Online Appendix to

"Inferring Mutual Fund Intra-Quarter Trading: An Application to ESG Window Dressing"

A Other Tests on ESG Window Dressing

A.1 Directional vs. Round-trip trades in ESG window dressing

As mentioned in Section 2.1.2, we classify trades into two categories: (1) directional trades, which involve either increasing or decreasing holdings during a quarter and whose quantities can be directly inferred from the quarterly changes of reported holdings, and (2) round-trip trades, which involve both buying and selling within a quarter, resulting in zero net change in shares. Both directional and round-trip trades can be used to manipulate the ESG performance. For example, ESG window dressing via directional trades could be to sell an owned high-ESG stock at the beginning of a quarter or to buy a new high-ESG stock at the end of a quarter. To examine the proportion of directional vs. round-trip trades in ESG window dressing, we rerun the regression of the trading test, i.e., Eq.(18), by decomposing the dependent variable into these two components. Because we use a sequential estimation procedure to infer trade as mentioned in Section 2, the directional and round-trip trades are obtained from the first-stage and second-stage estimation, respectively.

We report the results of the trading decomposition in Table A-1. Both directional and round-trip trades exhibit significant patterns of ESG window dressing. The estimation shows that directional trades contribute to 62% (0.746/1.211) of the total effect of ESG window dressing, while round-trip trades contribute to 38% (0.465/1.211). Recall that overall round-trip trades account for approximately 20% of total trades (Puckett and Yan, 2011). This suggests that in a relative sense, round-trip trades are more intensively used by fund managers to window-dress their ESG performance.

A.2 Evidence from stock trading volumes

In this subsection, We test the ESG window dressing hypothesis by examining whether the trading volumes of high- and low-ESG stocks are abnormally large around quarter ends. For each stock, we define the abnormal trading volume on the day t as the percentage change of day t's dollar trading volume relative to the average of dollar trading volumes in the past three days. We report the test results in Table A-2. Consistent with the hypothesis of ESG window dressing, we find a significant increase in the trading volume of high- and low-ESG stocks around quarter ends.

B Other Applications

B.1 Performance window dressing

Popular wisdom among practitioners is that institutional investors have incentives to "reshuffle" or "window dress" their portfolios in order to make their holdings look impressive in their reports. Prior studies (e.g., Agarwal, Gay, and Ling, 2014; He, Ng, and Wang, 2004; Lakonishok et al., 1991; Meier and Schaumburg, 2006; Ng and Wang, 2004) focus on quarterly or semi-annual holding data and find supporting evidence consistent with "window dressing" behavior before the end of the quarter or the year. In this section, we take advantage of our methodology and revisit "window dressing" behavior of mutual funds. Specifically, we apply our methodology to estimate mutual funds' intra-quarter trading and investigate mutual funds' trading on the winner and loser stocks around the end of the quarter, supplementing the literature on "window dressing".

We take the following steps to investigate mutual funds' "window dressing" behavior. First, at each month's end, we sort stocks based on their cumulative returns in the past 12 months (skipping the current month) and define stocks in the top (bottom) decile as the winner (loser) stocks. Second, we examine mutual funds' trading on the winner and loser stocks around the quarter end. That is, for each fund each week, we calculate the fraction of trading in the winner (loser) stocks by taking the ratio between the trading volume in these stocks and the total trading volume. We calculate this ratio for buy-trades, sell-trades, and net-trading (buy minus sell), respectively. After that, we re-run the regression of Eq.(18).

Table A-3 reports the results. The patterns are like those in ESG window dressing and are consistent with "window dressing". As we can observe, mutual funds buy winner stocks and sell loser stocks right before the quarter ends: their abnormal net buy of the winner (loser) stocks account for 0.19% (-0.64%) of total trading volume in the first week prior to the quarter ends, and the difference 0.83% is statistically significant with a t-stat of 4.42. The magnitude of abnormal trading diminishes in the prior weeks: the difference in net trading between the winner and loser stocks becomes 0.78% (t-stat = 5.05) and 0.39% (t-stat = 3.08) in the second and third week before the quarter ends. On the other hand, mutual funds reverse these trades at the beginning of the next quarter: the difference in net buy between the winner and loser ESG stocks is -0.49% (t-stat = -2.85) in the first week in the next quarter.

B.2 Portfolio pumping

In addition to "window dressing", the other common strategic behavior among institutional investors is "portfolio pumping." "portfolio pumping" refers to the excess buying of stocks that mutual funds heavily own. The purpose of "portfolio pumping" is to inflate the funds' closing net asset value and consequently exaggerate the funds' performance (see evidence from Ben-David et al., 2013; Bernhardt and Davies, 2005; Bhattacharyya and Nanda, 2013; Carhart et al., 2002; Hu et al., 2013). In this section, we take advantage of our methodology again and revisit "portfolio pumping" behavior of mutual funds. Specifically, we apply our methodology to estimate mutual funds' intra-quarter trading and investigate mutual funds' trading on stocks in which mutual funds overweight or underweight.

We take the following steps to investigate mutual funds' "portfolio pumping" behavior. First, for each fund at the beginning of each quarter, we focus on its portfolio stocks and sort the portfolio stocks based on portfolio weights within this fund. For stocks taking account for the top (bottom) 10% of the fund's portfolio, we define them to have top (bottom) positions. Second, we examine mutual funds' trading on stocks with top and bottom positions around the quarter end using the regression of Eq.(18).

Table A-4 reports the results and provides evidence consistent with "portfolio pumping". As we can observe, mutual funds buy stocks with top positions in their portfolio and sell stocks with bottom positions right before the quarter ends: their abnormal net buy of top-position (bottom-position) stocks account for 1.13% (−2.18%) of total trading volume in the first week prior to the quarter ends, and the difference 3.30% is statistically significant with a t-stat of 17.17. The magnitude of abnormal trading diminishes in the prior weeks: the difference in net trading between the top-position and the bottom-position stocks becomes 2.50% (t-stat = 16.12) and 1.54% (t-stat = 12.46) in the second and third week before the quarter ends. Again, mutual funds reverse these trades at the beginning of the next quarter.

In sum, applying our methodology, we revisit the common strategic behavior of mutual funds–"window dressing" and "portfolio pumping"–and find evidence consistent with them. This revisit is an external validity of our methodology and has demonstrated the generalization and robustness of our methodology.

B.3 Trading around M&A

As a validation of our method, we apply our trading inference method to examine how mutual funds trade the acquisition targets around M&A announcements. Based on quarterly holdings, Fich, Lantushenko, and Sialm (2024) document that mutual funds reduce their equity holdings in impending targets. We replicate their findings by increasing the frequency from a quarterly to a daily basis.

Following Fich, Lantushenko, and Sialm (2024), we obtain M&A deals from the SDC database and filter the data by requiring deal form in one of "mergers", "acquisitions", and "acquisitions of a majority interest", and deal status to be "completed" or "withdrawn". We also eliminate targets that are not publicly traded and those that have a market capitalization of less than \$25 million four quarters prior to the deal announcement. The sample period is from 2000 to 2022.

Consistent with Fich, Lantushenko, and Sialm (2024), we find that the aggregate daily holdings of mutual funds in targets show a significant decrease surrounding M&A announcements. Furthermore, our daily-level analysis indicates that during a one-quarter window, i.e., $[t-30, t+30]$, approximately 32% of the decrease in ownership occurs before M&A announcements.

References

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Table A-1: Directional vs. Round-trip trades in ESG window dressing. This table shows the decomposition of the trading of high- and low-ESG stocks around quarter ends. We classify trades into two categories: (1) directional trades, which involve either increasing or decreasing holdings during a quarter and whose quantities can be directly inferred from the quarterly changes of reported holdings, and (2) round-trip trades, which involve both buying and selling within a quarter, resulting in zero net change in shares. We report the ending-minus-beginning abnormal trading for each type of trade, which is the coefficient difference, $b^c_{E,1} - b^c_{B,1}$, of the regression $y^c_{i,t,l} = b^c_0 + \sum_{j=1}^{3} b^c_{E,j} \times \mathbb{I}_{E,j} + \sum_{j=1}^{3} b^c_{B,j} \times \mathbb{I}_{B,j} + \gamma \times buy\_ratio_{i,t,l} + \alpha_{i,t} + \epsilon^c_{i,t,l}$ for trade type $c \in \{\text{directional, round-trip}\}$. The dependent variable is directional or round-trip trading volume, for panel A or panel B respectively, divided by total trading volume for fund i in quarter t and week l. We obtain directional and round-trip trading volume from our sequential trading inference procedure. The sample period and the definition of high- and low-ESG stocks are the same as those in our main results, i.e., Table 5. t-statistics, shown in brackets, are double clustered at both the fund and year-quarter levels. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	High-ESG trading			Low-ESG trading			High - Low
	Net	Buy	Sell	Net	Buy	Sell	Net
Panel A: Directional trades							
Ending - Beginning							
End. 1st -	0.711**	0.472**	-0.239	-0.036	-0.055	-0.019	0.746**
Beg. 1st	[2.68]	[2.69]	[-1.66]	[-0.42]	[-0.92]	[-0.27]	[2.56]
Panel B: Round-trip trades							
Ending - Beginning							
End. 1st -	0.389***	0.146***	-0.244***	-0.076**	-0.076**	-0.000	0.465***
Beg. 1st	[5.07]	[3.05]	[-5.30]	[-2.42]	[-2.75]	[-0.03]	[5.10]

Table A-2: High-ESG vs. Low-ESG stock trading volume. This table reports stock-level abnormal trading volume of high- and low-ESG stocks around quarter ends. The sample period is from 2015Q1 to 2022Q2. At each quarter end, high-ESG (low-ESG) stocks are defined as the top (bottom) 200 stocks sorted by the average rank-normalized ESG scores from Sustainalytics, MSCI, and Refinitiv in the previous month. We define the abnormal trading volume on day t as the percentage change of day t's dollar trading volume relative to the average dollar trading volume in the past three days. t-statistics, shown in brackets, are computed based on standard errors with Newey-West corrections of 8 lags (quarters). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	High-ESG stocks		Low-ESG stocks	
	EW	VW	EW	VW
Ending				
1-day window	0.173***	0.164***	0.256***	0.137***
	[8.51]	[8.48]	[3.66]	[4.87]
3-day window	0.081***	0.061***	0.138***	0.071***
	[5.19]	[3.56]	[4.10]	[3.08]
5-day window	0.036	0.013	0.144***	0.057**
	[1.53]	[0.53]	[2.99]	[2.18]
Beginning				
1-day window	0.127***	0.111***	0.123***	0.149***
	[5.35]	[3.94]	[4.74]	[6.04]
3-day window	0.086***	0.062***	0.095***	0.093***
	[4.78]	[3.47]	[2.80]	[7.31]
5-day window	0.063***	0.041***	0.117***	0.079***
	[6.34]	[4.28]	[3.15]	[6.67]

Table A-3: Performance window dressing. We test performance window dressing using a similar regression of testing ESG window dressing but change the dependent variable accordingly. The sample period is from 2000Q1 to 2022Q2. For each month t, winner (loser) stocks are defined as the top 10% (bottom 10%) stocks sorted by the cumulative return from month $t-12$ to $t-2$. t-statistics, shown in brackets, are double clustered at both the fund and year-quarter levels. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Winner trading			Loser trading			Winner - Loser
	Net	Buy	Sell	Net	Buy	Sell	Net
Ending							
End. 1st week	0.192	-0.211	-0.403***	-0.635***	-0.461***	0.175***	0.827***
	[1.14]	[-1.46]	[-3.81]	[-9.99]	[-8.95]	[3.85]	[4.42]
End. 2nd week	0.354***	0.077	-0.277***	-0.423***	-0.223***	0.200***	0.777***
	[2.74]	[0.61]	[-2.79]	[-7.17]	[-4.78]	[4.47]	[5.05]
End. 3rd week	0.107	0.019	-0.089	-0.280***	-0.035	0.245***	0.387***
	[0.96]	[0.15]	[-0.91]	[-6.41]	[-0.90]	[5.94]	[3.08]
Beginning							
Beg. 1st week	-0.492***	-0.276**	0.216	0.539***	-0.013	-0.552***	-1.032***
	[-2.85]	[-2.31]	[1.41]	[8.46]	[-0.25]	[-10.98]	[-5.27]
Beg. 2nd week	-0.423***	-0.319***	0.104	0.227***	-0.080*	-0.307***	-0.650***
	[-3.05]	[-3.15]	[0.75]	[5.76]	[-1.96]	[-6.43]	[-4.20]
Beg. 3rd week	-0.307**	0.010	0.316**	0.106**	-0.001	-0.108**	-0.413***
	[-2.22]	[0.10]	[2.36]	[2.04]	[-0.04]	[-2.32]	[-2.72]
Ending - Beginning							
End. 1st -	0.684***	0.066	-0.619***	-1.175***	-0.448***	0.727***	1.859***
Beg. 1st	[2.76]	[0.30]	[-2.98]	[-12.06]	[-6.04]	[10.34]	[6.55]

Table A-4: Portfolio pumping. We test portfolio pumping using a similar regression of testing ESG window dressing but change the dependent variable accordingly. The sample period is from 2000Q1 to 2022Q2. For each fund quarter, we sort stocks by quarter-beginning holding value in descending order among those with positive values. Top-position (bottom-position) stocks are defined as the top (bottom) stocks cumulatively accounting for 10% of total holding values. *t*-statistics, shown in brackets, are double clustered at both the fund and year-quarter levels. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Top-position trading			Bottom-position trading			Top - Bottom
	Net	Buy	Sell	Net	Buy	Sell	Net
Ending							
End. 1st week	1.125***	0.819***	-0.305***	-2.175***	-1.535***	0.640***	3.300***
	[15.76]	[18.23]	[-6.47]	[-15.37]	[-20.11]	[7.16]	[17.17]
End. 2nd week	0.788***	0.567***	-0.221***	-1.713***	-1.281***	0.433***	2.502***
	[12.84]	[14.74]	[-5.44]	[-14.56]	[-19.28]	[5.50]	[16.12]
End. 3rd week	0.514***	0.307***	-0.207***	-1.022***	-0.708***	0.314***	1.536***
	[9.93]	[10.87]	[-5.83]	[-10.80]	[-12.92]	[4.56]	[12.46]
Beginning							
Beg. 1st week	-1.614***	-0.328***	1.287***	1.805***	0.541***	-1.264***	-3.419***
	[-17.92]	[-14.26]	[16.34]	[11.99]	[6.80]	[-9.75]	[-16.50]
Beg. 2nd week	-0.801***	-0.242***	0.558***	1.518***	0.896***	-0.622***	-2.318***
	[-11.00]	[-9.33]	[8.73]	[12.85]	[15.52]	[-6.32]	[-15.02]
Beg. 3rd week	-0.326***	-0.139***	0.187***	0.547***	0.720***	0.173**	-0.873***
	[-4.14]	[-5.76]	[2.70]	[5.09]	[12.73]	[2.27]	[-5.64]
Ending - Beginning							
End. 1st -	2.739***	1.147***	-1.592***	-3.980***	-2.075***	1.905***	6.719***
Beg. 1st	[22.06]	[21.37]	[-18.25]	[-15.84]	[-18.39]	[10.61]	[19.46]

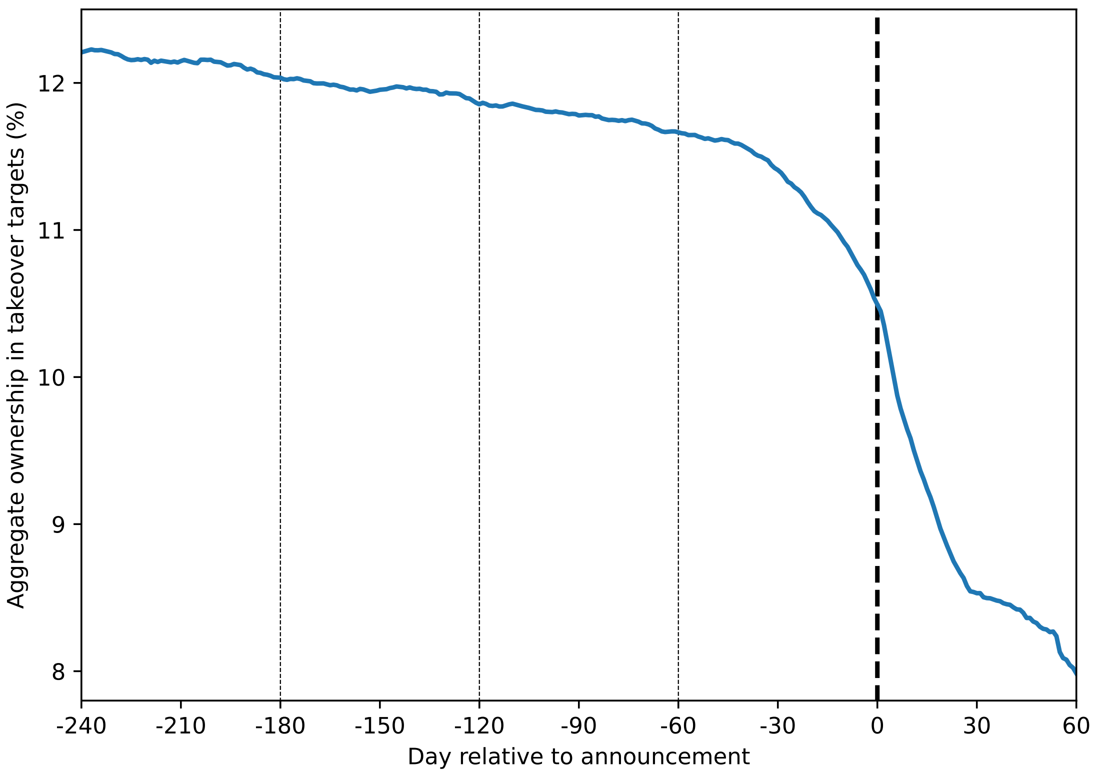

Figure A-1: Estimated daily ownership around M&A announcements. This figure illustrates the evolution of aggregate mutual fund ownership in acquisition targets around M&A announcements. Using our trading inference method, we first estimate daily holding shares for each fund on each day. Then, we obtain the aggregate mutual fund ownership by dividing the summed shares by the total shares outstanding. Finally, we plot the average ownership evolution across different M&A deals.