The Year-End Trading Activities of Institutional Investors: Evidence from Daily Trades

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At year-end, some allege that institutional investors try to mislead investors by placing trades that inflate performance (portfolio pumping) or distort reported holdings (window dressing). We contribute direct tests using daily institutional trades and find that year-end price inflation derives from a lack of institutional selling rather than institutional buying. In fact, institutional buying declines at year-end. Consistent with pumping, institutions tend to buy stocks in which they already have large positions. We find no evidence of window dressing, as institutions are not more likely to buy high-past return stocks or sell low-past return stocks at year- or quarter-end. (*JEL* G20, G23, G28, G29)

Previous studies suggest that institutional investors engage in two different types of quarter-end, and especially year-end, trades that may mislead investors. One such trade is commonly referred to as "portfolio pumping" or "tape painting." Portfolio pumping refers to quarter-end and year-end price manipulation on the part of fund managers via the excessive buying of securities that they already own. The idea is that excessive buying on the last day of

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the quarter or year inflates the fund's closing net asset value, which in turn exaggerates the fund's performance.[1]

The second type of trade is called "window dressing." Window dressing involves buying (selling) securities that have performed well (poorly) toward the end of the quarter or year, to make investors believe that these were the firm's holdings throughout the quarter or year. Window dressing therefore undermines the mandated SEC disclosure of portfolio holdings. In their investments textbook, Bodie, Kane, and Marcus (2010) note that, "… if window dressing is quantitatively significant, even reported quarterly composition data can be misleading."[2]

Despite the fact that both portfolio pumping and window dressing consist of managers making misleading trades, the previous literature has not focused on trade data. Rather, it presents indirect evidence from holdings data, mutual fund return data, and stock return data. To our knowledge, the only study that uses trade data is Sias and Starks (1997), who use data from 1990 to study window dressing. Carhart et al. (2002) (CKMR hereafter) recognize the value of trade data when they state, "We would like more direct evidence, like audit trails, showing the actual trades these mutual funds' managers ordered."

We begin our analyses by studying portfolio pumping. Although previous research has inferred that institutions cause year-end price inflation, no study has shown a direct link using institutional trades. We find that both abnormally high institutional buying and abnormally low institutional selling are associated with price inflation. We further show that the portion of buy trades increases sharply on quarter-end, and especially year-end, days. Further analyses reveal that institutional buying declines at year-end, whereas institutional selling has an even larger decline at year-end, thereby creating the high portion of buys.

Our findings support the idea that institutional trading is the source of market-wide, year-end price inflation. CKMR (2002) report that the prices of nine different Lipper equity mutual fund indexes are inflated at year-end. Each Lipper index tracks the returns of thirty different mutual funds, so the nine indexes reflect the prices of a large number of stocks. If mutual funds are causing such widespread price inflation, then it must be that a large number of funds are pumping the prices of a large number of stocks. Our findings suggest that this is the case, as a larger decline in selling relative to buying is observed at year-end among the institutions in our sample.

In contrast to the previous literature, which hypothesizes that year-end price inflation is caused by a surge in institutional buying, we show that buys decline and sells decline even more. Hence, a good deal of the year-end price inflation

[1] Evidence of portfolio pumping is provided in Carhart et al. (2002), who show that both fund net asset values (NAVs) and the share prices of stocks that are widely held by funds are inflated on quarter-end, and especially on year-end, days. In a more recent study, Ben-David et al. (2013) find similar inflation in stocks that are widely held by hedge funds.

[2] Another end-of-the-year agency conflict occurs when mutual fund managers alter the risk profile of the fund (for example, Brown, Van Harlow, and Starks 1996).

documented in previous studies (e.g., CKMR 2002; Ben-David et al. 2013) could be due to depressed selling, rather than excessive buying. Although this is still consistent with pumping, the idea that year-end prices are inflated as a result of depressed institutional selling has not been mentioned in the literature previously.

Although buying is lower at year-end, it still could be the case that year-end buys are more focused on stocks in which institutions have large existing positions. We consider this possibility by testing whether year-end buying is more likely to occur in stocks that have relatively large weights in the institution's portfolio.[3] In value-weighted specifications that we think are more closely linked to institution-induced price pressure, we find that, conditional on buying at year-end, institutions tend to buy stocks in which they already have large positions. This finding is consistent with intentional pumping. We do not find evidence of targeted trading with year-end sales; the decline in selling is not greater for stocks of which institutions hold large positions. However, unlike buying a stock, delaying the sale of a stock is in most cases costless. It therefore makes sense for managers to not sell any stock at year-end if they are concerned about year-end net asset values.

We conclude our study by examining window dressing. Window dressing should be associated with an increase in the selling of poorly performing stocks during December and an increase in the buying of the best-performing stocks during December. The existing empirical evidence of window dressing is circumstantial at best. The prior window dressing evidence is that mutual funds are more likely to sell poorly performing stocks during the last quarter of the year as compared with the first three quarters.[4,5] Our trade data provide an opportunity to take a closer look at December trades that are possibly motivated by window dressing. Our examination is important, because it has implications for both regulators and investors. Window dressing implies that quarterly holdings data, which are used by both academics and investors, are not reliable and more frequent reporting might be necessary.

3 The incentives for tape painting are described in CKMR (2002), Bernhardt and Davies (2005, 2009), and Bhattacharyya and Nanda (2008). These studies build on papers by Spitz (1970), Smith (1978), Patel, Zeckhauser, and Hendricks (1991), Kane, Santini, and Aber (1991), and Lakonishok, Shleifer, and Vishny (1992), all of whom find evidence of a positive relation between investment performance and subsequent investment flows, suggesting that managers have an incentive to exaggerate their performances. More recent studies have shown that this performance-flow relation is nonlinear, in that the best performing funds receive especially high flows, whereas poor performing funds do not receive low flows. These studies include Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Goetzmann and Peles (1997), and Sirri and Tufano (1998).

4 One exception is Sias and Starks (1997), who find some evidence of window dressing with trade data from December 1990.

5 Papers that study window dressing and its effect on security prices include Haugen and Lakonishok (1988), Lakonishok et al. (1991), Chevalier and Ellison (1997), Musto (1997, 1999), He, Ng, and Wang (2004), Ng and Wang (2004), Meier and Schaumburg (2006), Morey and O'Neal (2006), and Sias (2007). Somewhat in contrast to window dressing, Kacperczyk, Sialm, and Zheng (2008) and Puckett and Yan (2011) provide evidence that within-quarter trades are typically informative and positively related to fund performance.

We do not find evidence of window dressing; institutions do not appear to be more likely to buy winners or sell losers in December. One might also expect that in December institutions are more likely to buy winners for which they do not have large existing positions and sell losers for which they already have large existing positions. In the Appendix, we report tests for these effects but still find no evidence of this window dressing. Hence, the average institution in our sample does not engage in window dressing. It could be the case that some institutions window dress, but it is not a widespread phenomenon. The rest of the paper is organized as follows. Section 1 describes our sample and provides summary statistics. Section 2 describes our portfolio pumping results. Section 3 describes our window dressing results, and Section 4 concludes the paper.

1. Data and Summary Statistics

Our sample consists of transaction-level institutional trading data from Abel Noser Solutions, a leading execution quality measurement service provider for institutional investors. The transaction data are transferred directly from the institutions' trading systems to Abel Noser Solutions.[6] The data cover equity trading transactions made by a large sample of institutions from January 1999 through December 2010. For each transaction, the data include the date of the transaction, the stock traded (identified by both symbols and CUSIPs), the number of shares traded, the dollar principal traded, commissions paid by the institution, and whether the trade is a buy or a sell. As mentioned above and shown in Table 1, the institutions in our sample are large and important, representing a significant percentage of the total trading volume in the U.S. stock market.

The names of the institutions are removed from the data. However, identification codes are provided, enabling us to identify each institution separately, so we can track an institution's trades across stocks and over time. We do not have a reliable fund-level identifier, so we cannot track the trades of individual funds within an institution.

The institutions in the Abel Noser Solutions sample are classified as either plan sponsors or investment managers. Examples of plan sponsors include the California Public Employees' Retirement System (CalPERS), the Commonwealth of Virginia, and United Airlines. Examples of investment managers are mutual fund families, such as Fidelity Investments, Putnam Investments, and Lazard Asset Management. In some cases, investment managers could be trading on behalf of plan sponsors, and we cannot separately

6 Over time, the name of the data provider has changed. Earlier it was referred to as "ANcerno" or "Ancerno." The data source is the same as that used by Goldstein et al. (2009), Hu (2009), and Anand et al. (2012) and is similar in nature to those used by several earlier studies on institutional trading costs, such as Keim and Madhavan (1995), Conrad, Johnson, and Wahal (2001), and Jones and Lipson (2001).

Table 1
Summary statistics

		Percent of total market trading volume					
Year	# of institutions	All stocks	Small stocks	Q2	Q3	Q4	Large stocks
1999	37	6.41	2.77	3.84	4.87	5.89	6.22
2000	43	6.15	2.50	4.37	5.18	6.02	5.79
2001	64	7.11	4.85	6.04	6.46	6.60	6.61
2002	81	8.20	6.85	8.25	7.67	7.69	7.41
2003	86	7.95	5.48	7.38	6.96	7.56	7.33
2004	117	8.15	6.62	8.22	7.51	7.63	7.11
2005	134	8.15	7.17	8.35	8.23	8.21	6.88
2006	158	8.51	8.11	8.64	8.09	7.72	7.07
2007	158	6.46	7.43	7.39	6.84	6.13	4.93
2008	152	5.64	7.46	6.84	5.96	5.39	4.53
2009	146	5.51	6.67	7.37	6.30	5.35	4.39
2010	141	4.68	5.42	6.58	5.25	4.32	3.50

This table reports summary statistics for the institutions in our sample and the magnitude of their trading activities. The second column reports the number of institutions in each year of the sample. Columns 3 through 8 report the aggregate dollar value of institutional trading as a percentage of the dollar trading volume in CRSP. The third column shows the trading percentage for all stocks traded in our sample, whereas Columns 4 through 8 report statistics within each of the five NYSE-size quintiles.

identify these trades, so it is likely that such trades are included in the investment manager data.

We believe that the incentive to distort performance might be greater for investment managers, so we only report results for these institutions and not for plan sponsors (although as we mention above, it is likely that the investment manager data contain some trades that are made on the behalf of plan sponsors). Although a pension plan's choice of manager may be affected by past performance, pension plan contributions from individuals are not dependent on performance, so although a pension fund manager may want good performance because of internal pressures, the typical pension fund manager faces lower external pressure relative to a mutual fund manager. Moreover, some plan sponsors base their portfolios on the recommendations of external advisors. For these reasons, we focus on the sample of the investment managers. In the Appendix, we report results for plan sponsors, and these results produce similar inferences to the results in the paper.

2. Portfolio Pumping Results

2.1 Does institutional trading inflate quarter-end share prices?

Because the previous literature on portfolio pumping has not used trade data, it has not been able to show a direct link between institutional trades and price inflation. Our first question is whether abnormal levels of institutional trading affect stock prices.

We create a monthly abnormal buy (sell) measure for each stock on the last day of each month. Our abnormal buy (sell) measure is the dollar volume of institutional buying (selling) on the last day of each month, minus the average daily dollar volume of institutional buying (selling) over the last five days of the month, all divided by the average daily dollar volume of institutional buying (selling) over the last five days of the month:

$$Abnormal\ Buying_{st} = (Buys_{st} - Average(Buys_{st\ to\ st\text{-}4}))/Average(Buys_{st\ to\ st\text{-}4})$$

$$Abnormal\ Selling_{st} = (Sells_{st} - Average(Sells_{st\ to\ st\text{-}4}))/Average(Sells_{st\ to\ st\text{-}4}).$$

These measures reflect the percentage deviation in the last day's institutional dollar volume relative to the average institutional dollar volume during the last five days. The measures control for seasonal effects that might affect institutional trading activity. In unreported tests, we create these measures using average institutional daily dollar volume during the last twenty trading days, and we do the same with average institutional daily dollar volume during the calendar month, and in both cases, we obtain similar findings.

We construct an abnormal turnover measure as a control variable. This measure is constructed like the abnormal buying and selling measures, only it is based on total turnover (from CRSP). This measure reflects the magnitude of the last day's total turnover (shares traded / shares outstanding) as compared with the average total turnover during the last five days of the month. We include this measure as a control variable because it could be that trading volume in general inflates prices, whereas we want to isolate the effects of trades made by the institutions in our sample.

We follow CKMR (2002) and define price inflation (PI) as the return on the last day of the month, minus the return on the first day of the subsequent month. To estimate the relation between price inflation and abnormal trading, we regress PI on the abnormal trading measures. Using Fama-Macbeth (1973) cross-sectional regressions, we estimate the relation between price inflation and institutional trading activity.

Table 2 reports our price inflation results. In the full sample regression, the abnormal buying coefficient is 0.162 (t-statistic = 8.79). The abnormal buying variable has a standard deviation of 1.50, so a one-standard-deviation increase in abnormal buying leads to price inflation of 24.3 basis points. The average daily return in our sample is only 2 basis points, so 24 basis points is an economically significant effect. In the full sample regression the abnormal selling coefficient is -0.091 (t-statistic $= -4.79$). Abnormal selling has a standard deviation of 1.566. Hence, a one-standard-deviation decline in abnormal selling leads to an increase of 14.3 basis points in price inflation. The abnormal buying coefficient is both positive and significant in 4 out of the 5 size quintiles, but not in the smallest size quintile.

2.2 Does the proportion of buys increase at quarter-end?

CKMR (2002) provide evidence that fund NAVs and the prices of some stocks that are widely held by funds are inflated on quarter-end days. These findings suggest that there could be an imbalance between institutional buying and selling on quarter-end days. To investigate this, we create a measure called the

Table 2
Institutional trading and price inflation

Abnormal buying, abnormal selling, and price inflation

	All	Small	2	3	4	Large
Intercept	−0.039	0.187	0.003	−0.010	0.015	−0.096
	(0.841)	(0.487)	(0.991)	(0.964)	(0.939)	(0.557)
ABUY	0.162	0.018	0.099	0.203	0.193	0.217
	(0.000)	(0.811)	(0.004)	(0.000)	(0.000)	(0.000)
ASELL	−0.091	0.038	−0.135	−0.089	−0.158	−0.173
	(0.000)	(0.678)	(0.026)	(0.001)	(0.000)	(0.000)
ATURNOVER	0.314	−0.127	0.805	0.325	0.554	0.012
	(0.008)	(0.618)	(0.003)	(0.033)	(0.001)	(0.936)
Avg. R^2	0.038	0.104	0.049	0.039	0.045	0.041
N	143	143	143	143	143	143

This table reports average slope coefficients from Fama-Macbeth (1973) cross-sectional regressions that estimate the relation between price inflation and abnormal trading. For each stock, price inflation (PI) is defined as the difference between the return on the end of the each month and the return on the first day of the subsequent month. Abnormal buying (Selling) (ABUY or ASELL) is defined for each stock as the dollar value of buys (sells) on day t minus the average dollar value of buys (sells) over days t to $t-4$, all scaled by the average dollar value of buys (sells) over days t to $t-4$. Abnormal turnover (ATURNOVER) is defined for each stock on each day as the dollar value of turnover on day t minus the average dollar value of turnover over days t to $t-4$, all scaled by the average dollar value of turnover over days t to $t-4$. The sample spans 1999 through 2010 and contains the trades of at least 37, and at most 158, different institutions in each year. The sample consists of 143 daily observations measured at each month-end. We report results for all stocks in the sample (All) and also separately for stocks in the five size quintiles (Small – Large). p-values are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

buy proportion. *Buy proportion* is the dollar volume of buy transactions on a day, divided by the dollar volume of total trades (buys + sells) on the same day. We create a daily buy proportion for each institution and then generate a single daily average across the institutions in our sample.

$$\begin{aligned} \textit{Institution i's Buy Proportion on Day t} &= \textit{Buy Proportion}_{it} \\ &= \textit{Buys}_{it}/(\textit{Buys}_{it}+\textit{Sells}_{it}) \end{aligned}$$

$$\textit{Day t's Buy Proportion} = \textit{Buy Proportion}_t = \frac{1}{I}\sum_{i=1}^{I}\textit{Buy Proportion}_{it}$$

We generate this daily buy proportion using equal weights, as shown above, and value weights, which weight each institution's *buy proportion* by the institution's dollar volume on the measurement day, scaled by the sample's aggregate dollar volume on the measurement day. Equal weighting provides a better description of how the typical institution in our sample is trading. Yet Table 2 shows that price inflation is associated with the total dollar volume of trading; thus, value weighting yields results that are more indicative of whether institutions are inflating prices. Because portfolio pumping is meant to inflate prices, we report the value-weighted results in Table 3 and the equal-weighted results in the Appendix. Both methods generate similar results.

Institutional investors may use excess cash or recent inflows to buy stocks that they already own, hoping to inflate prices and therefore portfolio value. This type of trading should lead to an increase in the buy proportion. Not selling

Table 3
Time-series regression: Daily buy proportions

	Full Sample		Small		2		3		4		Large	
Variable	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	0.383	0.000	0.161	0.000	0.226	0.000	0.267	0.000	0.253	0.000	0.329	0.000
R1	0.698	0.000	0.272	0.006	0.611	0.000	0.812	0.000	0.837	0.000	0.668	0.000
R2	−0.015	0.768	0.374	0.000	0.289	0.001	0.221	0.009	0.057	0.435	−0.119	0.045
R3	−0.078	0.114	0.288	0.004	0.053	0.563	0.160	0.058	−0.023	0.759	−0.145	0.015
R4	−0.123	0.013	0.213	0.034	0.185	0.042	0.061	0.470	0.019	0.798	−0.224	0.000
R5	−0.012	0.811	0.144	0.147	0.133	0.140	0.139	0.098	0.039	0.595	−0.064	0.279
V1	−0.476	0.720	−2.381	0.366	−2.720	0.248	1.031	0.636	0.394	0.837	−0.784	0.633
V2	−1.721	0.190	−2.126	0.412	−0.404	0.862	−2.913	0.176	−1.574	0.407	−0.738	0.649
V3	−0.862	0.523	−5.682	0.034	−2.879	0.229	−4.356	0.050	−1.696	0.385	0.687	0.681
V4	0.359	0.783	−5.465	0.034	−2.865	0.213	−2.444	0.252	1.126	0.550	0.465	0.773
V5	2.084	0.113	−2.954	0.257	−3.269	0.160	1.015	0.638	2.210	0.244	3.239	0.047
MON	−0.006	0.007	−0.001	0.873	−0.001	0.805	−0.001	0.765	−0.007	0.028	−0.006	0.013
TUE	−0.001	0.600	0.004	0.351	0.007	0.044	−0.001	0.872	−0.002	0.594	−0.001	0.828
THUR	0.001	0.566	0.000	0.915	0.007	0.039	0.003	0.358	0.001	0.710	0.001	0.686
FRI	0.001	0.514	0.008	0.037	0.006	0.064	0.003	0.384	0.000	0.869	0.002	0.549
L-RATIO1	0.132	0.000	0.283	0.000	0.261	0.000	0.281	0.000	0.252	0.000	0.150	0.000
L-RATIO2	0.046	0.013	0.086	0.000	0.128	0.000	0.057	0.005	0.070	0.000	0.078	0.000
L-RATIO3	0.039	0.038	0.185	0.000	0.071	0.001	0.075	0.000	0.065	0.001	0.056	0.003
L-RATIO4	0.033	0.078	0.072	0.000	0.041	0.042	0.028	0.168	0.070	0.000	0.057	0.002
L-RATIO5	−0.016	0.381	0.063	0.001	0.065	0.001	0.046	0.016	0.044	0.020	−0.005	0.789
NEWM5	0.004	0.009	−0.002	0.479	−0.001	0.743	0.002	0.522	0.001	0.680	0.005	0.014
MEND	0.007	0.054	−0.010	0.163	0.007	0.249	0.011	0.068	0.001	0.857	0.007	0.103
NEWQ5	0.002	0.553	−0.003	0.570	−0.002	0.624	−0.003	0.477	0.000	0.951	0.004	0.154
QEND	**0.027**	**0.000**	**0.037**	**0.001**	**0.052**	**0.000**	**0.022**	**0.022**	**0.020**	**0.019**	**0.032**	**0.000**
NEWY5	−0.005	0.265	−0.006	0.527	−0.003	0.725	−0.007	0.407	−0.005	0.456	−0.007	0.207
YEND	**0.060**	**0.000**	**0.052**	**0.010**	**0.043**	**0.016**	**0.064**	**0.000**	**0.057**	**0.000**	**0.056**	**0.000**
R^2	0.119		0.290		0.181		0.143		0.155		0.120	
T	2,973		2,973		2,973		2,973		2,973		2,973	

This table reports the results from time-series regression. The dependent variable is the buy proportion ratio; it is the total value of institutional buys scaled by the total value of the institutional trades. Institutional buy proportions are averaged using value-weights to come up with a single buy proportion for each day. To create the value-weights, we scale each institution's dollar volume on the measurement day by the sample's aggregate dollar volume on the same day. Dummy variables that signal the last day of a non-year-end quarter (QEND) and the last day of the year (YEND) are used to test whether the buy proportion is abnormally high on these days. QEND and YEND are never both equal to one. The control variables include the CRSP value-weighted market return for each of the five previous days (R1, R2, R3, R4, and R5), the volatility of this return, which is measured as the return squared, for each of the five previous days (V1, V2, V3, V4, and V5), dummy variables indicating the day of the week (MON, TUE, THUR, FRI), the previous five days' buy proportion ratios (L-RATIO1, L-RATIO2, L-RATIO3, L-RATIO4, L-RATIO5), dummy variables for the first five days of the month (NEWM5), the first five days of the quarter (NEWQ5), the first five days of the year (NEWY5), and finally the last day of the month that is non-quarter-end (MEND). The sample spans 1999 through 2010 and contains the trades of at least 37, and at most 158, different institutions in each year. We report results for all stocks in the sample (Full sample) and also separately for stocks in the five size quintiles (Small – Large). Statistics associated with QEND and YEND are in bold.

stocks on a particular day, while holding buying constant, would also inflate that day's buy proportion. Alternatively, institutions could sell large stocks, which are unlikely to suffer price impacts, and take the proceeds to buy smaller stocks that are easier to pump. This type of trading could also cause price inflation but would not result in higher buy proportion. A change in the buy proportion on year-end days would therefore suggest that managers are at least engaging in the first two types of pumping that we describe above. If the buy proportion does not change on the last day of the year, then it would suggest that managers are not engaged in the first two types of pumping but could still be engaged in the third type. We conduct our analyses using the following regression equation:

$$\text{Buy Proportion}_t = \alpha + \beta_1 QEND_t + \beta_2 YEND_t + \sum B_i X_{it} + \varepsilon_t. \tag{1}$$

In Equation (1) dummy variables that signal the last day of a non-year-end quarter (QEND) and the last day of the year (YEND) are used to test whether the buy proportion is abnormally high on these days. The control variables (X) include the CRSP value-weighted market return for each of the five previous days (R1, R2, R3, R4, and R5), the volatility of the CRSP value-weighted market return, which is measured as the return squared, for each of the five previous days (V1, V2, V3, V4, and V5), dummy variables indicating the day of the week (MON, TUE, THUR, and FRI), the previous five days' buy proportions (L-RATIO1, L-RATIO2, L-RATIO3, L-RATIO4, and L-RATIO5), dummy variables for the first five days of a month (NEWM5), the last day of the month (MEND), the first five days of the quarter (NEWQ5), and the first five days of the year (NEWY5). Like the YEND and QEND variables, these dummy variables are never both assigned to one for the same time period. Thus, for example, month ends that are also quarter ends have MEND values equal to zero, and the first five days for the year are assigned a NEWY5 value of one but a NEWM5 and NEWQ5 value of zero. We estimate the above regression equation both in our full sample and within size quintiles. We report these results in Table 3.

Before discussing the Table 3 results, we describe the patterns in Figure 1, which illustrate the Table 3 results. Panel A of Figure 1 displays average buy proportions at each month-end for the entire 1998–2010 period. Buy proportions are abnormally high at quarter-end, and especially at year-end. This effect can be seen in both small and large stocks. Panel B displays monthly average buy proportions that are calculated excluding the last day of the month for the entire 1998–2010 sample period. The lines are essentially flat, showing that the buy proportion does not spike in quarter-ending and year-ending months, except on the last day of these months.

Like Figure 1, the Table 3 results show that buy proportions are significantly higher on both quarter-end and year-end days. Using the full sample of stocks, buy proportions are higher by 0.027 at quarter-end and 0.060 at year-end. These results are statistically significant, not only using the full sample but for each and every size quintile. The month-end estimate is also positive for the

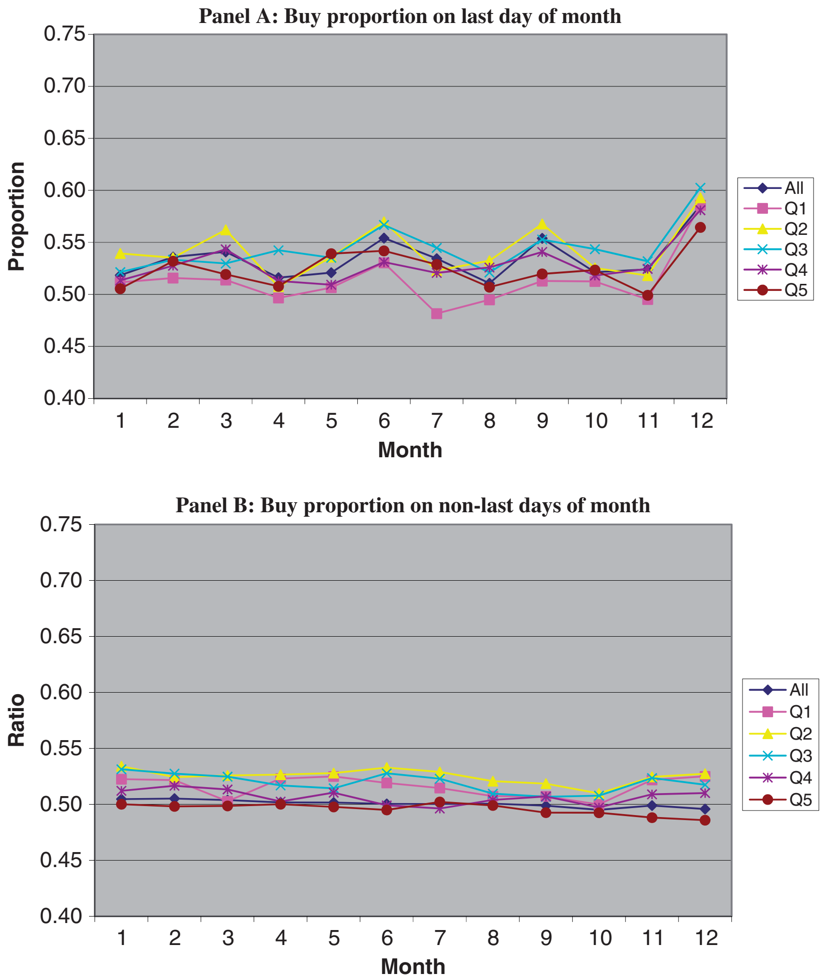

Figure 1
Buy proportion on last day and non-last days of month
The figure depicts the average "buy proportion" on the last day of each month (Panel A) and on nonlast days of each month (Panel B). To measure the buy proportion, we aggregate the value of buy (sell) transactions based on dollar value on the last day of each month. For each institution, we compute the buy proportion using the value of buys relative to the sum of buys and sells. We compute value-weighted buy proportion ratios across all institutions for each month. To create the value weights, we scale each institution's dollar volume on the measurement day by the sample's aggregate dollar volume on the same day. We calculate the buy proportion ratios for all stocks in the sample (ALL) and also separately for stocks in the five size quintiles (Q1 (small) – Q5 (large)). The sample spans 1999 through 2010 and contains the trades of at least 37, and at most 158, different institutions in each year.

full sample, 0.007, and for 4 of 5 quintiles, although these results tend to be insignificant or marginally significant. Taken together, Figure 1 and Table 3 show that there is an imbalance in institutional trading on the last day of the quarter, and especially on the last day of the year.

There is the possibility that the CKMR's (2002) study drew the attention of regulators, which in turn could have caused pumping to decline after the paper was circulated in 2001 (as is argued by Duong and Meschke 2011). Estimation for the separate subperiods is included in the Appendix (Table A4). Consistent with Duong and Meschke (2011), year-end buy proportions are lower in the second subsample, although evidence of pumping remains—in the second subsample, we can still reject the null of no increase in year-end buy proportions. The quarter-end results tell a different story. In the early subsample, the quarter-end coefficients reject the null using equal-weight estimation, but not using value-weight estimation, whereas in the latter subsample both estimates of quarter-end buying reject the null. The evidence of increased relative buying at year- and quarter-end in the post-2001 part of our sample is consistent with Ben-David et al. (2013), who find evidence that is consistent with pumping by hedge funds during the period 2000 to 2010, although as we explain above the institutions in our sample do not include hedge funds.

2.3 Abnormal institutional buying and abnormal institutional selling at quarter-end

Table 3 shows that the institutions in our sample have high buy proportions on quarter-end, and especially year-end, days. Such trading imbalances could be caused by excessive buying, depressed selling, or both. In this section, we determine which of these explanations is correct. We do so by studying the year-end and quarter-end levels of abnormal buying and abnormal selling separately.

We create measures of abnormal buying and selling at the institution level (in Table 2 the measures are constructed at the stock level). For each institution i on day t, abnormal trading is measured as the dollar volume of the institution's trading on the last day of each month, minus the average daily dollar volume of institution's trading over the last five days of the month, all divided by the average daily dollar volume of institution's trading over the last five days of the month.

$$Abnormal\ Buying_{it} = (Buys_{it} - Average(Buys_{it\ to\ it\text{-}4}))/Average(Buys_{it\ to\ it\text{-}4})$$

$$Abnormal\ Selling_{it} = (Sells_{it} - Average(Sells_{it\ to\ it\text{-}4}))/Average(Sells_{it\ to\ it\text{-}4})$$

We also create these measures using average daily dollar volume during the last twenty trading days, and we do the same using average daily dollar volume during the calendar month, and in both cases, we obtain similar findings, which are reported in the Appendix. As with the buy proportion, we construct our abnormal trading measures for each institution and then generate a daily average for our entire sample. We compute the abnormal trading ratios using both equal-weighted and value-weighted averages. Again, we report value-weighted results because they are more closely associated with price pressure. The equal-weighted and value-weighted results are similar, so we report the equal-weighted results in the Appendix.

We re-estimate Equation (1) but replace the buy proportion with the abnormal buying and abnormal selling measures, as well as the difference between these measures. If institutions engage in excessive buying at year-end and quarter-end, then the YEND and QEND coefficients should both be positive when abnormal buying is the dependent variable. If institutions engage in depressed selling at year-end and quarter-end, then the YEND and QEND coefficients should both be negative when abnormal selling is the dependent variable.

The abnormal buy proportion regression column in Table 4 shows that the QEND coefficient is insignificant. The YEND coefficient is negative and insignificant. Hence, there is not a surge in institutional buying during the last day of the quarter or year. With respect to selling, the second column shows an insignificant decline in abnormal selling at quarter-end, whereas the YEND coefficient is -0.140 (p-value = 0.001), reflecting a significant decline in institutional selling at year-end.

The final regression in Table 4 examines the difference between buying and abnormal selling. Although the independent variable in this regression is the difference between independent variable in the first two regressions, some of the right-hand side variables, such as the year-end dummy, are not differences, whereas other right-hand side variables are differences (e.g., lagged values of the dependent variable). Because of this, the slope coefficients in this regression are not necessarily equal to the difference between the slopes in the first two regressions. This point carries over to other regressions with dependent variable that are differences in Tables 5 and 6.

In the third regression, both the QEND and YEND coefficients are positive and significant, reflecting an increase in institutional buying relative to selling at quarter-end and especially at year-end. These results are similar to the buy proportion results in the previous section.

To summarize, the results in Table 4 show that on average institutional buying does not change by much at quarter-end or year-end. However, abnormal selling declines by a large amount at year-end, and we find some evidence of a decline in selling at quarter-end. As previously mentioned, there is the possibility that the publication of CKMR (2002) drew the attention of regulators, in turn causing a decline in pumping. In the Appendix (Table A5), we report separate results for the 1999–2001 and 2002–2010 subperiods. Both subsamples produce similar differences in the magnitudes of buys minus sell orders at quarter- and year-end. Both subsamples reject the null of no year-end difference in buys minus sells. The second subperiod rejects the null of no quarter-end difference in buys minus sells, although, because of higher standard errors from the smaller sample size, the first period fails to reject the null.

The finding of flat-to-lower institutional trading on the last day of the year is consistent with general market conditions. Using volume data from CRSP from 1970 to 2012, we find that volume is 3.4% lower on the last day of the year relative to the five days before. Recently, this year-end drop is more

Table 4
Time-series regression: Abnormal buying and selling

Value-weighted regressions

	Abnormal buy ratio		Abnormal sell ratio		Buy minus sell	
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.027	0.000	0.027	0.000	−0.003	0.569
R1	0.849	0.000	−1.828	0.000	2.167	0.000
R2	−0.740	0.000	−0.101	0.625	−0.156	0.304
R3	−0.481	0.017	−0.259	0.211	−0.375	0.013
R4	−0.312	0.121	0.085	0.680	−0.476	0.002
R5	−0.014	0.946	−0.160	0.434	−0.050	0.742
V1	3.138	0.571	6.107	0.273	0.423	0.917
V2	−10.715	0.049	−6.791	0.212	−3.584	0.366
V3	−6.007	0.287	−5.461	0.333	−2.557	0.539
V4	−0.963	0.858	−2.589	0.632	1.894	0.630
V5	2.010	0.714	−5.062	0.358	5.727	0.153
MON	−0.101	0.000	−0.076	0.000	−0.019	0.007
TUE	0.020	0.025	0.021	0.018	−0.005	0.490
THUR	−0.006	0.513	−0.012	0.197	0.007	0.284
FRI	−0.083	0.000	−0.088	0.000	0.007	0.310
L-RATIO1	0.215	0.000	0.231	0.000	−0.046	0.014
L-RATIO2	−0.088	0.000	−0.110	0.000	−0.114	0.000
L-RATIO3	−0.090	0.000	−0.079	0.000	−0.141	0.000
L-RATIO4	−0.160	0.000	−0.180	0.000	−0.228	0.000
L-RATIO5	0.009	0.606	0.036	0.041	−0.093	0.000
NEWM5	0.003	0.697	−0.002	0.850	0.008	0.159
MEND	0.087	0.000	0.086	0.000	0.007	0.526
NEWQ5	−0.009	0.427	−0.003	0.820	0.001	0.854
QEND	**0.023**	**0.638**	**−0.074**	**0.296**	**0.096**	**0.000**
NEWY5	0.254	0.000	0.286	0.000	−0.009	0.486
YEND	**−0.016**	**0.711**	**−0.140**	**0.001**	**0.145**	**0.000**
R^2	0.273		0.280		0.211	
T	2,968		2,968		2,968	

This table reports the results from time-series regressions. Abnormal buying (Selling) is defined for each institution on each day as the dollar value of buys (sells) on day t minus the average dollar value of buys (sells) over days t to $t-4$, all scaled by the average dollar value of buys (sells) over days t to $t-4$. We then take a value-weighted average of this measure across the institutions in our sample to estimate a daily measure. To create the value weights, we scale each institution's dollar volume on the measurement day by the sample's aggregate dollar volume on the same day. Dummy variables that signal the last day of a non-year-end quarter (QEND) and the last day of the year (YEND) are used to test whether the buy proportion is abnormally high on these days. QEND and YEND are never both equal to one. The control variables include the CRSP value-weighted market return for each of the five previous days (R1, R2, R3, R4, and R5), the volatility of this return, which is measured as the return squared, for each of the five previous days (V1, V2, V3, V4, and V5), dummy variables indicating the day of the week (MON, TUE, THUR, FRI), the previous five days' ratios (L-RATIO1 to L-RATIO5), dummy variables for the first five days of the month (NEWM5), the first five days of the quarter (NEWQ5), the first five days of the year (NEWY5), and finally the last day of the month that is non-quarter-end (MEND). For the buy-minus-sell specification, the L-RATIO is the difference between the L-RATIOs in the buy and sell specification. The sample spans 1999 through 2010 and contains the trades of at least 37, and at most 158, different institutions in each year. Statistics associated with QEND and YEND are in bold.

pronounced. Using data from 2000 to 2012, volume on the last day of the year is 21% lower than the 5 days before.

An additional question is whether the relative buying deficit that we observe is related to fund flows. Perhaps our results are associated with less monies flowing to funds at year-end and portfolio managers responding by buying fewer shares and selling even fewer shares. In tests reported in the Appendix, we examine this possibility with daily fund flow data from EPFR Global and

Table 5
Abnormal trading and portfolio weights

	High-weight buy		Low-weight buy		High-weight buy – Low-weight buy		High-weight sell		Low-weight sell		High-weight sell – Low-weight sell		(High-wt buy–Low-wt buy) – (High-wt sell–Low-wt sell)	
Variable	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	0.040	0.000	0.083	0.000	−0.021	0.000	0.080	0.000	0.119	0.000	−0.008	0.022	0.000	0.936
R1	−0.143	0.004	0.105	0.033	−0.249	0.010	−0.147	0.004	0.126	0.012	−0.274	0.006	−0.022	0.870
R2	−0.067	0.180	0.043	0.392	−0.109	0.269	0.008	0.877	0.014	0.780	−0.008	0.941	−0.211	0.114
R3	−0.044	0.384	0.022	0.663	−0.065	0.508	−0.026	0.614	0.003	0.947	−0.031	0.761	−0.116	0.389
R4	0.010	0.838	−0.009	0.864	0.018	0.859	0.041	0.433	−0.031	0.545	0.070	0.493	−0.127	0.343
R5	−0.037	0.458	0.044	0.380	−0.081	0.408	−0.046	0.367	0.038	0.454	−0.086	0.395	−0.059	0.659
V1	−1.081	0.415	1.361	0.306	−2.420	0.355	1.780	0.193	−2.027	0.135	3.801	0.157	−7.702	0.031
V2	1.472	0.257	−1.370	0.294	2.898	0.258	0.915	0.495	−1.129	0.397	2.036	0.441	−0.596	0.866
V3	−0.010	0.994	−0.345	0.797	0.356	0.893	3.108	0.025	−2.858	0.038	5.964	0.029	−6.601	0.066
V4	−1.904	0.141	2.235	0.085	−4.104	0.108	−0.580	0.664	0.423	0.750	−1.014	0.700	−4.300	0.221
V5	0.584	0.656	0.135	0.918	0.498	0.847	−1.402	0.300	1.161	0.387	−2.562	0.335	1.417	0.688
MON	0.005	0.010	−0.007	0.001	0.012	0.003	0.000	0.864	−0.001	0.624	0.001	0.874	0.011	0.034
TUE	0.002	0.410	−0.002	0.363	0.003	0.382	−0.003	0.206	0.002	0.226	−0.005	0.209	0.009	0.096
THUR	0.001	0.715	−0.001	0.577	0.002	0.636	−0.002	0.419	0.001	0.501	−0.003	0.450	0.004	0.435
FRI	0.003	0.185	−0.003	0.179	0.005	0.175	0.001	0.720	−0.001	0.721	0.001	0.718	0.004	0.414
L-RATIO1	0.433	0.000	0.424	0.000	0.430	0.000	0.326	0.000	0.322	0.000	0.324	0.000	0.302	0.000
L-RATIO2	0.121	0.000	0.114	0.000	0.118	0.000	0.132	0.000	0.122	0.000	0.127	0.000	0.039	0.043
L-RATIO3	0.061	0.003	0.032	0.114	0.045	0.028	0.073	0.000	0.052	0.008	0.063	0.001	0.030	0.125
L-RATIO4	0.079	0.000	0.071	0.001	0.075	0.000	0.100	0.000	0.095	0.000	0.097	0.000	0.019	0.315
L-RATIO5	0.200	0.000	0.206	0.000	0.206	0.000	0.193	0.000	0.168	0.000	0.184	0.000	0.168	0.000
NEWM5	0.025	0.000	−0.027	0.000	0.052	0.000	−0.025	0.000	0.025	0.000	−0.049	0.000	0.113	0.000
MEND	0.021	0.000	−0.020	0.000	0.041	0.000	0.013	0.001	−0.014	0.001	0.027	0.001	−0.009	0.363
NEWQ5	0.026	0.000	−0.029	0.000	0.055	0.000	−0.024	0.000	0.025	0.000	−0.049	0.000	0.119	0.000
QEND	**0.007**	**0.273**	**−0.010**	**0.127**	**0.017**	**0.179**	**−0.005**	**0.438**	**0.003**	**0.585**	**−0.009**	**0.495**	**0.007**	**0.670**
NEWY5	0.021	0.000	−0.019	0.000	0.040	0.000	−0.012	0.014	0.017	0.001	−0.029	0.003	0.090	0.000
YEND	**0.049**	**0.000**	**−0.047**	**0.000**	**0.096**	**0.000**	**0.005**	**0.616**	**−0.004**	**0.675**	**0.010**	**0.642**	**0.071**	**0.010**
R^2	0.663		0.620		0.647		0.532		0.471		0.506		0.449	

This table reports the results from time-series regressions. For each institution, and for each stock, we accumulate the institution's trades in the stock over our sample period and use this as an estimate of the institution's position in the stock. We update this measure each month and require at least twelve months of data to construct the measure. If the accumulated position is negative, then we assign it a value of zero. Once we have the positions, we estimate the weight of each stock in the institution's portfolio. We call this W_i. Then within each institution, we sort the stocks on W_i and place each stock into a tercile based on its W_i rank. The highest tercile stocks are defined as high weighted, the middle tercile stocks are defined as medium weighted, and the lower tercile stocks are defined as low weighted. Next, for each institution, we calculate the ratio of the dollar value of high-weighted buys (sells) to the dollar value of the high-weighted stocks in the portfolio and then obtain value-weighted average across institutions to come up with a single daily measure. Dummy variables that signal the last day of a non-year-end quarter (QEND) and the last day of the year (YEND) are used to test whether the buy proportion is abnormally high on these days. QEND and YEND are never both equal to one. The control variables include the CRSP value-weighted market return for each of the five previous days (R1, R2, R3, R4, and R5), the volatility of this return, which is measured as the return squared, for each of the five previous days (V1, V2, V3, V4, and V5), dummy variables indicating the day of the week (MON, TUE, THUR, FRI), the previous five days' ratios (L-RATIO1 to L-RATIO5), dummy variables for the first five days of the month (NEWM5), the first five days of the quarter (NEWQ5), the first five days of the year (NEWY5), and finally the last day of the month that is non-quarter-end (MEND). The sample spans 2000 through 2010. For specifications in which the dependent variable is a difference, the L-RATIOs are the differences of L-RATIOs. The sample begins in 2000 because we require at least one year of data to construct our weighting measures. All estimates use 2,743 observations. Statistics associated with QEND and YEND are in bold.

TrimTabs that covers the time period of February 1998 to December 2011. We construct fund flow measures at the daily level and also use moving averages of 3 days and 5 days. We estimate increases in fund flows at year-end (contained in the Appendix) that are very close to zero. For example, the smallest p-value is 0.415, and the sign changes depending on specification. The quarter-end results are similar. These findings suggest that net fund flows around quarter- and year-ends are not unusual.

2.4 Do portfolio weights affect institutional trading at quarter-end?

The findings in Table 2 suggest that an increase in net buying affects prices in a manner that is consistent with the price inflation results reported in both CKMR (2002) and Ben-David et al. (2013). The pumping hypothesis also predicts an increase in the buying of stocks in which the institution already has a large position. In this section we test whether, conditional on buying on the last day of a quarter or year, an institution is more likely to buy a stock, which has a large weight in the institution's portfolio. We also test whether, conditional on selling on the last day of a quarter or year, an institution is less likely to sell a stock, which has a large weight in the institution's portfolio.

Alternatively, a more subtle version of portfolio pumping could involve not selling any stocks on the last day of the year. Unlike buys, delayed selling is in most cases costless, so it makes sense to delay sales for all stocks, even if the benefit of not selling stocks with smaller weights is lower. The results in the Table 4 are consistent with this type of pumping.

The Abel Noser Solutions trade data do not contain the name of the institution, so we cannot link our trading to data to institutional holdings data. We therefore estimate an institution's position in a stock by accumulating the institution's trades in the stock. We update this measure each month and require at least twelve months of data to construct the measure. If the accumulated net position is negative, then we assign it a value of zero. For each institution, we sum the individual stock positions to create an estimate of the institution's total portfolio. We divide each individual stock's position by the total value of the portfolio; this is an estimate of the stock's weight for a particular institution, W_i.

We sort the stocks on W_i for each day and within each institution's portfolio and place each stock into a tercile based on its W_i rank. The highest tercile stocks are defined as high weighted; the middle tercile stocks are defined as medium weighted; and the lower tercile stocks are defined as low weighted. For each institution, and on each day, we calculate the ratio of the dollar value of high-weighted buys (sells) to the dollar value of high-weighted stocks in the institutional portfolio and average this ratio across institutions to determine a single daily measure. We repeat the exercise with low-weighted buys (sells). We therefore create four separate measures: high-weighted buys, high-weighted sells, low-weighted buys, and low-weighted sells.

Our portfolio weight measure is a proxy for the actual portfolio weight. This creates an errors-in-variable problem, which makes it more difficult to reject the null hypothesis. We think this problem is, at most, minor. Edelen, Evans, and Kadlec (2010) report that for the sample of equity mutual funds with CRSP coverage from the 1995–2005, average turnover is 94%, and we only use our portfolio weight measure after we have twelve months of data. Because we have a twelve-year sample, we expect the initial years of data to provide a good proxy for whether a stock is in the portfolio, and we expect the latter years to provide a very good proxy. Moreover, in untabulated tests, we conduct our estimation by weighting the latter years of data more heavily, and this generates results that are very similar to unweighted estimation, suggesting we have a good proxy for all of our sample years.

Price manipulation, especially in the case of excessive buying, could be associated with abnormal trading in high-weighted stocks on quarter-ending and year-ending days. On any given day, we might expect managers to trade this way, as their beliefs about a stock's prospects are likely reflected in portfolio weights. However, a spike in this kind of trading on the last day of the year would be suggestive of portfolio pumping. We estimate this effect using the same regression equation as in the previous tables, where the dependent variables are the high-weighted and low-weighted buy and sell ratios described above.

Our findings for this section are reported in Table 5. Consistent with managers pumping to induce higher end-of-the-quarter and end-of-the-year portfolio values, quarter- and year-end buying is higher in high-weighted stocks, and quarter- and year-end buying is depressed in low-weighted stocks. At quarter-end the buy results command p-values between 12% and 27%, but the year-end buy results are very strong, with p-values lower than 0.01%.

The last three columns examine the propensity of portfolio managers to sell high-or low-weighted stocks on the last day of the quarter or year. All specifications produce slopes that are very close to zero. Thus, it appears that end of period selling is not influenced by the trade's impact on portfolio value. As we mention previously, delaying sales until after the New Year is costless or at least nearly costless. It is therefore reasonable for a manager to not sell any position at year-end, no matter how small its weight.

Viewed in isolation, Columns 3 and 6 might be misleading if differences in buying and selling are affected by end-of-the-year declines in institutional trading. The final column therefore reports a net difference-in-differences estimator ([high-weighted buy – low-weighted buy] – [high-weighted sell – low-weighted sell]). This estimator reinforces the interpretation that end-of-the-year trades are the result of targeted pumping, as both the year-end and quarter-end slopes are positive and the year-end slope is also significant.

2.5 Intraday timing of trades

In Table 2, we demonstrate that both abnormally high institutional buying and abnormally low institutional selling can inflate stock prices. In Table 4, we show that both institutional buying and selling decline on year-end days, with selling having the larger decline. Taken together, Tables 2 and 4 suggest that the larger decline in institutional selling leads to an increase in the ratio of institutional buys to sells, in turn causing the year-end price inflation observed in previous studies.

Although our year-end trade data do not contain reliable time stamps, buy trades occurring at the end of the day are not necessary to explain why prices are inflated at year-end; our results show that the imbalances between buying and selling cause price inflation and that such imbalances arise during the last day of the year. Hence, any evidence of late-in-the-day trades would serve as a complement to our findings reported in Tables 2 and 4.

3. Window Dressing Results

In this section we examine whether institutions engage in window dressing. Window dressing involves altering a portfolio at the end of an evaluation period so as to make the holdings appear to be better than they were throughout the quarter or year. A manager can do this by buying stocks that performed well (winners) and by not buying stocks that performed poorly (losers) toward the end of the quarter or year. Managers can also make their year-end holdings look more attractive by selling losers and not selling winners toward the end of the quarter or year.

Window dressing also can be detected by examining trades made at the beginning of the year. If institutional investors buy winners for the purpose of window dressing at the end of the year, then we ought to observe less buying of and an increase in selling of winners at the beginning of the year. By the same token, if institutional investors sell losers for the purpose of window dressing at the end of the year, then we ought to observe less selling and more buying of losers at the beginning of the year.

We estimate the change in these trading behaviors during the last month of the quarter and year. Our data contain trades made by mutual funds held in taxable accounts, so focusing on December trades is advantageous because the Internal Revenue Service requires mutual funds to distribute capital gains realized as of October 31. Due to this cutoff date, December trades should not be influenced by tax-loss selling, as tax-loss selling is more likely to occur in October (see Gibson, Safieddine, and Titman 2000).

The first set of window dressing tests is reported in Table 6. In Table 6 we report the results from equal-weighted tests, whereas in the Appendix we report similar results from value-weighted tests. We focus on equal-weighted tests, because the previous literature has focused on whether or not the typical institution window dresses, and unlike portfolio pumping, window dressing does not involve price pressure. In Panel A of Table 6 we test whether funds are more likely to buy winners and less likely to buy losers during the last month

Table 6
Window dressing tests: Buying winners and selling losers

Panel A: Buying results

	Buy winner		Buy loser		Winner minus loser	
Variable	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	0.001	0.434	0.005	0.000	−0.002	0.275
R1	−0.054	0.196	0.043	0.184	−0.097	0.101
R2	−0.019	0.660	0.030	0.365	−0.053	0.373
R3	0.046	0.284	−0.003	0.926	0.046	0.443
R4	−0.122	0.004	0.044	0.183	−0.178	0.003
R5	0.041	0.343	−0.007	0.832	0.047	0.436
V1	0.070	0.952	0.181	0.841	−0.139	0.932
V2	−0.728	0.524	−0.505	0.566	−0.358	0.823
V3	−0.744	0.534	−0.444	0.629	−0.424	0.800
V4	0.570	0.616	−1.267	0.147	1.820	0.252
V5	0.720	0.533	0.706	0.427	−0.127	0.937
MON	0.005	0.007	−0.006	0.000	0.011	0.000
TUE	0.002	0.180	−0.004	0.002	0.006	0.011
THUR	0.002	0.174	−0.001	0.258	0.004	0.094
FRI	−0.001	0.499	−0.001	0.484	0.000	0.906
L-RATIO1	0.483	0.000	0.453	0.000	0.491	0.000
L-RATIO2	0.163	0.000	0.182	0.000	0.170	0.000
L-RATIO3	0.081	0.000	0.090	0.000	0.079	0.000
L-RATIO4	0.127	0.000	0.124	0.000	0.130	0.000
L-RATIO5	0.139	0.000	0.130	0.000	0.123	0.000
NEWM5	−0.006	0.000	0.002	0.107	−0.008	0.000
MEND	0.003	0.338	0.001	0.798	0.002	0.608
NEWQ5	−0.005	0.032	0.000	0.880	−0.005	0.114
QEND	**0.001**	**0.791**	**−0.007**	**0.102**	**0.008**	**0.263**
NEWY5	−0.007	0.060	0.000	0.919	−0.006	0.264
YEND	**0.006**	**0.491**	**0.000**	**0.969**	**0.005**	**0.679**
R^2	0.8411		0.7366		0.8356	
T	2,973		2,973		2,973	

(*continued*)

of the quarter and year. A winner is defined as a stock with a past one-year buy-and-hold return that places it in the highest-return quartile among all CRSP stocks, whereas a loser is a stock in the lowest-return quartile.[7] In Panel B we test whether funds are more likely to sell losers and less likely to sell winners, during the last month of the quarter and year.

In the "Buy Winner" regression the dependent variable is the day's dollar volume of winner buying, scaled by total buying dollars on that day. In the "Buy Loser" regression the dependent variable is the day's dollar volume of loser buying, scaled by total buying dollars on the day. Our "Sell Winner" and "Sell Loser" measures are constructed similarly. As in the previous analyses, we create each measure for each institution on each day and then take a daily average across all institutions to create a single time series.

7 Our results are robust to various definitions of winner and loser. As an example, we segmented our sample into stocks with positive and negative returns over the previous year. We then define winners as stocks with returns above the median of our positive-return sample and losers as stocks with returns below the median of our negative return sample. The results were similar with these specifications.

Table 6
Continued

Panel B: Selling results

	Sell winner		Sell loser		Winner minus loser	
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.001	0.471	0.004	0.001	−0.001	0.517
R1	−0.013	0.768	0.092	0.005	−0.111	0.070
R2	−0.021	0.639	0.060	0.070	−0.081	0.191
R3	0.068	0.133	0.008	0.799	0.053	0.396
R4	0.008	0.865	−0.027	0.427	0.032	0.607
R5	−0.037	0.419	−0.002	0.947	−0.035	0.572
V1	1.650	0.188	−0.782	0.390	2.368	0.169
V2	1.066	0.384	−0.822	0.355	1.539	0.360
V3	0.767	0.549	−0.508	0.584	1.172	0.504
V4	−0.666	0.584	−0.110	0.901	−0.617	0.711
V5	−2.266	0.067	0.666	0.458	−2.972	0.081
MON	0.007	0.000	−0.006	0.000	0.013	0.000
TUE	0.003	0.151	−0.003	0.024	0.006	0.031
THUR	0.001	0.687	0.000	0.967	0.001	0.782
FRI	−0.004	0.040	−0.001	0.358	−0.003	0.266
L-RATIO1	0.451	0.000	0.489	0.000	0.489	0.000
L-RATIO2	0.181	0.000	0.155	0.000	0.156	0.000
L-RATIO3	0.099	0.000	0.114	0.000	0.129	0.000
L-RATIO4	0.112	0.000	0.122	0.000	0.107	0.000
L-RATIO5	0.149	0.000	0.099	0.000	0.111	0.000
NEWM5	−0.003	0.050	0.004	0.000	−0.007	0.001
MEND	0.001	0.694	−0.004	0.113	0.005	0.296
NEWQ5	−0.002	0.300	0.002	0.323	−0.004	0.220
QEND	**0.002**	**0.665**	**−0.003**	**0.411**	**0.005**	**0.550**
NEWY5	−0.008	0.047	0.002	0.505	−0.009	0.093
YEND	**0.008**	**0.392**	**0.006**	**0.404**	**0.002**	**0.869**
R^2	0.8317		0.7593		0.8312	
T	2,973		2,973		2,973	

This table reports the results from time-series regressions. We rank each stock on each day based on its past returns over the last twelve months. We then form quartiles based on the ranking. “Winners” are stocks in the highest return quartile, whereas “Losers” are stocks in the lowest return quartile. The variable “Buy Winner (Loser)” is the ratio of dollar winner (loser) buying scaled by total dollar value of buying on that day. The variable “Sell Winner (Loser)” is the ratio of dollar selling scaled by total dollar value of selling on that day. We estimate these measures for each institution and then average this measure across institutions to come up with a single daily measure. Dummy variables that signal the last month of a non-year-end quarter (QEND) and the last month of the year (YEND) are used to test whether the buy proportion is abnormally high on these months. QEND and YEND are never both equal to one. The control variables include the CRSP value-weighted market return for each of the five previous days (R1, R2, R3, R4, and R5), the volatility of this return, which is measured as the return squared, for each of the five previous days (V1, V2, V3, V4, and V5), dummy variables indicating the day of the week (MON, TUE, THUR, FRI), the previous five days’ ratios (L-RATIO1 to L-RATIO5), dummy variables for the first five days of the month (NEWM5), the first five days of the quarter (NEWQ5), the first five days of the year (NEWY5), and finally the last day of the month that is non-quarter-end (MEND). For specifications in which the dependent variable is a difference, the L-RATIOs are the differences between the L-RATIOs. The sample spans 2000 through 2010. The sample begins in 2000 because we require at least one year of data to construct our weighting measures. Statistics associated with QEND and YEND are in bold.

These tests use definitions of the QEND and YEND variables that are different from the pumping tests. In these tests the QEND and YEND variables indicate whether the trade was made during the last month of the quarter or year, and we obtain similar findings when we use higher-frequency definitions of quarter- or year-end (e.g. last day or last 5 days of the quarter and year). In Panel A of Table 6, the QEND and YEND coefficients in the “Buy Winner” and “Buy Loser” regressions are all insignificant, thus we are unable to reject the null that purchases of well-performing and poor-performing stocks are different during the last month of the quarter or year. The coefficient on NEWYEAR5 is also insignificant in all of the specifications, so managers do not appear to delay trades for window dressing reasons.

The results in Panel B do not support the window dressing hypothesis. The YEND and QEND coefficients often have the opposite sign than predicted by window dressing, and for all specifications, the slope coefficients are insignificant. The one significant result that is consistent with window dressing is the positive coefficient on NEWYEAR5 in the "Sell Winners" regression. Institutions are more likely to sell winners in the beginning of the year, possibly reflecting less selling of winners during the end of the previous year. However, the YEND coefficient is not negative and significant in the "Sell winners" regression, and this is the most direct test of the delayed selling of the winners hypothesis.

In the Appendix we report the results from window dressing tests that incorporate portfolio weights. Portfolio weights are estimated using the methods described in Section 2.4. Portfolio weights could matter if investors look at not only which securities a fund owns but also at how much of each security the fund owns. Perhaps a fund that is underweight in the best performing stocks is viewed by investors in a negative light. Window dressing therefore predicts year-end buying to shift from high-weighted losers to low-weighted winners; however, we do not find such evidence.

4. Conclusion

Using a large sample of daily, institutional trade data, we directly examine whether quarter-end and year-end institutional trades are consistent with either portfolio pumping or window dressing. Prior studies suggest that institutions engage in both of these activities; however, these conclusions are primarily based on indirect tests done using quarterly holdings data, mutual fund return data, and stock return data.

With respect to portfolio pumping, we show that both abnormally high buying and depressed selling can inflate daily closing prices. On the last day of the year there is a large decline in institutional trading, with both buying and selling declining to below normal levels. The decline in selling is larger, and the net imbalance helps explain why previous studies find that prices are inflated on the last day of the year. To the best of our knowledge, depressed institutional selling has not been previously offered as an explanation for year-end price inflation. We also find that buying at year-end, although reduced, is focused on stocks in which institutions have large existing positions, consistent with pumping.

Prior evidence on window dressing is mostly circumstantial, and our more direct tests with trade data cast doubt on the notion that most institutions engage in this activity. Window dressing involves the buying of winners and the selling of losers toward the end of each quarter, especially the fourth quarter. We find no direct evidence that at the end of the year or in the last month of a quarter institutions are more likely to buy winners or sell losers on average.

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