The London School of Economics and Political Science

Essays on Empirical Asset Pricing

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Declaration:

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consist of 17,650 words excluding references, tables, and figures.

I confirm that Chapter 3 is jointly co-authored with Dong Lou and Lauren Cohen, on which I contributed one third of the work.

Thesis Abstract:

My thesis consists of three papers on empirical asset pricing. The first two papers explore the ways through which mutual fund companies impact the market. The last one explores a strategic behavior of firms toward investors.

In my first paper, I examine the price impact of portfolio balancing by professional investment managers. I find that asset managers tend to rebalance their portfolios seasonally, adjusting around the earnings announcement periods of the underlying, and in turn causing fluctuations in the cross section of assets beyond those documented in the literature. The asset management industry trades more with outside market participants during the earnings season than the rest of the quarter. Consequently, these trades have price impact and generate a seasonal variation in Momentum returns across the cross section of equities.

The second paper explores the intermediation of profits by asset managers to investors. Asset managers distribute capital gains and dividends at fixed dates even though the accrual of gains and dividends occur throughout the year. I exploit this staggered nature of capital distribution in asset intermediation to study the influence of institutional money management on asset prices. These results indicate that institutional structures contribute to the daily variation of stock market returns and that manager preference has significant impact over the co-movement of his managed assets.

My third paper is joint work with Dong Lou and Lauren Cohen. We explore a mechanism through which investors take correlated shortcuts, and present strong evidence that firm managers undertake actions in response to these shortcuts. Specifically, we exploit a regulatory provision governing firm classification into industries, wherein a firm's primary industry is determined by the segment with the highest sales. We find that

investors overly rely on this classification: Firms just above the industry classification cutoff have significantly higher betas with respect to that industry.

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Chapter 1

Portfolio Rebalancing, Momentum, and the Earnings Season

1.1 Introduction and Related Literature:

The asset management industry as a whole experienced an unprecedented inflow over the past 25 years. Mutual funds alone now account for about 20% of the aggregate equity market, up from about 5% in 1990 and 2% in 1980[1]. This increase in presence also coincides with significant shifts in the cross section of asset returns. Since 1990, the average returns from momentum trades have decreased and are much more volatile. A cursory hypothesis is that the underlying factors that had made these strategies profitable have been traded away by the larger dedicated money management industry. However this cannot be the entire story- the absolute dispersion of the future returns between high and low past return characteristic stocks has also increased. A simple test of variances shows that the volatility of monthly (2-12) momentum returns have increased significantly from 3.7% between 1970 and 1989 to 5.0% between 1990 and 2013 ([Pr > F] < 0.0001). This paper argues that portfolio composition targeting by mutual fund managers are the drivers of these cross sectional changes.

When an asset experiences high returns relative to the rest of a portfolio, its relative weight in this portfolio increases. To rebalance the portfolio to a target composition, the asset

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[1] The Thomson Financial CDA/Spectrum Holdings Database is used to calculate these percentages. The reported percentage (an underestimate) is the sum of the total equity holdings of the end of the quarter reporting funds divided by the aggregate CRSP Market Cap.

manager must sell the asset and use the excess balance to purchase other securities adequate for her portfolio. Given that asset returns are correlated to their respective changes in portfolio weight across funds, i.e. a high return stock will have increased its weight in most equity portfolios, trades to rebalance inherently demand liquidity from outside of the rebalancing shareholders. This reversal pricing pressure drives down the prices of the high past return stocks, thereby decreasing the dispersion of cross sectional returns.

The intensity of rebalancing across the asset management industry coincides with the quarterly earnings announcements. Since rebalancing demands liquidity provision from other investors, rebalance should be done when outside investor attention for and public information about the underlying are at their highest. I show that the largest liquidity demanding trades from institutional investors occur following a stock's quarterly earnings announcement, during which the information asymmetry between informed and uninformed agents is low, and market liquidity is high. The intensity of this liquidity demand by asset managers correlates with the degree of return predictability from the portfolio-rebalancing channel. When rebalancing is at its highest intensity, current returns are most negatively correlated with past return-driven portfolio weight changes, and in consequence to past returns. Because this rebalancing channel drives negative autocorrelation in asset returns at intra quarterly frequencies, it negates return dispersion at the quarter to annual frequencies and dampens momentum related return effects.

This study is composed of three parts. First, I establish that mutual funds do rebalance their portfolios at the quarterly horizon, resisting changes caused by the dispersion of cross sectional returns. Within each portfolio/quarter observation, I separate the change in the weight of each stock to the weight change caused by the dispersion of returns and that caused by discretionary action by the investment manager. Then I run cross sectional regressions for each set of portfolio/quarter observations using return driven weight deviations from t to $t+1$ to forecast $t+1$ to $t+2$ period discretionary and total change in stocks weights. The Fama Macbeth panel average of these coefficients indicates that for each unit of return driven increase (decrease) in the weight of an asset, a fund manager rebalances by discretionarily decreasing (increasing) the unit by 22.77% (t=15.61). The total decrease (increase) in the position is by 25.27% (t=10.55). The null hypothesis that portfolio managers don't rebalance their portfolios at the quarter-to-quarter horizon is essentially a statistical impossibility. These rebalancing trades don't appear to be absorbed by other mutual fund investors, and instead are absorb by other market participants. I show that the average change in the portfolio weight for each stock has predictive power on its total proportion held by mutual funds. One standard deviation of this variable indicates a 7-basis point increase in the proportion of a stock that is held by the entire equity fund universe.

Second, given that individual mutual funds rebalance their positions and that these trades don't get fully absorbed by other mutual funds, I investigate the timing and the liquidity demands of these rebalancing trades. Using a specialized dataset of institutional trades, I find that these trades cluster in the first half of each quarter. On average, money managers trade 13% more in the first month than during the other months of the quarter. At the daily frequency, theses trades coincide after the earnings announcements by each stock. Trades from money managers immediately following an announcement are more contrarian in nature- the sign of the excess demand for each stock is more negatively correlated to past returns as well as to the share-weighted average of return driven weight change across mutual funds ($\overline{RDWGHT}$). Each quarter, before the last 10% of the S&P500 constituent make their earnings announcement, more net buys and sells from the money management industry to other market participants appear than during any other periods of the year. This indicates a predictable industry wide timing pattern that coincides with the earnings announcements season. These results are consistent with money managers exploiting the environment of low asymmetric information, high market liquidity, and high investor attention after earnings reports. Net excess demand from rebalancing trades occur during this period for the aggregate of this sample of money managers, which also indicates that the immediate liquidity providers to rebalancing trades are likely not other mutual funds, pension funds, or insurance portfolios.

Lastly, I link the timing of trades by the money management industry to the variation in the cross section of asset returns. $\overline{RDWGHT}$ strongly predicts stock returns throughout the earnings announcement season. A one standard deviation increase in this variable implies 0.52% higher returns in the underlying stock during the dates before the last 10% of the S&P500 constituents make their earnings announcements each quarter[2]. A value-weighted portfolio holding the bottom decile and shorting the top decile of $\overline{RDWGHT}$ large cap stocks earns 2.83% raw and (2.60% adjusted) returns during the earnings season. The lowest decile portfolio earned an average of 0.32% return while the highest decile earned 3.15%. The cumulative returns around individual firm's quarter earnings announcements indicate that most of the return predictability occurs during and after the release of earnings information into the market. This predictability is strong even after adjusting for contemporaneous standardized unexpected earnings (SUE). Finally, I show that rebalancing pressure has dampened momentum returns between January 1990 and December 2013. The 12-month momentum returns (UMD) are increased from 0.35% to 1.49% during the same earnings sub-period each quarter after hedging out this long/short portfolio.

One of the first mentions (See also Tobin 1958, 1969) of the channel through which an appreciating financial asset drives up the relative prices of other securities in a portfolio is in Milton Friedman and Anna Schwartz's 1963 magnum opus, *The Monetary History of the United States*. In it, the authors state "It seems plausible that both nonbank and bank holders of redundant balances will turn first to securities comparable to those they have sold... as they seek to purchase these they will tend to bid up the prices of those issues..." To paraphrase, the free cash balances from the sale of an appreciating asset, in their case treasuries, ends up triggering the bidding up of other related securities. Despite the pedigree, this channel has lacked micro level support in the literature[3], and less so as

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[2] I define this as the earnings season- the quarterly period before the last 10% of the S&P 500 constituents make their quarterly earnings announcements.

[3] Interest in the portfolio-balancing channel however resurged when the former Fed chairman Ben Bernanke gave it as the explanation of the Fed's quantitative easing policies. See Greenwood and Vayanos (2013) for references to the literature on supply of bonds and the yield curve related to the portfolio-balancing channel. A major advantage of using

applied to the cross section of equity assets. One reason for this may be that this channel is difficult to disentangle from other channels of asset spillover, especially in the bond market, where asset substitutability is inherently linked by the term structure of expectations and micro portfolio level data is scant. Another reason is that the portfolio channel may not have been important prior to the growth of asset management institutions in the financial sector. This paper presents evidence from the equity markets to validate the hypothesis that preferences for portfolio balancing affects relative prices.

This paper is directly related to two prior studies on the portfolio balancing by investors. Calvet, Campbell and Sodini (2009) study the household rebalancing of stocks, mutual funds, and bonds using a detailed comprehensive household dataset. Hau and Rey (2010) track the global flow from portfolios of a set of international mutual funds. This current paper joins them in documenting the active rebalancing of portfolios by investors against the pressures of cross sectional price changes. However, distinct from the previous studies, the current study focuses on the timing and price impact of this behavior. I find pricing pressure arising from rebalancing trades and argue a causal link between the portfolio balance channel and the relative returns of assets.

This paper is also related to the seasonal effect found in the finance literature. Ritter (1988), and Ritter and Chopra (1989) study the turn of the year effects in which low capitalization stocks have higher returns than high capitalization stocks during the January of each year. Ritter and Chopra (1989) argues that shifts in risks cannot explain this phenomenon and that portfolio rebalancing, potentially related to accounting incentives, is the most consistent hypothesis for this effect. The phenomenon reported in this paper is distinct from size related effects in the cross section of asset prices. In fact, the rebalancing pricing pressure by the asset management industry exists after controlling for size, is the

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equity portfolios to study rebalancing is that the values of equity in the cross section are much more volatile than that of treasury bonds. In addition, the amount of debt held in the Fed's balance sheet is of course very much persistent and predictable, whereas turnover by retail investors and other market participants is volatile and much more difficult for managers to forecast.

strongest among the largest capitalized stocks in the market, and is mainly driven outside of the first quarter of the year.

On the subject matter, this paper is also related to the literature that connects mutual funds to stock returns. Anton and Polk (2014) studies the reversal of correlated positive movement between assets held under the same mutual funds. Coval and Stafford (2007) and Lou (2012) study mutual fund trading in the presence of asset flows under the assumption of proportional flow from mutual funds to their stock components. An implicit consequence of this literature is that excess correlation at the monthly frequency between the underlying assets is generated by flows in and out by fund investors. A missing piece in this literature is the how these funds trade in response to the changes in the relative price levels of its holdings. This response is, for the existing holdings, orthogonal to flows in and out of each fund. In presence of positive flow, a fund will rebalance by simply purchasing its relatively low return assets without selling any of its high return assets. I argue that this portfolio channel negates dispersion in asset prices. This paper fills in on how portfolio targeting by mutual funds, for potentially various purposes, impact the equity market.

2.1 Data:

The CDA/Spectrum mutual fund holdings dataset is used for the mutual fund portfolio holdings. The data is observed at the quarterly frequency and is compiled from both mandatory SEC filings and voluntary disclosures. Funds that report prior to the end of the quarter are assumed to have held the same portfolio at the quarter end date. To separate out the index funds, I drop funds that have the words “INDX”, “IDX”, or “INDEX” in their names. Although some funds had reported at semi-annual frequency prior to mandatory changes in 2003, the majority of funds voluntarily report holdings at the quarterly even prior to these changes. The variables constructed and the tests conducted are done on quarterly reporting portfolios.

I supplement the holdings information with the Ancerno/Abel Noser data on institutional trading to investigate the timing of rebalancing trades. Large institutional money managers, brokerages, insurance companies, and pension funds, submit the stock transactions of their various accounts to the Ancerno/Abel Noser Corporation for trading cost analysis. Each trade is linked to a unique account code (clientmgrcode). Two data filters are used. Since most of the calculations are based on the relative intra-quarter trades per stock, I ensure that each trade observation used comes from firms that were first observed prior to the beginning and last observed after the end of that quarter in the whole sample. I also drop funds that have the words “INDX”, “IDX”, “INDEX”, or “BANK” appearing in the either name of the specific account level or that of the specific manager. After applying data filters, the data sums to about 300 billion dollars of trade volume each quarter and spans 376,200 different accounts from January 2000 to December 2010. See Puckett and Yan (2011) for a more detailed discussion of the data and its selection issues. To calculate each intra-quarterly volume of trades, I aggregate total dollar buy and sell volumes based on last period prices.

Stock returns, prices, and other stock related characteristics come from the CRSP database. Tests forecasting future returns are done with common stocks traded on AMEX, NYSE, and

NASDAQ exchanges. The standard Size/Momentum and Size/Reversal portfolio returns, as well as the usual cross sectional factors, are taken from Ken French's website.

Quarterly earnings announcement dates for the S&P500 constituents are obtained from the Compustat database. Standardized Unexpected Earnings (SUE) is calculated using quarterly earnings announcements and code provided by WRDS.

<INSERT TABLE 1>

2.3 Portfolio Rebalancing:

There are several strong reasons to rebalance a portfolio. First, the dedicated inactive fund strategies such as momentum and value intrinsically require periodic rebalancing. The classical studies of these strategies usually involved monthly rebalancing of holdings, and funds that use these strategies will have to periodically adjust the composition of their portfolios. Secondly, benchmarking by non-index funds will also require rebalancing over time- as a particular stock picks become higher/lower weighted in a portfolio, the fund manager will have to rebalance in order for the portfolio to not deviate too far from a particular benchmarks. Third, risk management strategies will also induce rebalancing. Historically a portfolio that maintains a 40-60% composition of bonds and stocks had lower portfolio volatility than one that had allow its composition to drift. An equal weighted market portfolio has historically higher Sharpe Ratios and lower volatilities than the valued weighted portfolio. These portfolios are of course empirically difficult to maintain in the presence of return dispersion and any portfolio managers committing to these measures will find themselves rebalancing very often. Lastly, end of the quarter return manipulation and portfolio window dressing may induce compositions that are different from the manager's ideal portfolio. To undo these compositional shifts, a manager will have to rebalance her portfolio in the subsequent quarter.

An important caveat, however, is that the act of rebalancing consumes liquidity from outside of the managers that have portfolio balancing incentives as the need to rebalance is correlated per stock across portfolios. Appreciated assets have to be sold to investors outside of the asset managers that have portfolio-rebalancing incentives. Therefore, a major empirical consequence of stock rebalancing is that for assets that form large portions of an investment portfolio, contemporaneous return driven changes in weight will negatively forecast the future changes in weight, unless the portfolio manager rotates out of her positions entirely. To document this pattern of portfolio balancing, I separate changes in the portfolio to changes that are return driven from change that are made at the discretion of the portfolio managers. If a manager didn't trade discretionarily and only scaled his existing holdings between the two periods, the composition difference in the portfolio would be entirely return driven.

Let fund *j* have stocks $\{w_{1,j,t},\ldots,w_{i,j,t},\ldots,w_{I,j,t}\}$. For each component in a portfolio *j*, I separate changes in the weight of stock *i* to that by discretion of the manager and that by return dispersion.

$$\underbrace{w_{i,j,t+1} - w_{i,j,t}}_{Total\ Change\ (TDWGHT)} = \underbrace{w_{i,j,t+1} - \widehat{w}_{i,j,t+1}}_{Discretionary\ Change\ (DDWGHT)} + \underbrace{\widehat{w}_{i,j,t+1} - w_{i,j,t}}_{Return\ Driven\ Change\ (RDWGHT)}$$

where

$$\widehat{w}_{i,j,t+1} = \frac{w_{i,j,t+1}(1 + r_{i,t})}{\sum_{n=1}^{N} w_{n,j,t}(1 + r_{n,t})}$$

is the predicted weight of stock *i* in portfolio *j* due to returns.

The variable $RDWGHT_{i,j,t}$ is assigned as the return driven change for each stock *i* in portfolio *j* between quarters *t* to *t+1.* Another interpretation of this variable is simply the interaction of the scaled individual stock return and its weight within a portfolio minus the initial weight.

I regress the position changes, $RDWGHT_{i,j,t}$, along with initial weight and the stock's scaled return, to positions changes at *t+1* to *t+2* for each portfolio/quarter sample collection. The regression coefficients are collected in a panel and averaged through Fama Macbeth procedure. I find that the return driven changes are negative predictors of discretionary weight changes in the subsequent quarter. This effect is complementary to return chasing by mutual fund managers. Lagged quarterly returns predict discretionary weight increases while the $RDWGHT_{i,j,t}$ predicts discretionary weight decreases (Table 2a). Overall, $RDWGHT_{i,j,t}$ also predicts $TDWGHT_{i,j,t+1}$, the total weight change in a position, since subsequent price effects on average are in the same direction as the discretionary trading and only mildly attenuate the statistical significance.

<INSERT TABLE 2>

The results indicate that for their existing positions, mutual funds have historically managed to rebalance their position weights. For a single position, a unit increase in its weight caused by returns is met with 22.34% (*t*=15.46) discretionary decrease, and a 25.03% (*t*=10.32) total decrease. A second set of coefficient averages are reported in columns 5 to 8. The weighted average is based on the quarterly fraction of total mutual fund assets held by each individual portfolio. The magnitudes of the rebalancing coefficients decrease to 15.26 (t=8.25) and 17.68% (t=5.61) respectively, indicating that larger funds rebalance less intensely than smaller funds. However, both sets of results conclude that the hypothesis that mutual funds don't rebalance at the quarterly horizon is statistically impossible.

Importantly, these rebalancing trades are not absorbed by the mutual fund industry. Table 2a regresses the difference of the proportion of stock shares held by the sum of all mutual funds each quarter against past 3-month returns, lagged share-weighted average values of return driven deviation, and lagged share-weighted average weights in a portfolio. While the overall industry exhibit strong return chasing behavior based on past returns, this behavior is severely decreased for high weight and high weight gained shares. One standard deviation of $\overline{RDWGHT}$ forecasts a 7 basis point decrease in the total proportion of a stock held by all mutual Funds. These results indicate that high average weights and high return driven deviations in weights forecast net decreases in the proportion of shares held by mutual funds. The largest rebalancing trades are not absorbed by the mutual fund industry on average.

Next, I investigate the timing and pricing effects of these rebalancing trades.

2.4 Trading by Asset Managers:

To an individual portfolio manager, trades to rebalance portfolios should be managed during periods when liquidity provision is at its highest and trading frictions are at their minimal. Whether these trades actually coincide with any seasonal pattern related to the structure of the financial markets is an empirical question, and one that I address by using a specialized sample of institutional trades.

I use the Ancerno database to explicitly identify trades by professional asset managing institutions.

The data is filtered in 2 ways:

1) Observations of a portfolio in the quarters where the fund is first observed or is last observed are deleted from the sample.

2) Observations with the words 'INDX', 'IDX', 'INDEX', and 'BANK' in their reported names are eliminated to drive out index funds and banks.

<INSERT FIGURE 1>

I then aggregate the buy and sell orders from all accounts each month using lagged quarter prices from CRSP. The fraction of buys and sells in each month relative to that of the entire quarter is then calculated for the data period. Figure 1 panels A and B plot the average monthly dollar fraction of quarterly buys and sells. Evidently, more trades come in January, April, July, and October when compared to the rest of the quarter. This effect is very apparent when comparing money managers to the aggregated equity volume Panel C. On average, institutional managers trade more intensely during these periods than the other market participants. In fact, these trades do not cancel out within the money management sector. More net trades between money managers and other market participants occur during these months, panel D. Statistical tests of the difference are presented in Table 3.

<INSERT TABLE 3>

On a more granular level, I study the daily variation of these trades. From Figure 2, we observe that more trades and more liquidity demands occur in the first half of the quarter by institutional traders.

<INSERT FIGURE 2>

In Table 4, I show that the net sign of excess demand for each stock is correlated to its share weighted average of return driven weight changes in the past quarter during the earnings season. On average, one standard deviation of $\overline{RDWGHT}$ predicts 7.6% decreased likelihood of net excess demand from asset managers.

<INSERT TABLE 4>

2.5 Predictability and Returns:

The intra-quarter variation in money manager rebalancing causes variation in the cross section of equity returns. Table A1a (A1b) shows the long-short returns of portfolios sorted on size and 12-month momentum (size and short-term reversal) from January 1990 to December 2013 and January 2000 to December 2013. On average, the long-short momentum portfolios have had negative returns during January, April, July, and October; while most of their portfolio returns come at the end of the quarter. Figure 3 includes the average intra quarter cumulative daily returns of 2-12 momentum sorted on size, rebalanced at month end, between Q1 1990 and Q4 1999 (top), and Q1 2000 and Q4 2013 (bottom). On average, momentum returns are the lowest during the earnings announcement season, where there is aggressive trading by institutions into the market. The largest size momentum portfolio, in particular, experienced the largest negative returns during this intra-quarter period. This effect is not apparent in the periods from 1970 to 1990 or from 1950 to 1970, table A2a. As documented in the literature, for much of its history, momentum effects tend to be more concentrated in smaller and more illiquid stocks. However, as I document in the most recent era, the dispersion of momentum returns became concentrated mainly in the largest and ideally most liquid stocks of the market rather than in the small ones. A very similar pattern can be observed for short-term reversal portfolios in table A2b.

Now I now use the $\overline{RDWGHT}$ variable calculated in the previous section to forecast returns. Description of the variable, and its correlation to past returns is given in table 5.

<INSERT TABLE 5>

First I perform Fama Macbeth regressions of total quarterly returns during the earnings announcement period on $\overline{RDWGHT}$ and related characteristics. Quarterly returns prior to the last 10% of the S&P constituent announcements are regressed cross-sectionally each quarter on lagged $\overline{RDWGHT}$. The second stage coefficient averages are reported in Table

6a. The variable $\overline{RDWGHT}$ subsumes the negative predictability of the past return characteristics. This effect is stronger between 2000 and 2013, and robust to the exclusion of the 'Momentum Crash' in 2009. Next I investigate the timing of this predictability per stock. Table 6b records Fama Mabeth regressions of cumulative returns on $\overline{RDWGHT}$ and various controls including contemporaneous SUE. As related to cumulative returns, most of the effects of rebalancing pressure come from during and after the earnings announcement per firm.

Second, I form quarterly portfolios based on the ranking sortings of $\overline{RDWGHT}$. The long short portfolio returns are reported in TABLE 7 with various factor adjustments.

<INSERT TABLE 7>

As documented in figure 4 and table 7, the highest $\overline{RDWGHT}$ portfolio has had zero to negative returns until the last thirds of the quarter, while the lowest $\overline{RDWGHT}$ portfolio experienced almost 3% returns.

<INSERT TABLE 8>

Lastly, I use the portfolio rebalancing pressure to explain the variation in (2-12) momentum returns. I find that the UMD returns each quarter before the last 10% of the S&P500 constituents make their earnings announcements are increased by adjusting for the $\overline{RDWGHT}$ portfolio. The unadjusted intra-quarter return of UMD from Q1 1990 to Q4 2013 is -0.34% (t=-0.46). After adjusting for the standard 3 factors, the return is increased to 0.35% (t=0.53). After incorporating the low minus high $\overline{RDWGHT}$ portfolio, the 4 factors adjusted return of UMD is increased to 1.28% (t=2.22).

2.6 Conclusion:

The growth of the dedicated asset management industry in the last 20 years represents a major structural change in the financial markets. Coinciding with this change is a decrease in the various momentum-based stock returns and an increase in their volatility. I argue that this change is expected in part because past returns are imprecise signals of how much assets have changed in their proportional weights in the average portfolio. Because dedicated asset managers have incentives to target and balance their portfolio holdings, we observe an active leveling of returns in high weight high past-return stocks. This active rebalancing of portfolios coincides with the earnings announcement period, when market liquidity is high and information asymmetry is low. I show that momentum returns can be increased after hedging the portfolio that shorts high weight deviation stocks and longs low weight deviation stocks during the earnings season.

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2.8 Tables and Figures:

	Summary Statistics							
	Mean	Std	Min	25 P.	Median	75 P.	Max	N
N. of Account Per Quarter	8,550	14,069	3,649	6,748	8,550	19,966	53,510	44
N. of Trades Per Account/Qtr	279	10,415	1	11	24	69	3839056	697807
Dollar Value of Buy Trade	161,421	1,390,599	0.19	1,632	8,470	50,611	4,000,000,000	109,210,492
Dollar Value of Sell Trade	168,576	1,357,989	0.08	1,494	8,344	50,560	2,406,170,000	108,250,017
Total Sum of Quarter's Buys	305 B	71 B	191 B	238 B	311 B	350 B	488 B	44
Total Sum of Quarter's Sells	314 B	78 B	207 B	244 B	305 B	366 B	474 B	44
Qtrs Observed Per Account	6.97	5.23	1	4	6	8	44	100,155

Table 1. Summary Statistics of the Ancerno Database used in this study. Trades from the starting quarter and ending quarter of individual accounts are drop. Furthermore, accounts with words 'INDEX,' 'INDX,' 'IDX', or 'BANK' in either the account or manager names are dropped. The data cover January 2000 to December 2010.

	Equal Weighted Coefficients				Value Weighted Coefficients			
	$DDWGHT_{i,j,t+1}$		$TDWGHT_{i,j,t+1}$		$DDWGHT_{i,j,t+1}$		$TDWGHT_{i,j,t+1}$	
$RDWGHT_{i,j,t}$	-0.159	-0.224	-0.170	-0.251	-0.114	-0.155	-0.126	-0.179
	(-16.82)	(-15.55)	(-8.77)	(-10.39)	(-8.25)	(-8.52)	(-5.83)	(-6.61)
$WGHT_{i,j,t}$		-0.124		-0.126		-0.107		-0.108
		(-30.77)		(-27.43)		(-23.48)		(-22.15)
$SRET(1,3)_{i,j,t}$		0.110		0.125		0.067		0.075
		(7.19)		(6.47)		(5.98)		(5.82)
Port/Qtr	135292	135292	135292	135292	135292	135292	135292	135292
Qtr	96	96	96	96	96	96	96	96

Table 2a. Fama Macbeth regressions of discretionary changes in weight (DDWGHT) against lagged return driven change in weight (RDWGHT), initial weight (WGHT), and 3 month returns scaled by total holdings return (SRET). The first stage coefficients are obtained by regressing for each portfolio/quarter subsample, requiring at least 20 degrees of freedom per regression. The coefficients are then pooled into a panel and averaged. Columns 1 through 4 compute the equal weight averages, whereas columns 5 through 8 compute the averages as weighted by the fraction of the fund's value to the total mutual fund value for that quarter. The standard errors are clustered quarterly. All right hand side regression variables are winsorized at 2.5% to 97.5% level per portfolio/quarter. The sample is from Q1 1990 to Q4 2013.

	Net Increase in Prop Held by Mutual Funds at t+1		
	Weighted Least Squares		
	1990 to 2013	1990 to 1999	2000 to 2013
$\overline{RDWGHT}_{i,t}$	-0.001	0.000	-0.001
	(-6.37)	(-2.97)	(-5.87)
$\overline{WGHT}_{i,t}$	-0.061	-0.062	-0.061
	(-3.32)	(-2.16)	(-2.49)
$RET(1,3)_{i,t}$	0.008	0.010	0.007
	(7.12)	(5.33)	(4.81)
Qtrs	96	40	56

Table 2b. Fama Macbeth regressions of the change (difference) in proportion of stocks held (Shares in Mutual Funds/Total Shares Outstanding) by $\overline{RDWGHT}$, $\overline{WGHT}$, and past 3-month returns. The right hand side regression variables are winsorized at 2.5% to 97.5%. The left hand side variable is winsorized at 1% and 99% level per quarter to level off extreme observations. The first stage coefficients are obtained by weighted least squares based off of the stock's market cap at the end of past June. The sample is from Q1 1990 to Q4 2013.

	S&P 500 Trade Intensity by Money Managers					
	2000 to 2010		2000 to 2005		2006 to 2010	
	Sell	Buy	Sell	Buy	Sell	Buy
Average Start of Quarter Relative Adjusted Volume	0.359	0.360	0.364	0.362	0.354	0.358
Average Rest of Quarter Relative Adjusted Volume	0.321	0.320	0.318	0.319	0.323	0.321
Diff	0.038 (6.48)	0.040 (7.02)	0.046 (5.92)	0.043 (6.02)	0.031 (3.24)	0.037 (3.96)
Number of Start of Quarter Months	44	44	24	24	20	20
Number of Rest of Quarter Months	88	88	48	48	40	40

Table 3a. This table presents the fraction of each quarter's buy and sells (share traded multiplied by last quarter prices) in the months at the start of the quarter versus the months in the rest of the quarter. The average January, April, July, and October relative trades are reported in the top row, while the rest of the quarter months' relative trades are reported in the second row. The pooled t-score for the difference in fractions is reported.

	Fraction Buy/Sell versus Aggregate S&P Volume in Start of Qtr					
	2000 to 2010		2000 to 2005		2006 to 2010	
	Sell	Buy	Sell	Buy	Sell	Buy
Relative Money Manager Sells/Buys in	0.359	0.360	0.364	0.362	0.354	0.358
Relative S&P Volume	0.348	0.348	0.351	0.351	0.344	0.344
Diff	0.011 (3.59)	0.013 (4.59)	0.013 (3.96)	0.011 (3.64)	0.010 (1.65)	0.014 (2.99)
Number of Start of Quarter Months	44	44	24	24	20	20

Table 3b. This table compares the relative trade fractions of beginning month of each quarter in the money manager trades to the relative volume of the S&P aggregate. The pooled t-score for the difference in fractions is reported.

	Weight LS		Weighted Logit	
	Net Buy$_{i,t+1}$			
$\overline{RDWGHT}_{i,t}$	-0.035	-0.076	-0.072	-0.165
	(-2.38)	(-3.31)	(-2.37)	(-3.29)
$\overline{WGHT}_{i,t}$		-5.936		-12.462
		(-3.12)		(-3.11)
$RET(1,3)_{i,t}$		0.365		0.796
		(3.04)		(3.08)
Qtrs	44	44	44	44

Table 4. This table records the Fama Macbeth coefficients for regressing at the net excess demand of each of the S&P 500 constituents as predicted by $\overline{RDWGHT}$ over the earnings season. The left hand side variable is an indicator dummy for the sign of the net share demand from the institutional holders up to before the last 10% of the S&P 500 constituents make their announcements each quarter. I regress the sign of the excess demand by weighted least squares and weight logit regressions on $\overline{RDWGHT}$ and various controls. The weights are based on the market capitalization at the last June. All right hand side regression variables are winsorized at 2.5% to 97.5% level per portfolio/quarter. $\overline{RDWGHT}$ is standardized by its unconditional standard deviation. The second stage averages of the coefficients between Q1 2000 and Q4 2010 are reported.

Top Size Quintile Correlation				
	RDWGHT	Ret(1,3)	Ret(4,6)	Ret(7,12)
RDWGHT	1.000			
Ret(1,3)	0.755	1.000		
Ret(4,6)	0.020	0.044	1.000	
Ret(7,12)	0.032	0.080	0.040	1.000

4th Size Quintile Correlation				
	RDWGHT	Ret(1,3)	Ret(4,6)	Ret(7,12)
RDWGHT	1.000			
Ret(1,3)	0.767	1.000		
Ret(4,6)	-0.002	0.000	1.000	
Ret(7,12)	0.029	0.069	0.028	1.000

3rd Size Quintile Correlation				
	RDWGHT	Ret(1,3)	Ret(4,6)	Ret(7,12)
RDWGHT	1.000			
Ret(1,3)	0.755	1.000		
Ret(4,6)	0.004	-0.002	1.000	
Ret(7,12)	0.018	0.076	0.029	1.000

2nd Size Quintile Correlation				
	RDWGHT	Ret(1,3)	Ret(4,6)	Ret(7,12)
RDWGHT	1.000			
Ret(1,3)	0.737	1.000		
Ret(4,6)	0.000	-0.019	1.000	
Ret(7,12)	0.023	0.075	0.036	1.000

Bottom Size Quintile Correlation				
	RDWGHT	Ret(1,3)	Ret(4,6)	Ret(7,12)
RDWGHT	1.000			
Ret(1,3)	0.573	1.000		
Ret(4,6)	0.018	-0.003	1.000	
Ret(7,12)	0.027	0.075	0.089	1.000

Table 5. The correlation of $\overline{RDWGHT}$ to past returns at various horizons is measured per each size ranking. The size ranks are based quintile market capitalization sorts with breakpoints based on the NYSE percentiles at the end of last June. All variables are winsorized at 2.5% and 97.5% each quarter. The sample period is from Q1 1990 to Q4 2013.

	Intra Quarter Return at t+1		
$\overline{RDWGHT}_{i,t}$	-0.005	-0.004	-0.005
	(-3.36)	(-2.79)	(-3.72)
$\overline{WGHT}_{i,t}$		-0.202	-0.284
		(-0.67)	(-1.62)
$RET(1,3)_{i,t}$		-0.013	-0.006
		(-0.59)	(-0.33)
$RET(4,6)_{i,t}$			-0.015
			(-1.23)
$RET(7,12)_{i,t}$			0.006
			(0.78)
$BM_{i,t}$			(-0.00)
			(-0.22)
$IdioVol_{i,t}$			-0.106
			(-0.35)
$InstOwn_{i,t}$			0.009
			(1.42)
$LogMktCap_{i,t}$			0.002
			(1.54)
Qtrs	96	96	96

Table 6a. Fama Macbeth regressions on intra quarter returns (up until the last 10% of the S&P 500 constituents report their earnings) on $\overline{RDWGHT}$ and various return controls. The size ranks are based quintile market capitalization sorts with breakpoints based on the NYSE percentiles at the end of last June. $\overline{RDWGHT}$ is standardized by its unconditional standard deviation. All right hand side regression variables are winsorized at 2.5% and 97.5% each quarter. The sample period is from Q1 1990 to Q4 2013.

	Cumulative Returns Around Earnings Announcement Date					
	Ret(-10,-3)		Ret(-2,2)		Ret(3,10)	
$\overline{RDWGHT}_{i,t}$	0.000	0.000	-0.001	-0.002	-0.002	-0.002
	(-0.34)	(-0.10)	(-1.89)	(-3.17)	(-3.36)	(-3.73)
$SUE_{i,t}$		0.063		0.211		0.064
		(3.89)		(11.51)		(3.86)
$BM_{i,t}$		0.001		-0.001		-0.002
		(0.67)		(-0.91)		(-1.21)
$IdioVol_{i,t}$		0.320		-0.114		-0.141
		(2.97)		(-1.28)		(-1.34)
$InstOwn_{i,t}$		0.001		0.008		0.000
		(0.30)		(3.16)		(-0.15)
$LogMktCap_{i,t}$		0.001		-0.001		0.000
		(1.95)		(-1.64)		(-0.98)
Qtrs	96	96	96	96	96	96

Table 6b. Fama Macbeth regressions on cumulative returns around the earnings announcement dates. $\overline{RDWGHT}$ is standardized by its unconditional standard deviation. All right hand side regression variables are winsorized at 2.5% and 97.5% each quarter**.** The sample period is from Q1 1990 to Q4 2013.

RDWGHT Returns						
	LS (D - U)					
	Raw		3 Factors Adjusted		4 Factors Adjusted	
	1990-2013	2000-2013	1990-2013	2000-2013	1990-2013	2000-2013
Size 1	0.001	0.005	-0.004	0.002	-0.003	-0.002
	(0.09)	(0.48)	(-0.67)	(0.26)	(-0.45)	(-0.19)
Size 2	0.014	0.021	0.008	0.017	0.010	0.012
	(1.70)	(1.55)	(1.02)	(1.48)	(1.50)	(1.27)
Size 3	0.017	0.026	0.008	0.022	0.011	0.015
	(1.55)	(1.46)	(0.76)	(1.40)	(1.33)	(1.18)
Size 4	0.021	0.027	0.011	0.022	0.014	0.015
	(1.84)	(1.49)	(1.08)	(1.43)	(1.72)	(1.22)
Size 5	**0.028**	**0.039**	**0.024**	**0.036**	**0.026**	**0.033**
	(3.80)	**(3.53)**	**(3.31)**	**(3.62)**	**(4.20)**	**(3.61)**

Table 7a. Long short raw and adjusted returns from portfolios sorted on size and RDWGHT (the average past quarter return driven weight change cross all mutual funds for each stock). The Long Short portfolio is calculated using the lowest decile (D) of RDWGHT minus the highest decile (U) of RDWGHT. Market cap values and the size breakpoints are from the end of last June. The size breakpoints follow the Fama and French and uses percentile cutoff values from the NYSE stock exchange.

Raw RDWGHT Returns								
	LS (D - U)							
	Q1		Q2		Q3		Q4	
	1990-2013	2000-2013	1990-2013	2000-2013	1990-2013	2000-2013	1990-2013	2000-2013
Size 1	0.008	-0.001	0.008	0.024	-0.011	-0.007	-0.003	0.004
	(0.48)	(-0.05)	(0.74)	(1.45)	(-1.33)	(-0.59)	(-0.17)	(0.16)
Size 2	0.012	0.004	0.018	0.034	0.004	0.012	0.024	0.033
	(0.73)	(0.16)	(1.15)	(1.35)	(0.40)	(0.80)	(1.00)	(0.86)
Size 3	-0.012	-0.018	0.043	0.077	0.002	0.004	0.035	0.043
	(-0.82)	(-0.82)	(1.54)	(1.67)	(0.17)	(0.19)	(1.33)	(0.96)
Size 4	-0.008	-0.022	0.041	0.062	0.013	0.020	0.038	0.047
	(-0.52)	(-0.89)	(1.56)	(1.39)	(0.90)	(1.01)	(1.27)	(1.01)
Size 5	0.015	0.019	**0.040**	**0.066**	**0.029**	**0.040**	0.030	0.032
	(1.18)	(1.16)	**(2.03)**	**(2.16)**	**(2.58)**	**(2.42)**	(1.92)	(1.40)

Table 7b. Long short raw from portfolios sorted on size and RDWGHT (the average past quarter return driven weight change cross all mutual funds for each stock) separated by the 4 quarters. The Long Short portfolio is calculated using the lowest decile (D) of RDWGHT minus the highest decile (U) of RDWGHT. Market cap values and the size breakpoints are from the end of last June. The size breakpoints follow the Fama and French and uses percentile cutoff values from the NYSE stock exchange.

	Intra Quarter UMD Return at t		
Intercept	-0.003	0.003	0.015
	(-0.46)	(0.53)	(2.54)
$Mktrf_{i,t}$		-0.527	-0.346
		(-5.25)	(-3.81)
$SMB_{i,t}$		0.013	0.054
		(0.09)	(0.42)
$HML_{i,t}$		-0.291	-0.204
		(-2.09)	(-1.71)
$LMW_{i,t}$			-0.479
			(-5.98)
Qtrs	96	96	96

Table 8. Intra-quarter returns of (2,12) Momentum return from 1990 to 2013. The intra-quarter period is from the beginning to before the last 10% of the S&P 500 constituents make their quarterly earnings announcements. The losers minus winners (LMW) portfolio is constructed by holding bottom decile and shorting the top decile of $\overline{RDWGHT}_{i,t}$ sorted stocks from the top quintile in NYSE breakpoint stocks.

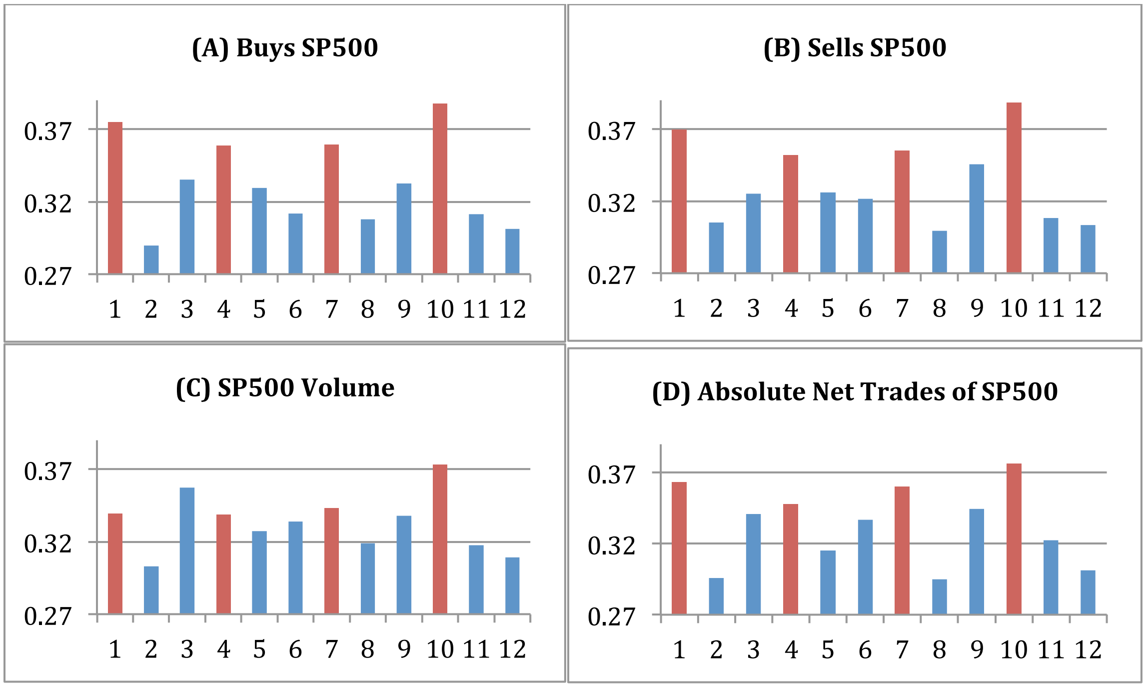


Figure 1. The seasonal pattern of Asset Managers trades. Panel A plots the relative fraction of each month over each quarter's total buys from the Ancerno database. Panel B plot the relative fraction of each month over each quarter's total sells. Panel C plots the same account from the aggregate S&P 500 volume. Panel D plots the fraction of each month's net un-cancelled buys and sells over quarter.

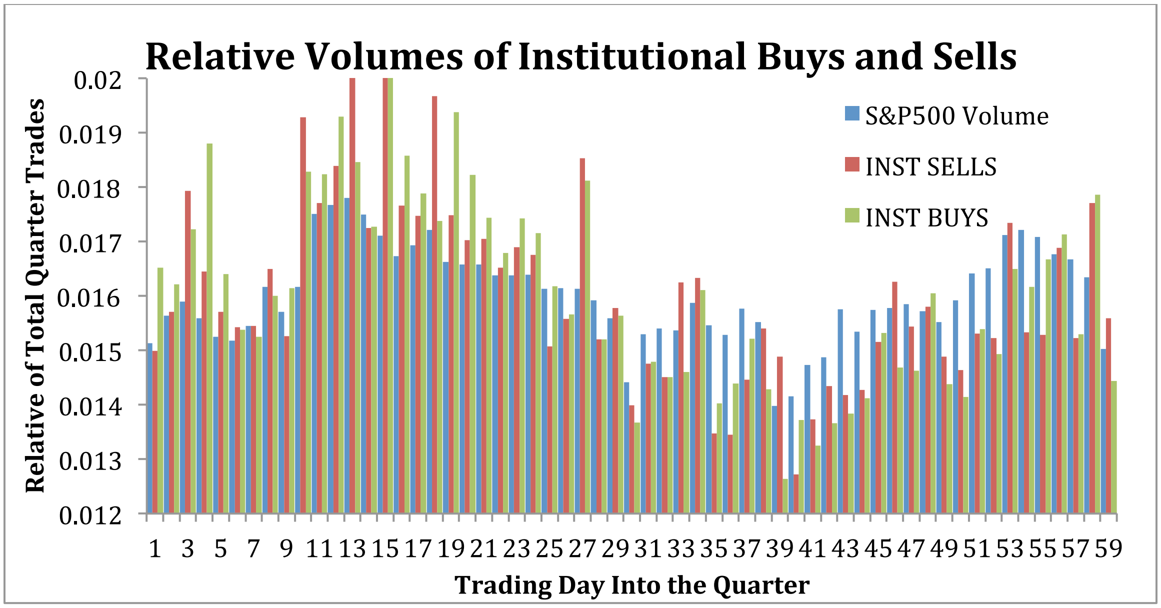
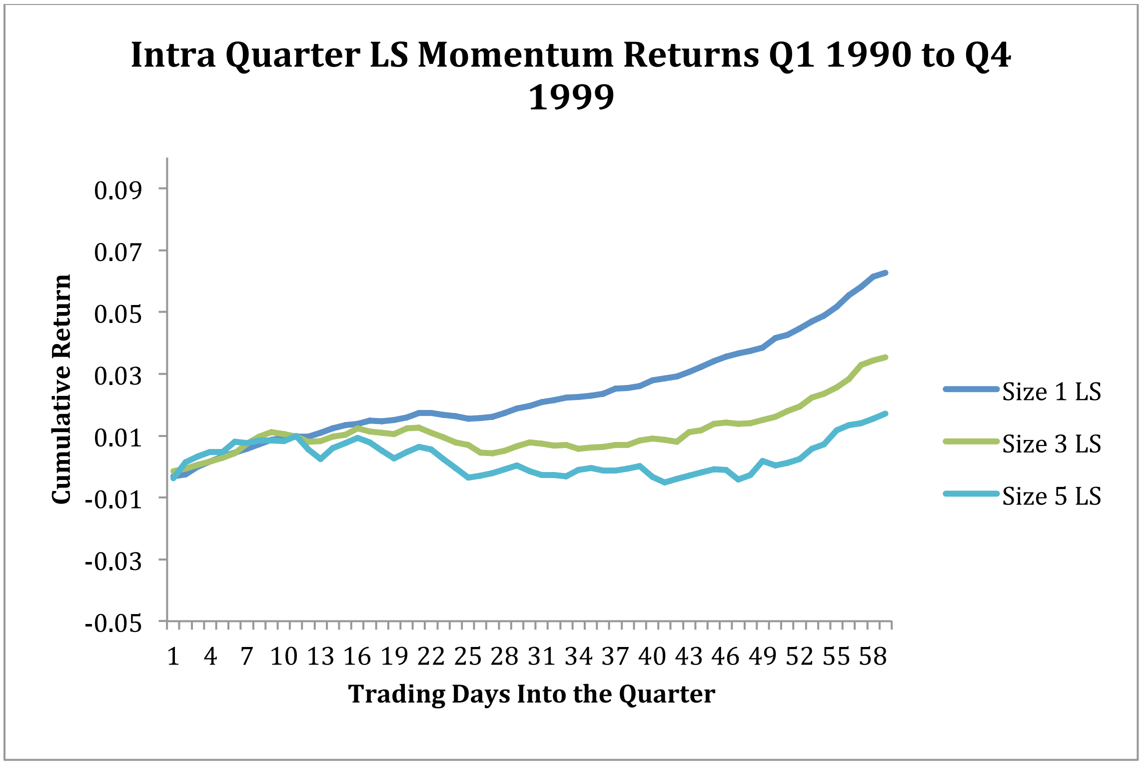


Figure 2. The intra quarter pattern of Asset Managers trades. The blue bars represent the average S&P500 volume, whereas the red and green represent the sells and buy volumes originating from asset managers.



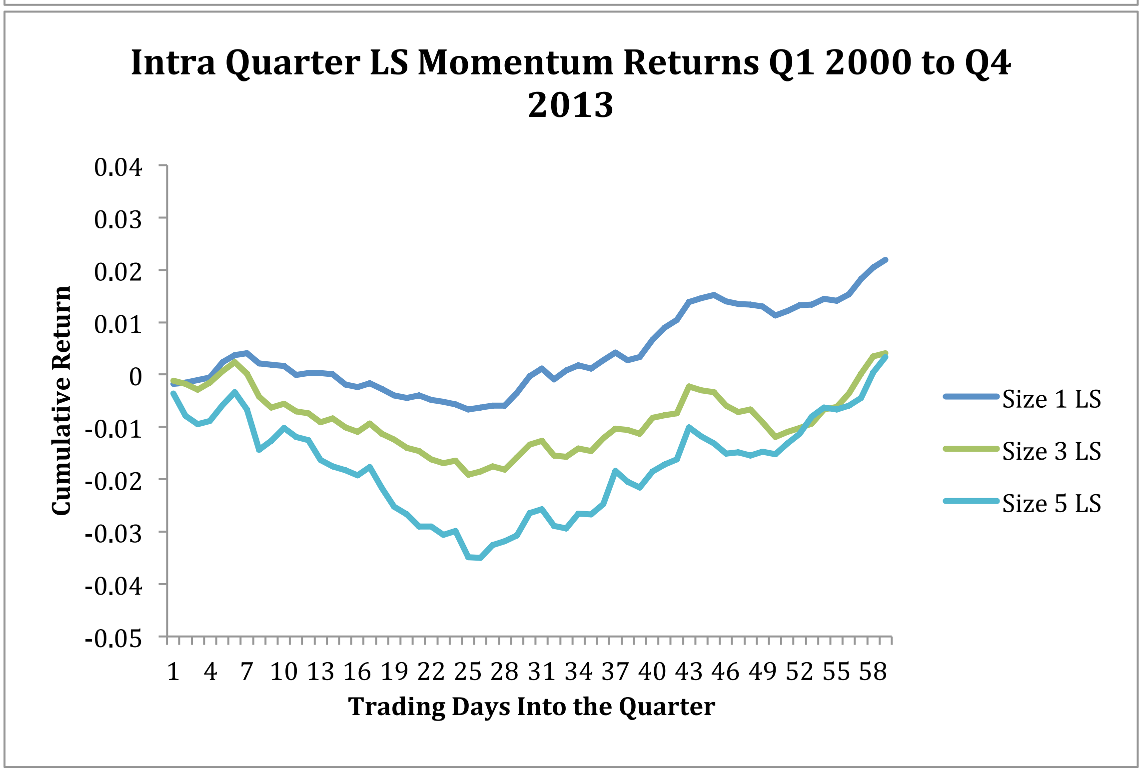
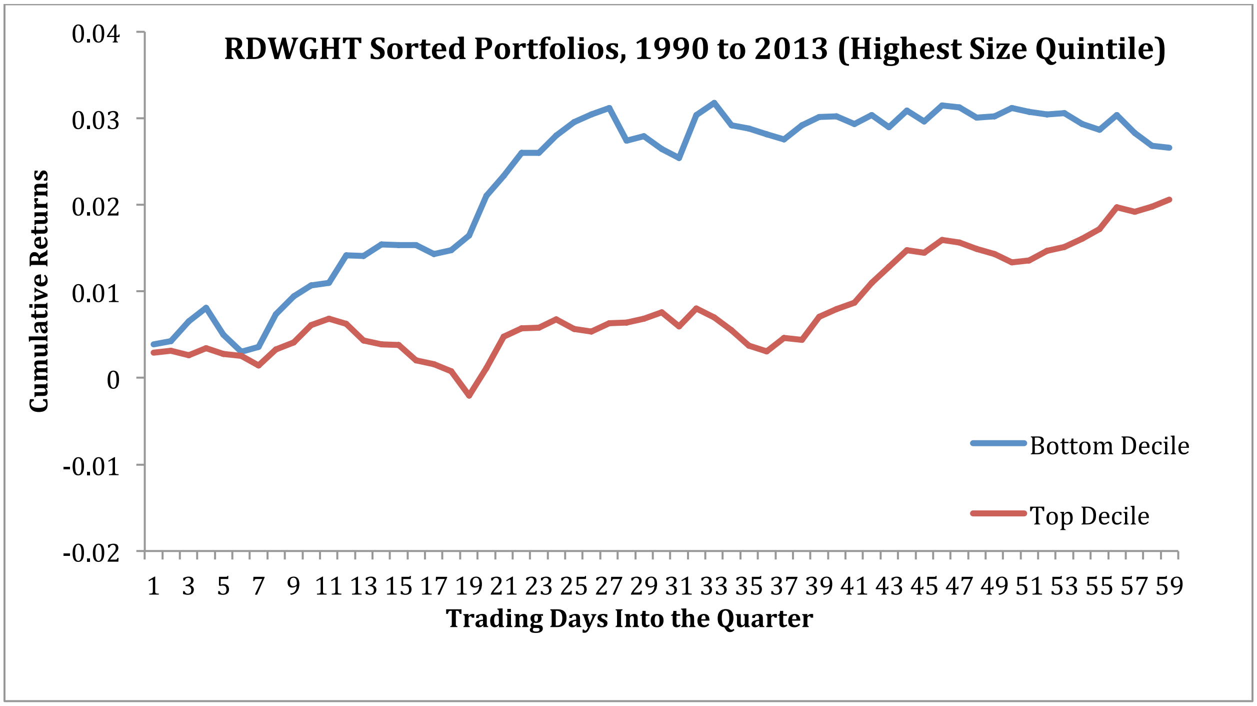


Figure 3. Return patterns for the momentum and size sorted portfolios from Q1 1990 to Q4 1999 (top) and Q1 2000 to Q4 2013 (bottom).



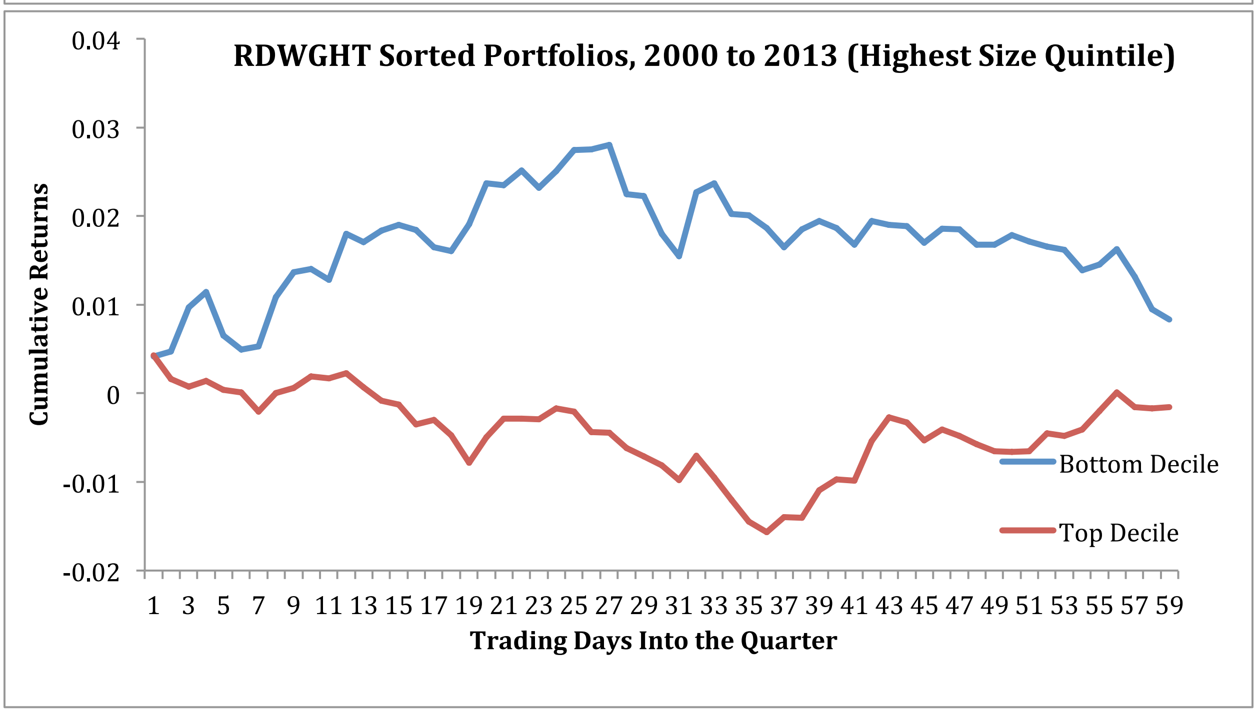


Figure 4. Portfolio returns of the top decile and the bottom decile of $\overline{RDWGHT}$ sorted portfolios.

2.9 Appendix Tables and Figures:

	Momentum (2 to 12 Month Returns)					
	LS (U - D)					
	1st of Quarter		Ignoring Jan		Rest of Quarter	
	1990-2013	2000-2013	1990-2013	2000-2013	1990-2013	2000-2013
Size 1	-0.008	-0.015	0.006	-0.004	**0.016**	0.009
	(-0.90)	(-1.14)	(0.75)	(-0.31)	**(3.80)**	(1.34)
Size 2	-0.003	-0.014	0.000	-0.013	**0.012**	0.007
	(-0.43)	(-1.07)	(-0.01)	(-0.86)	**(2.85)**	(1.19)
Size 3	-0.006	-0.016	-0.004	-0.015	**0.011**	0.010
	(-0.73)	(-1.38)	(-0.49)	(-1.14)	**(2.60)**	(1.56)
Size 4	-0.008	-0.017	-0.005	-0.015	**0.013**	0.014
	(-0.96)	(-1.40)	(-0.52)	(-1.06)	**(2.74)**	(1.87)
Size 5	-0.011	**-0.027**	-0.005	-0.019	**0.013**	**0.018**
	(-1.39)	**(-2.47)**	(-0.59)	(-1.67)	**(2.98)**	**(2.78)**

Table A1a. Momentum portfolio returns (25 portfolios) sorted by size. Each long short portfolio is calculated using the top quintile (U) return minus the bottom quintile (D) return.

	Reversal (1 Month Returns)					
	LS (D - U)					
	1st of Quarter		Ignoring Jan		Rest of Quarter	
	1990-2013	2000-2013	1990-2013	2000-2013	1990-2013	2000-2013
Size 1	**0.022**	**0.024**	0.008	0.011	-0.005	-0.005
	(3.27)	**(2.33)**	(1.33)	(1.24)	(-1.56)	(-0.97)
Size 2	**0.015**	**0.020**	0.010	0.014	-0.001	-0.003
	(2.73)	**(2.31)**	(1.56)	(1.51)	(-0.44)	(-0.60)
Size 3	**0.016**	**0.018**	0.012	0.014	-0.003	-0.004
	(3.01)	**(2.26)**	(1.95)	(1.52)	(-0.82)	(-0.81)
Size 4	0.008	0.015	0.003	0.007	-0.003	-0.006
	(1.43)	(1.78)	(0.47)	(0.74)	(-0.83)	(-1.07)
Size 5	**0.013**	**0.023**	0.009	0.019	-0.004	-0.005
	(2.21)	**(2.65)**	(1.33)	(1.83)	(-1.21)	(-0.88)

Table A1b. Short-Term Reversal portfolio returns (25 portfolios) sorted by size. Each long short portfolio is calculated using the bottom quintile (U) return minus the top quintile (D) return.

	Momentum (2 to 12 Month Returns)					
	LS (U - D)					
	1st of Quarter		Ignoring Jan		Rest of Quarter	
	1970-1990	1950-1970	1970-1990	1950-1970	1970-1990	1950-1970
Size 1	0.004	0.000	0.023	0.016	0.023	0.015
	(0.57)	(-0.06)	(4.54)	(3.42)	(7.20)	(5.50)
Size 2	0.012	0.008	0.022	0.019	0.016	0.012
	(2.17)	(1.64)	(3.98)	(4.34)	(5.24)	(4.75)
Size 3	0.013	0.011	0.019	0.019	0.013	0.012
	(2.34)	(2.55)	(3.07)	(3.92)	(3.84)	(4.60)
Size 4	0.006	0.008	0.014	0.014	0.013	0.013
	(0.98)	(1.67)	(2.09)	(2.69)	(3.72)	(5.25)
Size 5	0.006	0.006	0.009	0.012	0.008	0.011
	(0.93)	(1.38)	(1.30)	(2.26)	(1.84)	(4.25)

Table A2a. Momentum portfolio returns (25 portfolios) sorted by size at other holding periods. Each long short portfolio is calculated using the top quintile (U) return minus the bottom quintile (D) return.

	Reversal (1 Month Returns)					
	LS (U - D)					
	1st of Quarter		Ignoring Jan		Rest of Quarter	
	1970-1990	1950-1970	1970-1990	1950-1970	1970-1990	1950-1970
Size 1	0.025	0.022	0.007	0.005	0.004	0.009
	(4.21)	(4.76)	(1.52)	(1.41)	(1.71)	(4.62)
Size 2	0.018	0.012	0.010	0.002	0.008	0.006
	(3.75)	(3.58)	(2.11)	(0.68)	(3.12)	(3.00)
Size 3	0.014	0.010	0.011	0.005	0.009	0.008
	(3.37)	(3.56)	(2.34)	(1.43)	(3.82)	(3.97)
Size 4	0.011	0.009	0.008	0.004	0.010	0.009
	(2.59)	(3.12)	(1.78)	(1.13)	(3.79)	(4.98)
Size 5	-0.003	0.004	-0.005	0.000	0.005	0.006
	(-0.67)	(1.09)	(-1.03)	(0.12)	(1.38)	(2.63)

Table A2b. Short-term Reversal portfolio returns (25 portfolios) sorted by size at other holding periods. Each long short portfolio is calculated using the top quintile (U) return minus the bottom quintile (D) return.

Chapter 2
Mutual Fund Impact From

Distribution Flows

2.1 Introduction and Related Literature:

The asset management industry in the US follows a specific distribution scheme. As mandated by the Investment Company Act, all capital gains and dividends accumulated to an asset manager must be redistributed back to the original investors before the yearend, regardless of the investors' plans. For many funds, the dividends that accrue to a particular asset portfolio are stored as cash equivalents until the prescheduled distribution date. Investors of a fund place standing orders to reinvest or to receive the distributions as cash. Prior to these events, the accrued dividend distributions are not reinvested and are not under the discretion of the portfolio manager or the original investor. Additionally, fund investors have to pay taxes on the distributions they obtain regardless of the holding period of their investment. Many fund families, including Vanguard and Fidelity, explicitly warn investors not to invest until after their funds' distributions. In effect, these combined factors generate calendar time discontinuities in the availability of investible cash at the hands of asset managers. This paper first documents the direct price and covariance effects of the distribution scheme in aggregate and in the cross section of equity assets. From January 1980 to December 2013, days after major equity fund distributions are associated with about 9 basis points of market return each day compared to 2 basis points on the other trading days. On average, portfolios under a mutual fund's management experience 6 basis points increase in daily returns 5 days after a distribution when compared to the 5 days before. Then, exploiting this staggering of fund cash flow, I study the impact of professional asset management on relative asset returns. I show that fund managers, in general, exhibit a purchasing bias toward their own past losses. Within each equity mutual fund portfolio, assets that incurred the most losses experienced the greatest distribution flow induced pricing pressure. The sub-portfolio of relative losers incurred a larger increase in daily returns after a distribution event than the sub-portfolio of relative winners by an average of 26 (58) basis points in the 5 (10) days after versus before a distribution event. These results indicate that institutional structures contribute to the daily variation of stock market returns and that manager preference has significant impact over the relative prices of his managed assets.

The current paper is relevant to a few branches of the empirical asset pricing literature. One branch is on the price impacts of mutual funds and professional asset management. Coval and Stafford (2007) and Lou (2012) show that fund flow affects the underlying assets under the same mutual fund umbrella. Anton and Polk (2014) documents excess covariance and reversals of assets connected by the same mutual fund ownership. The current paper contributes over these studies by documenting the aggregate impact of mutual fund structure. In contrast to recent literatures on FOMC predictability (Lucca and Moench, 2013) and investor attention (Frazzini and Lamont, 2007), I show that institutional features are also a significant source of daily variations in equity return and by extension in the equity risk premium. Methodologically, I also extend the mutual fund literature by introducing plausibly exogenous inflows unrelated to events in the financial markets.

This paper is also related to the empirical behavior of investors. As demonstrated by a literature starting with Kahneman and Tversky's (1979) seminal prospect theory, investors experience losses differently from gains. This has led to the discovery of the well-known phenomenon of the disposition effect (Shefrin and Statman, 1985; Odean, 1998; Frazzini, 2006; Calvet, Campbell, and Sodini 2009), in which retail investors are shown to resist selling assets that have experienced losses and readily liquidate assets that have experienced gains. However, unlike retail investors in the case of the disposition effect, money managers are large collective traders. Their portfolios are driven by investor deposits to purchase shares and they have the market power to impact prices. In this paper, I show that, when experiencing distribution related inflows, professional asset managers drive up the prices of assets on which they have experienced the most loss. More than just not selling their losers, money managers induce pricing pressure on these assets; thereby partially reversing the returns they have experienced. This also contrasts the prior literature on mutual fund flows, which assume that the underlying assets within a portfolio are homogenously affected by additional in and outflow. Instead, the current paper finds that asset managers affect their winnings and losses differently. When given additional inflow, asset managers impact their losses significantly more so than their winnings.

This paper is related to a set of papers that argue institutional features generate variations in aggregate returns. Settlements of funds are classically used to explain turn over the month increases in market returns in Odgen (1990). The current paper directly studies one specific institutional feature, and most of the analyses here are conducted with month end fixed effects. In fact, the only other paper that I'm aware of that involves mutual fund distribution is Rinne, Suominen, and Vaittinen (2015). The authors hypothesize that institutional cash demands prior to the month-end due to distributions and related cash requirements place excess liquidity demand on the market prior to the month end, and this coincides with a reversal of aggregate market returns prior to the month end. My paper instead studies the price impact of mutual fund distribution reinvestment by documenting the increased cross sectional and aggregate returns after a distribution event. I also subsequently use distributions as a potentially exogenous variation in investment cash to understand asset managers' behavior in portfolio choice.

Data is introduced in the next section and the rest of the paper is organized as follows. First, I demonstrate that distribution events are associated with subsequent pricing pressure on equity assets. I aggregate the distributions by equity funds into a time series and show that this series contains predictability about market returns at the daily frequency. Event studies of the distribution period around equity funds are formed and shown. Returns of portfolios under mutual fund management experience an increase of 6 basis points per day in the five days after the fund's distribution. Aggregate daily market returns increases by 9 to 10 basis points in the days following major aggregate distributions. I then use the distribution events to study the cross section of price impact by mutual fund inflow. I divide each mutual fund portfolio into sub-portfolios based on the characteristics of the underlying assets. The most important of the characteristics is the historical gains and losses of the assets under management. I show that the sub-portfolios of losers tend to receive the greatest price impact around the distribution event. A formal statistical test of the difference between the sub-portfolio of losers and the sub-portfolio of winners is conducted. The last section discusses the results and concludes.

2.2 Data and Methods:

I use the CRSP Stock Return, CRSP Mutual Fund, and the Thomson Reuter/Spectrum databases for the current analysis. All stock returns come from CRSP Daily and Monthly Stock Returns database. Data related to dividend and capital gain distributions, as well as asset portfolio compositions come from CRSP Mutual Fund database. The equity funds used are match to the Thomson Reuter/Spectrum holdings through a given linkage table from Wharton Data Services, and the Thomson Reuter/Spectrum holdings are used to calculate portfolio related returns. Table 1 contains the basic summary statistics on the data used.

<Table 1>

2.2 Price Impact from Mutual Fund Distributions:

Assets under a fund management experience a significant increase in the daily average return in the trading week after the fund's distribution date. In figure 1, I show a selection of large US equity funds and market returns around the date of these distributions.

<INSERT FIGURE 1>

I expand the distribution event window to all equity funds[4] and study the returns of their value-weighted portfolio (using the last holdings data from Thomson Reuters as reference) in the days prior to the days after their distributions.

<INSERT FIGURE 2>

The underlying portfolios on average experienced an average of 0.06 (2.22) basis points each day in the 5 days after a mutual fund distribution when compared to the days before.

If the average distribution is cyclical and impacts the cross section of asset prices, then total distribution by mutual funds should affect the market in aggregate. I sum up the distributions by equity funds into a time series and use this series to forecast market returns from 1980 to 2013. First, I use log of the daily distribution normalized by the past 252 trading day total distributions to forecast market returns at the 5-day horizons. I add in monthly fixed effects to account for seasonality in the equity returns. Newey-West adjustments with 30 trading day lags are used to calculate the standard errors.

[4] I define an equity fund as any fund that contains at least 95% of its assets in cash equivalents and us common stocks and 0% in municipals, bonds, and treasuries. Mixed and bond funds tend to pay distributions monthly, whereas equity funds tend to pay quarterly and semi-annually.

<INSERT TABLE 2>

To account for the magnitude of this predictability, I devise a simple event day investment strategy by investing only in periods after a major distribution event in the yearly calendar. A plot of distributions from 2013 is included in panel (a) of Figure 3. The distribution events show a clustering of large distributions around certain dates and close to nil distributions on the rest. I call a day, a distribution event, if that day contains more distributions than 90% of the distributions in the past year. This method is reasonable at capturing a large number of the peaks in the distribution time series, without overweighing the capital gain events in December. This can be seen in the panel (b) of Figure 3, which marks event days with a higher asterisk.

<INSERT FIGURE 3>

I call a day a post distribution event day if it is within 5 days after a distribution event. I then regress the previous dummy variable on daily market returns. This is in line with an investment strategy that only invests in those days after a large distribution period and demonstrates that days following large mutual fund distributions have more returns than any other day of the year.

<INSERT TABLE 3>

In fact for the entirety of January 1980 to December 2013, despite only accounting for about 30% of the trading days, these post distribution event dates account for 78% of the aggregate valued weighted market return and 87% of the S&P 500 return in log scale. For the sample period from January 2000 to December 2013, the effect is even more severe, with these dates accounting for over 178% of the market return, and 390% of the S&P 500 return. An investment strategy that invests in the valued weighted market only during post distribution periods and the risk free asset in the rest has an annualized sharp ratio of over 90%.

<INSERT FIGURE 4>

2.3 Stock Selection and Impact:

I use the distribution events as a window to observe mutual funds' discretionary usage of investor flow for investment activities. The major limitation of the existing literature of mutual fund purchases and sales is that researchers cannot easily control for changes in mutual fund size and investment flow. Even worse, retail investment flows are endogenous to investment decisions. Specifically, investment flows are very much forecastable by market returns (Edelen and Warner, 2000), past investment flows (Coval and Stafford, 2007), and investor sentiments (Kumar and Lee, 2006). The event window study of the returns of the holding portfolio of mutual funds allow for a cleaner event study of the characteristics of assets that make them attractive to mutual fund managers.

In this section, I divide each equity fund portfolios into five sub portfolios based on size, past quarter returns ending at the last holdings date, and investment gains and losses in the past quarter. Investment gains and losses are calculated using the portfolio weight coming from the quarter before the last holding record date, assuming non-trading between the two holding periods. I sort the portfolio assets into the sub-portfolios based on these characteristics and then examine the returns of these sub-portfolios in the periods before and after a distribution period for each mutual fund.

In table 5, I record the average returns of equal weighted sub-portfolios based on asset size in event windows ranging from [-5,5], [-10,10] days, and [-15,15] days around a distribution period. I find that mutual funds don't seem to bias their portfolios toward any particular direction based on the size of the underlying stocks after a distribution period. The average sub-portfolio returns are decreasing based on size both before and a distribution event. While, the returns of the subportfolios all increased after a distribution event, the difference in the change of average returns between the smallest size and the largest size subportfolios is small and insignificant.

<INSERT TABLE 4>

In table 6, I record a similar sorting based on past returns. This time, I find some evidence that within a mutual fund portfolio, the sub-portfolio of past winners tend to underperform the sub-portfolio of past losers. After a distribution event, the subportfolio of losers tend to outperform the winners by 10 basis points in the 5 day horizon, by 41 basis points in the 10 day horizon, and 61 basis points in the 15 day horizon. This is compared to an underperformance of 6 basis points in the 5 days prior, 16 basis points in the 10 days prior, and 10 basis points in the 15 days prior. The difference in difference of returns is significant at the 95% using double clustered standard errors at the 10 days event horizon.

<INSERT TABLE 5>

Finally, to adjust the sorting on returns, I use the average within portfolio gains and losses. There is a large behavioral literature that documents the separation of gains and losses in the mental accounting of investors. This has been largely explored in the disposition effect literature on retail investments. The stylized documented fact is that investors tend to sell their losses much slower than their gains. The question here is whether the logic of the disposition effect can be extended to mutual fund purchases. Given an exogenous inflow of investible capital, how do asset managers invest?

In Table 7, I document that funds tend to drive up the prices of their largest losses as opposed to their largest gains. With in each fund/event portfolio observation, the subportfolio of the assets that the fund had experienced its largest losses had 16 basis point higher returns than the subportfolio of the assets with the largest gains in the 5 days horizon. In the 10 days and 15 days horizon, the differences are up to 43 and 57 points respectively. This is in contrast to the days before the mutual fund's distribution, in which the subportfolio of losses underperformed the gains by 8, 17, and 9 basis points respectively for the 5, 10, and 15 days horizon. The difference in the difference of returns at 24 points and 58 points is significant at the 95% confidence.

<INSERT TABLE 6>

2.5 Conclusion:

In this paper, I examine the effect of the equity distribution cycles on the equity assets. Due to tax demands and the staggering in reinvestment capital, distributions have predictability over both the cross section of mutual fund returns and the aggregate of market returns. Using distribution events as variations on inflows of capital, I contribute additional empirical facts about the nature of asset manager behavior. Such behaviors have impact on the cross section of asset returns and contribute to the relative valuation of assets in the financial markets.

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2.7 Figures & Tables:

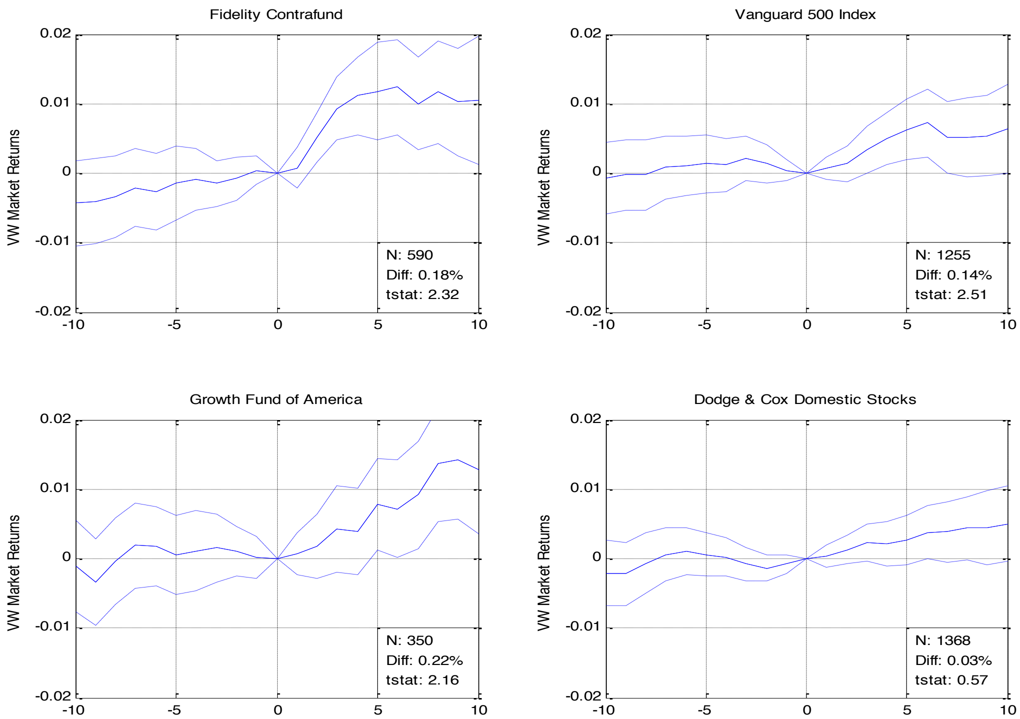

Figure 1. The figures above are event study graphs of the valued-weighted market returns around the distribution dates (both capital gains and dividends) of 4 of the current largest open-ended mutual funds. The solid lines are the cumulative returns around the distribution dates, while the dashed blue lines are the 95% confidence interval. Market returns of 5 days before the events are compared to those of 5 days after in the boxes on the lower right hand corner. For example, daily market returns in the 5 days after a Fidelity Contrafund distribution event are on average 18 basis points higher than in the 5 days before. The sample runs from January 1980 to 2013. Funds within the same mutual fund institution tend to have similar distribution dates, so Vanguard Total Stock Market fund has a similar pattern to the Vanguard 500 plotted above.

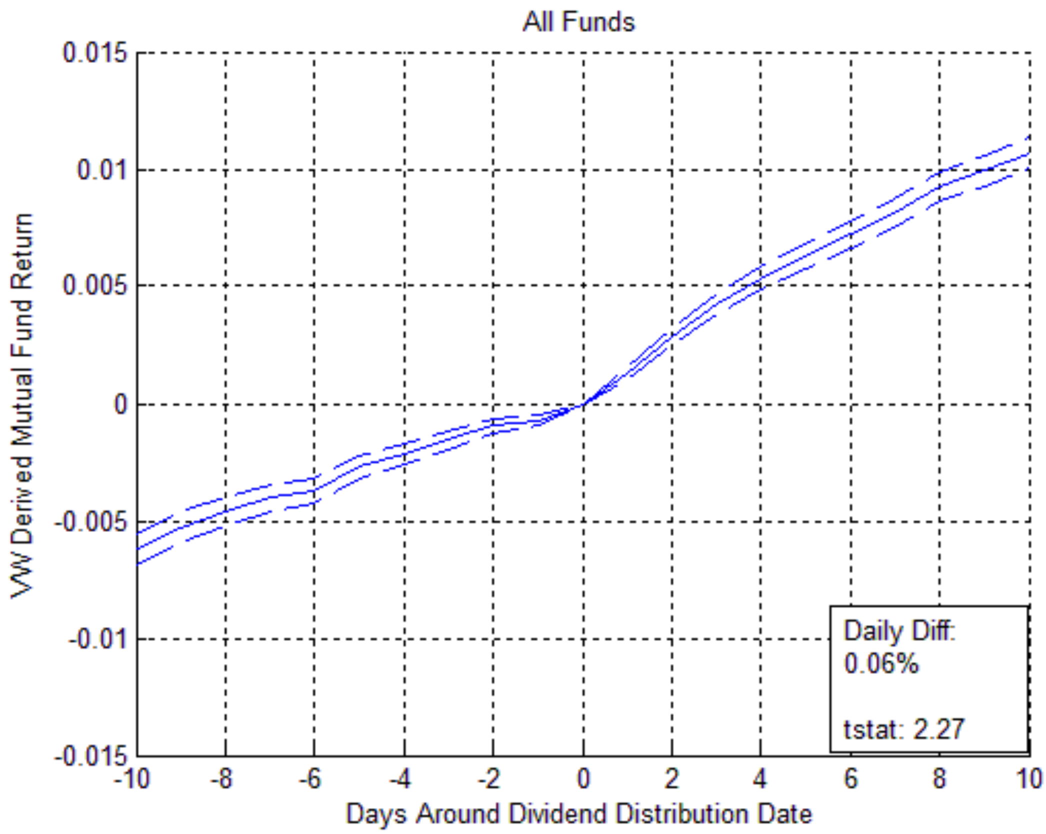

Figure 2. The graph documents the VW returns of mutual fund holdings in the -10 to +10 days window around a distribution event date. While on average, holding returns tend to be positive both before and a distribution event, the returns after is higher sloped than the days before. The cumulative 5 day returns after a distribution event per mutual fund on average is 30 basis points higher than the 5 days before. The difference is significant at the 95% confidence under double clustering of fund and quarter.

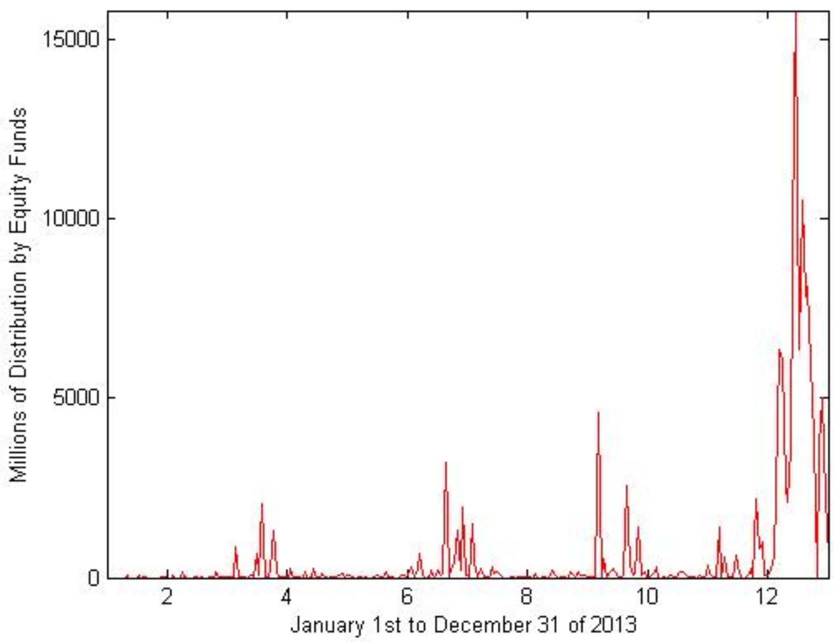

Figure 3a. Total equity fund distributions in 2013 according to the CRSP Mutual Fund database.

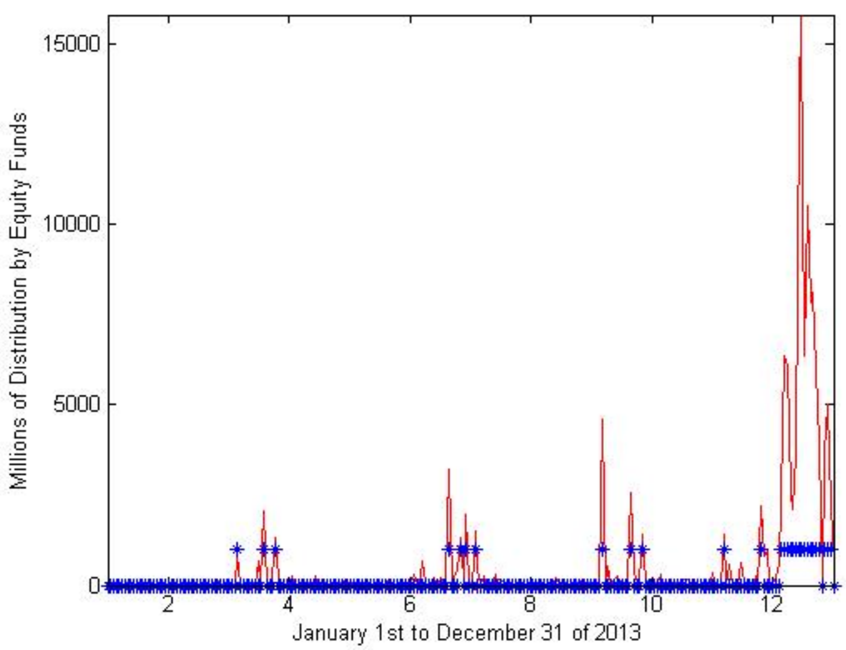

Figure 3b. Dates coinciding with major equity distributions are marked with higher leveled asterisks. This is defined as dates that have more distribution passed through than 90% of the 252 trading days immediately prior. This method gives approximately 27 event dates per trading year on average.

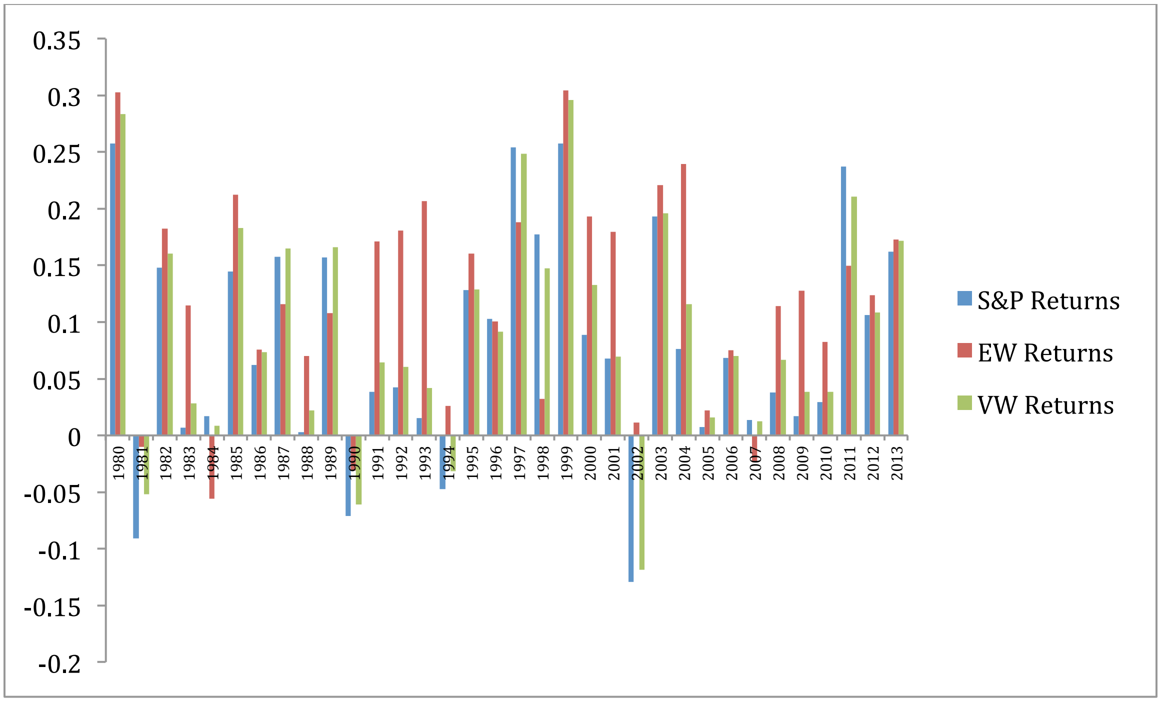

Figure 4. The figure documents the trading returns of a strategy that only invests during the 5 days after a large distribution event.

	Summary Statistics							
	Mean	Std	Min	25 P.	Median	75 P.	Max	N
N. of Equity Fund Per Year	4499	4385	140	217	3919	8199	14796	34
N. of Events Per Year	7899	7132	240	329	8113	14405	20010	34
Fund Size (Year/Fund Obs in M.)	350	1817	0.001	5.1	35.2	178	105938	150632
Daily Distribution Size (M.)	258	1496	0	0	3.76	45.3	72871	8577
Number of Stocks Held (Event/Portfolio Obs)	135	214	31	50	74	119	3102	74285

Table 1. Summary statistics of the sample of equity funds used. The sample period is from January 1980 to December 2013.

	VW Market Return		
	1980 to 2013	1990 to 2013	2000 to 2013
Intercept	0.6400	0.5600	0.2500
	(2.49)	(1.97)	(0.68)
ScaledDistr	0.0500	0.0500	0.0400
	(2.50)	(2.51)	(1.72)
Monthly Fixed	YES	YES	YES
R^2	0.0047	0.0075	0.0090

Table 2. I generate the variable *ScaledDistr* as defined as the log of one plus equity fund distributions divided by the total distribution summed over the past 252 trading days. I forecast total forward 5 days market returns with this variable.

	VW Market Return		
	1980 to 2013	1990 to 2013	2000 to 2013
Intercept	0.0210	0.0130	-0.0070
	(1.47)	(0.76)	(-0.30)
EventDum	0.0910	0.1040	0.1320
	(3.60)	(3.21)	(2.57)
R^2	0.0014	0.0015	0.0016
	EW Market Return		
	1980 to 2013	1990 to 2013	2000 to 2013
Intercept	0.0580	0.0630	0.0280
	(4.97)	(4.33)	(1.28)
EventDum	0.0870	0.1010	0.1530
	(4.16)	(3.70)	(3.40)
R^2	0.0019	0.0021	0.0029
	S&P 500 Return		
	1980 to 2013	1990 to 2013	2000 to 2013
Intercept	0.0130	0.0060	-0.0160
	(0.90)	(0.35)	(-0.62)
EventDum	0.0840	0.0980	0.1230
	(3.20)	(2.98)	(2.41)
R^2	0.0011	0.0013	0.0014

Table 3a. I generate the total distribution by equity funds (non-ETF) from the CRSP open ended mutual fund database each day. I call a day that has more total distribution than 90% of the past 252 trading days a distribution event. Approximately 30% of the trading days in the sample are within 5 days after a distribution event. I assign 1 to the EventDum if a day occurs within 5 days after a major distribution event. Since these events are known ahead of time, I regress dummies of these dates against various market returns in a predictive regression. The t-stats are from OLS. White and NW standard errors have higher the significance.

	VW Market Return					
	1980 to 2013			2000 to 2013		
Intercept	0.0204	0.0123	-0.0090	-0.0156	-0.0291	-0.0472
	(1.40)	(0.84)	(-0.56)	(-0.58)	(-1.07)	(-1.58)
EventDum	0.0927	0.0907	0.0791	0.1628	0.1643	0.1551
	(3.42)	(3.34)	(2.89)	(2.73)	(2.76)	(2.60)
FOMC Dates		0.2654	0.2631		0.3915	0.3867
		(4.03)	(4.00)		(3.16)	(3.12)
Turn of Month			0.0874			0.0719
			(3.34)			(1.45)
Month Fixed	YES	YES	YES	YES	YES	YES
R^2	0.0009	0.0026	0.0038	0.0001	0.0026	0.0029

Table 3b. I regress dummies of these event dates against value weighted market returns in a predictive regression as in the table above, but now include various controls. The t-stats are from OLS. White and NW standard errors have higher significance.

	5 Days			10 Days			15 Days		
	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff
Smallest Size	0.0058	0.0088	0.0030	0.0105	0.0140	0.0035	0.0143	0.0181	-0.0002
	(3.79)	(3.77)	(1.95)	(3.51)	(3.73)	(1.25)	(3.71)	(4.04)	(-0.03)
2	0.0052	0.0078	0.0026	0.0096	0.0126	0.0031	0.0147	0.0162	-0.0005
	(3.82)	(3.88)	(1.84)	(3.73)	(3.86)	(1.20)	(3.29)	(4.07)	(-0.09)
3	0.0049	0.0074	0.0025	0.0092	0.0120	0.0028	0.0159	0.0153	-0.0006
	(3.64)	(3.71)	(1.84)	(3.75)	(3.76)	(1.13)	(3.25)	(3.99)	(-0.11)
4	0.0045	0.0073	0.0028	0.0083	0.0117	0.0034	0.0167	0.0148	0.0001
	(3.45)	(3.79)	(2.22)	(3.54)	(3.92)	(1.56)	(3.25)	(4.09)	(0.03)
Biggest Size	0.0041	0.0066	0.0026	0.0080	0.0105	0.0025	0.0183	0.0128	-0.0016
	(3.62)	(4.04)	(2.19)	(4.05)	(4.01)	(1.27)	(3.08)	(3.92)	(-0.35)
Difference			0.0004			0.0010			0.0013
			(0.62)			(0.71)			(0.59)
N		14401			14142			13861	

Table 4. Stocks for each portfolio event observation are divided into 5 subportfolios based on their market cap at the last fund holding date. Stocks with prices less than 5 and market caps lower than the 10th percentile of the NYSE trade stocks are kicked out. I calculate the average return of the portfolios in the 5, 10, 15 days before and after the return date while making sure that the sorting times don't overlap with the calculated time. The difference between the cumulative returns before and after the distribution event is calculated in the diff column. I record the average returns of equal weighted sub-portfolios based on asset size in event windows ranging from [-5,5], [-10,10] days, and [-15,15] days around a distribution period. The average sub-portfolio returns are decreasing based on size both before and after a distribution event. While, the returns of the subportfolios all increased after a distribution event, the difference in the change of average returns between the smallest size and the largest size subportfolios is small and insignificant. The sample period is from January 1980 to December 2013.

	5 Days			10 Days			15 Days		
	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff
Lowest Weight	0.0052	0.0085	0.0032	0.0098	0.0140	0.0042	0.0174	0.0180	0.0006
	(3.34)	(3.75)	(2.26)	(3.21)	(3.64)	(1.51)	(2.80)	(3.96)	(0.10)
2	0.0050	0.0079	0.0028	0.0093	0.0127	0.0034	0.0164	0.0164	-0.0001
	(3.50)	(3.68)	(1.97)	(3.50)	(3.79)	(1.38)	(3.07)	(4.10)	(-0.01)
3	0.0047	0.0074	0.0026	0.0089	0.0120	0.0031	0.0157	0.0152	-0.0005
	(3.68)	(3.74)	(1.98)	(3.73)	(3.83)	(1.36)	(3.29)	(4.08)	(-0.11)
4	0.0048	0.0072	0.0024	0.0088	0.0115	0.0026	0.0153	0.0145	-0.0008
	(3.94)	(3.95)	(1.87)	(4.02)	(4.00)	(1.19)	(3.60)	(4.14)	(-0.18)
High Weight	0.0047	0.0069	0.0022	0.0088	0.0106	0.0018	0.0150	0.0131	-0.0019
	(4.04)	(4.06)	(1.87)	(4.32)	(3.92)	(0.86)	(4.10)	(3.80)	(-0.42)
Difference			0.0010			0.0024			0.0025
			(1.54)			(1.90)			(1.10)
N		14401			14142			13861	

Table 5. Stocks for each portfolio event observation are divided into 5 subportfolios based on their 3 month past returns at the last fund holding date. Stocks with prices less than 5 and market caps lower than the 10th percentile of the NYSE trade stocks are kicked out. I calculate the average return of the portfolios in the 5, 10, 15 days before and after the return date while making sure that the sorting times don't overlap with the calculated time. The difference between the cumulative returns before and after the distribution event is calculated in the diff column. I record the average returns of equal weighted sub-portfolios based on asset size in event windows ranging from [-5,5], [-10,10] days, and [-15,15] days around a distribution period. The average sub-portfolio returns are decreasing based on past returns after a distribution event, and increasing before a distribution event. The sample period is from January 1980 to December 2013.

	5 Days			10 Days			15 Days		
	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff	Pre Ret	Post Ret	Diff
Highest Loss	0.0042	0.0083	0.0041	0.0079	0.0146	0.0066	0.0150	0.0181	0.0031
	(2.57)	(3.41)	(2.45)	(2.47)	(3.18)	(2.02)	(2.30)	(3.46)	(0.51)
2	0.0047	0.0079	0.0032	0.0089	0.0135	0.0046	0.0158	0.0167	0.0009
	(3.32)	(4.05)	(2.50)	(3.16)	(3.82)	(1.80)	(2.95)	(4.02)	(0.18)
3	0.0048	0.0072	0.0024	0.0089	0.0119	0.0029	0.0157	0.0148	-0.0009
	(3.93)	(4.43)	(1.96)	(3.77)	(4.18)	(1.29)	(3.37)	(4.39)	(-0.18)
4	0.0049	0.0069	0.0020	0.0093	0.0109	0.0016	0.0158	0.0135	-0.0022
	(4.31)	(4.30)	(1.68)	(4.25)	(4.11)	(0.74)	(3.90)	(4.17)	(-0.48)
Highest Gain	0.0050	0.0067	0.0017	0.0096	0.0103	0.0008	0.0159	0.0124	-0.0035
	(4.43)	(3.74)	(1.19)	(4.67)	(3.46)	(0.31)	(4.66)	(2.96)	(-0.70)
Difference			0.0024			0.0058			0.0066
			(2.18)			(2.22)			(1.75)
N	12611			12380			12120		

Table 6. Stocks for each portfolio event observation are divided into 5 subportfolios based on their 3 month past gains and loss from the last holdings to holdings date. Stocks with prices less than 5 and market caps lower than the 10th percentile of the NYSE trade stocks are kicked out. I calculate the average return of the portfolios in the 5, 10, 15 days before and after the return date while making sure that the sorting times don't overlap with the calculated time. The difference between the cumulative returns before and after the distribution event is calculated in the diff column. I record the average returns of equal weighted sub-portfolios based on asset size in event windows ranging from [-5,5], [-10,10] days, and [-15,15] days around a distribution period. After a distribution event, the average sub-portfolio returns are decreasing based on the assets' gain and loss, while the returns are increasing based on gains before a distribution event. The sample period is from January 1980 to December 2013.

Chapter 3

Industry Window Dressing

3.1 Introduction:

Investors are continuously faced with a large number of potential signals that are available to collect and process. Faced with these, investors need to solve the complex time allocation problem with respect to selecting an processing each potential signal. If investors specialized in collecting disjoint signals, the processing constraints of each disparate investor would not matter for aggregate prices, as prices would reflect the sum of their investment capacity. If, however, investors take correlated shortcuts in their investing, then simple pieces of information can remain systematically unreflected in firm prices. Moreover, if firm managers are aware of these shortcuts and their implications, managers may take specific actions to exploit these investment shortcuts.

In this paper, we identify one such shortcut that financial agents take and document how it affects both prices and resulting managerial behavior. Specifically, we examine the primary industry into which each firm is classified. The Securities and Exchange Commission (SEC), in classifying firm operations, designates that each firm have a primary industry, which is determined by the segment with the highest percentage of sales.[5] Using this rule, we exploit situations in which firms tightly surround the discontinuity point of industry classification. For example, a firm that gets 51% of its sales from technology and 49% of sales from lumber is classified as a technology firm, whereas a firm with nearly

[5] Many large and diversified firms fall into multiple SIC categories; hence, the category that accounts for the largest share of sales is known as the company's "primary" industry (Guenther and Rosman, 1994; and Kahle and Walkling, 1996).

identical operations but that gets 49% of its sales from technology and 51% of sales from lumber is classified as a lumber firm.

If investors overly rely on this primary industry classification in their investment decisions without factoring in the underlying economic operations of firms, they may perceive or treat nearly identical firms around the discontinuity point in substantially different ways. We examine this idea of naive categorization by examining both stock return patterns and (more directly) investor behavior. First, we explore how investors price these firms. We find that despite being nearly identical, firms just over the 50% point (in terms of percentage sales from a particular industry) have significantly higher betas with respect to that industry than firms just below the 50% point. So, in the example above, the 51% technology firm's price moves much more closely with the technology industry than the 49% technology firm's price does. The difference in industry beta is large both economically and statistically: those directly over the 50% discontinuity, on average, have a 60% larger beta (t = 4.19) with respect to the industry in question than those firms just under the threshold. Importantly, there are no other jumps in industry beta anywhere else in the distribution of firm operations (that is, solely at the 50% classification point).

Second, corroborating the evidence on industry beta, we find that mutual fund managers exhibit differential investing behavior around the industry classification discontinuity. In particular, we focus on mutual funds with a significant sector tilt. For firms that are nearly identical in their exposures to a particular industry, with the only difference being directly above versus below the discontinuity, mutual funds that specialize in that industry are significantly more likely to hold firms right above the discontinuity than firms right below it. Specifically, the fraction of sector mutual funds investing in the firm is 40% larger (t = 2.55) for firms right above the 50% point (in terms of sales from that sector), relative to firms just below the discontinuity. Like the beta test, this is the only jump in sector mutual fund holdings throughout the distribution of firm operations.

We see the same behavior from sell-side analysts. For each firm, we measure the percentage of sell-side analysts covering the firm from each sector. We find a significant jump in sell-side analyst coverage at the industry classification discontinuity. In particular, firms right above the discontinuity have significantly more coverage from the classification industry than nearly identical firms just below the cutoff; they have a 50% (t = 2.27) higher fraction of analysts from the classification industry covering them. Again, we see no similar jumps in coverage percentage anywhere else in the distribution. Although these results on both analyst and mutual fund manager behavior are consistent with correlated shortcuts, they could also be driven by institutional constraints.

We next explore how managers may take advantage of these investor shortcuts. In particular, we examine the actions managers can take to fool investors into thinking that they are part of an industry. To do this, we identify situations in which it would be advantageous to be considered part of a given industry (relative to other industries). For this purpose, we use periods in which certain industries have higher valuation (that is, lower cost of capital) than others. We measure industry valuation in several ways: a proxy for investor preferences and beliefs based on capital flows into mutual funds investing in given industries, and an industry B/M measure; both produce identical results. Importantly, this higher valuation need not be misvaluation (for instance, it could represent increased future growth options).[6] Firms in these higher-valuation industries: (a) enjoy higher announcement day returns around being classified into those highly valued industries; (b) engage in significantly more equity issuance at the higher valuation; and (c) engage in more stock-financed M&A activities.

To capture managerial behavior precisely to gain this favorable industry classification, we again exploit the discontinuity of industry classification. In particular, we focus on firms that cluster tightly around this discontinuity point precisely when valuation of one of its industry segments is particularly high relative to the other segment. Specifically, we examine how managers industry window dress their firms at times when

[6] In fact, the only friction needed throughout the paper is that investors use the shortcut of categorizing firms based on primary industry instead of economic operations. In the presence of this, regardless of the reason of the higher valuation, managers will have an incentive to be classified into these higher-valued industries.

one industry is favorable and the other is not; more important, the discontinuity identification allows us to pin down opportunistic firm behavior by examining how two firms operating in the exact *same* industries behave if they are near versus far from the industry classification discontinuity at the same point in time. Additionally, the identification allows us to examine the behavior of two firms at the same point in time both facing a discontinuity, but one with a choice of favorable versus non-favorable industry, and the other with two favorable (or two non-favorable) industries.

We find strong evidence across the universe of conglomerate firms whose two largest segments are one favorable and one non-favorable. In particular, firms near the industry assignment discontinuity are considerably more likely to be just over the cutoff point to be classified into the favorable industry (a 29% jump at the 50% cutoff point, (t = 2.59)). We find no such jumps anywhere else in the distribution of these favorable versus non-favorable segment firms; they occur solely at the industry classification cutoff point of 50% of sales, suggesting this is managerial behavior specifically to exploit the industry classification.

As further evidence of these firms taking actions to achieve sales-levels that allow them to be classified into favorable industries, we find that these "discontinuity firms" (those clustered just above the 50% sales cutoff in the favorable industry) have significantly lower segment profit margins and inventory growth rates relative to other firms in the same industry, consistent with these firms slashing prices to achieve sales targets in the favorable industry. Again, we do not observe any changes in segment profit margins and inventory growth rates anywhere else in the distribution of favorable versus non-favorable segment firms. Further, these exact *same* discontinuity firms do not exhibit different behavior in any other aspect of their business (for instance, capital expenditures and R&D expenditures), suggesting that it is not a firm-wide shift of focus toward the favorable industry.

Another way that firms work to gain classification into the favorable sector is by manipulating accounting statements (without any real changes in sales). If firms are purely manipulating sales, this manipulation will eventually need to be undone in a future restatement that correctly states firm operations. We find evidence of this going on, as well, in future restatements.

The paper proceeds as follows. Section 2 lays out the background for the setting we examine in the paper. Section 3 presents our data collection procedures and summary statistics. Section 4 provides our results on the impact of investor shortcuts on investor behavior and asset prices. Section 5 presents results on industry window dressing by firm managers, and the benefits of doing so. Section 6 concludes.

3.2 Background:

Our findings are closely tied to recent studies on managerial behavior to manipulate market perceptions and short-term stock prices. Stein (1996) argues that in an inefficient financial market, managers with a short horizon exploit investors' imperfect rationality by catering to time-varying investor sentiment. In a related vein, Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2004) model managers' strategic disclosure behavior in a setting with attention-constrained investors. Many empirical studies confirm these predictions: important firm decisions including dividend policy, issuance, stock splits, firm name, and disclosure policy are motivated at least in part by short-term share price considerations. See, for example, Aboody and Kasznik (2000); Cooper, Dimitrov, and Rau (2001); Baker, Stein, and Wurgler (2003); Baker and Wurgler (2004a,b); Gilchrist, Himmelberg, and Huberman (2005); Baker, Greenwood, and Wurgler (2009; Polk and Sapienza (2008); Greenwood (2009); and Lou (2011). Baker, Ruback, and Wurgler (2007) provide an excellent review of this topic. This paper contributes to this fast-growing literature by adding evidence that managers also make investment decisions, in part, to influence short-term firm value.

There is also an extensive literature on investors' limited attention to information. On the theoretical front, a number of studies (e.g., Merton, 1987; Hong and Stein, 1999; and Hirshleifer and Teoh, 2003) argue that, in economies populated by investors with limited attention, delayed information revelation can generate expected returns that cannot be fully explained by traditional asset pricing models. Subsequent empirical studies find evidence that is largely consistent with these models' predictions. For example, Huberman and Regev (2001), DellaVigna and Pollet (2006), Menzly and Ozbas (2006), Hong, Torous, and Valkanov (2007), Hou (2007), Barber and Odean (2008), Cohen and Frazzini (2008), and Cohen and Lou (2012) find that investors respond quickly to information that attracts their attention (for example, news printed in the *New York Times*, stocks that have had extreme returns or trading volume in the recent past, and stocks that more people follow) but tend to ignore information that is less salient yet material to firm values. In addition, investors' limited attention can result in significant asset return predictability in financial markets.

Prior research has also examined investors' biased interpretations of information. Kahneman and Tversky (1974) and Daniel, Hirshleifer, and Subrahmanyam (1998), among many others, argue that investors tend to attach too high a precision to their prior beliefs (or some initial values) and private signals, and too low a precision to public signals, which can result in predictable asset returns in subsequent periods. Many recent empirical studies confirm these predictions. For instance, Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), Hong, Lim, and Stein (2000), Chan, Lakonishok, and Sougiannis (2001), Ikenberry and Ramnath (2002), Kadiyala and Rau (2004), and Cohen, Diether, and Malloy (2012) find that investors usually underreact to firm-specific (public) information (for example, earnings reports, R&D expenditures, and forecast revisions) and to various (publicly announced) corporate events (for example, stock splits, share issuances, and repurchases). Furthermore, investors' under- (over-) reaction leads to significant return predictability based only on publicly available information.

Finally, this paper is also related to the literature on style investment, categorization, and co-movement. Barberis and Shleifer (2003) argue that a number of investors group assets into categories in order to simplify investment decisions. This causes the flows into the assets within a category to be correlated and induces excess correlation in asset price movements (relative to actual underlying cash flow correlations). Vijh (1994) and Barberis, Shleifer, and Wurgler (2005) show one example of this using S&P 500 Index inclusion, as well as correlation to other constituent firms in the index before and after inclusion (or deletion). Other examples shown in the empirical literature are Froot and Dabora (1999), Cooper, Gulen, and Rau (2005), and Kruger, Landier, and Thesmar (2012), who find evidence that mutual fund, industry structure, and country all appear to be categories that have a substantial impact on investor behavior (and asset price movements), while Mullainathan (2002) provides a more general framework for categorization in decision making.

3.3 Data:

Our main dataset is the financial data for each industry segment within a firm. Starting in 1976, all firms are required by Statement of Financial Accounting Standard (SFAS) No. 14 (Financial reporting for segments of a business enterprise, 1976) and No. 131 (Reporting desegregated information about a business enterprise, 1998) to report relevant financial information of any industry segment that comprises more than 10% of total annual sales. Among other things, we extract from the Compustat segment files conglomerate firms' assets, sales, earnings, and operating profits in each segment.

Industries are defined using two-digit Standard Industrial Classification (SIC) codes. Conglomerate firms in our sample are defined as those operating in more than one two-digit SIC code industry. We require that the top two segments of a conglomerate firm account for more than 75% and less than 110% of the firm's total sales. The relative sales of the two top segments are then used to sort these conglomerate firms into different bins in our analyses. The lower cutoff of 75% ensures that the top two segments comprise the majority of the operations of the firm,[7] whereas the upper cutoff of 110% weeds out apparent data errors. At the end of paper, we also report results based on two-segment conglomerate firms alone.

The segment data is then merged with Compustat annual files to obtain firm-level financial and accounting information, such as book equity, total firm sales, inventory growth, etc. We then augment the data with stock return and price information from Center for Research in Security Prices (CRSP) monthly stock files. We require that firms have non-missing market and book equity data at the end of the previous fiscal year end. Moreover, to mitigate the impact of micro-cap stocks on our test results, we exclude firms that are priced below five dollars a share and whose market capitalizations are below the tenth

[7] This also ensures that the larger of the two segments will determine the primary industry of the firm. For robustness, we have experimented with this percentage from 2/3 (the lower bound to ensure that this is true) through 85%, and the results are unchanged in magnitude and significance.

percentile of NYSE stocks in our calculation of industry average variables, such as industry returns, and industry average fund flows.

Our main measure of industry favorability among investors is motivated by recent studies on mutual fund flows. Coval and Stafford (2007) and Lou (2012) find that mutual fund flows to individual stocks are positively associated with contemporaneous stock returns and negatively forecast future returns. We follow Lou (2012) to compute a $FLOW$ measure for each individual stock, assuming that fund managers proportionally scale up or down their existing holdings in response to capital flows. We then aggregate such $FLOW$ to the industry level by taking the equal-weighted average across all stocks in a two-digit SIC code industry, excluding all micro-cap stocks. We define an industry as favorable if it belongs to one of the top twenty industries (i.e., the top 30%) as ranked by mutual fund flows in the previous year, and as non-favorable otherwise.[8] We use equal-weighted industry $FLOW$ in our main analyses because capital flows to smaller stocks in an industry may better reflect investor views and preferences. In robustness checks, we also use value-weighted industry $FLOW$, and all our results go through, which is not surprising given that the correlation between the equal- and value-weighted measures is greater than 0.9.

Mutual fund flow data are obtained from the CRSP survivorship-bias-free mutual fund database. In calculating capital flows, we assume that all flows occur at the end of each quarter. Quarterly fund holdings are extracted from CDA/Spectrum 13F files, which are compiled from both mandatory SEC filings and voluntary disclosures. Following prior literature, we assume that mutual funds do not trade between the report date and the quarter end. The two datasets are then merged using MFLINKS provided by Wharton Research Data Services (WRDS). Because the reporting of segment financial information is first enforced in 1976 and the mutual fund holdings data start in 1980, our sample of conglomerate firms covers the period 1980 to 2010.

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[8] Again, we experimented with defining favorable industries as the top 20%, 25%, 30%, 35%, and 40%, and the results are very similar in magnitude and significance.

In further analyses, we obtain information on merger and acquisition (M&A) transactions from Thomson Reuter's Security Data Corporation (SDC) database in order to examine whether firms in more favorable industries engage in more M&A. We also analyze firms' equity issuance decisions in response to industry favorability. To construct a comprehensive issuance measure (which captures both public and private issuance), we follow Greenwood and Hanson (2012) to define net issuance as the change in book equity over two consecutive years divided by lagged assets. We then label a firm as an issuer if its net issuance in the year is greater than 10%, and as a repurchaser if its net issuance in the year is below -0.5%. Finally, we extract, from Institutional Brokers' Estimate System (IBES), information on analyst coverage for each conglomerate firm. In particular, we classify analysts into different industries based on the stocks they cover in the past five years and then calculate analyst coverage for a conglomerate firm from each industry segment in which the firm operates.

The data selection and screening procedures described above yield a sample of 45,904 firm-year observations. We then categorize these firm-year observations into smaller bins based on the relative sales of the top two segments. Summary statistics for our sample are shown in Table I. Specifically, the first bin includes all conglomerate firms whose smaller segment out of the top two contributes less than 10% of the combined sales of these two segments, and the second bin includes all conglomerate firms whose smaller segment out of the top two contributes between 10% and 20% of the combined sales, and similarly for other bins. There are, on average, between 396 and 566 firms per annum in each of these sales-based bins. The distribution also has a clear U-shaped pattern: there are significantly more firms whose top two segments are of vastly different sizes. In addition, 138 firms on average change their SIC industry classifications – that is, cross the 50% line – in each year. The summary statistics of other variables are in line with prior literature. For example, the average industry $FLOW$ over a year is a positive 8.1%, consistent with the rapid growth of the mutual fund industry in our sample period.

3.4 Investment Shortcuts:

The main thesis of the paper is that investors take correlated shortcuts that cause simple pieces of information to be systematically unreflected in firm prices. We then test whether managers are aware of these shortcuts and then act to take advantage of the shortcuts' implications. In this section we focus on one shortcut that financial agents take – a firm's primary industry classification versus its actual fundamental operations – and document how it affects both financial agent behavior and prices.

3.4.1 Shortcuts and Betas:

We examine whether investors' overreliance on industry classification aggregates to affect the return correlation between each conglomerate firm and the industries it operates in, and how this correlation changes as we vary the fraction of sales from these segments. More specifically, at the end of each quarter, we sort all two-segment firms into twenty 5% bins based on percentage sales from either segment; that is, each firm in our sample appears in two of these 5% bins, one on either side of the 50% point. For example, a firm that receives 49% of its sales from industry A and 51% of its sales from industry B appears in both the 45%–50% bin (when ranked based on industry A) and the 50%–55% bin (when ranked based on industry B). We focus on two-segment firms in this analysis because the presence of a third segment adds noise to our estimation of industry betas.[9] We then compute the industry beta with regard to either segment for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC-code industry in which the conglomerate firm operates, using data from months 6 to 18 after the fiscal year ends. We skip 6 months in our analysis because some firms delay reporting their accounting statements by as much as 6 months. We also exclude the stock in question from

[9] For instance, consider a firm that receives 34%, 34% and 32% from industries A, B, and C, respectively, and another firm that receives 45%, 45%, and 10% from the same three industries. While both firms receive equal fractions of the total sales from the top two segments, the industry loadings of the two firms' returns on industries A and B can be vastly different.

calculating the corresponding industry returns to avoid any mechanical correlation. Finally, we control for known common risk factors, such as market, size, value, and momentum factors, in our regression specification.

If investors have no processing constraints in assessing the details of firm operations in different segments, we expect to see a gradual increase in industry beta as we move from bins of lower fractional sales to bins of higher fractional sales. The results, as shown in Table II, indicate otherwise. While the industry beta generally increases as we move from the bottom bin to the top bin, there is a clear structural break at the 50% point. The average industry beta for firms in the 50%–55% bin, after controlling for known risk factors, is 0.286, whereas that in the 45%–50% bin is 0.178. The difference of 0.107, representing a 61% increase, is highly statistically significant (t = 4.91). The difference in industry beta between any of the other two bins is statistically zero. The structural break can be seen more easily in a diagram. As shown in the top left panel of Figure 1, while there is a mildly increasing trend in industry beta in both the below-50% and above-50% regions, there is a clear jump in industry beta at the 50% point.

3.4.2 Sector Mutual Funds:

To provide evidence of this behavior by a set of (arguably) sophisticated investors, we examine mutual fund managers' holdings. We first identify those mutual funds that concentrate on a specific sector. As very few mutual funds list their sector in their fund name, we examine the actual fund holdings. If a fund invests the majority of its portfolio in a single industry (i.e., >50%), either by choice or through institutional constraints, we classify the mutual fund as concentrating on that given sector.[10] For every two-segment conglomerate firm, we then count the number of sector mutual funds that hold the firm in months 6 to 18 after the fiscal year end. We further require that the two segments be in

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[10] Given that nearly all mutual funds have concentration limits on individual positions of 5% or less, 50% does require the mutual fund to take, for instance, 10 maximally concentrated positions in the same industry, which is suggestive that the fund is concentrating investment efforts there.

two distinct one-digit SIC code industries, since sector mutual funds may also hold stocks from related sectors.

We then compute the proportion of sector funds from each industry in which the conglomerate firms operate. For instance, if a conglomerate firm operates in industries A and B, we calculate the percentage of industry A sector mutual funds and industry B sector mutual funds that hold the firm.

Table III reports the distribution of sector mutual fund holdings. Panel A reports the proportion of the sector mutual funds covering the sector as that sector moves from a 30% segment to a 70% segment in the firm. As expected, the proportion of sector funds holding the conglomerate firm increases as the percentage of the conglomerate sales from that sector increases. As with beta, though, instead of observing a steady increase in sector fund ownership as sales increase, we see a large and significant discontinuity at the 50% classification cutoff. The increase in proportion from the 45%–50% bin to the 50%–55% bin of 9.8% (t = 2.55) represents more than a 40% jump in the percentage of sector mutual funds holding the stock (23.1 to 32.8). This pattern can also be seen in the bottom left panel of Figure 1, where we plot the proportion of sector funds owning the conglomerate firm against the percentage of sales from that industry: there is a discrete jump in sector fund ownership at the 50% cutoff point. Consistent with the results on beta, these results suggest that in their investments, mutual fund managers also rely on conglomerate firms' primary industry classification rather than actual firm operations.

3.4.3 Analyst Coverage:

We also examine another set of financial agents who are particularly important in gathering, processing, and conveying information in financial markets: sell-side analysts. Research shows that investors closely follow analysts' guidance when making investment decisions. Given that individual analysts usually specialize in and follow stocks in one or two industries (e.g., Boni and Womack, 2006), it is conceivable that analyst coverage is strongly determined by firms' primary industry classifications, which may affect how investors view these firms, helping drive the beta results we document in Table II.

As in our tests on sector mutual funds, at the end of each quarter, we sort all two-segment firms with at least some analyst coverage into twenty 5% bins based on percentage of sales from either segment. We then assign each sell-side analyst (covering five or more firms) to an industry if that industry accounts for more than half of the analyst's covered firms. We use coverage data provided by IBES in the previous three years for each analyst (our results are robust if we use coverage information in the previous one to five years). We exclude the stock in question in the procedure of analyst industry assignments to ensure that our results are not mechanically driven. We then compute the proportion of analyst coverage from each industry that the conglomerate firm operates in using coverage data in months 6 to 18 after the fiscal year ends. So, for example, for a firm that operates in industries A and B and is covered by five analysts from industry A, four from industry B, and one from another industry, we label the firm as having 50% of its coverage from its operations in industry A and 40% of its coverage from its operations in industry B.

If firms' primary industry classifications indeed determine analyst coverage, we expect a jump in the fraction of analysts covering the firm when the segment in question crosses the 50% percentage sales point. The results, shown in Table III, Panel B, confirm this prediction. While the fraction of analysts covering a firm from a particular industry generally increases as the industry accounts for a larger fraction of the firm's sales, there is a clear jump at the 50% cutoff point: for firms that derive 45%–50% of their total sales from the industry in question, 32.7% of the analysts covering these firms are from that industry; in contrast, for firms that derive 50–55% of their sales from the industry in question, 52.0% of these analysts are from that industry.[11] The difference in analyst coverage of 19.3%, representing an almost 60% increase from the lower bin, is economically and statistically significant (t = 2.27). On the other hand, the difference between any other two bins is much smaller in magnitude and statistically insignificant from zero. This pattern can be also seen from the bottom right panel of Figure 1, where we plot the proportion of analysts covering the firm from a particular industry against the segment percentage sales. There is a discrete jump in analyst coverage at the 50% cutoff point.

In sum, the results presented in this section provide evidence that investors take shortcuts, relying on firms' primary industry classification, in some cases more so than actual firm operations. This may arise from investors' limited attention or processing capacity to read through all segment-related information, forcing them to rely on simple statistics, from investors' reliance on analysts' guidance (who in turn use industry classifications to determine the stocks they follow), or from institutional constraints on holdings.

[11] The sum of the two fractions is less than one because firms are also covered by analysts from outside the two segments.

3.5 Industry Window Dressing:

3.5.1 Favorable Industries:

We next explore how managers can take advantage of implications from the investor behavior we document in Section 4. In particular, we examine what actions managers can take to fool investors into thinking that they are part of a given industry. We identify situations in which it would be advantageous to be considered part of a given industry (relative to other industries). For this purpose, we use periods in which certain industries have higher valuation (i.e., lower cost of capital) than others.

We begin by choosing a measure to capture these times of higher valuation. These could be times when an industry, for instance, has a shock of increased growth options, or could be periods of higher valuation driven by shifts in investor preferences. We are agnostic regarding the source of the higher valuation, as irrespective of the source, firms benefit from being classified into the high valuation industry (which we show evidence of below).

Specifically, we examine the behavior of investors allocating capital to mutual funds and the relation of these flows with firm (and industry) valuation. Lou (2012) shows that capital flows into mutual funds predict the price movements of stocks held by these mutual funds. We use a similar identification, but now aggregating these individual stock flows to the industry level. Table IV, Panel A, shows that industry flows are significantly related to industry valuation: in the year that investors move capital into an industry through their mutual fund purchase decisions, industry values rise significantly, by more than 100 basis points per month (t = 4.45). In the following two years, this 12% return completely reverses.[12] We label these high valuation industries (top 20 as ranked by industry $FLOW$) "favorable" industries.[13]

Using this favorable industry measure, we show that firms in these industries are afforded a number of benefits. In Table IV, Panel B we show that these firms engage in significantly more equity issuance at the higher industry valuation levels. The coefficient in Column 2 of 1.451 (z = 4.09) implies that a one standard deviation increase in investment flows into an industry increases the SEO likelihood by roughly 20% (from a baseline of 9.7%). In addition, they engage in significantly more M&A activity. Consistent with the firms exploiting the higher industry valuations, the increase in M&A activity comes solely through stock-financed M&As. The coefficient in Column 4 of 3.133 (z = 3.25) implies that a one standard deviation increase in investment flows into an industry increases the stock-financed M&A likelihood by roughly 26% (from a baseline of 1.1%).

3.5.2 Identification of Industry Window Dressing:

An innovation of the paper relative to the existing literature is the clean identification of firm behavior in direct response to this mispricing. In particular, we exploit a rule of the Securities and Exchange Commission (SEC) that designates how firms classify their operations. Using this rule, we exploit situations in which firms tightly surround the discontinuity point of industry classification (e.g., for two segment firms, this would be 50%).

By examining the distribution of conglomerate firms right around this discontinuity, we can focus cleanly on how the incentive for managers to join favorable industries relates

[12] Frazzini and Lamont (2008) use a similar measure and also find significant negative abnormal returns following investor flows into mutual funds.
[13] We show nearly identical results in magnitude and significance using industry M/B ratio as an alternative to the investor flows measure. These are shown in Table X and Figure 3, and are discussed in Section 5.7.

to how they classify their firms relative to non-favorable industries (i.e., the complement set to the favorable industries).

Many conglomerate firms have operations in both favorable and non-favorable industries. Each conglomerate firm in the favorable industry by definition has a sales weight in the industry between 10% and 90% (they need not report segments below 10%). If firms truly are manipulating operations opportunistically, we expect to see firms bunched just above the cutoff point of sales from favorable industries (e.g., 50% for two segment firms), so that they can take advantage of being classified as a member of these favorable industries.

To test this, we first examine the distribution of conglomerate firms' segment makeup. We examine the two largest segments of each conglomerate firm in terms of sales, which determine the primary industry classification, requiring that one of the top two segments is in a favorable industry and the other in a non-favorable industry. Figure 2 shows the distribution of conglomerate firms whose top two segments operate in a favorable and a non-favorable industry and are around the 50% cut-off in relative sales. The top two segments' sales in the firm are scaled against each other; the larger of the two determines the industry classification of the firm. The 50% sales cutoff is thus the relevant cutoff for industry status.

Included in Figure 1 are all conglomerate firms whose top, favorable segment accounts for between 40% and 60% of the combined sales of the top two segments (gray shaded area), as well as for 45% to 55% of the combined sales (patterned area). Any firm with sales over 50% from a favorable industry (x-axis) is classified into the favorable industry (whereas below that cutoff is classified into the non-favorable industry). If there is no opportunistic behavior by managers, we should see no significant difference in the proportion of conglomerate firms around the 50% point. In contrast, as this 50% discontinuity cutoff is precisely the point at which firms are classified into favorable versus non-favorable industries (e.g., the 51% Tech–49% Lumber firm will be presented to investors as a Tech firm, whereas the nearly identical 49% Tech–51% Lumber will be classified as a Lumber firm), we expect firms exhibiting opportunistic behavior to exploit industry mispricing by clustering just over the 50% classification cutoff.

Figure 2 shows strong evidence that firms in fact do cluster just above the 50% cutoff of sales from favorable industries, resulting in significantly more firms classifying themselves into favorable industries (relative to just below). For instance, looking at all conglomerate firms that have between 40% and 60% of sales from a favorable industry (and so the complement 60%–40% in a non-favorable industry), we see a much larger percentage of firms in the 50%–60% favorable industry sales bin than the converse. This difference becomes even greater if we look at the tighter band around the 50% cutoff only of firms that are between 45% and 55% in a favorable industry (versus the complement in a non-favorable industry). Note that an alternative story in which all firms with a favorable segment experience increasing sales in that segment would generate a very different pattern. In this case, we should see all firms containing a favorable industry segment increasing their weights in the favorable industry, which would result in a parallel shift for all firms such that the bins around 50% would experience the same increase, and so have no discontinuous jump between the two.

To test this jump around the 50% cutoff more formally, we look at the entire distribution of conglomerate firms. The estimation strategy of discrete jumps in firm distribution at the discontinuity point then follows the two-step procedure as outlined in McCrary (2008). In particular, we first group all observations into bins to the left and right of the discontinuity point of interest such that no single bin includes observations on both sides of the discontinuity point. The size of the bin is determined by the standard deviation of the ranking variable (e.g., segment percentage sales) and the total number of observations in our sample. We then smooth the distribution histogram by estimating a local linear regression using a triangle kernel function with a pre-fixed bandwidth over the bins. The estimated log difference in firm distribution at the discontinuity point is shown to be consistent and follows a normal distribution asymptotically by McCrary (2008).

Table V, Panel A, shows the entire distribution of conglomerate firms that operate in favorable versus non-favorable industries across 5% bins based on percentage sales from the favorable industry. From Table I, there is a clear U-shaped pattern in conglomerate firm distributions (conglomerate firms are mainly dominated by one segment or the other, with relatively fewer that are near the 50-50 cutoff). We see the same overall pattern for these favorable versus non-favorable conglomerates, with one distinct difference: there is a large jump in the fraction of firms directly over the 50% cutoff to qualify as a member of the favorable industry. The density difference at the 50% cutoff (following the McCrary procedure) is 0.254 (t = 2.59) compared to the preceding bin, a 29% jump.[14] For comparison, if these firms are uniformly distributed in sales weights, the distribution density change between two consecutive bins should be exactly zero. For the rest of the distribution, there is no change in density nearly as large, and none are significant. This same result can be seen in Figure 3. The top left panel shows the discontinuity at the 50% cutoff of segment sales.[15]

3.5.3 Falsification Tests:

Although the distinct discontinuous pattern in firm distribution is difficult to reconcile with stories other than reclassification that occurs directly at the discontinuity point, one might think that firms are simply ramping up all operations, such that sorting on any firm balance sheet or income statement variable will yield identical behavior. To be clear, the SEC rule states that sales <u>alone</u> determine industry classifications. Thus, if managers' opportunistic behavior to classify the firm is the driving force, the only variable the managers care to affect should be sales. Thus, we would not expect to see sorting on any other firm variables showing a discontinuity in distribution at 50%. In contrast, if what

[14] We have used a number of methods of adjusting these standard errors from the McCrary procedure; for instance, clustering by year or bootstrapping. The corresponding standard errors are a bit lower, with larger t-stats of t=3.52 and t=3.40, respectively.

[15] In addition to getting into favorable industries, firms may also want to avoid the least favorable industries. We test this by looking at difference in distribution jumps between avoiding being classified into the least favorable industries (negative jumps) and being classified into the most favorable industries (positive jumps). We see both of these in the data, and the difference between them is strongly statistically significant.

we document is some odd empirical pattern in firm operations unrelated to firms actively assuring they are just above the sales discontinuity, we should expect to see similar patterns based on other accounting variables.

To test this, we conduct the exact same sorts as in Table V, Panel A, with the *same* set of conglomerate firms, but instead of sorting on sales, we sort on other accounting variables, such as assets and profits. In other words, we rank these conglomerate firms by the percentage of profits (assets) they have in the favorable segment and show the entire distribution in Table III, Panel B (Panel C). From Panels B and C, we see no significant jumps between any two adjacent bins when sorting by these other firm variables, but rather a stable frequency in each of these bins. This is consistent with sales (the variable that drives industry classification) being the sole focus of firms. This lack of discontinuity when sorting by segment profits or assets can also be seen in the top right and bottom left panels of Figure 3, respectively.

These results, particularly those based on profits, also help rule out an alternative explanation of tournament behavior by divisional managers to be promoted to CEO. First, a nuanced version of the tournament explanation would be needed to differentially predict the desire (or ability) of managers in favorable industry segments to engage in this behavior relative to all other segment managers. Even if this were true, however, evidence shows that segment sales have no impact on the promotion of divisional managers (Cichello et al., 2009); profits are the only statistically and economically relevant predictor. However, we see no evidence of discontinuity when sorting on segment profits (or assets), but solely when sorting on firm sales. This is inconsistent with this tournament explanation, but consistent with the window dressing motive.

3.5.4 Mechanism:

We explore the mechanism through which firms may be opportunistically adjusting sales such that they are classified into favorable industries. There are two potential explanations for the results we find. The first is that firms are taking real actions to sell more in the favorable industry segment in order to be classified into favorable industries, and accrue the benefits we show in Section 5.1. The second explanation is that firms are simply fraudulently reporting sales (on the margin) in order to be classified into the favorable industries.

3.5.5 Window dressing through sales management:

First, if a firm is trying to increase sales revenue, one way to do this is to lower the price of goods. This can lead to more booked sales, but a lower profit margin, and a depletion of inventories as the abnormal sales volume is realized. We test both of these implications. We use the same sorting on favorable industry segment sales as in Table V. If firms truly are exhibiting this behavior, then the firms that are stretching to be classified in the favorable industry (i.e., firms just above the 50% sales classification cutoff) should also have lower profit margins and depleted inventories. Panel A of Table VI reports test results for profit margins *solely* in the favorable segment, and we see precisely this pattern: the drop in profit margins is economically meaningful at 20% lower (t = 2.93) compared to both adjacent bins. In theory, increasing favorable industry segment sales to just above the 50% cutoff could result either from cutting prices in the favorable industry segment to increase sales or from raising prices in the non-favorable segment to reduce sales. If firms did the latter, this would imply higher profitability in the non-favorable segments (since profitability is measured as (price-cost)*unit/price*unit, so (price-cost)/price, or 1-(cost/price)). In Panel B, we examine this implication by looking at the profitability in the non-favorable segment for firms that surround the 50% cutoff. Panel B of Table VI shows that firms around the 50% cutoff (which do have significant drops in favorable segment profitability) show no pattern in non-favorable segment profitability.

Next, we conduct the same test for inventories in Panel C of Table VI to examine if inventories are also depleted for these firms that are barely above the sales discontinuity. Because inventories are reported only at the firm level (not the segment level) and are more sparsely populated, we aggregate firm-year observations to 10% bins. Again, we see evidence consistent with firms increasing sales in order to be classified into favorable industries. Inventory growth is 30% lower (t = 2.28) for those firms right above the cutoff, and statistically identical (and nearly identical in magnitude) for all other bins.

We also run the falsification test examining firms that have both top segments as favorable industry segments (so there is no need to change real behavior to affect classification). Consistent with this idea, we see no differences in profit margins or inventories for these two favorable segment firms anywhere in the distribution.

Table VII reports an additional test of mechanism. One might think that instead of capturing firms that change their sales behavior opportunistically, we are merely capturing a firm-wide shift in policy toward the more favorable industry. This would not explain why we see a discontinuous jump in firm-wide policy "shifts" at the 50% cutoff, but it would be less of a manipulation of sales alone for industry classification and would signal more firm-wide behavior. We test this alternative story by exploring whether firm investment is in line with the sales increases we see in favorable industries. In particular, in Table VII we examine whether capital expenditures and R&D expenditures in the favorable industry line up with the strong sales behavior we see around the discontinuity. Panels A and B tell the same story: for both capital expenditures and R&D[16] we observe no difference in the investment behavior of these firms around the discontinuity. This is in sharp contrast to profit margins and inventory growth, and is more evidence that firms are changing their sales for the sole purpose of being classified into favorable industries.

An alternative explanation is that firms are signaling to the market that they are expanding into high-growth sectors by increasing their sales in the favorable segment. We have evidence that cuts against this signaling story. First, this signaling story makes no distinction at the 50% cutoff. Firms everywhere in the distribution (e.g., 27%, 42%, 61%, etc.) signal their movement by increasing sales to the favorable segments. However, this is not what we observe: firms are not uniformly increasing their exposures to the favorable segment, but instead we see a jump in the distribution only at the industry classification

[16] Like inventories, R&D expenditures are sparsely populated, so we aggregate to the 10% bin level.

cutoff of 50%. To accommodate this, the signaling story would need to be combined with an investor cognitive constraint in which these investors pay attention only to firms that cross the 50% threshold. Even if this combined story were true, we see no evidence that firms just above the 50% cutoff are actually moving into these favorable segments. For instance, in the two to three years following the industry classification, we see no increase in investment, R&D, or sales in the favorable segment. This then reduces to a pseudo-signaling story, which is nearly equivalent to the industry window dressing explanation.

3.5.6 Window dressing through accounting manipulation:

An alternative explanation to firms managing sales to be classified into the favorable industry is that they simply manipulate accounting statements to the same end (without any real changes in sales). Although this would not explain the inventory and profitability results at the favorable segment level, it could still be a complementary behavior that achieves the same goal. If firms are purely manipulating sales, this manipulation would eventually need to be corrected in a future restatement that accurately states firm operations. We thus test this implication using accounting restatements. We use those firms that actively switch into the favorable industry from an unfavorable industry as the sample of firms on which to examine future restatements. We show in Section 5.5 that these switcher firms do gain the same significant benefits of all favorable industry firms (in terms of stock issuance and stock-financed M&As).

The accounting restatement results are shown in Table VIII. Columns 1 and 2 run the accounting restatement test on all firms that switch industries: (a) from non-favorable to favorable; (b) from non-favorable to non-favorable; (c) from favorable to favorable; and (d) from favorable to non-favorable. From Column 2, the overall restatement likelihood of switchers is larger than that of other firms, but only marginally significantly so. Columns 3 and 4 then run the analysis examining only switchers from non-favorable to favorable industries. These firms, in sharp contrast, are significantly more likely to restate earnings. The coefficient in Column 4 of 0.382 (z = 3.35) implies that switchers are 39% more likely to restate in the future. This is significant even controlling for the change in percentage sales from the favorable segment (Δ%$SALES_{t-1}$), which itself is negatively related to restatements, as intuitively a firm that has moved from 40% to 80% sales in the favorable industry is less likely to have used accruals to do so than one that moved from 49% to 51%. Importantly, after controlling for ($\Delta\%SALES_{t-1}$), the switch dummy now captures solely the effect of crossing the 50% cutoff. Columns 5 and 6 then run the analysis for all other types of switchers (excluding non-favorable to favorable industry switchers). These firms have are no more likely to restate earnings, with a small negative and insignificant difference between their likelihood and all other firms. The combination of results suggest that the positive coefficients of switching on restatement probabilities in Columns 1 and 2 are being driven entirely by those firms that are switching from non-favorable to favorable industries.

In sum, Tables VI–VIII suggest that while firms are manipulating sales in order to be classified into favorable industries: by slashing prices, which reduces profitability and inventories, we also find evidence that firms switching from non-favorable to favorable industries are engaging in accounting manipulation to achieve that industry status.

3.5.7 Benefits to Switching:

Although we use the discontinuity approach throughout this paper to examine the behavior of firms to be classified into favorable industries, another sample of interest is firms that actively switch from non-favorable to favorable industries. While these will include many of the same firms right above the discontinuity, they will also include firms that make larger changes in firm operations or shifts in focus (i.e., mergers or dispositions of segments). We thus lose the identification of comparing two nearly identical firms right around the classification, since the decision to switch is not random. But we gain a group of firms that are acting decisively to move into the favorable segment.[17]

[17] We find that investors behave similarly with regard to these switching firms as they do around the discontinuity (shown in Table II and Figure 1). For instance, in the analog to the test to Table I, we find that the beta of switchers to the hot industry increases by 0.046 (t = 2.53), which represents a 20% increase in beta.

We show that these switchers accrue the same benefits of being in the favorable industry as other favorable industry firms. We run tests identical to Table IV (all favorable industry firms), except now only on the subsample of firms that switch from the non-favorable to the favorable industry. These results are reported in Columns 1–4 of Table IX. Despite the much smaller sample size of the switchers, Columns 1-4 show that these switchers engage in significantly more stock issuance and stock-financed M&As. The magnitudes are similar to those in Table IV (the point estimates are even larger), and all are highly significant, again even when we control for the change in percentage sales from the favorable segment ($\Delta\%SALES_{t-1}$). Another benefit that the literature shows to having overvalued equity is that managers are paid more. We find the same to be true. In the analog to Column 4 of Table IX (using total compensation as a percentage of market equity as the dependent variable), we find that the switchers increase total compensation to top managers by 15% (t=2.49).

If investors use shortcuts based on primary industry classifications in their investment decisions, a switch of a firm's primary industry could have a sizable impact on its valuation. We focus on stock returns around an important information event during which information regarding a firm's primary industry is announced: its annual release of financial statements. Specifically, we predict that firms that switch from non-favorable to favorable industries (e.g., from machinery to the tech during the NASDAQ boom) should have higher announcement day returns than their peers, in particular those firms that switch from favorable to non-favorable industries. It is also important to note that this test provides a lower bound for the return effect of industry switching, as annual sales information is gradually disseminated to the market and can be largely anticipated before official financial statements are released.

To test this prediction, we examine the cumulative stock return in the three-day window surrounding conglomerate firms' annual earnings announcements. Our results are also robust to other window lengths. We then regress the cumulative return on a $SWITCH$ dummy that takes the value of one if the firm's main industry classification switches from a non-favorable to a favorable industry in the current fiscal year, and zero otherwise. We also control for standardized unexpected earnings (SUE), defined as the difference between the consensus forecast and reported earnings scaled by lagged stock price, in the regression. Other control variables include firm size, the book-to-market ratio, lagged stock returns, share turnover, idiosyncratic volatility, institutional ownership, and number of analysts covering the firm. We also put in year-fixed effects to subsume common shocks to all firms.

The regression coefficients are reported in the last two columns of Table IX. In Column 5, a firm that switches from a non-favorable industry to a favorable industry has an announcement day return that is 140 basis points (t = 2.38) higher than all other firms. In the full specification (Column 2), where we control for other firm characteristics that are linked to average firm returns, firms that switch from non-favorable to favorable industries outperform their peers by 120 basis points (t = 2.08).

An alternative method for running this announcement return effect is to focus solely on those firms in which there is investor uncertainty over industry classification (i.e., firms that tightly surround the 50% discontinuity, between 45% and 55%). When we run the identical announcement return test on this subsample, even though the sample is much smaller, the returns double in magnitude and are more significant. For example, the analog of Column 6 for this sample has announcement returns of 260 basis points (t=3.27).

3.5.8 Regression Discontinuity (RD) vs. Discontinuity:

It is important to distinguish the different methodologies we use in the first and second parts of this paper. The investor and financial agent behavior section (Section 4) uses a regression discontinuity approach. The implicit assumption is that firms are randomly allocated to the left and right sides of the 50% cutoff.

In contrast, the second part, on firm actions (Section 5), uses a discontinuity approach relying on the 50% industry classification criterion. Here, firms are strategically selecting which side of the cutoff to be on. This is similar to the earnings management literature of firms manipulating earnings to meet or barely beat (by zero or one penny) earnings expectations.

Obviously, the potential issue is that the behavior of firms we document in Section 5 (firms selecting to be classified into favorable industries) violates the key assumption of regression discontinuity in Section 4.

To address this concern, we focus *solely* on the subsample of firms that operates entirely in non-favorable sectors. These firms have no apparent incentive to select, and by construction, in this sample there can be no jump at any percentile, because the distribution is entirely symmetric – every (49%, 51%) firm is also a (51%, 49%) firm. This sample thus adheres to the regression discontinuity assumption of random assignment around the 50% cutoff. We run our investor behavior tests on this subsample and see identical results to those reported in Section 4. For instance, Table X Panel A shows the jump in industry beta at the 50% cutoff for solely this subsample (analog to Table II). The average industry beta for firms in the 50%–55% bin, after controlling for known risk factors, is 0.219, whereas that in the 45%–50% bin is 0.143. The difference of 0.076, representing a 53% increase, is statistically significant (t = 2.58). The difference in industry beta between any of the other two bins is statistically zero.

3.5.9 Robustness Check:

We run a number of robustness checks to the discontinuity results regarding the sales of firms tightly surrounding the classification discontinuity. First, we run tests using different measures of industry classification. Throughout the paper we use the two-digit SIC code. However, when we run tests using NAICS, as well as the coarser one-digit SIC code classifications, we see the same discontinuity in sales behavior. Second, we run this analysis pre- and post-1998 (due to the accounting change from SFAS 14 to SFAS 131), and the results are nearly identical in magnitude and significance. Third, we look solely at the subsample of two segment conglomerate firms. This test is shown in Table X, Panel B.

Although the sample is smaller, the magnitude is nearly identical, and the jump is statistically significant.

We also use an alternative measure of industry valuation, industry M/B, in addition to the investor flow measure. Because there is large base-variation in M/B at the industry level (Cohen and Polk, 1996), we adjust for this using the method of Rhodes-Kropf, Robinson, and Viswanathan (2005). Using this measure of industry M/B, we define favorable industries and run the same analysis of firm behavior. We find nearly identical results with this alternative measure, shown in Figure 3 and Table X, Panel C. In particular, in the bottom right panel of Figure 3, there is a nearly identical jump in the distribution around the 50% sales cutoff as when classifying industries using the investor flow measure (top left panel), while in Panel C, the density jump of 0.242 (t = 2.54) at the discontinuity point is nearly identical to that in Table V.

3.6 Conclusion:

We document a shortcut that financial agents take and show how it impacts both prices and managerial behavior. Specifically, we exploit a regulatory provision governing firms' classification into industries and the resultant discontinuity it implies. A firm's industry classification is determined by the segment with the majority of sales. As this empirically always falls between the two largest segments, the 50% cutoff between these two segments determines the industry classification. We find evidence that investors overly rely on this industry classification in making investment decisions without sufficiently factoring in firms' underlying economic operations.

For instance, we find that even when firms have nearly identical sales profiles, firms just over the 50% point (in term of percentage sales from a particular industry) have significantly higher betas with respect to that industry than firms just below the 50% point. Sector mutual fund managers also invest significantly more in the firms just above the discontinuity point than directly below it. Sell-side analysts exhibit similar patterns in their coverage of these firms around the discontinuity. Importantly, the significant jumps in beta and behaviors we document occur solely at the 50% classification cutoff and nowhere else in the distribution of firm operations.

We also show evidence that managers take actions to fool investors into thinking that the firms are in favorable industries (i.e., those with high valuations). In particular, firms near the industry assignment discontinuity are considerably more likely to be just over the classification cutoff point. We find no such jumps anywhere else in the distribution of these favorable versus non-favorable segment firms; they occur solely at the industry classification cutoff point of 50% of sales, suggesting this is managerial behavior specifically to exploit the industry classification.

As further evidence that these firms take real actions to achieve sales that allow them to be classified into favorable industries, we find that firms just over the classification cutoff point have significantly lower segment profit margins and inventory growth rates relative to other firms in the same industry, consistent with these firms slashing prices to achieve sales targets in the favorable industry. Again, we observe no changes in segment profit margins and inventory growth rates anywhere else on the distribution of favorable versus non-favorable segment firms. Further, these *same* discontinuity firms do not exhibit different behavior in any other aspect of their business (for instance, capital expenditures and R&D expenditures), suggesting that they are not making a firm-wide shift of focus toward the favorable industry.

Last, we show that firms that switch into favorable industries have significantly higher announcement returns around the time of switching. In addition, they engage in significantly more SEOs and (stock-financed) M&A transactions after switching.

In sum, we provide evidence that investors take correlated shortcuts that cause simple pieces of information to be systematically unreflected in firm prices. We then show that managers take specific actions to take advantage of the investor shortcuts, providing tangible benefits to their existing shareholders.

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3.8 Tables and Figures:

Table I: Summary Statistics

This table reports summary statistics of our sample that spans the period 1980-2010. Panel A reports the statistics of our main variable, mutual fund flows to each industry over a year, based on two-digit SIC codes. Specifically, at the end of each quarter, we compute a $FLOW$ measure as the aggregate flow-induced trading across all mutual funds in the previous year for each stock. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. Panels B and C report segment and firm specific characteristics. Profit margin is defined as the segment's operating profit divided by segment sales. Both capital expenditures and R&D spending are scaled by total firm assets. Industry beta is from the regression of weekly stock returns on corresponding industry returns (excluding the stock in question) over a one-year horizon, after controlling for the Carhart four-factor model. The announcement return is the 3-day cumulative return around an annual earnings announcement. Panel D reports the distribution of conglomerate firms year by year. We classify conglomerate firms into four groups, based on the relative sales of the *top two* segments. For example, a 10-20% conglomerate firm has one of the top two segments contributing between 10-20% of the combined sales and the other segment contributing 80-90% of the combined sales of the top two segments. We also report the number of conglomerate firms that switch their major industry classifications in each year.

	Mean	Std. Dev.	Q1	Median	Q3
Panel A: Industry Characteristics					
$INDFLOW$	0.081	0.122	0.003	0.070	0.142
Panel B: Segment Characteristics					
Profit margin	0.076	0.145	0.023	0.081	0.150
Segment sales (millions)	1103	5789	13	70	421
Capital expenditures	0.024	0.027	0.005	0.013	0.032
R&D Spending	0.004	0.010	0.000	0.000	0.000
Panel C: Firm Characteristics					
Industry beta	0.228	0.685	-0.151	0.184	0.593
Announcement returns	0.007	0.083	-0.031	0.004	0.044
Panel D: Distribution of Conglomerate Firms Year by Year					
# 10%-20% conglomerates	566	102	493	558	633
# 20%-30% conglomerates	485	117	397	487	574
# 30%-40% conglomerates	424	102	332	440	509
# 40%-50% conglomerates	396	97	325	420	466
# industry classification changes	138	87	75	136	223

Table II: Naive Industry Categorization: Industry Beta

This table reports the average industry beta of conglomerate firms. At the end of each quarter, we compute an industry beta for each two-segment conglomerate firm with regard to each segment by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. We also control for common risk factors, such as the market, size, value, and momentum in the regression specification. We focus on conglomerate firms that operate in exactly two industries (i.e., excluding firms with greater than or equal to three segments). All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row reports the average industry beta with regard to the segment in question for all firms in each bin, the second and third rows report the difference in industry beta between the current bin and the preceding bin after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Industry Beta with Regard to the Segment in Question								
Industry beta	0.136	0.120	0.179	0.178	0.286	0.245	0.286	0.284
$beta_b$ - $beta_{b-1}$	-0.010	-0.020	0.055	0.003	0.107***	-0.033	0.043	-0.005
(year)	(-0.35)	(-0.81)	(1.23)	(0.10)	(4.91)	(-0.85)	(0.95)	(-0.13)
$beta_b$ - $beta_{b-1}$	-0.013	-0.005	0.043	0.012	0.085***	-0.039	0.046	0.008
(year + SIC)	(-0.45)	(-0.19)	(0.93)	(0.35)	(3.86)	(-0.92)	(1.03)	(0.20)
No. Obs.	730	616	590	638	638	590	616	730

Table III: Sector Mutual Fund Holdings and Analyst Coverage

This table reports the proportion of sector mutual funds that hold (Panel A) and analysts that cover (Panel B) a conglomerate firm from each segment the firm operates in. At the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than three firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers. We exclude the conglomerate firm in question in the procedure of mutual fund/analyst industry assignments. We then compute the proportion of sector mutual funds holding and analysts covering the conglomerate firm from each industry that the conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end. We focus on conglomerate firms that operate in exactly two segments based on two-digit SIC codes; in addition, we require the two segments to operate in two distinct one-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The first row of each panel reports the average proportion of sector mutual funds and analysts from the segment in question for all firms in each bin, the second and third rows report the difference in proportions between the current bin and the preceding bin after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Panel A: Proportion of Sector Mutual Fund Holdings from the Segment in Question								
Sector mutual funds	0.176	0.235	0.219	0.231	0.328	0.334	0.354	0.362
$prop_b$ - $prop_{b-1}$	-0.005	0.050	-0.018	0.015	0.098**	0.010	0.034	-0.004
(year)	(-0.19)	(1.54)	(-0.48)	(0.60)	(2.55)	(0.30)	(1.10)	(-0.15)
$prop_b$ - $prop_{b-1}$	-0.004	0.045	-0.020	0.005	0.081**	0.029	-0.005	-0.015
(year + SIC)	(-0.19)	(1.60)	(-1.12)	(0.27)	(2.35)	(0.92)	(-0.20)	(-0.66)
No. Obs.	402	381	309	295	295	309	381	402
Panel B: Proportion of Analyst Coverage from the Segment in Question								
Analyst coverage	0.161	0.219	0.288	0.327	0.520	0.564	0.613	0.663
$prop_b$ - $prop_{b-1}$	0.018	0.057	0.070*	0.039	0.193**	0.044	0.049	0.050
(year)	(0.52)	(1.32)	(1.89)	(0.70)	(2.27)	(0.80)	(1.34)	(1.00)
No. Obs.	91	92	88	62	62	88	92	91

Table IV: Mutual Fund Flows and Industry Valuation

This table shows the effect of mutual fund flows on industry valuation. Panel A reports the calendar-time monthly returns to industry portfolios ranked by $INDFLOW$. Specifically, at the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. We then sort all industries into decile portfolios based on $INDFLOW$ in each quarter and hold these decile portfolios for the next two years. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different quarters. Monthly portfolio returns with various risk adjustments are reported: the return in excess of the risk-free rate, CAPM alpha, and Fama-French three-factor alpha. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags (Newey and West 1987). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Panel A: Calendar-Time Portfolio Analysis									
Decile	Excess Return	1-Factor Alpha	3-Factor Alpha	Excess Return	1-Factor Alpha	3-Factor Alpha	Excess Return	1-Factor Alpha	3-Factor Alpha
	Formation Year			Year 1 after Formation			Year 2 after Formation		
1	1.01%	0.47%	0.25%	0.68%	0.14%	0.10%	1.02%	0.40%	0.19%
(Low)	(3.49)	(3.45)	(2.07)	(2.40)	(1.08)	(0.92)	(3.53)	(2.73)	(1.87)
2	1.06%	0.51%	0.36%	0.88%	0.32%	0.15%	0.98%	0.33%	0.18%
	(3.70)	(4.09)	(3.16)	(3.04)	(2.45)	(1.37)	(3.32)	(2.37)	(1.95)
3	1.20%	0.66%	0.53%	0.67%	0.10%	-0.08%	0.91%	0.26%	0.07%
	(4.18)	(5.04)	(4.50)	(2.26)	(0.78)	(-0.73)	(3.07)	(1.83)	(0.74)
4	1.28%	0.70%	0.58%	0.62%	0.07%	-0.12%	0.98%	0.32%	0.14%
	(4.23)	(5.27)	(5.01)	(2.16)	(0.56)	(-1.24)	(3.28)	(2.33)	(1.53)
5	1.37%	0.81%	0.67%	0.55%	0.01%	-0.18%	0.93%	0.29%	0.08%
	(4.72)	(6.74)	(6.37)	(1.96)	(0.09)	(-2.02)	(3.20)	(2.15)	(0.89)
6	1.53%	0.99%	0.84%	0.69%	0.16%	0.06%	0.65%	0.01%	-0.16%
	(5.35)	(7.40)	(8.62)	(2.50)	(1.33)	(0.64)	(2.28)	(0.09)	(-1.56)
7	1.54%	1.02%	0.91%	0.48%	-0.04%	-0.17%	0.69%	0.10%	-0.11%
	(5.51)	(7.22)	(8.88)	(1.75)	(-0.30)	(-1.55)	(2.54)	(0.74)	(-1.05)
8	1.68%	1.14%	1.10%	0.50%	-0.03%	0.00%	0.42%	-0.21%	-0.29%
	(5.58)	(7.13)	(9.34)	(1.68)	(-0.19)	(-0.02)	(1.47)	(-1.56)	(-2.23)
9	1.76%	1.25%	1.25%	0.33%	-0.20%	-0.14%	0.41%	-0.21%	-0.26%
	(5.79)	(6.90)	(8.52)	(1.10)	(-1.16)	(-1.09)	(1.36)	(-1.27)	(-1.50)
10	2.03%	1.46%	1.40%	0.21%	-0.37%	-0.30%	0.41%	-0.26%	-0.31%
(High)	(6.26)	(7.90)	(9.30)	(0.65)	(-1.94)	(-1.89)	(1.27)	(-1.55)	(-1.79)
L/S	1.02%***	0.99%***	1.15%***	-0.47%**	-0.51%**	-0.41%*	-0.62%***	-0.66%***	-0.50%***
	(4.45)	(4.45)	(4.92)	(-2.09)	(-2.12)	(-1.95)	(-3.21)	(-3.34)	(-2.57)

Table IV: Mutual Fund Flows and Industry Valuation (Continued)

This panel reports logit regressions of equity issuance and merger and acquisition activities of conglomerate firms. The dependent variable in columns 1 and 2 is an $Equity\ Issuance$ dummy that takes the value of one if the firm increases shares outstanding (after adjusting for splits) by more than 10% in fiscal year t, and zero otherwise. The dependent variable in columns 3 and 4 is a $Stock\ Financed\ M\&A$ dummy that takes the value of one if the firm has at least one 100% stock-financed acquisition in fiscal year t as reported in the SDC database, and zero otherwise; finally, the dependent variable in columns 5 and 6 is a $Cash\ Financed\ M\&A$ dummy that takes the value of one if the firm has at least one 100% cash-financed acquisition in fiscal year t, and zero otherwise. The main independent variable is the industry flow ($INDFLOW$) measured in the previous year (t-1). Other control variables include the firm-level aggregate flow-induced trading in the previous year ($FLOW$), firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Panel B: Equity Issues and M&As						
	Equity Issuance	Equity Issuance	Stock-Financed M&A	Stock-Financed M&A	Cash-Financed M&A	Cash-Financed M&A
	[1]	[2]	[3]	[4]	[5]	[6]
$INDFLOW_{t-1}$	1.419***	1.451***	2.383**	3.133***	-0.034	0.034
	(3.07)	(4.09)	(2.29)	(3.25)	(-0.35)	(0.48)
$FLOW_{t-1}$		0.346***		0.234***		0.096
		(3.37)		(3.44)		(1.04)
$MKTCAP_{t-1}$		-0.093***		0.317***		0.170***
		(-4.42)		(4.54)		(4.49)
BM_{t-1}		-0.246***		-0.245**		-0.045
		(-3.37)		(-2.06)		(-0.88)
$RET12_{t-1}$		0.053*		0.176**		-0.164***
		(1.87)		(2.26)		(-2.77)
$TURNOVER_{t-1}$		0.074***		0.085***		0.064***
		(5.01)		(5.69)		(4.45)
$IDIOVOL_{t-1}$		0.156***		0.169***		0.105
		(4.42)		(4.76)		(0.32)
$INSTOWN_{t-1}$		0.015		-0.575**		0.946***
		(0.15)		(-2.32)		(4.42)
Pseudo R^2	0.00	0.03	0.01	0.05	0.00	0.04
No. of Obs.	78,727	78,727	83,564	83,564	83,564	83,564

Table V: Discontinuity in Conglomerate Firm Distributions

This table reports the distribution of conglomerate firms based on the relative weights of the top two segments. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labeled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. All firms are then sorted into twenty 5% bins based on the weight of the favorable segment as a fraction of the top two segments. In the first row of each panel, we report the frequency of observations in each 5% bin, calculated as the proportion of the conglomerate firms in the bin as a fraction of the total number of conglomerate firms between 10% and 90% of the ranking variable. The second row of each panel reports the difference in distribution *density* at the lower bound of the bin. The density differences, along with the T-statistics shown in brackets, are calculated using the methodology outlined in McCrary (2008). In panel A, firms are sorted into 5% bins based on sales from the favorable segment as a fraction of combined sales from the top two segments. For example, bin 50-55% contains all the conglomerate firms whose favorable segment accounts for 50-55% of the combined sales of the top two segments. In panels B and C, such grouping is done on the basis of segment profits and segment assets, respectively. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Firms Sorted by %sales in the Favorable Segment								
Frequency	0.061	0.058	0.048	0.048	0.059	0.051	0.051	0.056
Density difference	-0.056	0.003	-0.056	0.080	0.254***	-0.156	0.056	0.117
at the lower bound	(-0.60)	(0.04)	(-0.52)	(0.76)	(2.59)	(-1.62)	(0.51)	(1.18)
No. Obs.	477	451	386	386	455	391	400	446
Panel B: Firms Sorted by %profit in the Favorable Segment								
Frequency	0.059	0.057	0.056	0.052	0.058	0.055	0.055	0.056
Density difference	0.019	-0.061	-0.082	-0.088	0.059	-0.120	-0.097	-0.018
at the lower bound	(-0.22)	(-0.66)	(-0.94)	(-1.28)	(0.65)	(-1.31)	(-1.14)	(-0.19)
No. Obs.	382	370	362	334	372	352	352	364
Panel C: Firms Sorted by %assets in the Favorable Segment								
Frequency	0.060	0.058	0.062	0.068	0.060	0.056	0.054	0.062
Density difference	-0.034	-0.047	0.087	0.103	-0.038	-0.083	-0.022	0.112
at the lower bound	(-0.29)	(-0.38)	(1.03)	(1.24)	(-0.33)	(-0.71)	(-0.18)	(1.45)
No. Obs.	266	254	273	299	266	248	240	276

Table VI: Discontinuity in Segment Profit Margins

This table reports segment profit margins of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, and the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panels A and B report the average segment profit margin, defined as the segment's operating profit divided by segment sales, in each bin. Panel C reports the average firm-level inventory growth rate between years t and t-1 for all firms in each bin. We require that the conglomerate firm's other top segment operates in a non-favorable industry. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Profit Margin in the Favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.104	0.101	0.100	0.104	0.081	0.099	0.094	0.101
vs. neighbors	0.001	-0.002	-0.002	0.014	-0.021***	0.013	-0.006	0.002
(year)	(0.18)	(-0.21)	(-0.24)	(1.57)	(-2.93)	(1.71)	(-0.74)	(0.23)
vs. neighbors	0.007	-0.007	0.000	0.014	-0.016***	0.013	-0.010	0.006
(year + SIC)	(0.84)	(-1.29)	(0.00)	(1.54)	(-2.79)	(1.61)	(-1.25)	(0.85)
No. Obs.	385	350	303	298	342	290	285	339
Panel B: Profit Margin in the Non-favorable Segment (Favorable vs. Non-favorable)								
Profit margin	0.099	0.091	0.085	0.089	0.087	0.094	0.088	0.091
vs. neighbors	0.007	0.000	-0.003	0.002	0.002	0.000	-0.006	0.008
(year)	(0.91)	(0.03)	(-0.48)	(0.31)	(0.23)	(-0.04)	(-0.80)	(1.11)
vs. neighbors	0.008	-0.002	-0.003	0.004	0.001	0.000	-0.007	0.007
(year + SIC)	(1.04)	(-0.38)	(-0.39)	(0.79)	(0.09)	(0.03)	(-0.86)	(0.88)
No. Obs.	385	350	303	298	342	290	285	339

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel C: Inventory Growth Rates (Favorable vs. Non-favorable)				
Inventory growth	0.083	0.086	0.060	0.084
vs. neighbors	0.000	0.014	-0.025**	0.004
(year)	(-0.01)	(1.19)	(-2.28)	(0.24)
No. Obs.	522	428	458	453

Table VII: Segment Capital Expenditures and R&D Spending

This table reports average segment capital expenditures and R&D spending of conglomerate firms. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The first row of each panel reports the average characteristic of all firms in each bin, the second and third rows report the difference in that characteristic between the current bin and the two neighboring bins after controlling for year fixed effects, while the fourth and fifth rows report the same difference after controlling for year and industry fixed effects. Panel A reports the average segment capex, defined as the segment capital expenditures divided by lagged firm total assets, in each bin. Panel B reports the average segment R&D, defined as the segment R&D spending divided by lagged firm total assets. T-statistics, shown in parentheses, are based on standard errors clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel A: Capital Expenditures in the Favorable Segment (Favorable vs. Non-favorable)								
CapEx	0.019	0.022	0.023	0.022	0.022	0.026	0.029	0.031
vs. neighbors	0.000	0.001	0.001	-0.001	-0.001	0.002	0.000	0.000
(year)	(0.18)	(0.78)	(0.83)	(-0.84)	(-0.68)	(0.86)	(0.15)	(-0.11)
vs. neighbors	0.001	0.001	0.000	0.000	-0.002	0.002	-0.001	0.000
(year + SIC)	(0.48)	(0.67)	(-0.04)	(-0.28)	(-1.22)	(1.25)	(-0.25)	(0.06)
No. Obs.	358	326	282	275	315	266	258	310

	30% to 40%	40% to 50%	50% to 60%	60% to 70%
Panel B: R&D in the Favorable Segment (Favorable vs. Non-favorable)				
R&D	0.003	0.002	0.003	0.003
vs. neighbors	0.001	-0.001	0.000	0.000
(year)	(1.12)	(-1.20)	(0.35)	(-0.33)
vs. neighbors	0.000	-0.001	0.000	0.000
(year + SIC)	(0.43)	(-1.05)	(0.27)	(-0.22)
No. Obs.	140	115	97	114

Table VIII: Accounting Restatements

This table reports logit regressions of accounting restatements on primary industry classification changes. The dependent variable in all columns is a dummy variable that takes the value one if there is an accounting restatement in the following year, and zero otherwise. The main independent variable is a $SWITCH$ dummy that takes the value of one if the conglomerate firm's main industry classification switches in the fiscal year, and zero otherwise. In columns 1 and 2, we include all switchers in our sample; in columns 3 and 4, we only include switchers from a non-favorable to a favorable industry in the sample; finally, in columns 5 and 6, we include all the other switchers (i.e., those switching from non-favorable to non-favorable, from favorable to favorable, and from favorable to non-favorable industries) in the sample. We also control for the growth in the fraction of sales contributed by the favorable segment ($\Delta\%SALES$). Other control variables include firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy	Restate Dummy
	All Switchers		Non-Favorable to Favorable		Other Switchers	
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.080	0.179*	0.285***	0.382***	-0.093	-0.025
	(0.86)	(1.85)	(2.93)	(3.35)	(-0.67)	(-0.16)
$\Delta\%SALES_{t-1}$		-0.739**		-0.803***		-0.583
		(-1.99)		(-2.27)		(-1.30)
$MKTCAP_{t-1}$		0.042		0.033		0.040
		(0.86)		(0.66)		(0.85)
BM_{t-1}		0.049		0.070		0.051
		(0.67)		(1.01)		(0.70)
$RET12_{t-1}$		-0.132		-0.131		-0.137
		(-1.17)		(-1.12)		(-1.18)
$TURNOVER_{t-1}$		0.076*		0.073*		0.076*
		(1.80)		(1.74)		(1.78)
$IDIOVOL_{t-1}$		0.278***		0.278***		0.293***
		(5.63)		(5.45)		(5.82)
$INSTOWN_{t-1}$		3.192***		3.211***		3.264***
		(2.77)		(2.67)		(2.99)
Pseudo R^2	0.00	0.09	0.00	0.09	0.00	0.09
No. Obs.	23,769	23,769	22,338	22,338	22,827	22,827

Table IX: Benefits to Industry "Window Dressing"

This table reports regressions of earnings announcement day returns, and SEO and M&A activities on primary industry classification changes. The dependent variable in columns 1 and 2 is an $Equity\ Issuance$ dummy that takes the value of one if the firm increases shares outstanding (after adjusting for splits) by more than 10% in the fiscal year, and zero otherwise; the dependent variable in columns 3 and 4 is a $Stock\ Financed\ M\&A$ dummy that takes the value of one if the firm has at least one 100% stock-financed acquisition in fiscal year t as reported in the SDC database; finally, the dependent variable in columns 5 and 6 is the cumulative 3-day return around an annual earnings announcement. The main independent variable is a $SWITCH$ dummy that take the value of one if the conglomerate firm's main industry classification switches from a non-favorable to a favorable industry in the fiscal year, and zero otherwise. We also control for the growth in the fraction of sales contributed by the favorable segment ($\Delta\%SALES$). Other control variables include the standardize unexpected earnings (SUE), defined as the difference between the actual earnings and consensus analyst forecast scaled by lagged stock price, firm size, book-to-market ratio, lagged one-year stock return, monthly share turnover, stock idiosyncratic volatility, and proportion of institutional ownership. Year-fixed effects are included in columns 5 and 6. T-statistics and Z-statistics, shown in parentheses, are based on standard errors that are clustered at the year level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Equity Issuance	Equity Issuance	Stock-Financed M&A	Stock-Financed M&A	Anncmnt Return	Anncmnt Return
	[1]	[2]	[3]	[4]	[5]	[6]
$SWITCH_{t-1}$	0.475***	0.414***	1.150***	1.260***	0.014**	0.012**
	(4.45)	(3.90)	(3.77)	(3.35)	(2.38)	(2.08)
SUE_t					0.199***	0.240***
					(5.47)	(5.02)
$\Delta\%SALES_{t-1}$		-0.142		-1.573		0.006
		(-0.47)		(-1.39)		(0.42)
$MKTCAP_{t-1}$		-0.075***		0.242***		-0.001
		(-4.24)		(2.71)		(-1.25)
BM_{t-1}		-0.222***		-0.063		0.001
		(-3.61)		(-0.17)		(0.39)
$RET12_{t-1}$		0.072		0.106		-0.005
		(1.23)		(0.86)		(-1.63)
$TURNOVER_{t-1}$		0.075*		0.030*		0.000
		(1.70)		(1.81)		(0.23)
$IDIOVOL_{t-1}$		0.158***		0.196***		-0.065
		(3.09)		(3.88)		(-0.34)
$INSTOWN_{t-1}$		-0.151		0.324		0.011**
		(-0.88)		(0.45)		(2.21)
Adj./Pseudo R^2	0.01	0.03	0.01	0.04	0.03	0.03
No. Obs.	24,504	24,504	23,577	23,577	10,648	10,648

Table X: Robustness Checks

This table reports some robustness checks. At the end of each quarter, we compute a $FLOW$ measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. We then take the average $FLOW$ across all stocks in each two-digit SIC code industry to derive $INDFLOW$. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. All firms are then sorted into twenty 5% bins based on the weight of the favorable segment as a fraction of the top two segments. Panel A reports the discontinuity in industry beta for a subsample of firms that operate in two non-favorable industries. The first row reports the average industry beta with regard to the segment in question, and the second row reports the difference in industry beta between the current bin and the preceding bin. Panels B and C report the distribution of conglomerate firms whose top two segments are in one favorable industry and one non-favorable industry. In the first row of either panel, we report the frequency of observations in each 5% bin. The second row reports the difference in distribution *density* at the lower bound of the bin. The density differences, along with the T-statistics shown in brackets, are calculated using the methodology outlined in McCrary (2008). In panel B, we include only two-segment firms in the sample (that is, we exclude all firms with more than two segments). In Panel C, an industry is labelled as favorable if it is one of the top 20 industries as ranked by the industry market-to-book ratio in that year (following the M/B industry decomposition in Rhodes–Kropf, Robinson, and Viswanathan, 2005). *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60%to 65%	65% to 70%
Panel A: Industry Beta (non-favorable vs. non-favorable)								
Industry beta	0.131	0.132	0.115	0.143	0.219	0.185	0.193	0.264
$beta_b$ - $beta_{b-1}$	0.016	-0.002	-0.020	0.022	0.076***	-0.027	0.007	0.066
	(0.47)	(-0.04)	(-0.31)	(0.38)	(2.58)	(-0.56)	(0.16)	(1.38)
No. Obs.	644	522	504	546	546	504	522	644

	30% to 35%	35% to 40%	40% to 45%	45% to 50%	50% to 55%	55% to 60%	60% to 65%	65% to 70%
Panel B: Discontinuity in Distribution, Two Segment Firms Only								
Frequency	0.059	0.054	0.046	0.044	0.053	0.047	0.050	0.052
Density difference	0.074	-0.061	0.027	0.142	0.267**	-0.198	-0.043	0.171
at the lower bound	(0.63)	(-0.48)	(0.20)	(0.99)	(2.01)	(-1.62)	(-0.28)	(1.28)
No. Obs.	277	250	223	212	256	223	241	250
Panel C: Discontinuity in Distribution, Industries Ranked by M/B								
Frequency	0.056	0.053	0.050	0.049	0.060	0.059	0.059	0.062
Density difference	0.102	0.055	0.020	-0.073	0.242**	0.031	-0.058	0.110
at the lower bound	(1.07)	(0.58)	(0.21)	(-0.74)	(2.54)	(0.35)	(-0.53)	(1.23)
No. Obs.	386	365	347	338	411	404	403	426

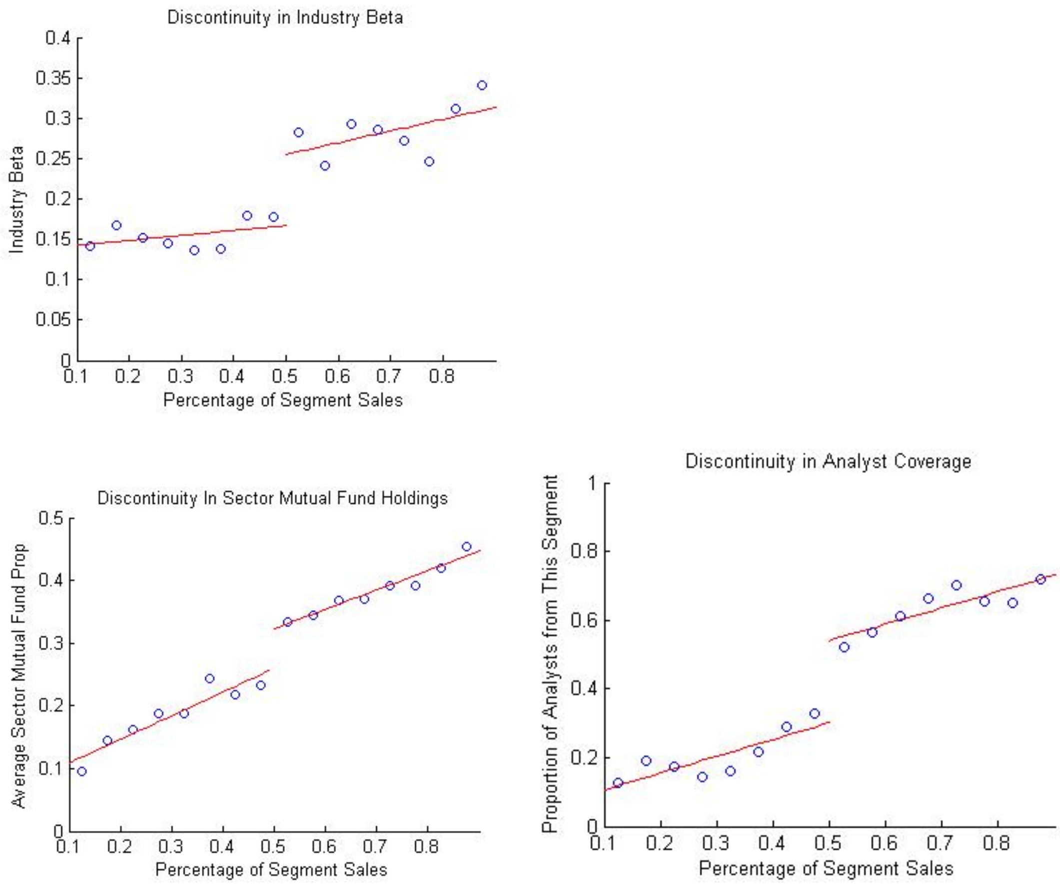

Figure 1: This figure shows the average industry beta and proportion of sector mutual funds that hold and analyst that cover the firm from each segment a conglomerate firm operates in. We focus only on conglomerate firms that operate in two two-digit SIC code industries. All firms are then sorted into twenty 5% bins based on the sales from one of the two segments as a fraction of the combined sales. The blue circles represent the average characteristics of all firms in each bin, while the red curves represent the smoothed estimated linear functions that fit over these observations. The top left panel shows the average industry beta. Specifically, at the end of each quarter, we compute an industry beta for each conglomerate firm in our sample by regressing weekly stock returns on the weekly returns of the two-digit SIC code industry that the conglomerate firm operates in, using data from months 6 to 18 after the fiscal year end. We exclude the stock in question from calculating the corresponding industry returns. The bottom two panels report the proportion of sector mutual funds that hold and analysts that cover the firm from each segment, respectively. Specifically, at the end of each quarter, we assign a mutual fund holding more than ten stocks to a two-digit SIC code industry, if that industry accounts for more than half of the fund's portfolio value; similarly, we assign each sell-side analyst covering more than four firms to a two-digit SIC code industry, if that industry accounts for more than half of all the firms that the analyst covers, using coverage data in the previous three years. We exclude the stock in question in industry assignments to ensure that our results are not mechanical. We then compute the proportion of sector mutual funds and analysts from each industry that the

conglomerate firm operates in using fund holdings and analyst coverage data in months 6 to 18 after the fiscal year end.

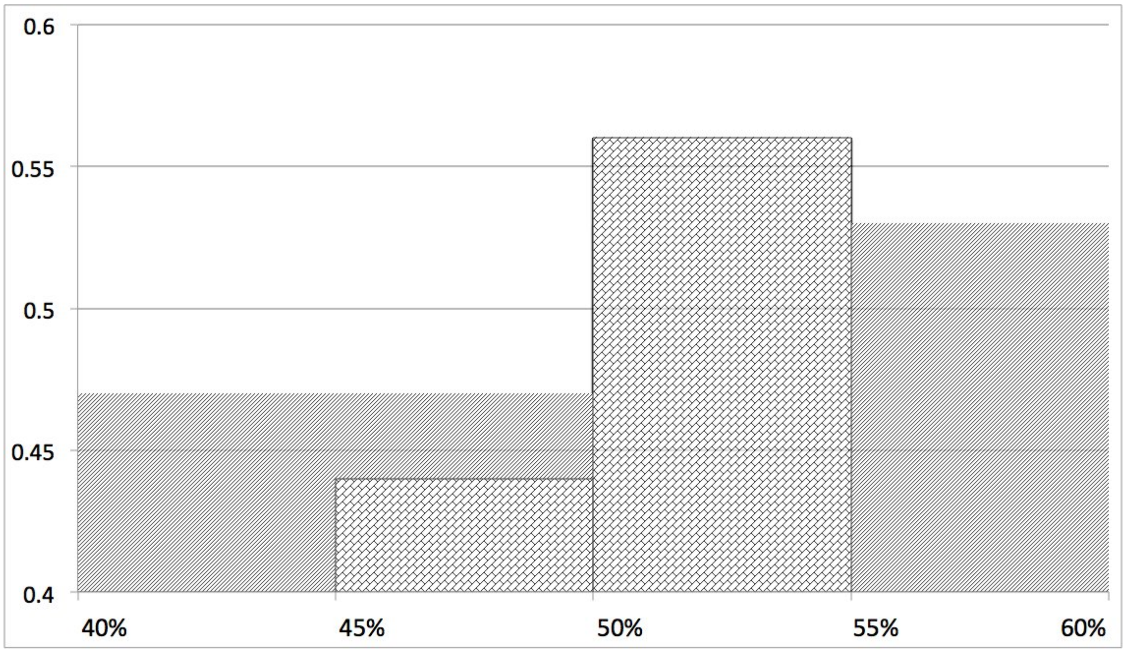

Figure 2: This figure shows the distribution of conglomerate firms based on relative sales weights of the top two segments. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry, where an industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. Since the larger of the two segments determines the industry classification of the conglomerate firm, the 50% point in relative sales is the discontinuity point in our empirical analysis. The grey area shows the distribution of conglomerate firms whose sales from favorable industries account for 40%-60% of the total sales, while the block area shows the distribution of conglomerate firms whose sales from favorable industries account for 45%-55% of the total sales. Any firm over the 50% point in this figure is classified to a favorable industry, whereas any firm below 50% is classified to a non-favorable industry.

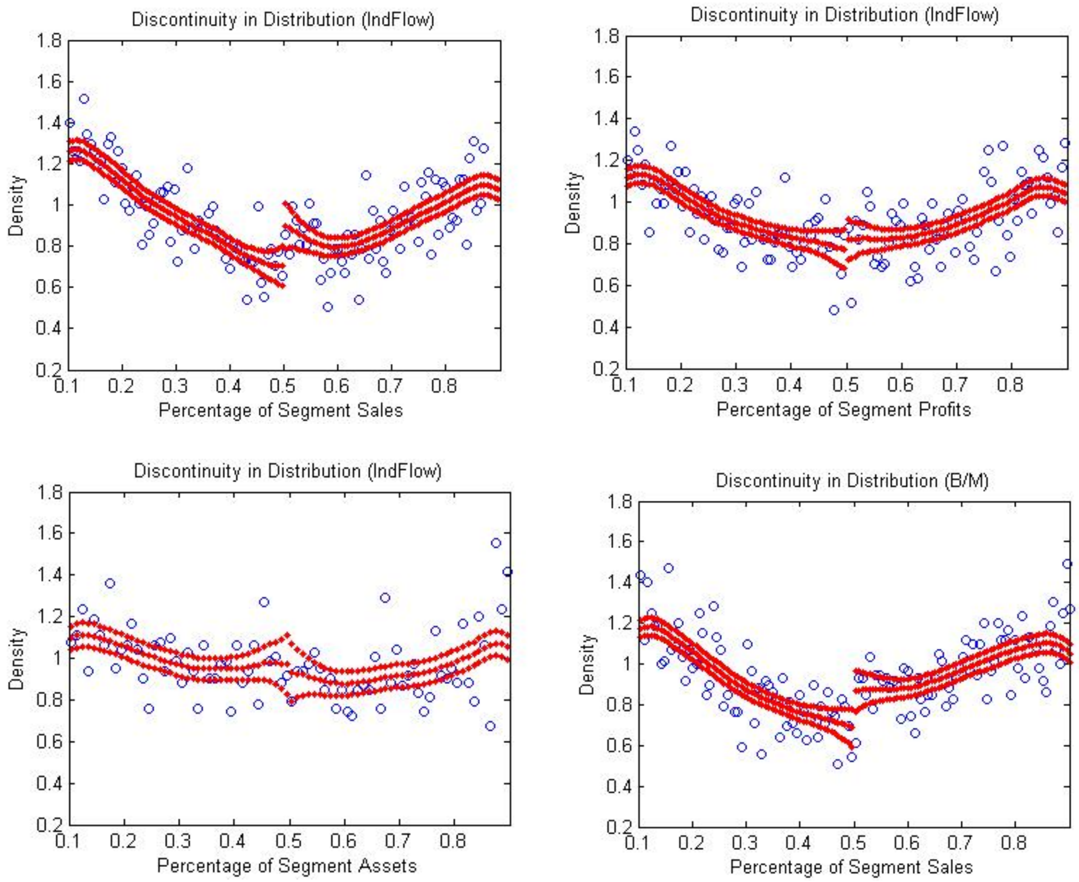

Figure 3: This figure shows the smoothed density functions based on the relative weights of the top two segments of conglomerate firms. The estimation methodology is outlined in McCrary (2008). The blue circles represent the distribution density of each bin grouped by the sorting variable. The red curves are the estimated smoothed density functions, and the 2.5% to 97.5% confidence intervals of the estimated density. Both the bins size and bandwidth are chosen optimally using the automatic selection criterion. The densities to the left and right of the discontinuity point (the 50% cut-off in our case) are then estimated using local linear regressions. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other in a non-favorable industry. In the first three panels, an industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. In the last panel, an industry is labelled as favorable if it is one of the top 20 industries as ranked by the industry book-to-market ratio in that year (following the B/M industry decomposition in Rhodes–Kropf, Robinson, and Viswanathan, 2005). In the top left and bottom right panels, firms are ranked based on sales from the favorable segment as a fraction of combined sales from the top two segments. In the top right and bottom left panels, such grouping is done on the basis of segment profits and segment assets, respectively.

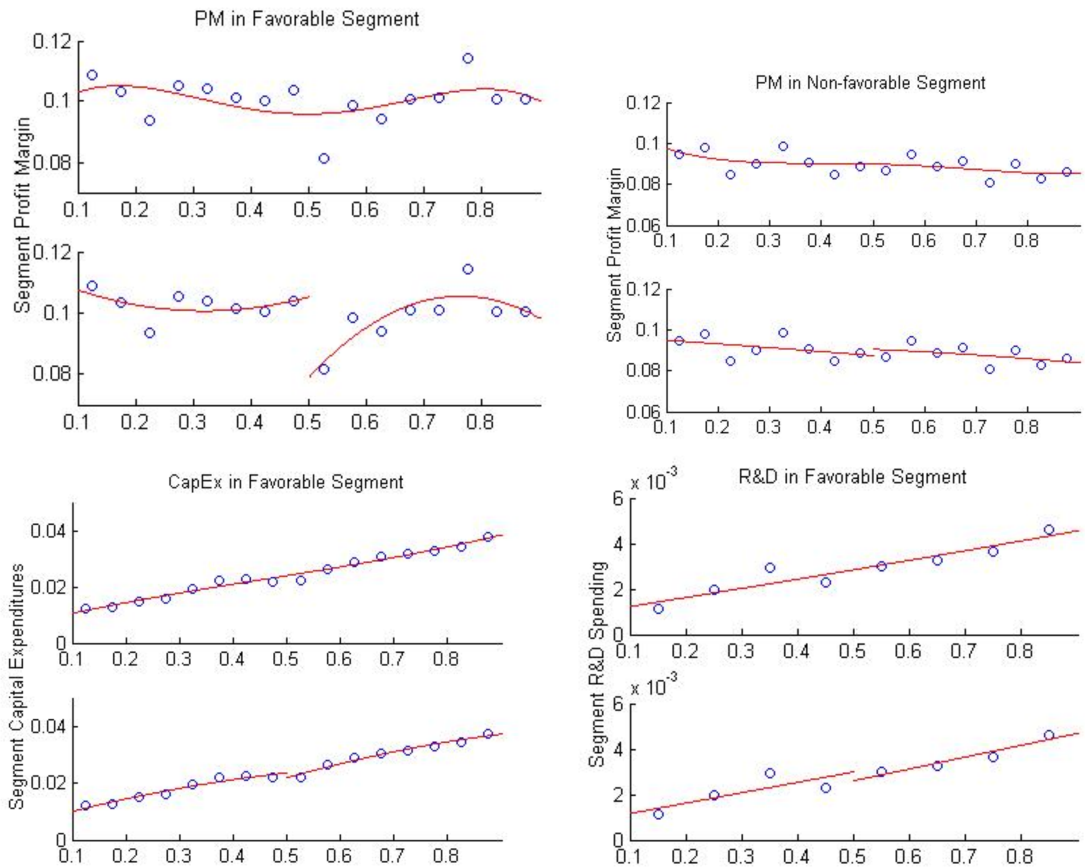

Figure 4: This figure shows various financial/accounting characteristics of conglomerate firms. For each conglomerate firm in our sample, we require one of the top two segments to operate in a favorable industry and the other to operate in a non-favorable industry. An industry is labelled as favorable in a year if it is one of the top 20 industries as ranked by $INDFLOW$ in that year. All firms are then sorted into twenty 5% bins based on the sales from the favorable segment as a fraction of the combined sales from the top two segments. The blue circles represent the average characteristics of all firms in each bin, while the red curves represent the smoothed estimated polynomial functions (up to three degrees) that fit over these observations. The top left panel shows the average profit margin in the favorable segment, defined as the segment's operating profit divided by segment sales, in each bin. The top right panel shows the average profit margin in the non-favorable segment. The bottom left panel shows the average capex in the favorable segment, defined as the segment capital expenditures divided by lagged firm assets, in each bin, and the bottom right panel shows the average R&D in the favorable segment, defined as the segment R&D spending divided by lagged firm assets.