Window Dressing in Mutual Funds: New Evidence

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Abstract

Fund managers around the world cosmetically adjust their portfolio just prior to the declaration date to make it look more attractive to the investors. This behaviour is called Window dressing. The existing literature has identified multiple ways through which fund managers window dress. We propose a new unified framework to study Return window dressing, buying winner and selling looser stocks just prior to the declaration date; and Risk-shifting window dressing, reducing the risk of the portfolio just prior to the declaration date. We follow Barras, Scaillet, and Wermers (2010) to control for false discoveries in identifying window dressing in our multiple hypothesis testing framework. While Risk-shifting window dressing has not received much attention in equity fund literature, we find that it is in fact three times more prevalant than Return window dressing. Our empirical results suggest that investment choices of retail investors are not impacted by window dressing.

I. Introduction

Investors primarily look at past performance in evaluating a fund. However, past performance is limited by the noise in stock returns in detecting managerial skill. Therefore, regulators around the world (e.g., SEBI in India, SEC in the US) mandate funds to periodically disclose their portfolio holdings. The underlying belief is that investors use fund holdings data, in addition to past returns, in evaluating a fund. However, this causes a common agency problem called window dressing whereby, fund managers cosmetically adjust their portfolio just before the portfolio declaration date. Literature has identified several ways through which fund managers window dress. A fund manager may window dress

1. by reducing the risk of the portfolio just before the declaration date called Risk-shifting window dressing (RSWD) and

2. by picking recent winner stocks and selling looser stocks just before the portfolio declaration date called Return window dressing (RWD)

3. by buying stocks already held in the portfolio to inflate the value of portfolio artificially just before declaration date called "Portfolio pumping"[1].

The first two forms of window dressing involve changing the composition of securities in the portfolio with no special effort to affect changes to prices of securities itself. However, in "portfolio pumping" fund managers try to affect changes to prices of securities held in the portfolio without changing the composition of the portfolio itself. In this essay, we focus on return and risk-shifting window dressing in equity mutual funds.

Risk shifting window dressing has been discussed primarily in the context of bond funds. Musto (1997, 1999) show that bond funds reduce the risk of the portfolio around disclosure dates. However, Ortiz, Ramírez, and Sarto (2013) show that Spanish bond funds reduce the exposure to public debt around disclosure dates. While evidence for RSWD in bond funds is unclear, ours is the first paper to explore RSWD in equity funds. The rationale for risk-shifting window dressing is that fund managers show a low risk portfolio to the

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[1] "Portfolio Pumping" is also commonly known as "Net Asset Value (NAV) inflation", "Marking up", "Painting the tape" etc.

investors to justify the low returns over the reporting period. While there are several risk factors that have been identified in the literature, fund managers would have most incentive to reduce risk along the risk dimensions which investors are aware of. We therefore restrict ourselves to three popular risk factors as identified in Fama and French (1992) i.e., Market risk, Size risk and BE/ME or Value-Growth risk. We refer to these as Market RSWD, Size RSWD and Value-Growth RSWD respectively.

The evidence for return window dressing in equity funds is mixed. Lakonishok et al. (1991, LSTV) and He, Ng, and Wang (2004) find evidence in support of return window dressing, while Sias and Starks (1997) and Poterba and Weisbenner (2001) argue that the observed "turn-of-the-year" can be attributed to tax motivated selling. Return window dressing has traditionally been measured by comparing holding of the portfolio across various quarters (Lakonishok et al. 1991) or in relation to "turn-of-the-year" effect (Sias and Starks 1997). More recently, Meier and Schaumburg (2006) and Agarwal, Gay, and Ling (2014, AGL) compare holdings data with NAV return of the fund to identify window dressing.

Agarwal, Gay, and Ling (2014) propose a return window-dressing measure, Backward Holding Return Gap (BHRG), defined as difference in returns of a hypothetical portfolio declared at the end of the quarter with actual gross returns of the fund. However, if a fund manager simultaneously reduces the risk of the portfolio while indulging in return window-dressing, their measure wouldn't be able to detect it. Similar to Meier and Schaumburg (2006), we argue that studying the return series at a daily frequency will help us in better identifying window dressing. We propose a new variable, Daily Return Gap (DRG), which is very similar in spirit to AGL's BHRG measure but calculated daily. Daily Return Gap (DRG) is defined as difference between daily holding return of a hypothetical portfolio at the end of the month (DBHR) and actual gross return of the fund.

$DRG_t = Daily\ Backward\ Holding\ Return\ (DBHR_t) - Gross\ Return\ (GR_t)$ .... (1)

For every portfolio declaration we calculate the above variable, DRG_t. We then regress our Daily Return Gap variable on Fama-French-Carhart's (FFC) four factor model. The underlying idea is that, if a fund manager declares a portfolio which has significantly lesser market risk than actual portfolio held during the course of the month we would find the

coefficient of market risk (β_{MKT}) to be negative and significant in equation below. Similar logic can be extended to Size and Value-Growth risk factors. On the other hand, if a fund manager buys winners and sells losers just before the declaration date we would expect coefficient of momentum factor (β_{WML}) to be positive and significant.

$$DRD_t = \alpha + \beta_{MKT} * r_{MKT,t} + \beta_{SMB} * r_{SMB,t} + \beta_{HML} * r_{HML,t} + \beta_{WML} * r_{WML,t} + \epsilon_t \qquad \text{.... (2)}$$

We repeat the above process for every portfolio declaration. We control for false discoveries in our multiple hypothesis testing using the False Discovery Rate (FDR) framework of Storey (2002) and Barras, Scaillet, and Wermers (2010). We discuss our methodology in detail in section V. Our method has some advantages over the simple AGL's BHRG measure. First, we can identify if a fund manager has window dressed even if he indulges in return and risk-shifting window dressing simultaneously. Second, we can identify the risk dimensions along which fund manager window dress the most. Our results suggest that 21.3%, 1.1% and 10.9% of the portfolio declarations are Market RSWD, Size RSWD and Value-Growth RSWD respectively. Our results are consistent with Barber, Huang, and Odean (2016) who show that investors attend most to market risk when evaluating funds. Therefore funds have most incentive to reduce the market risk of the portfolio. Similarly we find that 7.5% of the declarations are return window dressed, consistent with Ortiz, Ramírez, and Sarto (2013) who find 7% of Spanish portfolio declarations are return window dressed.

It is argued that window dressing makes the portfolio more attractive to the investors and helps managers attract more fund flow. However it is not clear why investors do not see through the discrepancies between portfolio holdings and fund performance. Window dressing has some implicit and explicit costs to the investors. First, cosmetic rebalancing of a portfolio attracts transaction costs. Second, investors might be misled into investing in funds managed by subpar managers or even holding portfolio not appropriate for their risk profile. Therefore, the decision to window-dress a portfolio by a fund manager depends on a careful cost-benefit analysis of costs of portfolio churning vis-a-vis benefits of masking the portfolio.

Our paper contributes to the window dressing literature in two ways. First, we provide the first evidence for risk-shifting window dressing in equity mutual funds. In fact, we show that market risk RSWD is three times more prevalent than return window dressing. Second, we provide a frame work to simultaneously identify both risk-shifting and return window dressing.

Rest of the paper is organized as follows. In section II, discusses the relevant literature. In Section III we briefly motivate the use of Indian data and introduce Indian Mutual fund industry. Section IV describes our data and fund selection process. We discuss our methodology in detail in Section V. We present our results in section VI and conclude in section VII.

II.   Literature Review

Window dressing has been observed across industries in different forms. Non- financial firms are known to window dress their financial statements to smoothen reported earnings (Healy and Wahlen 1999), banks window dress to upward adjust their assets at the end of each quarter (Allen and Saunders 1992) and companies window dress their sales figures to alter their primary industry classification (Chen, Cohen, and Lou 2016). In this paper, we focus window dressing in equity mutual funds. Specifically we focus on risk-shifting window dressing and return window dressing.

While risk-shifting window dressing in bond funds has been studied earlier, to our knowledge, we are the first to study it in equity funds. Risk shifting behaviour of the equity fund managers has been studied earlier in the context of "mutual fund tournaments". Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that career concerns and performance incentives of fund managers may increase the risk of their portfolio in the later part of the year. Risk-shifting window dressing differs from "mutual fund tournaments" literature in two ways. First, while the mutual fund tournaments literature argues that funds with poor performance at the reference point increase their risk, we argue that funds reduce the risk of the portfolio around disclosure dates. Second,

while we focus on risk shifting for a few days around the portfolio disclosure, tournaments literature focuses on risk shifting over a much longer horizon.

Musto (1999) finds that funds hold more government issues around disclosure date consistent with the theory that funds prefer to declare safer portfolios. Musto (1997) finds that commercial papers maturing next calendar year trade at an extra discount while Treasury bills do not. This is consistent with risk shifting window dressing hypothesis. However, Griffiths and Winters (2005) argue that these can be explained using preferred habitat hypothesis. Morey and O'Neal (2006) use quarterly survey data from Morningstar to compare credit quality of disclosed and undisclosed US bond funds and find evidence consistent with Musto (1999). Contrary to expectation, Ortiz, Sarto, and Vicente (2012) find that Spanish bond funds hold less public debt around disclosure dates.

While return window dressing has received some attention in the literature the evidence is still mixed. Return window dressing has been primarily studied in the form of anomalies in literature. Fund managers generally have the greatest incentive to window dress at year end, post which investors are more likely to evaluate fund performance. However fund managers may also sell poorly performing stocks in their portfolio at year end to book capital losses and reduce tax. Lakonishok et al. (1991) show weak evidence that the pace of dumping poorly performing stocks in the portfolio increase in fourth quarter consistent with return window dressing. He, Ng, and Wang (2004) find that institutions which invest internally like pension funds and universities, tend to window-dress less when compared to institutions like mutual funds and banks who manage client money, consistent with window dressing hypothesis. Meier and Schaumburg (2004) compare the realized return with the hypothetical return of the portfolio declared by the fund. They find that the hypothetical fund returns are higher than the realized return which indicates window dressing. Sias and Starks (1997) find that stocks dominated by individual investors experience greater turn of the year effect. This is more consistent with tax-loss selling hypothesis. Poterba and Weisbenner (2001) exploit changes in tax laws to find that tax loss selling contributes to turn of the year effect. Sias (2007) shows that both window dressing and tax-loss selling contribute to stock return momentum.

Thus evidence for window dressing is at best mixed. The rationale for window dressing is that it helps the portfolio manager to avoid awkward questions regarding his stock selection ability and probably improve fund inflow by showing a better picture to the fund investors. Agarwal, Gay, and Ling (2014) argue that mutual fund managers take a risky bet on fund performance while indulging in window dressing. Solomon, Soltes, and Sosyura (2014) show that mutual fund holdings with high past returns are rewarded by investors, with higher fund inflow, only if they feature in the media. Their evidence shows that media coverage leads to investors chasing past performance and that is the primary mechanism through which window dressing becomes effective. Wang (2014) finds investors have limited attention and make investment decisions based on the performance of top 10 portfolio holdings. Wang also shows that mutual fund managers realise investor's behaviour and manipulate their disclosure accordingly. We follow this section with a brief introduction to Indian mutual fund industry.

III.   Indian mutual fund industry

We use Indian mutual fund data for our analysis. There are some advantages of using Indian data. First, Indian Mutual funds disclose their portfolio at the end of every month compared to quarterly disclosure by US mutual funds. Elton et al. (2010) show that quarterly holdings data misses about 18.5% of all trades found using monthly data. They find that using monthly data can change and in some cases even reverse conclusions of some popular hypothesis. Second, due to differences in tax regimes, our tests of window dressing are not confounded by tax loss selling like in the US. In US, all mutual funds have to distribute their gains at least once a year. Also, the treatment of gains as long term or short term depends on the holding period of the security by the mutual fund. However, in India, the treatment of gains as long term or short term is not dependent on the holding period of the assets by mutual funds. Capital gains are considered long term if the investor holds his investments with the mutual fund for more than a year and short term otherwise (Section 10(23D), Income Tax Act). Hence, mutual funds have no reason to indulge in tax loss selling.

Securities Exchange Board of India (SEBI), the Indian equivalent of SEC, regulates the mutual funds in India. The Indian mutual fund history can be broadly divided in four distinct phases[2]. In the first phase (1964-1987) only Unit Trust of India (UTI), a government of India entity, was allowed to float mutual funds. The second phase (1987-1993) saw the entry other public sector banks. In the third phase (1993-2003), SEBI (Mutual fund) regulations act, 1993 allowed the entry of private sector companies into mutual fund industry. In the fourth phase (2003-present), which started with the repealing of UTI act, the Assets Under Management (AUM) of the industry has grown from Rs. 891.7 billion in February 2003 to Rs 13.8 trillion as of 31st May 2016, i.e. more than 15 fold increase in 13.25 years.[3]

As of 31st March 2016 there are 35.75 million non-institutional accounts[4] only in equity oriented schemes in India and 47.2 million across all types of funds. The Indian mutual fund industry has total assets under management (AUM) of about 160 billion dollars which accounts for less than 0.5% of the 38.6 trillion dollars AUM worldwide[5]. With gross savings at 31% of GDP[6] and AUM/GDP ratio less than 10%[7], the Indian Mutual fund industry has tremendous potential for growth in near future.

IV. Data

We get all our mutual fund data from Lipper for Investment Management database. Agarwalla, Jacob, and Varma (2013) provide risk factor returns of Fama-French-Carhart's four-factor model, and risk-free rate. Indian listed equity securities data is taken from Prowess - CMIE. Following the extant literature, we consider equity mutual funds with investment focus and domicile in India. We remove all Closed-ended funds, Index tracking funds, Fund-of-Funds.

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[2] Association of mutual funds In India (AMFI)
[3] Unless otherwise mentioned we use AMFI definition of mutual fund which includes money market funds as mutual funds
[4] A single person may have multiple accounts.
[5] https://ici.org/research/stats - Quarterly Worldwide Mutual Fund Market – First Quarter of 2016 data – Accessed on 02/07/2016 – Mutual Fund as defined by ICI
[6] World bank's World Development Indicators. 2015 estimates.
[7] Source: RBI's – 'Handbook of Statistics on Indian Economy 2014-15'. All statistics are as of 31st March, 2015 (AUM = 1082,757 Crores, GDP = 11550240 Crores).

Indian mutual funds typically offer three different plans for distributing the money back to the investors. Namely, Dividend, Dividend reinvestment, and Growth plans. In a dividend plan, investors receive a periodical dividend according to the pay-out policy of fund. In a Dividend reinvestment plan, the fund automatically reinvests the dividends into the fund. In a growth plan, mutual funds do not give any dividends, and the only way for the investors to get their money back is to sell the mutual fund units/shares. Further, depending on the channel used for investing, mutual funds offer two options, Direct and Standard. As the name suggests, when an investor directly approaches the mutual fund to invest it is called 'direct' option. When an investor invests in the fund through an intermediary/investment advisor, it is called 'standard' option. Since the mutual fund companies have to compensate the intermediaries for bringing business to them, 'standard' options charge higher fees than their counterpart 'direct' option. However, the underlying portfolio for all the six sub-classes (3 plans * 2 options) of a given fund is same. Rarely funds also offer sub-classes for Institutional investors too. Since our unit of analysis is a portfolio, we use only the primary sub-class of each fund in our analysis so that we do not over-sample our data. Primary sub-class in Lipper is the oldest sub-class with the largest amount of assets, which is typically a growth plan with standard option. Using the above filtering criteria and removing multiple sub-classes for same fund we narrow our analysis to 566 unique funds. Of these, we remove funds less than 2 years old and hybrid funds classified by AMFI as either balanced or Income funds. We only consider declarations where equities as percentage of total declared assets lie between 85% and 105%. We further remove declarations with less than 20 securities and where at least 80% of the portfolio composition data is not available. This leaves us with 326 funds and 17704 portfolio declarations from June 2008 to June 2016, the period for which Lipper has reliable data. We present a summary statistics of the data in Table 1.

Total Number of Declarations		17704	
Year	Number of declarations	Year	Number of declarations
2008	531	2013	2742
2009	1863	2014	2732
2010	2140	2015	2693
2011	1750	2016	1297

2012	1956		
Month	Number of declarations	Month	Number of declarations
January	1421	July	1314
February	1388	August	1349
March	1593	September	1594
April	1460	October	1436
May	1443	November	1405
June	1715	December	1586
AMFI Classification		Number of declarations	
Growth		14871	
Equity Linked Savings scheme		2585	
Unclassified		248	

Table 1

We construct define below the construction of certain variables used in the following sections. In the later part of paper we study the impact of window dressing on fund flow. We define flow as,

$$Flow = \frac{(AUM_t - AUM_{t-1} * (1 + R_t))}{AUM_{t-1}}$$

Where AUM_t stands for Assets Under Management at time t. We calculate AUM by summing the total value of investments in different securities in the portfolio declared at the end of every month.

V. Methodology

Window dressing measures have traditionally used only portfolio holding data. They either compare year end portfolio data with other non-year-end declarations or public disclosures with private disclosures (Lakonishok et al. 1991, Ortiz, Sarto, and Vicente 2012). However just using holdings data will not reveal the timing of the trades. Meier and Schaumburg (2006) argue that we can learn more about window dressing by comparing buy-and-hold returns of the declared portfolio with actual return of the fund. Agarwal, Gay, and Ling (2014) also propose a window dressing measure, called Backward Holding Return Gap (BHRG), using both actual return data and portfolio data. As discussed earlier, our

window dressing measure, Daily Return Gap (DRG), is defined as difference between the daily buy-and-hold return of a hypothetical portfolio comprising month end holdings of a fund and daily gross return of the fund (See Appendix A1 for full details). Repeating our earlier equation,

$$DRG_t = Daily\ Backward\ Holding\ Return\ (DBHR_t) - Gross\ Return\ (GR_t) \qquad .... (1)$$

Our window dressing measure (DRG) is can be viewed as the return series of a long-short portfolio which is long on the on portfolio declared at the end of the month and short on the respective fund. AGL argue that their window dressing measure (BHRG) is positively related to return window dressing[8]. However BHRG is also negatively related to Risk-shifting window dressing[9]. If a fund manager indulges in both risk-shifting and return window dressing, BHRG may fail to identify window dressing. We overcome this problem by regressing our window dressing measure (DRG) on Fama-French-Carhart four factor model to identify the source of return for this long-short portfolio.

$$DRG_t = \alpha + \beta_{MKT} * r_{MKT,t} + \beta_{SMB} * r_{SMB,t} + \beta_{HML} * r_{HML,t} + \beta_{WML} * r_{WML,t} + \epsilon_t \qquad .... (2)$$

Where, $r_{MKT,t}$, $r_{SMB,t}$, $r_{HML,t}$ and $r_{WML,t}$ are standard Market, Size, Value-Growth and Momentum factor returns on day t and β_{MKT}, β_{SMB}, β_{HML} and β_{WML} are their respective factor loadings.

If the risk of the portfolio declared at the end of month is representative of the risk of the fund through the month we expect the factor loading to not be statistically different from zero. However, if the fund manager indulges in risk-shifting window dress i.e. reduces the Market, Size or Value-Growth risk of the portfolio just prior to declaration we expect the respective risk factor loadings to be negative and statistically significant. Similarly, if the portfolio declaration is return window dressed we expect the momentum risk factor loading to be positive and significant. We repeat the above exercise for every declaration. Since the declaration frequency in India is monthly, we have limited number of data points

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[8] Agarwal, Gay, and Ling (2014) paper only deals with return window dressing. They loosely use window dressing to refer to return window dressing.

[9] A simple pooled regressing of BHRG on our Risk-shifting and return window dressing dummies shows that it is negatively related to risk shifting window dressing (See Appendix A2).

per declaration. Therefore for consistent results, we use the bootstrap methodology proposed by Kosowski et al. (2006, KTWW) in identifying the above factor loadings. This has two advantages over simple OLS regressions.

First, funds exhibit non normal returns for various reasons including but not limited to holding concentrated portfolio of stocks which have non-normal properties, market benchmark returns which are non-normal, following dynamic strategies which change risk with market risk etc. Therefore using the regular standard errors of OLS regression may lead us to draw wrong conclusions. However bootstrap can be of much help in such situations as shown by Bickel and Freedman (1984) and Hall (1986). It helps that bootstrap does not assume a priori distribution. Second, KTWW show that t-statistic of β estimates are robust to cross sectional dependencies than β estimates themselves. In our study we therefore bootstrap t-statistics of β estimates and bootstrap β estimates for a robust check. For each of 17704 portfolio declarations we estimate the p-values of both, factor loading estimates and their t-statistics[10]. (See Appendix A3 for bootstrap methodology).

The standard approach in a single hypothesis testing is to control for type I error by choosing a significance level γ and to reject the null if the test statistic falls within the significance level. When we conduct the above regression for each declaration, we are conducting a multiple hypothesis test. Some of the declarations might show significant factor loading by pure luck alone. We control for this multiple hypothesis test problem by using False Discovery Rate (FDR) methodology proposed by Storey (2002).

V.1   False Discovery Rate (FDR):

We loosely follow Barras, Scaillet, and Wermers (2010; BSW) and Storey (2002) to control for false discoveries. The problem in multiple testing of a large number of declarations is that we have to choose a significance level γ and declare all declarations with p-value less than $\gamma/2$ as not belonging to the null. Let, π_X^0, π_X^+ and π_X^- represent proportion of declarations belonging to the null (no window dressing), proportion of declarations

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[10] See appendix A3 for detailed bootstrap methodology.

belonging to the alternative which are window dressed and proportion of declarations belonging to the alternative which are not window dressed respectively. Where, $X = \{MKT, SMB, HML, WML\}$. A declaration not belonging to the null is classified as window dressed if $\beta_{WML} > 0$ or $\beta_{MKT} < 0$ or $\beta_{SMB} < 0$ or $\beta_{HML} < 0$ for the respective type of window dressing. At a given significance level γ the proportion of null declarations which are wrongly classified as window dressed is:

$$E(F_{X,\gamma}^+) = \pi_X^0 * \frac{\gamma}{2}$$

If $E(S_{X,\gamma}^+)$ is the expected proportion of funds which are significant and are on the window dressing tail of the distribution, then the expected proportion of truly window dressed declarations at a given significance level γ is defined as:

$$E(T_{X,\gamma}^+) = E(S_{X,\gamma}^+) - E(F_{X,\gamma}^+) = E(S_{X,\gamma}^+) - \pi_X^0 * \frac{\gamma}{2}$$

As we vary the significance level γ, the proportion of truly window dressed declarations also varies. We estimate the proportion of window dressed portfolios in the population as:

$$\pi_X^+ = T_{X,\gamma^*}^+$$

Where γ^* is a sufficiently high significance value in the range 0.30 to 0.50. The optimal value of γ^* is determined using a MSE criteria explained in appendix A4. The False Discovery Rate (FDR) among the portfolios classified as window dressed at a given significance level γ is:

$$FDR_{X,\gamma}^+ = \frac{E(F_{X,\gamma}^+)}{E(S_{X,\gamma}^+)} = \frac{\pi_X^0 * \frac{\gamma}{2}}{E(S_{X,\gamma}^+)}$$

$E(S_{X,\gamma}^+)$ can be calculate as the percentage of funds which are significant at a given value of γ and are in the window dressing tail of the distribution. Therefore all we need is an estimate of π_X^0 to calculate FDR. If all the fund declarations are not window dressed then its p-values are uniformly distributed between 0 and 1. However if the portfolio is window dressed then its p-values are concentrated near zero. Let W(λ) be the number of portfolio

declarations with p-values greater than λ and M be the total number of portfolio declarations. If the p-values of null distribution are uniformly distributed then we can say

$$\pi_X^0 = \frac{W(\lambda)}{M} * \frac{1}{(1-\lambda)}$$

We estimate π_X^0 over a range of λ values from 0.30 to 0.70. We choose $\lambda = \lambda^*$ which minimizes the Mean Squared Error of π_X^0. Full estimation procedure can be found in Appendix A4. The benefit of using above method is that it is completely data driven. However BSW do a Monte Carlo study to show that the estimates are not too sensitive to the chosen levels of λ^* and γ^*. The procedure for estimating $\pi_X^-, T_{X,\gamma}^-, S_{X,\gamma}^-$ is same as above with all equations substituting plus with minus symbol.

Our primary interest is in controlling False Discoveries in identifying window dressing portfolio. There we estimate $FDR_{X,\gamma}^+$ for various values of γ (0.01, 0.02 …0.90). We identify the value of γ for which FDR is closest to 10% and declare all declarations with significance value less than γ as window dressed.

VI.   Empirical results

Our primary sample has 326 funds with 17,707 portfolio declarations over a period of 8 years. For each of the 17,704 declarations we do a bootstrap regression as given in equation 2. Histograms of P-values of t-statistic of the factor loadings are shown in figure 1 below[11]. If all the p-values are from null distribution i.e. none of the declarations have been window dressed, we would have had flat histograms. However, we find that p-values are clustered towards zero, indicating evidence for window dressing.

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[11] Appendix A5 has similar histograms but for p-values of coefficient of factor loadings
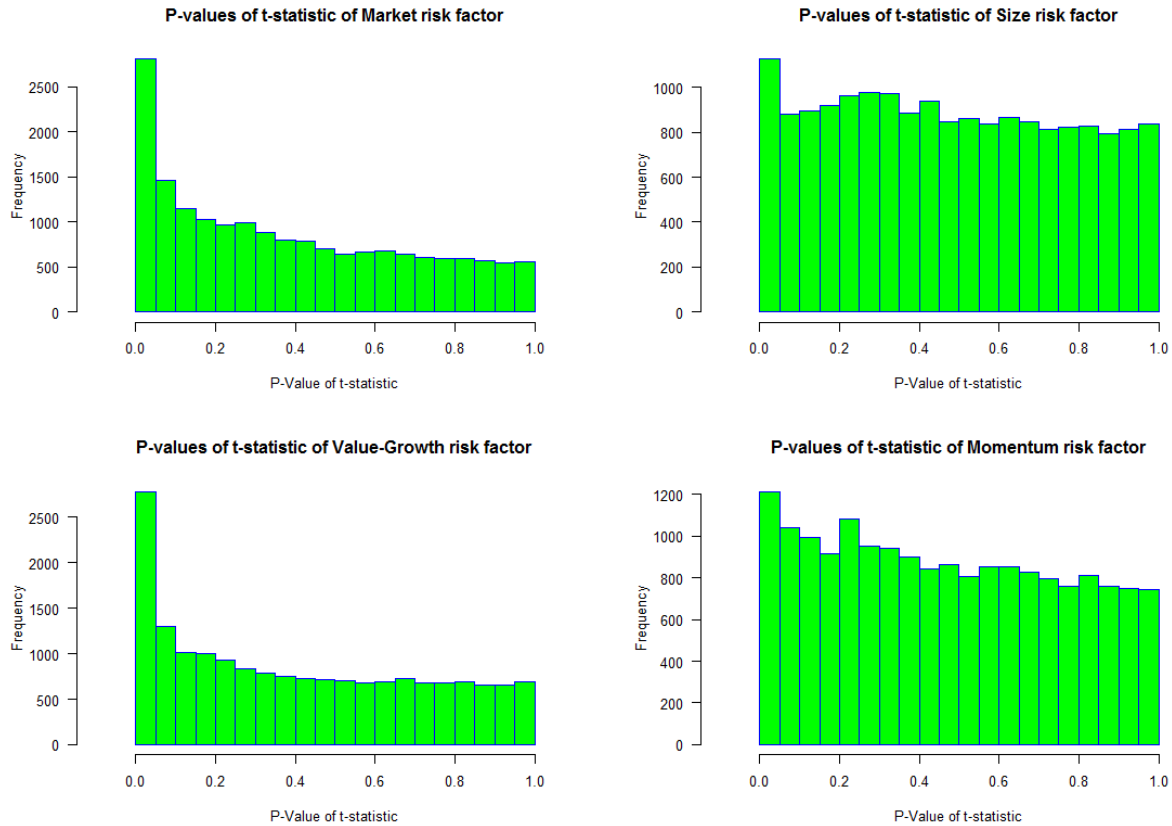
Figure 1: Histogram of P Values of t-statistics of β's in equation 2

VI.1   Evidence for window dressing

If the fund managers indulge in risk-shifting window dressing to deceive customers about the true risk of the fund, then they would have greatest incentive to window dress along the risk dimension investors give most importance to. Barber, Huang, and Odean (2016) show that investors pay most attention to market risk. This leads to our first hypothesis:

Hypothesis 1: Fund managers indulge the most in window dressing market risk of the portfolio.

A lot of funds in India market themselves as either Large Cap or Mid Cap or Small Cap funds. They also tend to mention the market capitalization of the companies they plan to invest in fund objectives. Therefore funds have the least flexibility in window dressing size risk of the portfolio. This leads to our second Hypothesis:

Hypothesis 2: Fund managers least window dress along the size risk dimension.

Using the above p-values and the FDR methodology outline in the previous section we calculate the proportion of declarations which are window dressed π_X^+, proportion of declarations which are non-window dressed π_X^0 and proportion of portfolio declarations which are not window dressed and do not belong to the null π_X^-. Results have been tabulated in Table 2. The terms in the brackets are standard errors. Refer to Appendix A4 for the procedure to calculate standard deviation.

		π^+	π^0	π^-
Return window dressing	WML	**7.5%**	88.1%	4.4%
		(0.99)	(1.00)	(0.49)
Risk Shifting window dressing	MKT	**21.3%**	67.0%	11.7%
		(0.91)	(0.92)	(0.47)
	SMB	**1.1%**	93.0%	5.9%
		(1.01)	(0.45)	(0.99)
	HML	**10.9%**	77.3%	11.8%
		(0.80)	(0.40)	(0.89)

Table 2: Percentage of Window dressed funds (π^+), Null funds (π^0) and Non-Window dressed funds (π^-). The numbers in the brackets below percentages are their respective standard deviations in percentage.

21.3% of the declarations are window dressed by reducing market risk of the portfolio just prior to declaration. The percentage of declarations which window dress by reducing size risk of the portfolio is statistically not different from zero. Therefore, our results are in conformity with Hypothesis 1 & 2. While the extant literature is focused on risk shifting window dressing only in bond funds we show that is equally important in equity funds. In fact our results suggest that equity fund managers are almost 3 times more likely to indulge in Market-risk shifting window dressing over return window dressing.

VI.2   Window dressing identification

Using the above estimates of π^0 we calculate $FDR_{X,\gamma}^+$ at various values of significance levels γ (0.01, 0.02, … 0.90) using the equation in section V.1 and reproduced below.

$$FDR_{X,\gamma}^+ = \frac{E\left(F_{X,\gamma}^+\right)}{E\left(S_{X,\gamma}^+\right)} = \frac{\pi_X^0 * \frac{\gamma}{2}}{E\left(S_{X,\gamma}^+\right)}$$

We identify the value of γ for which FDR is closest to 10% and treat all declarations with p-values less than γ as significant.

Targeted FDR		FDR = 10%		
		Significance level (γ)	FDR achieved	% of portfolios WD at γ
Return window dressing	WML	0.01	10.0	0.9%
Risk Shifting window dressing	MKT	0.01	13.6	4.1%
	SMB	0.01	71.0	0.7%
	HML	0.01	15.3	3.9%

Table 3

Although we have set FDR target levels at 10%, we don't achieve our target levels always. The FDR of size-risk shifting window dressing is too high to draw any meaningful conclusions. The FDR achieved by Market and Value-Growth risk dimensions is also off by a huge margin (13.6% and 15.3% respectively). Even at this level of significance the percentage of declarations which are considered window dressed is very small. For example only 0.7% of all fund declarations can be classified as size window dressed even at 71% FDR. We define a new binary variable, Window Dressing (WD), which equals one if a given portfolio has been window dressed at least in one form of window dressing discussed above. There are a total of 1585 (8.95%) portfolio declarations which are involved in at least one form of window dressing. We use this binary variable, WD, as our window dressing measure hence forth.

VI.3   Motivation for window dressing

A fund manager wouldn't ideally like to window dress their portfolio as it involves mindless churning of portfolio with no value add to the investors. Also churning the portfolio attracts transaction cost which reduces the return of the portfolio. We argue that managers window dress only when their recent performance has been very bad or when they are experiencing fund outflow. This leads to our third hypothesis:

Hypothesis 3: Window dressing is negatively related to fund performance and fund flow.

We test our hypothesis through a logistic regression of the equation below.

$$WD_t = \beta_0 + \beta_1(Pre - 3\ months\ alpha)_t + \beta_2(Size)_t + \beta_3(Pre - 3\ months\ flow)_t + \beta_4(turnover) + Controls$$

WD is binary variable indicating if the portfolio has been window dressed in at least one risk dimension. "Pre- 3 months alpha" is defined as daily alpha compounded over last 3 months. "Size" is defined as natural log of total assets. Turnover is defined as min {buy, sell} as percentage of lagged assets. "Pre – 3 months flow" is the average of last three months flow.

From table 4 below we can conclude that fund manager's propensity to window dress is negatively related to last 3 months performance and last 3 months average flow. Our results are consistent across various specifications of control variables. This proves our third hypothesis.

Table 4:

| | Window dressing (WD) | | | | |
	(1)	(2)	(3)	(4)	(5)
Pre - 3 Months alpha	-0.021***	-0.020***	-0.019***	-0.015***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Pre 3 Months flow	-0.622*	-0.623*	-0.673*	-0.914**	-0.683
	(0.375)	(0.375)	(0.379)	(0.396)	(0.420)
Size	0.041***	0.041***	0.041***	0.041***	0.042***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Turnover	0.160	0.172	0.142	0.046	0.114
	(0.169)	(0.169)	(0.170)	(0.180)	(0.228)
ELSS Dummy	0.032	0.032	0.030	0.027	0.017
	(0.040)	(0.040)	(0.040)	(0.040)	(0.042)
Quarter End Dummy		YES		YES	
Quarter Dummy			YES		
Month Dummy					YES

Year Dummy			YES		
Time Dummy				YES	
Constant	-2.078***	-2.102***	-2.042***	-1.698***	-2.249***
	(0.159)	(0.160)	(0.162)	(0.190)	(0.360)
Observations	15,399	15,399	15,399	15,399	15,399

Note: *p<0.1; **p<0.05; ***p<0.01

Dependent variable, WD, equals one if the declared portfolio has been either return window dressed or risk shifting window dressed. "Pre-3months alpha" is defined as funds daily 4 factor FFC alpha compounded over the last 3 months. "Size" is defined as natural log of total assets. Turnover is defined as the min {buy, sell} over the last month as percentage of lagged assets. "Pre-3 months flow" is defined as simple average of last three months flow. Quarter End Dummy = 1 if month = {March, June, September, December}. Quarter Dummy is a set of 3 dummies each indicating one of the 4 quarters in a year. Month Dummy is a set of 11 binary variables with each variable equal to one for a particular month and zero otherwise. Year Dummy is a set of 7 binary variables with each variable equal to one for a given year and zero otherwise. Time Dummy is a set of binary variables each representing a unique combination of year and month. ELSS Dummy = 1 if the fund is classified as ELSS fund by AMFI. ELSS funds typically have 3 year lock in period.

VI.4   Impact of window dressing

The motivation for window dressing is clear. Fund managers' window-dress their portfolios to avoid uncomfortable questions about their stock selection ability. Especially, when the recent performance of the fund is bad and when there is low fund inflow. However the impact of window dressing has not received much attention in the literature. Agarwal, Gay, and Ling (2014) argue that fund managers take risk bet when they indulge in window dressing. They model investors as rational agents who look at the performance of the fund in the "delay period" and reward those funds with good performance. For their model to work average investor will have to look at composition of the portfolio held by the fund. On the other hand, if we think of investor as a naïve agent who takes portfolio composition data at face value we expect higher fund inflow when the fund manager window dresses the portfolio. Finally, if we model investor as highly naïve agent who does not take portfolio composition into consideration, we can expect window dressing to have no influence on future fund flow. We test our hypothesis using the following equation.

$Lead\ Flow_{t+2,t+3}$

$$= \beta_0 + \beta_1(WD_t) + \beta_2(WD_t * Post\ Alpha_{t+1}) + \beta_3(Post\ Alpha_{t+1})$$
$$+ \beta_4(Pre - 3\ months\ Alpha_t) + \beta_5(Pre - 3\ months\ Alpha_t)\char`\^2 + \beta_6 * Size_t$$
$$+ \beta_7(turnover) + Controls$$

		Investor	
		Non-Naïve	Naïve
Takes portfolio composition into consideration	Yes	$\beta_1 < 0\ and\ \beta_2 > 0\ and\ \beta_1 + \beta_2 > 0$	$\beta_1 > 0$
	No		$\beta_1 = 0\ and\ \beta_2 = 0$

If the investors are not naïve agents as described by Agarwal, Gay, and Ling (2014) then we expect $\beta_1 < 0, \beta_2 > 0\ and\ \beta_1 + \beta_2 > 0$. If the investor is not naïve we expect him to look for information beyond NAV return data. Therefore we do not take the second case into consideration. On the other hand, if the investors are naïve who take portfolio composition data at face value we expect $\beta_1 > 0$. Finally if the investors are naïve and do not take portfolio composition data into consideration we expect $\beta_1 = 0\ and\ \beta_2 = 0$.

		Lead Flow		
	(1)	(2)	(3)	(4)
WD	0.001	-0.001	0.002	-0.0003
	(0.002)	(0.002)	(0.002)	(0.002)
I (WD * Post Alpha)			-0.002	-0.002
			(0.001)	(0.001)
Post Alpha			0.002***	0.003***
			(0.0004)	(0.0004)
Pre 3 – Months Alpha	0.002***	0.003***	0.002***	0.003***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
I(Pre 3 – Months Alpha^2)	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Size	0.002	0.002**	0.002	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Turnover	0.040***	0.037**	0.039***	0.036**
	(0.014)	(0.018)	(0.014)	(0.018)
ELSS	0.001	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Month Dummy	YES		YES	
Year Dummy	YES		YES	
Time Dummy		YES		YES
Constant	-0.060***	-0.108***	-0.058***	-0.106***
	(0.018)	(0.022)	(0.018)	(0.020)
Observations	14,996	14,996	14,996	14,996
Adjusted R2	0.116	0.234	0.118	0.237

Note: *p<0.1; **p<0.05; ***p<0.01

Lead flow is average flow in month 2 and 3 from the end of declaration date. For example, In January if the fund has declared the composition of the portfolio it held at the end of December, Lead flow is the average flow into the fund in February and March. Post Alpha is defined as daily compounded four factor alpha of the fund in January. "Size" is defined as natural log of total assets. "Turnover" is defined as the min {buy, sell} over the last month as percentage of lagged assets. "WD" is binary variable indicating if the portfolio has been window dressed. "Pre- 3 months alpha" is defined as daily four factor alpha compounded over last 3 months. ELSS Dummy = 1 if the fund is classified as ELSS fund by AMFI. ELSS funds typically have 3 year lock in period. Month Dummy is a set of 11 binary variables with each variable equal to one for a particular month and zero otherwise. Year Dummy is a set of 7 binary variables with each variable equal to one for a given year and zero otherwise. Time Dummy is a set of binary variables each representing a unique combination of year and month.

From the above table we conclude that $\beta_1 = 0$ and $\beta_2 = 0$. In other words, Indian investors do not look at portfolio composition when making investment decisions. Other coefficients like past 3 months performance, performance in the delay period are all positive and significant. This is blessing in disguise that Indian investors do not reward fund manager who window dress. However we do not go as far as to recommend investors to avoid looking for portfolio composition data. It is important that the investors monitor that the manager is investing in line with the objectives of the fund. The cost of holding a fund in

your portfolio not appropriate for your risk profile may be more than the cost of window dressing.

VII.   Conclusion

In this paper we use data of an emerging market, India. Indian data has several advantages for testing window dressing. First funds declare their portfolio monthly and second due to differences in the way tax is administered mutual funds do not indulge in tax motivated selling. With these advantages we propose a new methodology to test for window dressing. While the existing literature is quiet on risk-shifting window dressing in equity funds, we find that fund managers are three times more likely to indulge in (market) risk-shifting window dressing compared to return window dressing. A fund manager may also indulge in one or more forms of window dressing simultaneously. Our methodology is helpful in measuring each type of window dressing while simultaneously controlling for the others. In this aspect our methodology is an improvement over Meier and Schaumburg (2006). We are also the first paper to control for multiple hypotheses testing in the window dressing literature.

The decision to window-dress a portfolio by a fund manager depends on a careful cost-benefit analysis of costs of portfolio churning vis-a-vis benefits of masking the portfolio. Fund managers window dress when their fund performance is bad or when fund has low inflow. While the motivation for window dressing is clear, the impact of window dressing isn't. We find that investors do not take portfolio compositions data into consideration while making investment decisions. However, this leads us to ask the question - why do the fund managers' indulge in window dressing. We leave this as scope for future research.

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Appendix

A1.   Daily Return Difference (DRD)

Mathematically, we calculate Daily Return Difference (DRD) as

$$DRD_t = Daily\ Backward\ Holding\ Return\ (DBHR_t) - Gross\ Return\ (GR_t)$$

Where t = 1 to T, and T equals the total number of working days in a given month. Gross return is sum of actual realized return and daily expense ratio. Actual return is calculated using daily NAV and dividend data as given below.

$$Gross\ Return\ (GR_t) = Actual\ Return\ (AR_t) + Daily\ Expense\ Ratio_t$$

$$Actual\ Return\ (AR_t) = \frac{(NAV_t + DIV_t - NAV_{t-1})}{NAV_t}$$

Assuming 250 working days in year, $Daily\ Expense\ Ratio = (\frac{Annual\ Expense\ Ratio}{250})$

Daily Backward Holding Return, $DBHR_t = \sum_{i=1}^{n} w_{i,t-1} R_{i,t}$

$$w_{i,t} = \frac{\left(\dfrac{MV_{i,T}}{\prod_{k=t}^{T}(1 + R_{i,k})}\right)}{\sum_{i=1}^{n}\left(\dfrac{MV_{i,T}}{\prod_{k=t}^{T}(1 + R_{i,k})}\right)}$$

Where $MV_{i,T}$ is market value of asset i held by fund f at the end of the month. $R_{i,t}$ is return of asset i on day t. We use market value in calculating the weight of the asset in the portfolio on a given date, t, unlike number of shares as used in Kacperczyk, Sialm, and Zheng (2008). This is because we found the market value data to be error free relative to number of shares data. Also, CMIE Prowess our database for Indian stock return data doesn't have readymade adjustment factor for number of shares. For each of the 17,704 portfolio declarations we calculate DRD$_t$ for all the days in that given month.

A2. BHRG Vs Window Dressing Dummies

	BHRG measure of Agarwal, Gay, and Ling (2014)		
Risk Shifting WD	-0.006***		-0.006***
	(0.002)		(0.002)
Return WD		0.002	0.002
		(0.005)	(0.005)
Constant	1.019***	1.019***	1.019***
	(0.001)	(0.0005)	(0.001)
Observations	17,704	17,704	17,704
Adjusted R2	0.001	-0.0001	0.001

Note: *p<0.1; **p<0.05; ***p<0.01

A3. KTWW bootstrap

For each of the 17,704 portfolio declarations we run the regression in equation 2 of the main text and save β_{MKT}, β_{SMB}, β_{HML} and β_{WML} their respective t-statistics and residuals, ϵ_t. For each declaration we resample the errors as proposed by Politis and Romano (1994). For stationary time series Politis and Romano (1994) suggest using block sampling whose block length follows a geometric distribution. We resample the errors to get 2000 error series, ϵ_t^b where b = 1, 2, ...2000 represents bootstrap iterations. For each iteration, we calculate DRD_t^b under the null hypothesis β=0.

$$DRD_{t,MKT}^b = \alpha + \beta_{SMB} * r_{SMB,t} + \beta_{HML} * r_{HML,t} + \beta_{WML} * r_{WML,t} + \epsilon_t^b$$

$$DRD_{t,SMB}^b = \alpha + \beta_{MKT} * r_{MKT,t} + \beta_{HML} * r_{HML,t} + \beta_{WML} * r_{WML,t} + \epsilon_t^b$$

$$DRD_{t,HML}^b = \alpha + \beta_{MKT} * r_{MKT,t} + \beta_{SMB} * r_{SMB,t} + \beta_{WML} * r_{WML,t} + \epsilon_t^b$$

$$DRD_{t,WML}^b = \alpha + \beta_{MKT} * r_{MKT,t} + \beta_{SMB} * r_{SMB,t} + \beta_{HML} * r_{HML,t} + \epsilon_t^b$$

For each iteration we regress the new return series $DRD_{t,X}^b$ on Fama and French (1992) four factors as given in the equation below.

$$DRD_{t,X}^b = \alpha + \beta_{MKT}^b * r_{MKT,t} + \beta_{SMB}^b * r_{SMB,t} + \beta_{HML}^b * r_{HML,t} + \beta_{WML}^b * r_{WML,t} + \epsilon_t^b$$

Where X = *{MKT, SMB, HML, WML}.*

In the above four regressions we save β_X^b along with its t-statistic. Repeating the above bootstrap regressions 2000 times gives the distribution of β_X^b and its t-statistic under the null, $\beta_X^b = 0$. We then compare the β estimates and their t-statistics from equation 2 with the distribution of β and t-statistics generated from above bootstrap procedure. We calculate the two sided p-value as below.

$$P_{\beta,X} = 2 * \min(\frac{1}{2000} * \sum_{b=1}^{2000} F(\beta_X > \beta_X^b), \frac{1}{2000} * \sum_{b=1}^{2000} F(\beta_X < \beta_X^b))$$

$$P_{tstat,X} = 2 * \min(\frac{1}{2000} * \sum_{b=1}^{2000} F(tstat_X > tstat_X^b), \frac{1}{2000} * \sum_{b=1}^{2000} F(tstat_X < tstat_X^b))$$

Where $F(K) = 1$ *if K is True else* 0.

For each of the 17,704 portfolio declarations we calculate $P_{\beta,X}$ *and* $P_{tstat,X}$ where *X = {MKT, SMB, HML, WML}.* In total we run about 142 million regressions (17704 declarations * 2000 (number of bootstraps per declaration) * 4 (each for SMB, HML, WML and MKT)).

A4.   FDR

A4.1 Procedure for estimating λ^*

We use bootstrap procedure proposed by Storey (2002) to estimate the proportion of zero-alpha funds in the population, π_X^0. This resampling approach chooses λ from the data such that an estimate of Mean Squared Error (MSE) of $\pi_X^0(\lambda)$, defined as $E(\pi_X^0(\lambda) - \pi_X^0)\^2$, is minimized. First we compute $\pi_X^0(\lambda)$ using equation below across a range of λ values (λ = 0.30, 0.35,...., 0.70).

$$\pi_X^0 = \frac{W(\lambda)}{M} * \frac{1}{(1 - \lambda)}$$

Second, for each possible value of λ, we form 1000 bootstrap replications of $\pi_X^0(\lambda)$ by drawing with replacement from the Mx1 vector of fund p-values. These are denoted by

$\pi_X^{0,b}(\lambda)$ for b = 1, 2, ...2000. Third we compute the estimated MSE for each possible value of

:

$$\text{MSE}(\lambda) = \frac{1}{1000} \sum_{b=1}^{1000} [\pi_X^{0,b}(\lambda) - \min(\pi_X^0(\lambda))]^2$$

We choose λ^* such that $\lambda^* = \arg\min_\lambda MSE(\lambda)$. We repeat the above process for each x = {MKT, SMB, HML,WML}

A4.2 Procedure for estimating γ^*

To estimate the proportions of window dressed funds and non-window dressed funds not belonging to the null in the population, π_X^- and π_X^+, we use a bootstrap procedure that minimizes the estimated MSE of $\pi_X^-(\gamma)$ and $\pi_X^+(\gamma)$. First we compute $\pi_X^+(\gamma)$ using equations below for a range of values of γ (γ = 0.30, 0.35, ...0.60):

$$\pi_X^+ = T_{X,\gamma^*}^+; \ E(T_{X,\gamma}^+) = E(S_{X,\gamma}^+) - \pi_X^0 * \frac{\gamma}{2}$$

Second we form 1000 bootstrap replication of $\pi_X^+(\gamma)$ for each possible value of γ. These are denoted by $\pi_X^{+,b}(\gamma)$, for b = 1, 2, ..., 1000. Third we compute the estimated MSE for each possible value of γ.

$$\text{MSE}^+(\gamma) = \frac{1}{1000} \sum_{b=1}^{1000} [\pi_X^{+,b}(\gamma) - \max(\pi_X^+(\gamma))]^2$$

We choose γ^+ such that $\gamma^+ = \arg\min_\gamma MSE^+(\gamma)$. We use the same process to calculate $\gamma^- = \arg\min_\gamma MSE^-(\gamma)$. If $\min_\gamma MSE^-(\gamma) < \min_\gamma MSE^+(\gamma)$ we set $\pi_X^-(\gamma^*) = \pi_X^-(\gamma^-)$. To preserve the equality 1= $\pi_X^0 + \pi_X^+ + \pi_X^-$, we set $\pi_X^+(\gamma^*) = 1 - \pi_X^0 - \pi_X^-(\gamma^*)$. Otherwise we set we set $\pi_X^+(\gamma^*) = \pi_X^+(\gamma^+)$ and $\pi_X^-(\gamma^*) = 1 - \pi_X^0 - \pi_X^+(\gamma^*)$. We repeat the above process for each x = {MKT, SMB, HML, WML}.

A4.2 Procedure for estimating standard deviation of π_X^0, π_X^+ and π_X^-

We follow Genovese and Wasserman (2004) to calculate the standard errors of

π_X^0, π_X^+ and π_X^-. As the number of declarations, M, goes to infinity Genovese and Wasserman

(2004) show that $\sigma_{\pi_X^0} = \left(\frac{W(\lambda^*)(M - W(\lambda^*))}{M^3(1-\lambda)^2}\right)^{1/2}$. Similarly $\sigma_{S_{X,\gamma}^+} = \left(\frac{S_{X,\gamma}^+(1 - S_{X,\gamma}^+)}{M}\right)^{1/2}$ and $\sigma_{T_{X,\gamma}^+} =$

$\left(\sigma_{S_{X,\gamma}^+}^2 + (\gamma/2)^2\, \sigma_{\pi_X^0}^2 + 2\, \frac{(\gamma/2)}{1-\lambda^*}\, S_{X,\gamma}^+\, \frac{W(\lambda^*)}{M^2}\right)^{1/2}$. The standard deviation of estimators in the

Non-Window dressed tail, $S_{X,\gamma}^-$ and $T_{X,\gamma}^-$, are obtained by replacing + with – in the above

equations. If $\gamma^* = \gamma^+$, the standard errors of π_X^+ and π_X^- are given by, $\sigma_{\pi_X^+} = \sigma_{T_{X,\gamma^*}^+}$ and

$\sigma_{\pi_X^-} = \left(\sigma_{\pi_X^+}^2 + \sigma_{\pi_X^0(\lambda^*)}^2 - 2\left(\frac{1}{1-\lambda^*}\right) S_{X,\gamma^*}^+\, \frac{W(\lambda^*)}{M^2} - 2\left(\frac{\gamma^*}{2}\right) \sigma_{\pi_X^0}^2\right)^{1/2}$. If $\gamma^* = \gamma^-$ we have to

reverse + and – in the above two formulas.
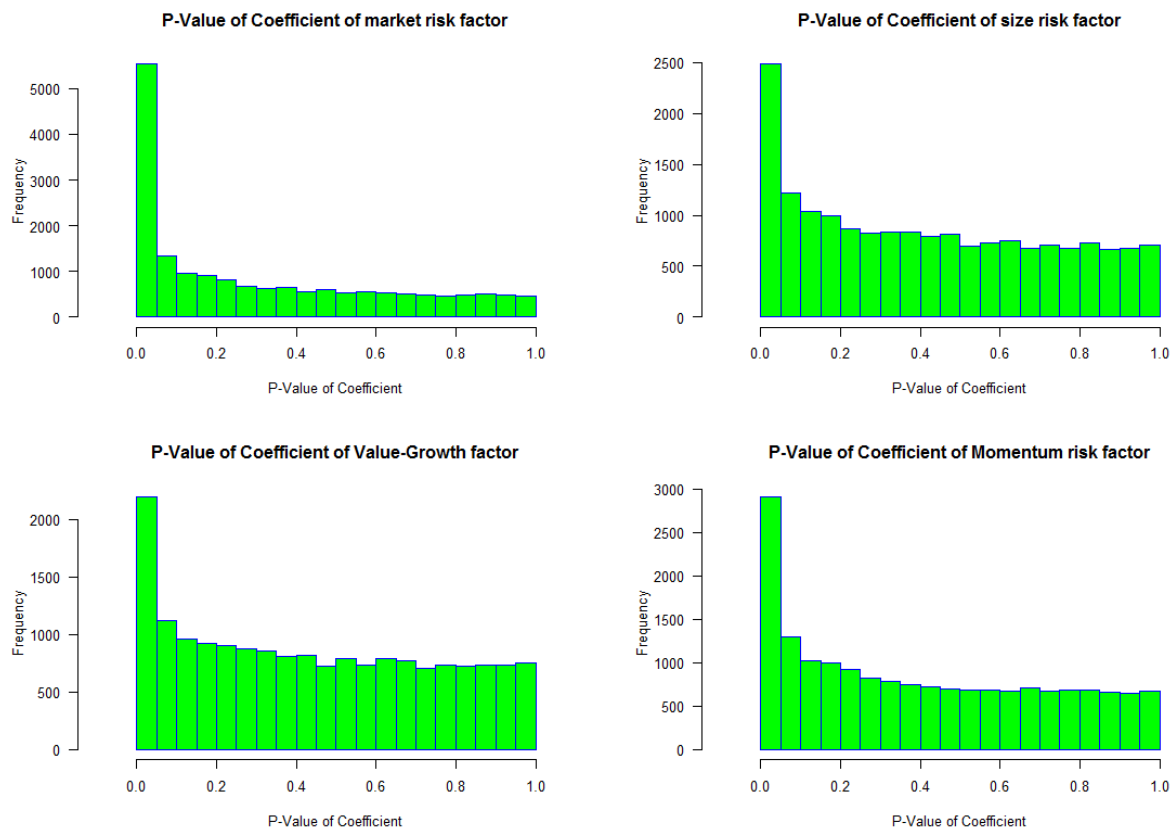
A5. Results

Figure: Histogram of P-values of co-efficients of various risk factors in equation 2.