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Window Dressing in Mutual Funds

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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 purchasing 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.

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 types of mutual funds are associated with

[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 (Musto (1997, 1999), 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); and (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). Our focus is on performance-based window dressing (i.e., buying winners and selling losers).

window dressing?; (2) How does window dressing affect future fund performance?; and (3) How do investors react to the window-dressing behavior of the managers by altering their capital flows into and out of the funds?

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 ascertain 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 likelihood of window dressing.

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. 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 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 portfolio 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 managerial skill (using the KSZ return gap measure) and positively related to expense ratio and turnover.

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 worse future fund performance as window dressing is a costly and value-destroying exercise only serving the purpose of 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. 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 have not switched to 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 the portfolio composition and fund performance. Second, SEC rules allow a delay of portfolio disclosure for up to 60 days that provides the manager an opportunity to benefit from good performance during the delay period.[3] 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 investment strategy. In this case 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 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

[3] 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 semiannually reports (N-CSR and N-CSRS, respectively); however, a large majority of managers voluntarily continued to disclose their portfolio holdings on a quarterly basis. 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.

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. We find that window dressers, conditional on good performance during the 60-day delay period following the quarter end, receive higher flows in the third month subsequent to the quarter end. In contrast, window dressers that perform poorly over the delay period have lower flows than do non-window dressers.

Our paper contributes to 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, 2010). Our paper shows how unintended consequences can potentially result from mandatory portfolio disclosure by institutional investors.

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 mutual 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. Section 7 concludes.

2. Related Literature and Testable Hypotheses

An earlier motivating study of window dressing by money managers is by Lakonishok, Shleifer, Thaler, and Vishny (1991) who examine the quarterly holdings of 769 equity pension funds over the period 1985 to 1989. They estimate quarterly purchase and sales of equity holdings based on portfolio changes over quarter-ends and compare trading in the first three quarters with that in the fourth quarter. Consistent with year-end window-dressing behavior, their results show that funds sell more losers in the fourth quarter. Sias and Starks (1997) examine the trading activity of individual and institutional investors at year-ends and find that institutions sell fewer winners in the fourth calendar quarter than the first quarter of the subsequent year, which is also consistent with year-end window-dressing behavior.

He, Ng, and Wang (2004) examine the quarterly holdings of different types of institutions to show that these institutions 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) investigate the relation between institutional trading and turn-of-the-year effect in stock returns. Their results indicate 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. They conclude that this trading pattern of institutions reflects investment strategies that are consistent with window dressing.

Meier and Schaumburg (2004) analyze the semiannual holdings and daily net asset values of 4,025 U.S. domestic equity mutual funds over the period 1997 to 2002. They compare the realized fund return with a hypothetical buy-and-hold return that the fund would have earned had it held the reported portfolio during the weeks leading up to the reporting date. If window-dressing activity has taken place towards quarter-end, they argue that the hypothetical holding-based return will outperform the realized return. Their empirical results show that the hypothetical returns are higher than the realized returns for some funds, thus suggesting window-dressing behavior, and that these same funds typically exhibited poorer recent performance.

Motivated by the insights in these studies, 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. Furthermore, 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. Finally, we hypothesize that funds involved in window dressing should also exhibit greater turnover resulting from portfolio churning around quarter ends. Our first hypothesis therefore is 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 maximum delay of 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 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 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: Window dressing should be associated with 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.[4] 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.

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 100th 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,

[4] 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.

with funds in the first percentile bin having the highest winner proportion and funds in the 100th 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 100th 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.[5] 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 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 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.

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

[5] 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.

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.[6] From Table 1 Panel B, we can see that the mean (median) quarterly portfolio turnover is 12% (10%).

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[6] 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.

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

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. Determinants of window dressing

Our first hypothesis is that relatively unskilled managers of funds performing poorly in the first two months of a quarter, and funds with higher expense ratios and greater portfolio turnover are more likely to be associated with window dressing. To test this hypothesis, we estimate two different specifications of multivariate regressions: (1) ordinary least squares (OLS) regressions using each of the two window dressing measures (rank gap and BHRG) as the dependent variable, and (2) logistic regressions using indicator variables of window dressing (based on the top 10% and top 20% values of the rank gap and BHRG measures) as the dependent variables. Our regression specifications are as follows:

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

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*; $\text{Manager Skill}_{i,t-1}$ is the lagged manager skill (i.e., 12-month moving average of the monthly return gap measure) for fund *i* as of the end of quarter *t-1*; $\text{Expense}_{i,t}$ 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 $\xi_{i,t}$ is the error term. Throughout the paper, we cluster the standard errors by fund to account for cross-correlations in our panel data.

Table 2 reports the results from the OLS regressions followed by findings from the logistic regressions first for rank gap and then for BHRG. Regardless of the window dressing measure used and its form (continuous or indicator), we observe the estimated coefficients of the two-month performance and manager skill variables to be negative and statistically significant at the 1% level.[7] For example, using rank gap as a continuous window dressing measure (column 2 of the table), we find the estimated coefficient on the average two-month four-factor alpha variable is −2.1914 and the estimated coefficient on the lagged manager skill variable is −1.9678, both significant at the 1% level. For BHRG used as the dependent variable (column 5), the corresponding estimated coefficients are −0.1246 and −0.6288, respectively, are both significant at the 1% level. Further, these findings for both specifications are also economically meaningful. To illustrate, a one standard deviation increase in the average two-month four factor 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 managerial 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

[7] In our reported empirical tests, 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.

deviation increases in alpha and managerial skill are 0.0019 and 0.0022 (18.6% and 21.6% of the average BHRG value of 0.0102), respectively.

For the regression specifications using indicator variables based on the top 10% values of rank gap (see column 3), we find that the estimated coefficients on alpha and managerial 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) managerial skill reduces the probability of window dressing by 1.12% (12.6% of the implied probability of 8.89%).[8] Using top 10% values of BHRG (see column 6), the estimated coefficients on alpha and managerial 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 who have performed poorly in the first two months of a quarter are more likely to window dress. The latter result regarding poorly performing funds more likely to window dress is consistent with prior studies such as He, Ng, and Wang (2004) and Meier and Schaumburg (2004).

Our first hypothesis also relates expense ratio and 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

[8] 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.

10% level. This finding is consistent with managers of funds with higher fees having greater 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.

Overall our findings in Table 2 reveal 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 3 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 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 4 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 3 — 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 4 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:

$$\begin{aligned}\text{Alpha}_{i,t} &= \beta_0 + \beta_1\text{WD}_{i,t-1} + \beta_2\text{Manager Skill}_{i,t-1} + \beta_3\text{Expense}_{i,t-1} + \beta_4\text{Turnover}_{i,t-1} \\ &+ \beta_5\text{Size}_{i,t-1} + \beta_6\text{Load}_{i,t-1} + \beta_7\text{Flow}_{i,t-1} + \text{Style dummies} + \text{Time dummies} + \varepsilon_{i,t}\end{aligned} \quad \textbf{(2)}$$

where $\text{Alpha}_{i,t}$ is the four-factor alpha of fund *i* during quarter *t*, $\text{Flow}_{i,t-1}$ is the percentage flows in fund *i* over prior quarter *t-1*, and the other variables are as defined earlier in equation (1).

Results using the continuous window-dressing measures are reported in panel A of Table, 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 5 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, fund managers may file their disclosure reports up to 60 days following the end of a quarter. If a manager window dresses and fund performance then 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 getting benefit of doubt from investors and receive higher flows in the following month than does a non-window dresser.

To investigate this, we estimate the following regression model:

$$\begin{aligned}\text{Flow}_{i,t} = {} & \gamma_0 + \gamma_1 \text{WDdummy}_{i,t-1} + \gamma_2 \text{WDdummy}_{i,t-1} \times \text{GoodPerfdummy}_{i,t} + \gamma_3 \text{Perf}_{i,t-1} \\ & + \gamma_4 \text{Manager Skill}_{i,t-1} + \gamma_5 \text{Expense}_{i,t-1} + \gamma_6 \text{Turnover}_{i,t-1} + \gamma_7 \text{Size}_{i,t-1} + \gamma_8 \text{Load}_{i,t-1} \\ & + \text{Style dummies} + \text{Time dummies} + \vartheta_{i,t}\end{aligned} \qquad \textbf{(3)}$$

where $\text{Flow}_{i,t}$ are the percentage flows for fund *i* during the third month of quarter *t*, $\text{WDdummy}_{i,t-1}$ 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-1*, $\text{GoodPerfdummy}_{i,t}$ is an indicator variable that equals 1 (0) if the return of fund *i* in quarter *t-1* is in the bottom (bottom) 80th percentile and its following two months' return in quarter *t* is in the top 20th (bottom 80th) percentile, and $\text{Perf}_{i,t-1}$ is the quarterly return of fund *i* over the previous quarter.[9] We follow Sirri and Tufano (1998) to select the top 20th and bottom 80th percentiles based on fund's returns to proxy for good and bad performance, respectively. The other independent variables are as defined earlier for equation (1) and are included to control for other fund characteristics.

Our third hypothesis predicts that a manager benefits from window dressing through higher flows if his performance over the delay period turns out to be superior. In other words, when

[9] Please note that we use the indicator (rather than the continuous) forms of the window dressing and performance measures for ease of interpretation of the interaction of the two measures.

both $\text{WDdummy}_{i,t-1}$ and $\text{GoodPerfdummy}_{i,t}$ equal 1, a window-dressing fund should have higher flows than a non-window dressing fund. Thus, we expect that the sum of γ_1 and γ_2 in equation (3) should be greater than zero. Higher flows capture the potential benefits of managers engaging in window dressing. Our third hypothesis also predicts the costs of window dressing in terms of lower flows when performance during the delay period turns out to be poor. In other words, when $\text{WDdummy}_{i,t-1}$ equals 1 and $\text{GoodPerfdummy}_{i,t}$ equals 0, we expect that a window dressing funds should experience lower flows than a non-window dressing fund. Thus, γ_1 should be negative to reflect the costs of window dressing in the form of lower flows. In equilibrium, a manager will choose to window dress if the marginal benefits are perceived to be greater than the marginal costs.

We report the results from the estimation of the flow regression (equation 3 above) in Table 6. There are two notable findings. First, we observe that the estimated coefficient for the window dressing dummy (γ_1) in each model specification is negative and significant (–0.0030 and –0.0028 for the top 10% and 20% rank gap dummies (Models 1 and 2); and –0.0021 and –0.0017 for the top 10% and 20% BHRG dummies (Models 3 and 4). This finding is consistent with the potential costs associated with window dressing in terms of lower flows. Second, we find the sum of the estimated coefficients of the window dressing indicator variable and its interaction with the good performance dummy (γ_1 + γ_2) to be positive and significant in each model specification (see the last row of Table 6). For example, in Model 1, the aggregate effect of window dressing on flows given good performance during the delay period is positive (sum = 0.0068) and significant at the 1% level. This finding reflects the potential benefits of window dressing in the form of higher flows.[10] Also, we note that both the costs and benefits are in terms of incremental flows after controlling for past performance. Furthermore, consistent with the extant literature (see, for example, Ippolito, 1992, Chevalier and Ellison, 1997, and Sirri and Tufano, 1998), we find that the estimated coefficient on past performance (γ_3) is positive and significant in all model specifications at the 1% level, indicating that flows are positively related to past performance.

Taken together, the results in Table 6 are consistent with our third hypothesis. For window-dressing managers that experience continued poor performance, investors will confirm the unobserved window-dressing behavior and withdraw their capital, while for managers whose performance improves during the delay period, investors may believe that such managers have stock selection ability as it is natural for investors to attribute the improved fund performance to the disclosed high (low) proportion of assets invested in winning (losing) stocks.

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

[10] For robustness, we repeat our analysis using four-factor alpha as an alternative performance measure. In results not reported, we find similar results using the 20% window-dressing dummy, but slightly weaker results using the 10% window-dressing dummy.

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 resulting from portfolio churning around quarter ends. Second, we find that window dressing is associated with worse fund performance in the following quarter, possibly due to the unnecessary trading costs.

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, window-dressing managers bear the costs in the form of capital withdrawals by the investors. 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.[11] As shown in KSZ (2008), return gap helps in correctly identifying the skilled manager.

[11] 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.

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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

Determinants of window dressing: Multivariate analysis

This table reports the estimated coefficients of regressions of the two window dressing measures (rank gap and backward holding-based return gap (BHRG)) on various fund attributes. 2-month 4-factor Alpha is the average of the two 4-factor monthly alphas for the first two months in a quarter. Rank Gap 10% (20%) Dummy is a dummy variable defined as 1 if rank gap is in the top 10^{th} (20^{th}) 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 10^{th} (20^{th}) percentile for a given fiscal quarter and 0 otherwise. LogTNA is the natural logarithm of Total Net Assets at the end of the quarter.Other variables are as defined in Table 1. All regressions include time dummies and investment style dummies, and standard errors are adjusted by clustering at the fund level. P-values have been reported below the estimated slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels, respectively.

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***	–0.1246***	–7.9389***	–5.5696***
	0.000	0.000	0.000	0.000	0.000	0.000
Lagged Manager Skill	–1.9678***	–42.6324***	–34.6055***	–0.6288***	–35.5941***	–27.8299***
	0.000	0.000	0.000	0.000	0.000	0.000
Expense	0.7650***	44.5877***	33.2871***	0.1754*	63.5067***	48.2017***
	0.000	0.000	0.000	0.081	0.000	0.000
LogTNA	–0.0359	0.4037	-0.2504	0.1067***	11.4764***	11.0056***
	0.569	0.856	0.870	0.000	0.000	0.000
Turnover	0.1666***	5.6834***	4.3012***	0.1198***	10.3600***	9.3163***
	0.000	0.000	0.000	0.000	0.000	0.000
Load	0.0040**	–0.0202	0.0272	–0.0005	–0.2394***	–0.0521
	0.027	0.727	0.508	0.602	0.009	0.434
Constant	0.4688***	–3.6315***	–2.4270***	–0.0053*	–4.5234***	–3.2755***
	0.000	0.000	0.000	0.050	0.000	0.000
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Style Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50172	50172	50172	52554	52369	52534
Adjusted R-squared	0.124			0.196		
Pseudo R-squared		0.102	0.0807		0.202	0.154

Table 3
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 4
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
	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
Manager Skill	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
	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
Manager Skill	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 5
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 10^{th} (20^{th}) 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 10^{th} (20^{th}) 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)
Lagged Rank Gap	–0.0087***		–0.0056**
	0.000		0.014
Lagged BHRG		–0.0299***	–0.0210**
		0.001	0.036
Lagged Manager Skill	0.3907***	0.3793***	0.3834***
	0.000	0.000	0.000
Lagged Expense	–0.2070***	–0.2236***	–0.2057***
	0.000	0.000	0.000
Lagged LogTNA	–0.0332***	–0.0318***	–0.0310**
	0.007	0.009	0.012
Lagged Turnover	-0.0017	0.0006	0.0004
	0.536	0.825	0.894
Lagged Load	–0.0007	–0.0006	–0.0007
	0.136	0.162	0.123
Lagged 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)
Lagged Rank Gap 10% Dummy	–0.0025***		–0.0020***			
	0.000		0.005			
Lagged BHRG 10% Dummy		–0.0018**	–0.0013			
		0.037	0.185			
Lagged Rank Gap 20% Dummy				–0.0012**		–0.0008
				0.016		0.118
Lagged BHRG 20% Dummy					–0.0015**	–0.0012*
					0.012	0.069
Lagged 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
Lagged 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
Lagged 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
Lagged 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
Lagged 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
Lagged 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 6 Window dressing and fund flows

This table reports the results from pooled regressions using fund flows in the third month of the quarter as the dependent variable. Independent variables include indicator variables for window dressing measures, an indicator variable Good Perf. that equals 1 (0) if a fund's quarterly return is in the bottom (bottom) 80th percentile and its following 2-month return is in the top 20th (bottom 80th) percentile. 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 estimated slope coefficients. *, **, *** denote significant differences from zero at the 10%, 5%, and 1% levels.

Variables	(1)	(2)	(3)	(4)
Lagged Rank Gap 10% Dummy	–0.0030***			
	0.003			
Lagged Rank Gap 10% Dummy x Good Perf.	0.0098***			
	0.000			
Lagged Rank Gap 20% Dummy		–0.0028***		
		0.000		
Lagged Rank Gap 20% Dummy x Good Perf.		0.0075***		
		0.000		
Lagged BHRG 10% Dummy			–0.0021*	
			0.087	
Lagged BHRG 10% Dummy x Good Perf.			0.0123***	
			0.000	
Lagged BHRG 20% Dummy				–0.0017**
				0.046
Lagged BHRG 20% Dummy x Good Perf.				0.0106***
				0.000
Lagged Quarter Return	0.1371***	0.1354***	0.1395***	0.1401***
	0.000	0.000	0.000	0.000
Lagged Manager Skill	0.5998***	0.5966***	0.6058***	0.6021***
	0.000	0.000	0.000	0.000
Lagged Expense	0.2509***	0.2531***	0.2474***	0.2474***
	0.006	0.005	0.006	0.006
Lagged LogTNA	0.0187	0.0189	0.0182	0.0186
	0.373	0.366	0.384	0.373
Lagged Turnover	–0.0164***	–0.0159***	–0.0181***	–0.0182***
	0.000	0.000	0.000	0.000
Lagged Load	–0.0029***	–0.0029***	–0.0029***	–0.0029***
	0.000	0.000	0.000	0.000
Constant	–0.0165***	–0.0166***	–0.0163***	–0.0165***
	0.001	0.001	0.001	0.001
Time and Style Dummies	Yes	Yes	Yes	Yes
Observations	36483	36483	36483	36483
R-squared	0.052	0.052	0.052	0.052
H0: Lagged WD Dummy + Lagged WD Dummy	0.0068***	0.0047***	0.0102***	0.0089***
x Good Perf. = 0	0.000	0.000	0.000	0.00