_{i,t+1}$ are the average percentage daily fund flows for fund *i* between the fund's filing date and end of quarter *t+1*, $\text{WDdummy}_{i,t}$ is an indicator variable which takes a value of 1 when the rank gap or BHRG window dressing measure for a fund *i* is either in the top 10% or in the top 20% of all funds in quarter *t*, $\text{GoodPerfdummy}_{i,t}$ is an indicator variable that equals 1 if

[12] When assets under management are not available for a particular date, we use the figure as of the prior month-end adjusted for the returns between that month-end and the filing date.

average daily return of fund *i* over the delay period (between the end of quarter *t* and the fund's filing date) is positive and 0 otherwise, and $\mathrm{Perf}_{i,t}$ is the quarterly alpha of fund *i* over quarter *t*. The other independent variables are as defined previously. Note that we use the indicator (rather than the continuous) forms for window dressing and performance in equation (4) so that we can compare the flows between window dressers and non-window dressers rather than the difference in the sensitivities of flows to either performance or window dressing for the two groups.

Our third hypothesis predicts that a manager benefits from window dressing through higher flows between the filing date and the end of quarter if he performs well over the delay period; however, he incurs a cost in terms of lower flows if the performance during the delay period is poor. Using the estimates from equation (4) above, the incremental flows (i.e., flows after controlling for past performance and the other fund characteristics) for the window dressers and non-window dressers corresponding to good and bad performance during the delay period can be illustrated as follows in a two-by-two matrix:

| | Window dressers | Non-Window Dressers | Column Diff. |
|---|---|---|---|
| Good Performance | $\gamma_1 + \gamma_2 + \gamma_3$ | $\gamma_3$ | $\gamma_1 + \gamma_2$ |
| Bad Performance | $\gamma_1$ | 0 | $\gamma_1$ |
| Row Diff. | $\gamma_2 + \gamma_3$ | $\gamma_3$ | |

In the first row of the above matrix, if the performance during the delay period is good, the difference in the flows for window dressers and non-window dressers is $\gamma_1 + \gamma_2$. Our third hypothesis predicting higher flows for window dressers attaining good performance implies that $\gamma_1 + \gamma_2$ should be positive. In contrast, in the second row, if the performance is poor, the difference in flows is simply $\gamma_1$. Our hypothesis also posits lower flows for window dressers if the performance is bad, thus implying that $\gamma_1$ should be negative. Together, these two predictions imply that $\gamma_2$ should be positive.

Examining equation (4) further, we observe that when we do not condition on performance during the delay period, that is, the good performance dummy equals 0, $\gamma_1$ captures the difference in the *unconditional* flows between window dressers and non-window dressers. Given that our hypothesis predicts $\gamma_1$ to be negative, this is turn implies that window dressers should thus receive lower unconditional flows. However, if we condition on good performance during the delay period, our hypothesis predicts windows dressers to receive higher *conditional* flows ($\gamma_1 + \gamma_2 > 0$). Taken together this suggests that window dressers are effectively taking a bet on flows that has a lower unconditional mean, but a non-zero probability of higher conditional mean. The riskiness of this bet can be gauged by comparing the dispersion in flows between the two states (good and bad performance) for window dressers and non-window dressers. The row differences show that window dressers will be taking a more risky bet compared to non-window dressers if $\gamma_2 + \gamma_3 > \gamma_3$, which will be the case if $\gamma_2$ is positive. Our earlier analysis found that window dressers typically have lower skill and poor recent performance, and thus may explain why they may be willing to engage in such higher risk-taking in an attempt to alleviate heightened career concerns (see Khorana, 1996 and Chevalier and Ellison, 1997).

We report the results from the estimation of equation (4) in Table 8. There are three findings generally consistent with our arguments above. First, we observe that the estimated coefficient for the window dressing dummy ($\gamma_1$) in three of the four model specifications is negative and significant (–0.0009 and –0.0007) for the top 10% and 20% rank gap dummies

(Models 1 and 2); and (–0.0007) for the top 10% BHRG dummy (Model 3). This finding is consistent with window dressers attaining lower flows when performance during the delay period is poor. Second, we find the sum of the estimated coefficients of the window dressing dummy and its interaction with the good performance dummy ($\gamma_1 + \gamma_2$) to be positive and significant in one of the four specifications (see results of the F-test in last row of Table 8) and insignificant in the others. This provides some evidence that window dressers obtain higher or no worse flows than non-window dressers if performance is good. Third, we observe that $\gamma_2$ is significantly positive in three of the four specifications consistent with greater risk-taking (i.e., a higher dispersion in flows between good and bad states) by window dressers.

Taken together, the results in Table 8 are consistent with our third hypothesis explaining the equilibrium of window dressing. If the performance during the delay period is good, our findings show that investors attribute the incongruence between holdings-based returns and actual returns to improved security selection and will reward the fund with higher flows. In contrast, if the fund performance is bad, then investors attribute the incongruence to window dressing and punish the fund with lower flows.

## 7. Concluding remarks

In this paper, we shed light on alleged window-dressing behavior of mutual fund managers using a large sample of actively managed U.S. equity funds over the period 1984-2008. We propose two measures of window dressing, rank gap and backward holding return gap (BHRG), both of which capture the inconsistency between actual performance based on net asset values and performance inferred from reported portfolio holdings.

In addition to proposing the two window-dressing measures, we contribute to the literature by documenting several interesting findings. First, window dressing is associated with unskilled managers who perform poorly during a quarter. Also, we find that funds with higher expense ratios exhibit greater window dressing, consistent with managers of such funds standing to gain more in terms of fees from investors. We also find that funds involved in window dressing show greater turnover that could be the result of portfolio churning around quarter ends. Second, we find that on average window dressers exhibit poor future performance, which helps us differentiate them from momentum traders and validate our measures of window dressing.

Third, we offer and test a rationale for why managers may engage in window dressing to potentially benefit from the delay allowed by the SEC for disclosing portfolio holdings. We find that if the fund performance (which can be observed) improves during the delay period, fund investors may attribute the disclosed holdings, tilted towards winner stocks, to stock selection ability rather than window-dressing behavior, and reward the managers with higher flows. In contrast, if the performance during the delay period turns out to be poor, investors may attribute the disclosed holdings to window-dressing and withdraw their capital. These costs and benefits of window dressing show how window dressing can exist in equilibrium where investors respond rationally to the signals of managerial ability as inferred from the fund's performance and reported portfolio holdings. Overall, these findings contribute to the debate on mandatory portfolio disclosure by institutional investors by highlighting some of the unintended consequences associated with such disclosure.

## Appendix A. Illustration of BHRG versus KSZ return gap measures

This Appendix illustrates how the backward holding return gap (BHRG) identifies window dressing while the KSZ return gap measure captures managerial skill.

Suppose there are two stocks in the market, A and B. A is the winner stock in the current quarter with a 10% actual return (AR), while B is the loser stock with a –10% AR. There are three types of managers. The first manager is *skilled* and who has the ability to select winner stocks at the outset of a given quarter. The second manager is a *window dresser* (presumably without any skill), who selects winner stocks ex post at the *end* of the quarter after he/she has observed how stocks have performed during that quarter. The third manager is *unskilled*, but also someone who does not window dress. Absent having skill, this manager always diversifies across the two stocks and invests 50% in A and 50% in B.

Table A1: Computing BHRG and Return Gap (KSZ) measures

Scenario 1: A is winner in the last quarter

| | portfolio holdings | | | measures | | | | |
|---|---|---|---|---|---|---|---|---|
| | Last quarter end | date1 | date2 | AR | BHR | FHR | BHRG | Return Gap |
| skilled manager | A: 100% | A: 100% | A: 100% | | | | | |
| | B: 0% | B: 0% | B: 0% | 10% | 10% | 10% | 0% | 0% |
| window dresser | A: 100% | A: 100% | A: 100% | | | | | |
| | B: 0% | B: 0% | B: 0% | 10% | 10% | 10% | 0% | 0% |
| unskilled manager | A: 50% | A: 50% | A: 50% | | | | | |
| | B: 50% | B: 50% | B: 50% | 0% | 0% | 0% | 0% | 0% |

Scenario 2: B is winner in the last quarter

| | portfolio holdings | | | measures | | | | |
|---|---|---|---|---|---|---|---|---|
| | Last quarter end | date1 | date2 | AR | BHR | FHR | BHRG | Return Gap |
| skilled manager | A: 0% | A: 100% | A: 100% | | | | | |
| | B: 100% | B: 0% | B: 0% | 10% | 10% | –10% | 0% | 20% |
| window dresser | A: 0% | A: 0% | A: 100% | | | | | |
| | B: 100% | B: 100% | B: 0% | –10% | 10% | –10% | 20% | 0% |
| unskilled manager | A: 50% | A: 50% | A: 50% | | | | | |
| | B: 50% | B: 50% | B: 50% | 0% | 0% | 0% | 0% | 0% |

Expected value of BHRG and Return Gap measure

| | BHRG | Return Gap |
|---|---|---|
| skilled manager | 0% | 10% |
| window dresser | 10% | 0% |
| unskilled manager | 0% | 0% |

Table A1 above shows how the BHRG window dressing measure is able to distinguish between the window dresser and the other two types of managers (skilled and unskilled), while the return gap measure is able to separate out the skilled manager from the other two types of managers (window dresser and unskilled). In the table, two scenarios are presented. In the first scenario, stock A is the winner in the prior quarter. Thus, both the skilled manager and window-dressing manager hold stock A as of the end of the last quarter, but for different reasons. While the skilled manager picks stock A at the beginning of the previous quarter due to stock selection ability, the window-dressing manager selects stock A only towards the end of the previous quarter after having observed its superior performance over the quarter. Finally, the unskilled manager invests equally between the two stocks A and B.

At the beginning of the current quarter (date 1 in the table), the skilled manager knows with certainty that stock A will be the winner and therefore continues to hold it at date 1 and until the end of the current quarter (date 2). In contrast, the window dresser begins the current quarter holding stock A and continues to hold it until date 2, because stock A continues to be the winner stock during the quarter. The unskilled manager continues to hold equal amounts of A and B.

For each manager, we next compute two types of holdings-based returns: the first assumes that the beginning-of-the-quarter portfolio is held throughout the quarter, which we denote as FHR (forward holdings return); and the second assumes that the end-of-the-quarter portfolio is held throughout the quarter, which we denote as BHR (backward holdings return). Based on using these two types of holdings-based returns, we next compute the return gap measure as the fund's actual return (AR) minus the FHR. We also compute BHRG as BHR minus AR.

Since the return on stock A is 10% over the current quarter, AR, BHR, and FHR for the skilled manager are all 10%, and accordingly BHRG (i.e., BHR – AR) and return gap (i.e., AR – FHR) are both 0%. Since the window dresser similarly held stock A, as in the case of the skilled manager, AR, BHR, and FHR are also all 10% and accordingly BHRG and return gap are both 0%. Finally, the unskilled manager invests 50% each in stocks A and B, and therefore AR, BHR, FHR, BHRG, and return gap are all 0%.

In the second scenario, stock B is the winner in the prior quarter. The skilled manager will therefore show 100% invested in stock B as of the end of the prior quarter, but will then switch 100% to stock A at date 1 and continue to hold it until date 2. Thus, for the skilled manager, AR and BHR both equal 10%, FHR equals –10%, BHRG equals 0%, and return gap equals 20%. In contrast, the window dresser who invested 100% in stock B as of last quarter end will continue to hold B through the current quarter. However, by the end of the current quarter, window dresser will realize that stock A is the winner in the current quarter, and will switch to stock A at date 2. As a result, BHRG and return gap for the window dresser are 20% and 0%, respectively. Since the window dresser picks the winner stock (and gets rid of the loser stock) towards quarter end, this will inflate BHR relative to the fund's actual return, thereby increasing BHRG. Finally, the unskilled manager who does not window dress will have both BHRG and return gap equal 0%.

Assuming that the two scenarios are equally likely (probability of 50%), we compute the expected values of BHRG for the skilled manager, window dresser, and unskilled manager to be 0%, 10%, and 0%, respectively. Hence, BHRG was successful in detecting the manager who engaged in window-dressing behavior. For return gap, the expected values for the three types of managers are 10%, 0% and 0% respectively.[13] As shown in KSZ (2008), return gap helps in correctly identifying the skilled manager.

[13] In the above illustration, we could have also assumed that the window dresser at date 1 switches to a 50%/50% strategy like the unskilled manager. Using this alternative assumption yields the same average BHRG and return gaps across the two scenarios for the window dresser.

## Appendix B. Construction of rank gap measure

This Appendix explains and illustrates the construction of the rank gap measure of window dressing. For each fiscal quarter that has at least 100 reported portfolios, we form three rankings. We first compute a performance rank in which we sort all the funds in descending order by their quarterly returns to compute their percentile ranks (1 to 100), with funds in the first percentile bin (rank equal to 1) being the best performing funds and funds in the 100th percentile bin (rank equal to 100) being the worst. Second, we then compute a winner ranking in which we sort all the funds in descending order according to their proportion of winner stock holdings and similarly assign ranks to this statistic. Funds in the first percentile bin have the highest winner proportion and funds in the 100th percentile bin have the lowest proportion. Third, we similarly compute a loser ranking by sorting all the funds in ascending order according to their proportion of loser stock holdings and again assigning a percentile rank. Hence, funds in the first percentile bin have the lowest loser proportion and funds in the 100th percentile have the highest. Note that we switch the sorting order for the loser stocks to make the interpretation of the loser ranking similar to that of the winner ranking. The following table illustrates the three percentile rankings:

| Rank | Fund Performance | Winner Proportion | Loser Proportion |
|---|---|---|---|
| 1 | 1 (best performance) | 1 (highest proportion) | 1 (lowest proportion) |
| 2 | 2 | 2 | 2 |
| 3 | 3 | 3 | 3 |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| 98 | 98 | 98 | 98 |
| 99 | 99 | 99 | 99 |
| 100 | 100 (worst performance) | 100 (lowest proportion) | 100 (highest proportion) |

In the absence of window dressing, a well-performing fund should have a high fund performance rank, a high winner rank, and a high loser rank. In contrast, a poorly performing fund should have a low performance rank, a low winner rank, and a low loser rank. If a fund has a low performance rank, but relatively high winner and loser ranks, such inconsistency would hint towards the fund manager being engaged in window dressing. The larger the rank inconsistency, the higher the probability that window dressing has occurred. Rank inconsistency is thus measured as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where *PerformanceRank* is the rank of fund performance, *WinnerRank* is the rank of winner proportion, and *LoserRank* is the rank of loser proportion. The theoretical range of rank consistency is [–99, 99]. We scale this rank inconsistency measure to obtain our window dressing measure, Rank Gap, such that it lies between 0 and 1 (similar to a probability measure):

$$[(PerformanceRank - \frac{WinnerRank + LoserRank}{2}) + 100] / 200$$

The theoretical bound of the rank gap measure is (0.005, 0.995) with a larger rank gap indicates a higher likelihood of window dressing.

## References


Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2011, Uncovering Hedge Fund Skill From The Portfolios They Hide, Working paper, Columbia University and Georgia State University.

Alexander, Gordon J., Gjergji Cici, and Scott Gibson, 2007, Does motivation matter when assessing trade performance? An analysis of mutual funds, *Review of Financial Studies* 20, 125–150.

Baker, Malcolm, Lubomir Litov, Jessica A. Wachter, and Jeffrey Wurgler, 2010, Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades Prior to Earnings Announcements, *Journal of Financial and Quantitative Analysis* 45, 1111–1131.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual Fund Flows and Performance in Rational Markets, *Journal of Political Economy* 112, 1269–1295.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the tape: Evidence of gaming behavior in equity mutual funds, *Journal of Finance* 58, 661–693.

Chen, Honghui, and Vijay Singal, 2004, All things considered, taxes drive the January effect, *Journal of Financial Research* 27,351-372.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343–368.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik, 2004, Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, *American Economic Review* 94, 1276–1302.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Cohen, Randolph B., Joshua D. Coval, Lubos Pastor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057–1094.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Frank, Mary M., James M. Poterba, Douglas A. Shackelford, and John B. Shoven, 2004, Copycat funds: information disclosure regulation and the returns to active management in the mutual fund industry, *Journal of Law and Economics* 47, 515–541.

Ge, Weili, and Lu Zheng, 2006, The frequency of mutual fund portfolio disclosure, Working paper, University of Washington and University of California, Irvine.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–259.

Grinblatt, Mark, and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business* 62, 394–415.

Grinblatt, Mark, and Sheridan Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 62, 394–415.

Haugen, Robert A., and Josef Lakonishok, 1998, The incredible January effect: The stock market's unsolved mystery, Dow Jones-Irwin, Homewood, Ill.

He, Jia, Lilian Ng, and Qinghai Wang, 2004, Quarterly trading patterns of financial institutions, *Journal of Business* 77, 493–509.

Huang, Lixin, and Jayant Kale, 2009, The effect of supplier and customer industry interrelations on mutual fund investment performance, Working paper, Georgia State University.

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45–70.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jiang, George J., Tong Yao, and Tong Yu, 2007, Do mutual funds time the market? Evidence from portfolio holdings, *Journal of Financial Economics* 86, 724–758.

Kacperczyk, Marcin, and Amit Seru, 2007, Fund manager use of public information: New evidence on managerial skills, *Journal of Finance* 62, 485–528.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity funds, *Journal of Finance* 60, 1983–2012.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Khorana, Ajay, 1996, Top management turnover An empirical investigation of mutual fund managers, *Journal of Financial Economics* 40, 403–427.

Lakonishok, Josef, Andrei Shleifer, Richard Thaler, and Robert Vishny, 1991, Window dressing by pension fund managers, *American Economic Review* 81, 227–231.

Meier, Iwan, and Ernst Schaumburg, 2004, Do funds window dress? Evidence for U.S. domestic equity mutual funds, Working paper, HEC Montreal and Kellogg School of Management.

Morey, Matthew R., and Edward O'Neal, 2006, Window dressing in bond mutual funds, *Journal of Financial Research* 29, 325–347.

Musto, David K., 1997, Portfolio disclosure and year-end price shift, *Journal of Finance* 52, 1563–1588.

Musto, David K., 1999, Investment decisions depend on portfolio disclosures, *Journal of Finance* 54, 935–952.

Ng, Lilian, and Qinghai Wang, 2004, Institutional trading and the turn-of-the-year effect, *Journal of Financial Economics* 74, 343–366.

Poterba, James M., and Scott J. Weisbenner, 2001, Capital gains tax rules, tax-loss trading, and turn-of-the-year returns, *Journal of Finance* 56, 353-368.

Ritter, Jay R., and Navin Chopra, 1989, Portfolio rebalancing and the turn-of-the-year effect, *Journal of Finance* 44, 149-166.

Sias, Richard W., 2007, Causes and seasonality of momentum profits, *Financial Analysts Journal* 63, 48–54.

Sias, Richard W., and Laura T. Starks, 1997, Institutions and individuals at the turn-of-the-year, *Journal of Finance* 52, 1543–1562.

Sias, Richard W., Laura T. Starks, and Sheridan Titman, 2006, Changes in institutional ownership and stock returns: Assessment and methodology, *Journal of Business* 79, 2869–2910.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Solomon, David H., Eugene F. Soltes, and Denis Sosyura, 2011, Winners in the spotlight: media coverage of fund holdings as a driver of flows, Working Paper, Harvard Business School, University of Michigan, and University of Southern California.

Starks, Laura T., Li Yong, and Lu Zheng, 2006, Tax-Loss Selling and the January Effect: Evidence from Municipal Bond Closed-End Funds, *Journal of Finance* 61, 3049–3067.

Wermers, Russ, 1999, Mutual fund herding and the impact on stock prices, *Journal of Finance* 54, 581–622.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses, *Journal of Finance* 55, 1655–1695.

Wermers, Russ, 2001, The potential effects of more frequent portfolio disclosure on mutual performance, *Investment Company Institute Perspective* 7, 1–12.

## Table 1
## Descriptive summary statistics and correlation coefficients

The table reports the summary statistics and correlation coefficients of the window dressing measures, performance measures, and other fund characteristics. Our sample includes 95,695 fund-quarter observations for 2,976 funds between January 1984 and December 2008. Our first window dressing measure is Rank Gap defined as the percentile rank of fund performance over a fiscal quarter minus the average of the rank based on winner and loser proportion over the same quarter. Winner (loser) proportion is the proportion of the fund's assets invested in winning (losing) stocks that achieve good (poor) performance over the quarter. We scale the rank gap to lie between 0 and 1 for which we add 100 to the difference in performance rank and average of the ranks based on winner and loser proportions, and then divide the resulting figure by 200. Our second window dressing measure is backward holding-based return gap (BHRG) defined as the quarterly return of a hypothetical portfolio that is assumed to have been invested at the beginning of the quarter in the fund's disclosed end-of-quarter holdings, minus the fund's reported return. Quarterly 4-factor Alpha is the sum of three 4-factor monthly alphas computed out-of-sample using three 24-month windows ending a month prior to each month of the quarter. For example, January alpha is the difference between the fund's return in January minus the sum product of the betas from the regression of fund's excess returns on the four factors over the 24-month window ending in December of the previous year and the factor returns in January. Manager skill is defined as the moving average of 12 monthly return gaps as in Kacperczyk, Sialm, and Zheng (2008). Expense is the annual expense ratio. TNA is the total net assets under management at the end of the quarter. Turnover is computed from the portfolio holdings data of mutual funds as the minimum of the total purchases and sales in a quarter divided by beginning-of-the-quarter assets. Load is a dummy variable defined as 1 if there is any front-end or back-end load and 0 otherwise. Flow is dollar fund flows over a quarter scaled by beginning-of-the-quarter assets. BHRG, Quarterly 4-factor Alpha, Manager Skill, Expense, TNA, Turnover, Flow are winsorized at the 1% and 99% percentiles.

| Variables | N | Mean | Median | Max | Min |
|---|---|---|---|---|---|
| Panel A: Window Dressing measures | | | | | |
| Rank Gap | 90731 | 0.5000 | 0.4975 | 0.9950 | 0.0375 |
| BHRG | 92694 | 0.0102 | 0.0040 | 0.1622 | –0.0849 |
| Panel B: Performance measure | | | | | |
| Quarterly 4-factor Alpha | 83792 | –0.0028 | –0.0029 | 0.1234 | –0.1277 |
| Manager Skill | 81302 | –0.0003 | –0.0002 | 0.0118 | –0.0126 |
| Expense | 92694 | 0.0126 | 0.0122 | 0.0290 | 0.0000 |
| TNA ($ million) | 94207 | 951 | 179 | 17678 | 2 |
| Turnover | 94555 | 0.12 | 0.10 | 0.47 | 0 |
| Load | 79335 | 0.6 | 1 | 1 | 0 |
| Flow | 84698 | 0.0354 | –0.0035 | 1.1101 | –0.2941 |

Panel C: Correlation

| | Rank Gap | BHRG | Alpha | Manager Skill | Expense | TNA | Turnover | Load |
|---|---|---|---|---|---|---|---|---|
| BHRG | 0.50*** | | | | | | | |
| Alpha | –0.37*** | –0.08*** | | | | | | |
| Manager Skill | –0.13*** | –0.19*** | 0.08*** | | | | | |
| Expense | 0.07*** | 0.07*** | –0.04*** | 0.02*** | | | | |
| TNA | –0.03*** | –0.02*** | 0.01*** | –0.02*** | –0.22*** | | | |
| Turnover | 0.15*** | 0.33*** | –0.01*** | 0.03*** | 0.21*** | –0.11*** | | |
| Load | 0.03*** | –0.01* | –0.03*** | 0.01*** | 0.20*** | 0.02*** | 0.02*** | |
| Flow | –0.11*** | –0.01*** | 0.12*** | 0.01*** | 0.03*** | –0.05*** | 0.01** | –0.04*** |

**Table 2**

**Lead quarterly flows regression on winner proportion and loser proportion**

This table reports the results from the pooled regressions using quarterly percentage net fund flows as the dependent variable. Independent variables include *WinnerProp* and *LoserProp*, the proportion of funds' assets invested in the top and bottom quintile of stock returns during the quarter. Lagged Manager Skill is defined as the moving average of 12 monthly return gaps ending in prior quarter. LogTNA is the natural logarithm of Total Net Assets at the end of the quarter. Other variables are as defined in Table 1. Standard errors are adjusted by clustering at the fund level. p-values are reported below the estimated slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels.

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| WinnerProp | 0.0773*** | 0.1207*** | 0.0787*** |
| | 0.000 | 0.000 | 0.000 |
| LoserProp | –0.0628*** | –0.1343*** | –0.0636*** |
| | 0.000 | 0.000 | 0.000 |
| Quarterly Alpha | 0.3512*** | | 0.3475*** |
| | 0.000 | | 0.000 |
| Lagged Manager Skill | 2.0817*** | | 1.7294*** |
| | 0.000 | | 0.000 |
| Manager Skill | | 2.3506*** | 0.5306* |
| | | 0.000 | 0.085 |
| Expense | 0.7068*** | 0.6464** | 0.6945*** |
| | 0.008 | 0.020 | 0.010 |
| LogTNA | –0.0505 | –0.1090* | –0.0351 |
| | 0.391 | 0.069 | 0.551 |
| Turnover | –0.0712*** | –0.0892*** | –0.0721*** |
| | 0.000 | 0.000 | 0.000 |
| Load | –0.0102*** | –0.0105*** | –0.0102*** |
| | 0.000 | 0.000 | 0.000 |
| Constant | 0.0343** | –0.0014 | 0.0343** |
| | 0.019 | 1.000 | 0.018 |
| Time Dummies | Yes | Yes | Yes |
| Style Dummies | Yes | Yes | Yes |
| Observations | 44339 | 46047 | 44208 |
| R-squared | 0.064 | 0.058 | 0.064 |

**Table 3**
**Prior Performance and Window dressing: Results with double 5x5 sorts**

This table reports means of rank gap (in Panel A) and backward holding-based return gap (BHRG in Panel B) for 25 portfolios of mutual funds sorted first by their manager skill measure and then by the alpha during the first two months of the quarter. 2-month 4-factor Alpha is the average of the two 4-factor monthly alphas for the first two months in a quarter. All other variables are as defined in Tables 1 and 2. P-values of t-test have been reported after adjusting the standard errors for clustering at the fund level.

Panel A: Averages of Rank Gap Measure

| | | 2-month 4-factor Alpha | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 (low) | 2 | 3 | 4 | 5 (high) | 5-1 |
| | 1 (low) | 0.5814 | 0.5571 | 0.5300 | 0.4969 | 0.4645 | –0.1169 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 2 | 0.5438 | 0.5227 | 0.5034 | 0.4771 | 0.4575 | –0.0863 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Manager Skill | 3 | 0.5364 | 0.5148 | 0.4939 | 0.4769 | 0.4524 | –0.0839 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 4 | 0.5355 | 0.5134 | 0.4904 | 0.4712 | 0.4521 | –0.0833 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 5(high) | 0.5456 | 0.5104 | 0.4829 | 0.4565 | 0.4342 | –0.1114 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 5-1 | –0.0357 | –0.0467 | –0.0471 | –0.0405 | –0.0302 | |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |

Panel B: Averages of BHRG measure

| | | 2-month 4-factor Alpha | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 (low) | 2 | 3 | 4 | 5 (high) | 5-1 |
| | 1 (low) | 0.0308 | 0.0197 | 0.0176 | 0.0162 | 0.0218 | –0.0090 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 2 | 0.0135 | 0.0089 | 0.0074 | 0.0068 | 0.0079 | –0.0056 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Manager Skill | 3 | 0.0101 | 0.0060 | 0.0048 | 0.0050 | 0.0044 | –0.0057 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 4 | 0.0094 | 0.0053 | 0.0041 | 0.0049 | 0.0041 | –0.0053 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 5(high) | 0.0123 | 0.0076 | 0.0064 | 0.0056 | 0.0047 | –0.0076 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 5-1 | –0.0184 | –0.0121 | –0.0112 | –0.0106 | –0.0171 | |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |

**Table 4**

**Determinants of window dressing: Multivariate analysis**

This table reports the coefficients of regressions of the two window dressing measures on fund characteristics. Rank Gap 10% (20%) Dummy is an indicator variable defined as 1 if rank gap is in the top 10th (20th) percentile for a given quarter and 0 otherwise; and Backward holding-based return gap (BHRG) 10% (20%) Dummy is an indicator variable defined as 1 if BHRG is in the top 10th (20th) percentile for a given quarter and 0 otherwise. Team is an indicator variable that takes a value of 1 if fund is team managed during a quarter and 0 otherwise. InstProp is the proportion of fund's assets during a quarter that are held in institutional share classes. OpenProp is the proportion of fund's assets in share classes that are open to new investment. All other variables are as defined in Tables 1 and 2. Standard errors are adjusted by clustering at the fund level. p-values are reported below the slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels, respectively.

Panel A

| VARIABLES | Rank Gap | Rank Gap 10% Dummy | Rank Gap 20% Dummy | BHRG | BHRG 10% Dummy | BHRG 20% Dummy |
|---|---|---|---|---|---|---|
| 2-month 4-factor Alpha | –2.1914*** | –36.1561*** | –37.4595*** | –0.1261*** | –7.9389*** | –5.6684*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Manager Skill | –1.9678*** | –42.6324*** | –34.6055*** | –0.6198*** | –35.5941*** | –27.4516*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Expense | 0.7650*** | 44.5877*** | 33.2871*** | 0.1784* | 63.5067*** | 48.3422*** |
| | 0.000 | 0.000 | 0.000 | 0.076 | 0.000 | 0.000 |
| LogTNA | –0.0359 | 0.4037 | –0.2504 | 0.1035*** | 11.4764*** | 10.9460*** |
| | 0.569 | 0.856 | 0.870 | 0.000 | 0.000 | 0.000 |
| Turnover | 0.1666*** | 5.6834*** | 4.3012*** | 0.1194*** | 10.3600*** | 9.3287*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Load | 0.0040** | –0.0202 | 0.0272 | -0.0005 | –0.2394*** | –0.0538 |
| | 0.027 | 0.727 | 0.508 | 0.604 | 0.009 | 0.419 |
| Constant | 0.4688*** | –3.6315*** | –2.4270*** | –0.0052* | –4.2733*** | –3.2007*** |
| | 0.000 | 0.000 | 0.000 | 0.055 | 0.000 | 0.000 |
| Time Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Style Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 50172 | 50172 | 50172 | 52369 | 52369 | 52369 |
| Adjusted R-squared | 0.124 | | | 0.195 | | |
| Pseudo R-squared | | 0.102 | 0.0807 | | 0.202 | 0.154 |

Panel B

| VARIABLES | Rank Gap | Rank Gap 10% Dummy | Rank Gap 20% Dummy | BHRG | BHRG 10% Dummy | BHRG 20% Dummy |
|---|---|---|---|---|---|---|
| 2-month 4-factor Alpha | –2.0197*** | –31.0736*** | –36.2056*** | –0.1402*** | –7.8511*** | –7.4144*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Manager Skill | –2.6833*** | –45.3375*** | –41.4981*** | –0.7853*** | –42.8823*** | –28.7800*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| Expense | 0.5279 | 58.0925*** | 44.1849*** | 0.2438 | 86.0745*** | 69.2248*** |
| | 0.215 | 0.000 | 0.000 | 0.268 | 0.000 | 0.000 |
| LogTNA | 0.1479 | 2.1653 | 3.2318 | 0.1386*** | 9.1147* | 11.1023*** |
| | 0.142 | 0.517 | 0.167 | 0.003 | 0.065 | 0.002 |
| Turnover | 0.1975*** | 6.8094*** | 5.0877*** | 0.1376*** | 11.6428*** | 10.6789*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Load | 0.0026 | –0.1472 | –0.0461 | –0.0032* | –0.4685*** | –0.2869*** |
| | 0.427 | 0.128 | 0.502 | 0.073 | 0.002 | 0.008 |
| Team | 0.0020 | 0.0409 | 0.0200 | 0.0006 | 0.1306 | 0.1221 |
| | 0.451 | 0.616 | 0.726 | 0.645 | 0.287 | 0.177 |
| InstProp | 0.0058 | 0.0915 | 0.0657 | 0.0042 | 0.0475 | 0.0718 |
| | 0.238 | 0.524 | 0.516 | 0.115 | 0.844 | 0.659 |
| OpenProp | 0.0175*** | 0.1398 | 0.0088 | 0.0088*** | 0.2516 | 0.3317 |
| | 0.005 | 0.390 | 0.943 | 0.009 | 0.338 | 0.113 |
| Constant | 0.4364*** | –4.3898*** | –4.0080*** | –0.0205*** | –2.3493* | –2.3789* |
| | 0.000 | 0.000 | 0.000 | 0.002 | 0.095 | 0.064 |
| Time Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Style Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18079 | 18079 | 18079 | 18551 | 18551 | 18551 |
| Adjusted R-squared | 0.119 | | | 0.180 | | |
| Pseudo R-squared | | 0.119 | 0.0917 | | 0.237 | 0.190 |

**Table 5**
**Window dressing and future fund performance: Results with single 10x1 sorts**

This table reports the means of next quarter's return, next quarter's 4-factor alpha, and momentum beta for decile portfolios of mutual funds sorted by the two window dressing measures (rank gap and backward holding-based return gap (BHRG)) over a quarter. Momentum beta is the average of the three estimated monthly coefficients on the momentum factor, where the coefficients are obtained from the regressions of monthly net-of-fee returns of the fund on the three factors of Fama and French (1993) (excess market returns, size and book-to-market factor returns), and Carhart (1997) momentum factor using three 24-month windows ending in each month of the quarter. Other variables are defined as in the previous tables 1 and 2. P-values of t-test have been reported after adjusting the standard errors for clustering at the fund level.

Panel A

| | decile | next quarter alpha | p-value | next quarter return | p-value | momentum beta | p-value |
|---|---|---|---|---|---|---|---|
| Rank Gap | 1 (low) | –0.0016 | 0.00 | 0.0217 | 0.00 | 0.002 | 0.67 |
| | 2 | –0.0014 | 0.00 | 0.0207 | 0.00 | 0.016 | 0.00 |
| | 3 | –0.0021 | 0.00 | 0.0189 | 0.00 | 0.020 | 0.00 |
| | 4 | –0.0028 | 0.00 | 0.0174 | 0.00 | 0.021 | 0.00 |
| | 5 | –0.0031 | 0.00 | 0.0161 | 0.00 | 0.024 | 0.00 |
| | 6 | –0.0035 | 0.00 | 0.0160 | 0.00 | 0.026 | 0.00 |
| | 7 | –0.0032 | 0.00 | 0.0137 | 0.00 | 0.034 | 0.00 |
| | 8 | –0.0034 | 0.00 | 0.0129 | 0.00 | 0.041 | 0.00 |
| | 9 | –0.0034 | 0.00 | 0.0130 | 0.00 | 0.065 | 0.00 |
| | 10 (high) | –0.0049 | 0.00 | 0.0118 | 0.00 | 0.126 | 0.00 |
| | 10-1 | -0.0033 | 0.00 | -0.0099 | 0.00 | 0.124 | 0.00 |

Panel B

| | decile | next quarter alpha | p-value | next quarter return | p-value | momentum beta | p-value |
|---|---|---|---|---|---|---|---|
| BHRG | 1 (low) | 0.0001 | 0.88 | 0.0171 | 0.00 | –0.054 | 0.00 |
| | 2 | –0.0017 | 0.00 | 0.0162 | 0.00 | –0.027 | 0.00 |
| | 3 | –0.0018 | 0.00 | 0.0178 | 0.00 | –0.020 | 0.00 |
| | 4 | –0.0025 | 0.00 | 0.0195 | 0.00 | –0.005 | 0.05 |
| | 5 | –0.0032 | 0.00 | 0.0184 | 0.00 | 0.007 | 0.01 |
| | 6 | –0.0034 | 0.00 | 0.0179 | 0.00 | 0.027 | 0.00 |
| | 7 | –0.0042 | 0.00 | 0.0155 | 0.00 | 0.047 | 0.00 |
| | 8 | –0.0040 | 0.00 | 0.0156 | 0.00 | 0.074 | 0.00 |
| | 9 | –0.0042 | 0.00 | 0.0136 | 0.00 | 0.118 | 0.00 |
| | 10 (high) | –0.0029 | 0.00 | 0.0145 | 0.00 | 0.200 | 0.00 |
| | 10-1 | –0.0030 | 0.00 | –0.0026 | 0.17 | 0.254 | 0.00 |

**Table 6**
**Window dressing and future fund performance: Results with double 5x5 sorts**

This table reports means of next quarter 4-factor alpha for 25 portfolios of mutual funds sorted first by their manager skill measure and then by one of the two window dressing measures (rank gap in Panel A or backward holding-based return gap (BHRG) in Panel B). All variables are as defined in Tables 1 and 2. P-values of t-test have been reported after adjusting the standard errors for clustering at the fund level.

Panel A

| | | Rank Gap | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 (low) | 2 | 3 | 4 | 5 (high) | 5–1 |
| Manager Skill | 1 (low) | –0.0037 | –0.0041 | –0.0045 | –0.0050 | –0.0074 | –0.0037 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 2 | –0.0027 | –0.0024 | –0.0039 | –0.0034 | –0.0043 | –0.0016 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 |
| | 3 | –0.0021 | –0.0024 | –0.0038 | –0.0029 | –0.0028 | –0.0007 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.45 |
| | 4 | –0.0017 | –0.0025 | –0.0026 | –0.0026 | –0.0028 | –0.0011 |
| | | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.24 |
| | 5(high) | 0.0006 | –0.0009 | –0.0015 | –0.0024 | –0.0025 | –0.0032 |
| | | 0.45 | 0.26 | 0.07 | 0.00 | 0.00 | 0.01 |
| | 5–1 | 0.0044 | 0.0032 | 0.0031 | 0.0026 | 0.0049 | |
| | | 0.00 | 0.01 | 0.01 | 0.02 | 0.00 | |

Panel B

| | | BHRG | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 (low) | 2 | 3 | 4 | 5 (high) | 5–1 |
| Manager Skill | 1 (low) | –0.0036 | –0.0032 | –0.0057 | –0.0061 | –0.0060 | –0.0024 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 |
| | 2 | –0.0021 | –0.0027 | –0.0036 | –0.0049 | –0.0030 | –0.0009 |
| | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.40 |
| | 3 | 0.0002 | –0.0022 | –0.0041 | –0.0044 | –0.0025 | –0.0028 |
| | | 0.74 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 4 | –0.0004 | –0.0025 | –0.0023 | –0.0026 | –0.0041 | –0.0037 |
| | | 0.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 5(high) | 0.0015 | –0.0018 | –0.0019 | –0.0023 | –0.0014 | –0.0029 |
| | | 0.09 | 0.02 | 0.00 | 0.00 | 0.16 | 0.03 |
| | 5–1 | 0.0051 | 0.0014 | 0.0038 | 0.0038 | 0.0046 | |
| | | 0.00 | 0.15 | 0.00 | 0.00 | 0.00 | |

**Table 7**
**Window dressing and future fund performance: Multivariate results**

This table reports the estimated coefficients of pooled regressions of quarterly 4-factor alphas on the two window dressing measures (rank gap and backward holding-based return gap (BHRG)) and various fund attributes. The dependent variables are quarterly 4-factor alphas. Panel A reports the results using continuous form of window dressing variables while Panel B reports the findings with the indicator variables for the two window dressing measures: Rank Gap 10% (20%) Dummy is a dummy variable defined as 1 if rank gap is in the top 10th (20th) percentile for a given fiscal quarter and 0 otherwise; and Backward holding-based return gap (BHRG) 10% (20%) Dummy is a dummy variable defined as 1 if BHRG is in the top 10th (20th) percentile for a given fiscal quarter and 0 otherwise. Other variables are as defined in Tables 1 and 2. All regressions include time dummies and investment style dummies, and standard errors are adjusted for clustering at the fund level. P-values are reported below the estimated slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels, respectively.

Panel A

| Variables | (1) | (2) | (3) |
|---|---|---|---|
| Rank Gap | –0.0087*** | | –0.0056** |
| | 0.000 | | 0.014 |
| BHRG | | –0.0299*** | –0.0210** |
| | | 0.001 | 0.036 |
| Manager Skill | 0.3907*** | 0.3793*** | 0.3834*** |
| | 0.000 | 0.000 | 0.000 |
| Expense | –0.2070*** | –0.2236*** | –0.2057*** |
| | 0.000 | 0.000 | 0.000 |
| LogTNA | –0.0332*** | –0.0318*** | –0.0310** |
| | 0.007 | 0.009 | 0.012 |
| Turnover | -0.0017 | 0.0006 | 0.0004 |
| | 0.536 | 0.825 | 0.894 |
| Load | –0.0007 | –0.0006 | –0.0007 |
| | 0.136 | 0.162 | 0.123 |
| Flow | 0.0044*** | 0.0050*** | 0.0048*** |
| | 0.006 | 0.002 | 0.003 |
| Constant | 0.0068*** | 0.0033** | 0.0052*** |
| | 0.000 | 0.016 | 0.003 |
| Time Dummies | Yes | Yes | Yes |
| Style Dummies | Yes | Yes | Yes |
| Observations | 44299 | 46687 | 44299 |
| Adjusted R-squared | 0.0401 | 0.0437 | 0.0403 |

Panel B

| Variables | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|
| Rank Gap 10% Dummy | –0.0025*** | | –0.0020*** | | | |
| | 0.000 | | 0.005 | | | |
| BHRG 10% Dummy | | –0.0018** | –0.0013 | | | |
| | | 0.037 | 0.185 | | | |
| Rank Gap 20% Dummy | | | | –0.0012** | | –0.0008 |
| | | | | 0.016 | | 0.118 |
| BHRG 20% Dummy | | | | | –0.0015** | –0.0012* |
| | | | | | 0.012 | 0.069 |
| Manager Skill | 0.3982*** | 0.3922*** | 0.3948*** | 0.4029*** | 0.3928*** | 0.3997*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Expense | –0.2051*** | –0.2217*** | –0.2015*** | –0.2084*** | –0.2207*** | –0.2038*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LogTNA | –0.0332*** | –0.0341*** | –0.0324*** | –0.0331*** | –0.0332*** | –0.0317** |
| | 0.008 | 0.005 | 0.009 | 0.008 | 0.007 | 0.011 |
| Turnover | –0.0017 | –0.0011 | –0.0006 | –0.0024 | –0.0008 | –0.0008 |
| | 0.531 | 0.693 | 0.848 | 0.391 | 0.792 | 0.789 |
| Load | –0.0007 | –0.0006 | –0.0007* | –0.0007 | –0.0006 | –0.0007 |
| | 0.109 | 0.148 | 0.097 | 0.117 | 0.166 | 0.112 |
| Flow | 0.0050*** | 0.0050*** | 0.0051*** | 0.0050*** | 0.0050*** | 0.0051*** |
| | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| Constant | 0.0027** | 0.0034** | 0.0026* | 0.0028** | 0.0035** | 0.0027** |
| | 0.047 | 0.015 | 0.053 | 0.040 | 0.014 | 0.046 |
| Time Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Style Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 44299 | 46687 | 44299 | 44299 | 46687 | 44299 |
| Adjusted R-squared | 0.0399 | 0.0433 | 0.0399 | 0.0397 | 0.0433 | 0.0398 |

**Table 8 Window dressing and fund flows**

This table reports the results from the pooled regressions using the average percentage daily fund flows between the filing date and the end of the leading quarter as the dependent variable. Independent variables include dummies for window dressing measures, Good Perf. Dummy that equals 1 if a fund's average daily return during the delay period between the quarter-end and filing date is positive, and 0 otherwise. Other variables are as defined in Tables 1 and 2. Last row of the table reports the sum of the lagged WD (window dressing) dummy and its interaction with the Good Perf. with the p-values from the F-test for the sum equaling zero. Standard errors are adjusted by clustering at the fund level. p-values are reported below the slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Rank Gap 10% Dummy | –0.0009*** | | | |
| | 0.005 | | | |
| Rank Gap 10% Dummy x Good Perf. | 0.0008* | | | |
| | 0.094 | | | |
| Rank Gap 20% Dummy | | –0.0007*** | | |
| | | 0.008 | | |
| Rank Gap 20% Dummy x Good Perf. | | 0.0003 | | |
| | | 0.402 | | |
| BHRG 10% Dummy | | | –0.0007** | |
| | | | 0.046 | |
| BHRG 10% Dummy x Good Perf. | | | 0.0012** | |
| | | | 0.039 | |
| BHRG 20% Dummy | | | | 0.0002 |
| | | | | 0.719 |
| BHRG 20% Dummy x Good Perf. | | | | 0.0010** |
| | | | | 0.013 |
| Good Perf. | 0.0005* | 0.0005* | 0.0004* | 0.0004 |
| | 0.067 | 0.070 | 0.088 | 0.163 |
| Quarter Alpha | 0.0039 | 0.0033 | 0.0048* | 0.0056** |
| | 0.164 | 0.241 | 0.077 | 0.045 |
| Manager Skill | 0.0958** | 0.0951** | 0.0987** | 0.0972** |
| | 0.047 | 0.048 | 0.040 | 0.043 |
| Expense | –0.0481 | –0.0481 | –0.0500 | –0.0545 |
| | 0.370 | 0.370 | 0.353 | 0.311 |
| LogTNA | 0.0701*** | 0.0702*** | 0.0701*** | 0.0705*** |
| | 0.001 | 0.001 | 0.001 | 0.001 |
| Turnover | 0.0015 | 0.0015 | 0.0012 | –0.0001 |
| | 0.405 | 0.376 | 0.536 | 0.924 |
| Load | –0.0013*** | –0.0013*** | –0.0013*** | –0.0013*** |
| | 0.003 | 0.003 | 0.004 | 0.003 |
| Constant | –0.0015 | –0.0023 | –0.0004 | –0.0015 |
| | 0.383 | 0.142 | 0.798 | 0.422 |
| Time and Style Dummies | Yes | Yes | Yes | Yes |
| Observations | 4149 | 4149 | 4149 | 4149 |
| R-squared | 0.110 | 0.110 | 0.110 | 0.111 |
| H0: WD Dummy + WD Dummy x Good Perf. = 0 | –0.0001 | –0.0004 | 0.0005 | 0.0012*** |
| | 0.746 | 0.304 | 0.372 | 0.011 |