

Selection Bias in Mutual Fund Fire Sales

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Abstract

Several prominent studies use mutual fund fire sales as exogenous price shocks. They find clear feedback effects, wherein stock prices affect firm policies. I show that selection bias invalidates fire sales. Large mutual fund outflows affect small and micro-cap mutual funds disproportionately, meaning fire sales are predicted by firm characteristics. Also, fund managers meet large redemption requests by preferentially selling liquid stocks with higher past returns. This pattern leads to imbalance in estimating treatment effects. I demonstrate how these factors invalidate the fire sales instrument. Conclusions drawn from using this instrument should be re-evaluated. There may be no feedback effect.

JEL classifications: G14; G23; G32

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17 Introduction

18 Is there a feedback loop between a firm's stock price and the firm's financial policies? The
19 answer to this question has very important implications for the efficiency of financial markets.
20 Finance theory suggests how such a feedback loop could arise (Chen, Goldstein, and Jiang, 2006;
21 Goldstein, Ozdenoren, and Yuan, 2013), but whether or not it exists in practice is an empirical
22 question. It is difficult to establish whether exogenous changes in the price of a firm's stock cause
23 its CEO to change firm policies because purported feedback loops are plagued by endogeneity —
24 by definition. There is little doubt that firm actions affect stock prices but the question at hand is
25 whether stock prices also affect firm actions. Proper identification requires an exogenous shock to
26 stock prices that is separate from firm actions and outside of this loop.

27 Mutual fund fire sales have been proposed as just such an exogenous shock to stock prices
28 (Coval and Stafford, 2007 and Edmans, Goldstein, and Jiang, 2012). The idea behind using mutual
29 fund fire sales to identify the feedback effect runs something like this. A mutual fund manager
30 constructs a portfolio by buying shares in many different firms. At some subsequent date, unusually
31 large redemption requests from the fund's investors force the manager to sell some portfolio shares.
32 The argument is that these redemption requests are not likely to be driven by firm-specific events,
33 policies, or characteristics. Stock prices shift as managers sell shares for liquidity reasons, not
34 because of any information they have about firm policies. The implicit assumption is therefore that
35 when fund managers sell shares for liquidity they do so without regard to firm fundamentals.

36 Fire sales will not satisfy the exclusion restriction for valid instruments if the managers strate-
37 gically sell off only some of their holdings. Edmans, Goldstein, and Jiang (2012) proposes an
38 empirical method to circumvent this concern. Instead of looking at which shares were actually
39 sold during the mutual fund fire sale, they construct *hypothetical sales* that are calculated using

each firm's pre-fire sale share in the mutual fund's portfolio. The argument is that large mutual fund outflows force the fund manager to sell some shares of *all* holdings and, indeed, that the needed liquidity is obtained by managers selling off fund shares *in proportion to their weights in the original pre-fire sale portfolio* (Coval and Stafford, 2007; Edmans, et al., 2012). This proportional sales assumption underlies the assertion that any resulting stock price fluctuations are independent of firm fundamentals. The identifying assumptions of the mutual fund fire sale measure are thus that fire sales are both large enough to significantly affect the share price of portfolio firms and *exogenous* to firm policies. Under these conditions, fire sales are outside of the feedback loop and can be used to identify the feedback effect.

Recent studies have used this method exhaustively. The emerging consensus is that stock price fluctuations distort many of the most fundamental decisions that firms make. Empirical results establish that fire sales influence takeover attempts (Edmans, et al., 2012), R&D expenditures (Phillips and Zhdanov, 2013), corporate investment (Dessaint, Foucault, Fresard, and Matray, 2019), shareholder activism (Derrien, Kecskes, and Thesmar, 2013; Norli, Ostergaard, and Schindele, 2014), analyst forecasts (Lee and So, 2017), corporate disclosures (Zuo, 2016), use of credit lines (Acharya, Almeida, Ippolito, and Perez, 2014), equity issuance (Khan, Kogan, and Serafeim, 2012), earnings forecasts (Lou and Wang, 2018), and option grant timing (Ali, Wei, and Zhou, 2011).

The focus of this paper is to provide the literature with critical input regarding the mutual fund fire sale measure. I construct my sample of U.S. equity mutual fund and firm-level data for the period from 1980 to 2007 to reflect the time period typically covered in the literature (Coval and Stafford, 2007; Edmans, et al., 2012).

Two events must occur in order for mutual fund outflows to produce a valid mutual fund fire sale instrument. The funds must experience a large outflow due to investor redemptions and the

64 fund's manager must then sell off stocks in proportion to their original weight in the portfolio. I
65 begin the empirical analysis by testing whether both the large outflow and the choice of stocks sold
66 are independent of firm characteristics.

67 I document that large mutual fund outflows affect a non-random subset of all mutual funds:
68 large outflows are more likely among funds that invest in small, illiquid, and poorly performing
69 stocks. This fact biases the instrument towards firms with these characteristics.

70 I also find that the initial mutual fund portfolio is not random – it is selected on both observable
71 and unobservable characteristics. Mutual fund manager characteristics such as skill and market
72 timing influence the initial portfolio selection. The selection bias compounds as the instrument is
73 constructed. Specifically, poor firm returns predict poor portfolio returns which predict negative
74 fund flows. Funds that have low or negative flows hold firms with low past returns. None of these
75 relationships is surprising but not one of them is what a good instrumental variable should deliver.
76 I document that (1) the large outflows, (2) the manager's portfolio prior to the shock, and (3) the
77 subset of stocks mutual fund managers choose to sell are correlated with firm characteristics. My
78 results show that these features of the data trigger the price shock, and I specifically discuss the
79 direct correlation with firm outcomes. These results mean that unobservable characteristics —
80 characteristics that cannot be accounted for with additional control variables— distort the mutual
81 fund fire sale instrument.

82 I provide examples in which selection bias in the fire sale instrument interferes with conclusions
83 about feedback effects on investment decisions and equity offerings. When characteristics are
84 observable, the fix is simple; include control covariates for any differences. But when the bias-
85 inducing characteristics are *not* observable, no remedy exists. Mutual fund fire sales will be directly
86 related to firm characteristics, and I discuss how unobservable characteristics interfere with any
87 causal conclusions. The results of this paper show that the mutual fund fire sale instrument is not

valid because it violates the exclusion restriction. There is no way around the fact that unobservable characteristics invalidate the instrument. This result suggests that any conclusions about the impact of stock prices on firm behavior that have been derived from mutual fund fire sale shocks should be re-examined.

Viewed most broadly, this paper is a contribution to the empirical methods and corporate finance literatures that study the feedback effect from stock price to firm policy. The results raise significant doubts about whether such a feedback effect exists. The results also contribute to the mutual fund literature by documenting that large outflows are more likely among small and micro cap funds and that fund managers minimize liquidity costs in times of distress.

I describe the sample in Section II and I construct the measure of mutual fund fire sales in Section III. I document the causes of selection bias in mutual fund fire sales in Section IV. Section V shows how selection bias links directly to firm characteristics. Concluding remarks are in Section VI.

II. Data and Methods

I construct my dataset to match the time period and data sources used in prior studies that examine mutual fund fire sales (e.g., Edmans, et al., 2012). The dataset spans the years 1980 to 2007. The final dataset contains 106,223 firm-year observations.

I use the Wharton Research Data Services (WRDS) MFLinks file to merge two mutual fund level databases: the Thompson Financial CDA/Spectrum holdings database and the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund database. The mutual funds must have holdings data in CDA/Spectrum, as well as a valid link to the CRSP Mutual Fund database over the full sample period. The final mutual fund sample includes equity mutual funds but not sector mutual funds that specialize in specific industries (Edmans, et al., 2012). To define

the set of passively managed funds, I identify index and target-date mutual funds by their fund names in the CRSP Mutual Funds database and by using the CRSP index fund flag (Kacperczyk, Sialm, and Zheng, 2008).

At the firm level, the data consist of firms with share codes 10 or 11, listed on Compustat with non-missing price and returns data reported in the CRSP monthly file. I exclude all financial (SIC 6000-6999) and utilities firms (SIC 4000 - 4949) from the sample. I gather data on M&A activity from the Securities Data Company (SDC Platinum) for 1980 - 2007. I include all bids, regardless of whether they are eventually completed (Edmans, et al., 2012).

Fund-level variables include total net assets (*TNA*), *gross returns*, *net returns*, and *expense ratios*. Where CRSP reports multiple share classes, *TNA* is the sum of *TNA* across all share classes, and returns and expense ratios are *TNA*-weighted averages across all share classes. Monthly fund gross returns are calculated as net monthly fund returns plus 1/12 of annual fees and expenses. Other multi-share class fund characteristics (e.g., investment objective codes) are set equal to the value of the share class with the largest *TNA*.

I compute a fund's quarterly *flow* as the sum of monthly asset flows net of merger assets in each calendar quarter. Consistent with the literature, I assume that flows occur at the end of each quarter and that investors reinvest dividends and capital appreciation distributions in the same fund (e.g., Coval and Stafford, 2007). New mutual funds have inflows equal to their initial *TNA*. Liquidated funds have outflows equal to their terminal *TNA*. I correct the fund flows measure for the potential distortions of fund mergers.¹

Flows to fund j in quarter t represent the growth rate of the *TNA* under management after

¹To calculate the increase in *TNA* caused by a merger in quarter t , $MGN_{j,t}$, I approximate the date on which a merger occurs, because neither CRSP nor CDA/Spectrum reports the exact date of the merger. In order to do this in a consistent manner, I adopt the convention that the net asset value (*NAV*) report date of the target fund is the merger date. To avoid mismatches, I match a target fund to its acquirer from one month before to five months after its last *NAV* report date and calculate the merger-adjusted flow for each of the months in this six-month window. I then select the month with the smallest absolute percentage flow as the event month (Lou, 2012).

adjusting for the market appreciation of the mutual fund's assets ($R_{j,t}$) and new cash from fund mergers ($MGN_{j,t}$) (Chevalier and Ellison, 1997; Lou, 2012). The flows to fund j in quarter t are defined as:

$$flow_{j,t} = TNA_{j,t} - TNA_{j,t-1} \times (1 + R_{j,t}) - MGN_{j,t} \quad (1)$$

$$FLOW_{j,t} = \frac{flow_{j,t}}{TNA_{j,t-1}}. \quad (2)$$

where $flow_{j,t}$ denotes the dollar value of flows into and out of fund j in quarter t and $FLOW_{j,t}$ measures the quarterly mutual fund flows for fund j in quarter t ($flow_{j,t}$) in proportion to TNA in the previous period.

Data from CDA/Spectrum are used to compute the number and value of shares of every equity held by each mutual fund as of the quarter end (Coval and Stafford, 2007).

$$Holdings_{j,i,t} : h_{j,i,t} = \frac{P_{i,t} \times S_{j,i,t}}{TNA_{j,t}}, \quad (3)$$

$Holdings_{j,i,t}$ measures a fund's holdings of stock i , as a fraction of its TNA , where $P_{i,t}$ and $S_{j,i,t}$ are the share price of firm i in quarter t and the shares of firm i held by fund j in quarter t , respectively.

If a given firm has an event that affects the number of shares outstanding, I use CRSP monthly stock data to adjust the reported number of shares that the mutual fund holds to be current as of the mutual fund report date and assume that the manager does not trade between the report date and the quarter-end (Coval and Stafford, 2007). To control for data discrepancies between the CDA/Spectrum equity holdings and the CRSP data, I compute the difference between the TNA data in the CRSP database (which includes the complete holdings) and the TNA data in the CDA/Spectrum database (which includes only the reported stock holdings) and require that the TNA s do not differ by more than a factor of two (i.e., $0.5 < \frac{TNA_{CDA}}{TNA_{CRSP}} < 2$) (Coval and Stafford,

2007). In addition, I require a minimum fund size of \$1 million (Coval and Stafford, 2007).

Table 1 reports the annual summary statistics as of December of each year for the sample of mutual funds. The full sample contains 29,552 fund-year observations for 3,388 distinct mutual funds. Column (2) reports the number of equity mutual funds by year, along with fund summary statistics. The number of mutual funds and average fund size increased ten-fold over the sample period and mutual fund ownership in the U.S. equity market grew from just 2% in 1980 to 16% in 2006. These statistics are comparable to those reported in Lou (2012).

[Insert Table 1]

The firm-level variables measure firm characteristics and financial policies that are potentially affected by market prices. Firm characteristics, which are the direct determinants of firm policies, include firm size, profitability, cash flows, Tobin's q , the Kaplan-Zingales financial constraint measure, and the Amihud illiquidity measure (Goyenko, Holden, and Trzcinka, 2009; Hasbrouck, 2009). I construct a firm-level Herfindahl-Hirschman Index (HHI) of mutual fund ownership to measure the relative concentration of each mutual fund's ownership of a firm.² The definitions of these variables are in the Appendix. The mutual fund *Fire Sale Shock* and the variable *Treatment Firm* are defined in Section III.

Table 2 reports the summary statistics for the sample of firms. Sample firms have non-missing values for cash flows, profits, returns, volatility, leverage, payout, equity issuance, capital expenditures, book assets, and market-to-book. All variables are winsorized at 1% and 99%. Between 1980 and 2007, institutional investors owned an average of 25% of outstanding firm shares and mutual funds owned another 8%. The mean value of the *Treatment Firm* variable indicates that firms experienced fire sales in about half of the sample firm-years.

²The HHI approaches zero when a large number of mutual funds hold positions in a firm of relatively equal size and approaches its maximum of one when a single mutual fund controls all of the shares of the firm.

III. The Mutual Fund Fire Sale Variable

III.A. Construction of the Variable

Mutual fund managers must hold some cash in reserve to offset regular fluctuations in investor demand. They balance this liquidity need and the low returns on cash against their fundamental objective of seeking higher returns by investing in equities. In equilibrium, managers hold enough cash to absorb small, foreseen redemption requests (outflows).

Unusually large outflows threaten to exceed cash holdings and force managers to sell assets. The literature typically classifies outflows as “large” if they reach 5% or more of *TNA* in a given quarter (Coval and Stafford, 2007; Edmans, et al., 2012). It is believed that these large outflows can have a large, negative impact on the share price of firms owned by the affected funds (Coval and Stafford, 2007; Edmans, et al., 2012; Khan et al., 2012).

I follow the descriptions in Edmans, et al. (2012) and Phillips and Zhdanov (2013) to construct the fire sales variable, *Fire Sale*. *Fire Sale* measures calendar year changes in the number of firm *i* shares held by mutual fund *j*. It is based on the disclosed investment portfolios of funds with large outflows.

Define a subset K_t of mutual funds in period *t* that experienced outflows that were large in relation to their *TNA* ($FLOW_{j,t} \leq -5\%$). In any given period, there are $K_{N,t}$ such funds.

For every fund $k \in K$ in each quarter *t*, I define the following variables:

$$Outflows : \phi_{k,t} = TNA_{k,t} - (1 + R_{k,t}) \times TNA_{k,t-1} - MGN_{k,t}, \quad (4)$$

where $k \in \{1, 2, \dots, K_{N,t}\}$.

The combination of *holdings* ($h_{j,i,t}$ in equation (3)) and *outflows* ($\phi_{k,t}$ in equation (4)) defines

the *Trades* variable:

$$Trades_{k,i,t} : T_{k,i,t} = \phi_{k,t} \times h_{k,i,t-1} = FLOW_{k,t} \times P_{i,t-1} \times S_{k,i,t-1}. \quad (5)$$

$Trades_{k,i,t}$ uses the portion of the fund's previously disclosed holdings in each firm to calculate a manager's trades in each firm i .

A firm's dollar trading volume is measured as the total trading volume for firm i in quarter t :

$$Trading\ Volume : V_{i,t} = P_{i,t} \times x_{i,t}, \quad (6)$$

where $x_{i,t}$ is the total shares of firm i traded in quarter t and $P_{i,t}$ is the price of firm i in quarter t .

The *Fire Sale* variable measures the total impact of mutual fund trades on the underlying firm i in each quarter t :

$$Fire\ Sale : Fire\ Sale_{i,t} = \sum_{k=1}^K \frac{T_{k,i,t}}{V_{i,t}} = \sum_{k=1}^K \frac{FLOW_{k,t} \times P_{i,t-1} \times S_{k,i,t-1}}{V_{i,t}}. \quad (7)$$

The annualized $Fire\ Sale_{i,t}$ measure for firm i is the sum of $Fire\ Sale_{i,q}$ over the four quarters q of each calendar year. If firm i incurs no mutual fund fire sales in year t , then $Fire\ Sale_{i,t} = 0$. The *Fire Sale* variable is non-positive, but for ease of interpretation, I adjust the variable to measure the absolute value of these shocks, so that a higher value is associated with a higher level of fire sales for that firm-year observation. I define the variable *Treatment Firm*, as an indicator variable equal to one in the years when a firm is involved in a fire sale ($FireSale > 0$).

III.B. Implementation of the variable

Mutual fund fire sale studies involve four types of data, namely (1) fire sales data (the fire sale instrument), (2) stock prices, (3) firm outcomes, and (4) observable and unobservable firm characteristics. Panels A through C of Figure 1 depict three ways of setting up the instrumental variable. Panel A maps out the correct relationships between the data. Fire sales alter stock prices and these prices then affect firm outcomes. This happens through mutual fund price pressure — only. Firm characteristics play no role.

[Insert Figure 1]

In the Panel B setup, some firm characteristics predict firm outcomes directly and all of these characteristics are observable. In this setup the fire sale instrument is not valid unless all firm characteristics are included as covariates in the model. If they are observed and included, then setup B reverts to a version of A with these firm control variables.

The diagram in Panel C represents the case where some of the characteristics that predict firm outcomes are not observable, the characteristics cannot be measured, and their impact is therefore not directly testable. These are the firm characteristics that invalidate the instrument.

The remainder of the paper will evaluate mutual fund fire sales along these dimensions.

IV. Large Mutual Fund Outflows and Portfolio Trading

To begin, I examine whether firm characteristics predict large fund outflows. I test the hypothesis that the likelihood that a given mutual fund falls victim to a large outflow depends on the set of firms that it holds at $(t - 1)$. This link leads to a correlation between large outflows and firm characteristics. I then turn to the question of which shares fund managers sell after experiencing a large outflow. I test whether imposing a proportional trading assumption alleviates or exacerbates selection bias.

IV.A. The Relation between Large Outflows and Firm Characteristics

The appeal of using large mutual fund outflows as shocks is that if they exceed cash reserves, fund managers must sell shares (Coval and Stafford, 2007; Edmans, et al., 2012). Such large outflows will be exogenous shocks to share prices if they are unrelated to characteristics of firms that constitute the portfolio. Only if this independence holds can outflows from the fund and any subsequent effect of those outflows on share prices be treated as exogenous to firm characteristics.

236 There is reason to suspect that these independence conditions do not hold for two reasons. First,
237 mutual fund regulations require that mutual fund managers commit to broad investment strategies.
238 Yet these strategies are defined by firm characteristics. For example, a fund that advertises itself as
239 having a “small-cap growth strategy” invests in small, high-growth firms, while one that promotes
240 itself as a “large-cap value strategy” fund will have a portfolio that consists almost entirely of large,
241 established firms.

242 Secondly, mutual fund managers actively select the $t - 1$ portfolio firms. The mutual fund
243 literature shows that managers may have skill in selecting specific firms and in timing the purchase
244 and sale of shares in those firms (Kacperczyk, Sialm, and Zheng, 2008). If fund managers do have
245 this skill and it is unobservable, then mutual fund trades are correlated with unobservable firm
246 characteristics during the portfolio formation period ($t - 1$) that precedes a fire sale shock. This
247 means that the types of firms that a fund has chosen to hold as well as the proportion of individual
248 firm shares in its portfolio are related to unobservable firm characteristics. For example, Chen,
249 Jegadeesh, and Wermers (2000) show that managers of growth-oriented funds exhibit better stock
250 selection skills than managers of income-oriented funds.

251 Both manager skill level and mutual fund style may therefore drive large outflows. Mutual
252 fund type is correlated with unobservable mutual fund management skill —skill that is defined as
253 selecting firms and structuring a portfolio on the basis of unobservables. Though manager skill is
254 unobservable, mutual fund regulations mandate that mutual fund investment style is observable,
255 albeit with broad brushstrokes. I use mutual fund investment styles to test whether there is a
256 relationship between large outflows and mutual fund investment strategies.

257 I perform a fund-level analysis to determine whether large fund outflows are correlated with
258 mutual fund investment strategies. Mutual funds in the sample invest in one of nine broad U.S. eq-
259 uity strategies: domestic income, domestic hedged, domestic growth, domestic growth and income,

domestic large cap, domestic mid cap, domestic small cap, domestic micro cap, and domestic fund (no style specified). To mitigate the influence of industry-specific, business cycle waves on large mutual fund outflows, I exclude funds that invest only in specific commodities, like gold and oil, or only in specific industries (Edmans, et al., 2012).

I use the following linear probability model to estimate whether large outflows are related to fund investment strategies:

$$\begin{aligned} Pr(Out\ flow \geq 5\%) = & \alpha_t + \beta_1\ Past\ Alpha + \beta_2\ Past\ Returns + \beta_3\ Past\ Flows \\ & + \beta_4\ Index\ Fund + \beta_5\ Fund\ Size + \gamma_j\ Fund\ Investment\ Objective_j + \varepsilon_{j,t}, \end{aligned} \quad (8)$$

where the dependent variable $Out\ flow \geq 5\%$ is an indicator that is equal to one if the fund receives large outflows ($\geq 5\%$) in quarter t and zero otherwise. The independent variables include the past four quarters of fund flows ($FLOW_{j,t-1}$ through $FLOW_{j,t-4}$), the monthly Carhart four-factor fund alpha computed from the fund's returns in the previous year, and the cumulative market-adjusted fund return in the previous year.

In addition to the typical predictors of mutual fund flows, the model includes additional fund characteristics. *Index Fund* is an indicator variable with a value of one for index funds and zero otherwise. *Fund Size* is the natural logarithm of the quarterly TNA from quarter $t - 1$. *Fund Investment Objective* is a vector of indicator variables that identify each fund manager's investment strategy. The omitted investment strategy category in the regression is domestic growth, which accounts for over 40% of fund-quarter observations in the sample. The regression specification includes year-quarter fixed effects and standard errors clustered by investment strategy.

Table 3, columns (1) and (2) report results from a linear probability model, predicting the probability of a large outflow. Column (1) reports results of a model in which the "typical" characteristics predict fund flows. The results suggest that funds with higher alphas, higher past returns, and positive past flows are less likely to experience large outflows. This result is broadly con-

sistent with previous findings (Coval and Stafford, 2007). Column (2) reports results of a model that includes the typical characteristics but also additional controls for fund investment styles. The results suggest that several important fund characteristics predict large mutual fund outflows. A fund's investment strategy predicts large mutual fund outflows. Large funds are less likely to have large outflows. Mid-cap, small-cap, micro-cap funds are all more likely to have large outflows compared to domestic growth funds. Micro-cap funds, which target firms with small market capitalizations, are 10% more likely to experience large outflows than domestic growth funds. The coefficient on index indicator suggests that index funds, the type of fund that the fire sales measure attempts to imitate, are 8% less likely to have large outflows.³

[Insert Table 3]

Large outflows are more frequent among mutual funds that share certain investment strategies. This can introduce selection bias into fire sales because these investment objectives are correlated with firm characteristics – firm characteristics that determine firm policies, whether or not a fire sale occurs. For example, firms with small market capitalizations are not only smaller, they are typically more financially constrained and have relatively lower market liquidity than other firms. These firm characteristics are in turn correlated with firm decisions.

IV.B. Fire Sales and Portfolio Trading

Portfolio trading decisions are related to firm characteristics. When a mutual fund faces large redemptions, the fund manager must decide which shares to sell. The manager's choice very likely reflects information about firm value.

To counteract this source of bias in the fire sales measure, the instrumental variable is constructed as though all shares were sold in proportion to pre-outflow holdings. The assumption is

³Index funds are less likely to receive large outflow shocks. As might be expected from their name, the investment strategy of index funds that receive outflows is to liquidate share holdings proportionally.

that the fund's share holdings scale down without affecting the proportion of any shares in the portfolio (e.g., Edmans, et al., 2012). This empirical strategy underlies the claim that fire sales are exogenous to firm fundamentals.

I argue that such a strategy can introduce selection bias if proportional trading is not the average trading strategy of fund managers. Lou (2012) shows that fund managers scale their portfolios proportionally in normal circumstances. However, in abnormal circumstances (i.e., when outflows are large) managers may retain poorly performing firms and firms with high liquidity costs (Duffie and Ziegler, 2003; Alexander, Cici, and Gibson, 2007; Brown, Carlin, and Lobo, 2010).

For example, fund managers may selectively refrain from selling off certain types of shares – types with specific characteristics like illiquidity or poor past performance. If firms with specific characteristics like poor performance and illiquid shares are rarely sold, but the fire sales variable follows a proportional trading strategy, then illiquid and poorly performing firms are more frequently assigned a treatment than they should be.

Essentially, the proportional fire sale method assumes that all firm types – on average – are equally likely to receive the treatment. But inserting firms that have a low probability of being treated into the treatment group introduces bias in the measured treatment effect. Treatment effects may come from observations that are very unlikely to have been treated (Roberts and Whited, 2013). The proportional selling strategy can introduce selection bias in this way —through the estimated treatment effect— and this generates erroneous negative returns outcomes. Share prices of poorly performing firms will appear to have fallen due to the fire sale, even though none of their shares were ever actually sold.

I analyze the trading strategy of fund managers when they receive large outflows in the following regression:

$$trade_{i,j,t} = \alpha_t + \beta_1 FLOW_{j,t} + \beta_2 X + \beta_3 FLOW_{j,t} \times X + \beta_4 Z + \beta_5 FLOW_{j,t} \times Z + \varepsilon_{j,t} \quad (9)$$

where the dependent variable, $trade_{i,j,t}$, is the percentage trading in stock i by fund j in quarter t , where fund j must have experienced outflows greater than or equal to 5%. In equation (9), the variable, $FLOW_{j,t}$, i.e., the capital flow to fund j in quarter t as a fraction of TNA in the previous quarter, measures the degree to which managers trade in proportion to outflows. If fund managers base their sale of shares on the proportional trading strategy, β_1 will equal one and all other coefficients will equal zero. The vectors X and Z reflect the fund manager's trading decisions. X is the vector of fund-level characteristics: the ownership share of mutual fund j in stock i ($own_{i,j,t-1}$), the Amihud illiquidity measure to control for individual firm liquidity costs ($liqcost_{i,t-1}$), the portfolio-weighted average ownership share ($own_{j,t-1}$), and fund-level liquidity costs ($liqcost_{j,t-1}$). Z is a vector of firm-level characteristics that includes lagged annual returns ($returns_{i,t-1}$), lagged annual volatility ($volatility_{i,t-1}$), the Kaplan-Zingales measure of financial constraints ($FinConstraint_{i,t-1}$), the market-to-book ratio ($MkttoBook_{i,t-1}$), and firm size ($Size_{i,t-1}$). The interactions of these variables with fund flows reflect the incremental effect of each characteristic on trading, conditional on the magnitude of outflows. Year-quarter fixed effects, t , control for market-wide fluctuations over time. Standard errors are clustered at the fund level.⁴

The results in Table 4 show that fund managers do not sell shares in proportion to their pre-outflow holdings after large outflows. The point estimate in column (1) for the impact of $FLOW_{j,t}$ is 0.71, which indicates that large outflows lead managers to liquidate only 71 cents on the dollar in proportion to portfolio weights. This leaves 29 cents for the managers to trade at their discretion.

[Insert Table 4]

I next examine the discretionary trading decisions of fund managers in columns (2) - (4) in Table 4. The negative coefficients on $flow_{j,t} \times liqcost_{i,t-1}$ imply that managers are reluctant to

⁴The number of observations in these tests is a subset, about one-third, of all fund-firm sales in the mutual fund universe. These trades reflect only the sales made by funds j with outflows greater than or equal to 5% in quarter t .

sell illiquid firms as outflows increase, consistent with theory (Brown, Carlin, and Lobo, 2010). The coefficients on additional firm characteristics in columns (2) - (4) show that fund managers' trading strategies are correlated with firm characteristics. For example, in column (4), the coefficient on $MkttoBook_{i,t-1}$ of 0.002 means that managers are more likely to sell firms with growth opportunities and the coefficient on $Size_{i,t-1}$ of -0.014 suggests that fund managers are more likely to sell smaller firms, after controlling for liquidity costs.

The results in Tables 3 and 4 reveal two sources of selection bias. First, large outflows are more likely among mutual funds that invest in smaller firms. Because the portfolios of these funds with large outflows are typically biased towards smaller firms, the proportional trading technique does not eliminate the small firm selection bias. Second, the assumption that managers typically adhere to a proportional trading strategy introduces selection bias to the treatment effect by incorrectly assigning firms to the treatment group although they are very unlikely to be treated.

V. Selection Bias and Firm Characteristics

V.A Fire Sales and Firm Returns

Next, I explore the relationship between returns and mutual fund fire sales. I follow the method in Coval and Stafford (2007) and Edmans, et al. (2012) by contrasting the abnormal returns of firms with extreme fire sales to the abnormal returns of firms that have only experienced non-extreme fire sales. Extreme fire sales consist of firm-month observations in which the quarterly fire sale measure is in the top decile of quarterly fire sales over the full sample period (1980 - 2007) (Edmans, et al., 2012). I define non-extreme fire sales as firm-month observations in which the quarterly fire sale measure does not fall into the top decile over the full sample period.

I compare extreme fire sale firm returns and non-extreme fire sale firm returns to the abnormal monthly returns based on the benchmark of CRSP equal-weighted index returns (Coval and

Stafford, 2007).⁵ Test statistics are calculated using event time fixed effects with standard errors clustered by month to control for potential cross-sectional dependence in the monthly abnormal returns (Coval and Stafford, 2007).

In Table 5, I contrast the cumulative average abnormal returns (*CAARs*) for extreme fire sale firms in columns (1), (2), and (3) and those of non-extreme fire sale firms in columns (4), (5), and (6). Extreme fire sale firms (column (1)) have negative abnormal returns *preceding* fire sales. Moreover, after an extreme fire sale, these firms exhibit large, negative abnormal returns (-6%) during the event quarter. In contrast, firms with non-extreme fire sales experience positive and statistically significant abnormal returns during the event quarter, which flatten after the event quarter (column (4)).⁶

[Insert Table 5]

Figure 2 illustrates the returns patterns. In Panel A, I plot the *CAARs* for the extreme fire sale firms and in Panel B, I plot them for non-extreme firms. The figure shows that negative returns precede extreme fire sales. These extreme fire sales are followed by large changes in firm share price, which lead to the largest price reactions (-6%). Panel B shows that non-extreme fire sales do not lead to negative price reactions.

[Insert Figure 2]

The results in Table 5 and Figure 2 document that fire sales are predictable. They can be predicted by the very firm characteristics that the fire sales variable seeks to randomize. A measured

⁵For each event month, I calculate the average abnormal returns (*AARs*) and compute the (*CAARs*) as the abnormal returns over the period beginning 12 months prior to the fire sale and extending 24 months after the fire sale (Coval and Stafford, 2007; Edmans, et al., 2012). There are three event-months for each fire sale due to the quarterly frequency of mutual fund holdings reports.

⁶These positive abnormal returns are consistent with flow-induced momentum documented in Lou (2012).

feedback effect using fire sales will actually reflect differences between firms with and those without extreme fire sales prior to the shock. They will not reflect the effects of fire sales on a randomly targeted group of firms. Taken together, the results show that past returns not only predict fire sales, but also the magnitude of fire sales.

V.B. Fire Sales and Firm Characteristics

In this section, I test the hypothesis that observable firm characteristics predict the occurrence of firm-level mutual fund fire sales and drive the magnitude of the treatment effect on firms. I discuss the impact of this analysis on the instrumental variable.

I group fire sales into two categories: extreme fire sales and non-extreme fire sales. I examine whether firm characteristics can predict extreme fire sales, essentially to determine if extreme fire sale firms are randomly drawn from the same population as all other treatment firms. I estimate the probability that a firm will experience an extreme fire sale as a function of its characteristics:

$$\begin{aligned} Pr(Extreme\ Fire\ Sale_{i,t} = 1) = & \alpha_i + \gamma_t + \beta_1 MFOwn(\%) + \beta_2 MFOwn(HHI) + \beta_3 Size \\ & + \beta_4 Age + \beta_5 Market - to - Book + \beta_6 Cash\ Flows + \beta_7 Returns \\ & + \beta_8 Financial\ Constraints + \beta_9 Volatility + \beta_{10} Liquidity + \varepsilon_{j,t}. \end{aligned} \quad (10)$$

Equation (10) includes variables that are relevant to the financial policies of a firm, including *Market - to - Book*, *Cash Flows*, *Size*, *Age*, past firm returns (*Returns*), return volatility (*Volatility*), *Financial Constraints*, and *Liquidity* in the year prior to the fire sale. It also includes control variables for the degree of mutual fund ownership of the firm (*MF Own (%)*) and the concentration of mutual fund ownership (*MF Own (HHI)*), as well as firm and year fixed effects. Standard errors are clustered at the 3-digit SIC level.

The results shown in Table 6 confirm that firm characteristics predict extreme fire sales (column (2)). Extreme fire sales are more likely among smaller, younger firms that have had relatively lower

returns in the past. These extreme fire sales also drive the returns shocks in Table 5 and Figure 2.

[Insert Table 6]

In terms of observable differences, the data show that out of the 14,297 unique firms in the sample, 29% have no mutual fund ownership over the entire sample period. The probability of being subjected to a fire sale is zero for these firms. Hence, fund managers systematically avoid buying shares in nearly one-third of publicly traded firms based on what are likely common characteristics that may be unobservable. The effects of this difference are that institutional ownership not only mechanically drives the probability that a firm has a mutual fund fire sale, they also drive differences in observable and unobservable firm characteristics, including payout, corporate governance, liquidity, and investment (Grossman and Hart, 1980; Shivdasani, 1993; Kisin, 2011; Crane, Michenaud, and Weston, 2016).

The results in Table 6 suggest that selection bias leads to systematic differences between firms in the extreme fire sales and non-extreme fire sales groups, which biases estimates of a feedback effect. Extreme firms differ from non-extreme fire sale firms in characteristics like market-to-book ratio, size, past returns, operating profits, and asset growth. These characteristics have been shown to independently and directly determine the financial policies of firms (Miller and Rock, 1985; Asquith and Mullins, 1986; Fazzari, Hubbard, and Petersen, 1988; Loughran and Ritter, 1995; Chen, et al., 2000; Subrahmanyam and Titman, 2001; Fama and French, 2005; Jenter, 2005; Fee, Hadlock, and Pierce, 2009; DeAngelo, DeAngelo, and Stulz, 2010; Bharath, Jayaraman, and Nagar, 2013; Edmans, Fang, and Zur, 2013; Anton and Polk, 2014).

V.B.1. Case Study in Investment

Corporate investment strategy is a good example of a firm characteristic that is both important to fund managers and not fully observable to the researcher. Consider the role of corporate

governance in the investment decisions of a CEO. Some firm idiosyncrasies—including board composition, equity positions, and management teams— affect investment decisions and can be observed. But some idiosyncrasies like the “threat of exit” cannot be fully observed (Bharath, et al., 2013). Yet threat of exit can influence the CEO’s investment strategy. Therefore, while an unexpected shock to stock prices may affect investment directly, that same shock may affect investment indirectly also, through the link between corporate governance and project selection (Hirshleifer and Suh, 1992 and Shivdasani, 1993).

A second example relates investment expenditures to stock price but also to investor incentives. Specifically, small firms with a high level of R&D investment could be venture capital-backed firms that have high R&D investment because of investor incentives that are unrelated to stock price movements. A sudden reduction in R&D investment could be driven by the stock price but could also be driven by unobservable changes in investor incentives.

V.B.2. Case Study in Seasoned Equity Offerings (SEOs)

Consider seasoned equity offerings (SEOs). DeAngelo, DeAngelo, and Stulz (2010) show that issuers tend to have high market-to-book ratios, high pre-offer abnormal returns, and low post-offer abnormal returns. They find that although these characteristics might be good to include as control variables, many firms that have the same observable characteristics fail to sell stock. Thus, controlling for these observable characteristics would not fully capture the motivation for issuing equity.

V.B.3. Unobservable manager responses to mutual fund fire sales

Now, consider the CEO’s decision-making process. There is little argument that CEO decisions can have an effect on firm valuations. The unresolved issue is whether causality can go in the opposite direction too. The mutual fund fire sale “shock” is designed to be a tool that can answer

this question. Can exogenous changes in firm valuation change the CEO's plans about firm policy? The researcher's problem is that the CEO's expectations about firm value can not be measured and this makes her reaction to a change in market valuation unobservable. Maybe the CEO agrees with the market valuation, or maybe she disagrees with it. We do not know. This determination is essential to her reaction, but it is unobservable. When she makes an observable policy decision, the CEO may be taking advantage of what she views to be a mispricing of her firm's stock, but maybe she is reacting for some other, unobservable reason (Jenter, 2005). The way that CEOs behave after a mutual fund fire sale could be driven by the fire sale itself, but it could also be driven by a set of characteristics that are both unobservable and common to some group of firms in the mutual fund's portfolio.

In the instrumental variable setting it is not enough to find one covariate to "control for" every relevant firm characteristic. Controlling for every characteristic does not mean that there are no omitted variables. For example, Edmans, Fang, and Zur (2013) note that even if "we were to explicitly control for governance using liquidity, we would be omitting the possibility that the relationship between liquidity and governance may be jointly determined by firms' unobservable characteristics."

VI. Conclusion

Studies that use mutual fund fire sales as an instrument to measure exogenous changes in stock price find that stock mispricing affects corporate finance decision making. This is a very disturbing result. It implies that the current organization of financial markets in the US and the mechanism that allocates some \$17 trillion in savings are flawed. It implies that crucial aspects of real economic outcomes are distorted. This result has enormous efficiency implications for the economy at large.

The corporate finance literature has given considerable traction to the mutual fund fire sale as

an exogenous shock to stock prices. Figure 3 illustrates its impact with citation trajectories for articles that establish and use the fire sale shock. The magnitude of the citation count is large and the trajectory of citations is growing, by 40% per year in recent years. This growth rate would predict that the lifetime impact of these articles will be considerably higher than what it is now.

[Insert Figure 3]

I examine mutual fund fire sales to determine if the instrumental variable has a selection bias problem. I construct a sample of firms and U.S. equity mutual funds for the period from 1980 to 2007, the period for which the fire sales method was developed.

I identify two sources of the selection bias. First, large mutual fund outflows, the sort that are large enough to induce fire sales, are more likely to occur among small and micro cap funds. This means that measured shocks fall disproportionately on small firms and not randomly across all firms. Second, within their portfolios of small firms, fund managers are more likely to sell shares of firms that have poor past returns and higher liquidity. Fire sales are therefore more prevalent among small firms in the sample that have these characteristics. The magnitude of fire sales is also predictable and correlates with firm characteristics. These sources lead fire sales to be predictable based on firm characteristics.

I cite prominent results in the literature to assert that these differences cannot be controlled for using additional covariates. There are unobservable factors that systematically correlate with firm outcomes. Given how widespread is the use of this shock and the magnitude of the economic implications of the findings in this literature, it is essential that we understand whether this instrumental variable is valid. I conclude that it is not.

The consequence of these findings is that a growing body of empirical results must be re-examined. The challenge is to find a new identification strategy that can convincingly measure the effects of the feedback loop on firm policy.

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Appendix: Variable Definitions

Variable	Definition
<i>Age</i>	The years from a firm's first appearance in CRSP.
<i>Amihud</i>	Illiquidity measure per Amihud (2002); yearly average of the square root of (Price x Vol)/Return.
<i>Asset Growth</i>	$\log(\text{book assets}(\#6)) - \log(\text{lagged book assets}(\#6))$.
<i>Beta Asset</i>	Beta on the market factor in a Fama-French three-factor model using daily data. from CRSP, and then unlevered.
<i>Capital Expenditures</i>	capital expenditures (#128)/lagged book assets (#6).
<i>Cash Flows</i>	(income before extraordinary items (#21) + depreciation (#14))/lagged book assets(#6).
<i>Dividends</i>	dividends(#21)/lagged book assets(#6).
<i>Financial Constraints</i>	Kaplan Zingales measure of financial constraints.
<i>Fire Sale</i>	$\text{abs}(\text{trading volume from mutual funds with outflows of 5\% or more})/\text{total trading volume}$.
<i>Fire Sale Indicator</i>	equal to 1 if <i>Fire Sale</i> > 0, equal to 0 if <i>Fire Sale</i> = 0 .
<i>Inst Own (%)</i>	Fraction of a firm's total shares outstanding owned by institutional investors.
<i>Inst Own (HHI)</i>	Herfindahl-Hirschman Index of the concentration of institutional ownership of shares outstanding.
<i>Investment</i>	capital expenditures (#128)/lagged book assets (#6).
<i>Issuance</i>	(change in common equity (#60) + change in deferred taxes (#74) - change in retained earnings (#36))/lagged common equity (#60).
<i>Leverage</i>	(Long-term debt (#9) + current liabilities (#34) - cash (#1))/(assets (#6)).
<i>Market-to-Book</i>	(book assets (#6) + Market Equity - Common Equity (#60) - Deferred Taxes (#74))/(book assets (#6)).
<i>MF Own (%)</i>	Fraction of a firm's total shares outstanding owned by mutual funds.
<i>MF Own (HHI)</i>	Herfindahl-Hirschman Index of the concentration of mutual fund ownership of shares outstanding.
<i>Payout</i>	(dividends (#21) + repurchases (#115) - sale of common and preferred stock (#108))/lagged book assets (#6); zero if numerator is zero or missing, and one if numerator>0 and denominator=0.
<i>R&D</i>	R&D expense (#46)/Sales (#12); zero if missing.
<i>Repurchases</i>	(repurchases (#115) - sale of common and preferred stock (#108))/lagged (book assets (#6)).
<i>Returns</i>	Cumulative monthly stock returns over the prior year (CRSP monthly file).
<i>ROA</i>	gross operating income (#13)/lagged book assets (#6).
<i>Sales Rank</i>	Rank of sales (#12) among all Compustat firms in a given year, ranging from zero to one.
<i>Size (ME)</i>	$\ln(\text{price}(\#199) * \text{shares outstanding}(\#25) \text{ at fiscal year end})$.
<i>Size (Assets)</i>	$\ln(\text{book assets}(\#6))$.
<i>Size (Asset Quintiles)</i>	Quintiles of book assets (#6).
<i>Tobin's Q</i>	(price (#199) * shares outstanding (#25)+long-term debt +short-term debt)/ (long-term debt +short-term debt+book equity).
<i>Takeover</i>	equal to 1 if a firm received a takeover bid in a particular calendar year and equal to 0 otherwise.
<i>Volatility</i>	standard deviation of daily stock returns over the past year.

Table 1: Summary of Mutual Funds

Table 1 reports fund statistics for the mutual fund dataset that spans 1980-2007. The annual statistics are for U.S. equity mutual funds as of December of each year. The CRSP survivorship-bias-free mutual fund database contains *mutual fund size*, *monthly returns*, and *flows*. Thompson Financial CDA/Spectrum database records fund holdings data. Number of Funds is the number of mutual funds in the sample at the end of each year; *TNA* is the total net assets for the average fund, reported in millions of dollars; *total equity holdings* is the value of the equity holdings in each mutual fund using the stock price and holdings as of December reported in millions of dollars; *fraction market held* is the share of the total value of the U.S. equity market that is held by the mutual funds in the sample.

Year	Number of Funds	(\$ Million) TNA	(\$ Million) Total Equity Holdings	Fraction Market Held
1980	217	163.48	142.38	0.02
1981	219	149.56	125.06	0.017
1982	221	181.80	150.13	0.018
1983	226	249.20	210.05	0.024
1984	254	246.53	202.60	0.026
1985	279	301.67	243.05	0.027
1986	308	346.50	273.88	0.028
1987	352	336.50	277.58	0.035
1988	388	329.80	271.62	0.031
1989	438	385.24	308.18	0.032
1990	456	351.79	283.24	0.034
1991	550	450.79	371.61	0.037
1992	566	556.85	447.32	0.048
1993	747	597.34	482.78	0.047
1994	939	544.71	444.55	0.054
1995	1070	737.25	607.60	0.058
1996	1086	937.97	794.41	0.068
1997	1342	1130.29	981.85	0.079
1998	1444	1294.26	1157.85	0.089
1999	1635	1472.73	1359.91	0.085
2000	1768	1411.24	1285.33	0.098
2001	2005	1072.42	989.15	0.087
2002	2133	832.41	766.71	0.112
2003	2195	1102.23	999.05	0.122
2004	2204	1263.60	1107.77	0.143
2005	2244	1408.81	1272.50	0.143
2006	2109	1651.54	1496.09	0.16
2007	2279	1603.55	1454.56	0.159
Mean	1102	783.23	688.32	0.07

Table 2: Summary of Firms

This table presents summary statistics for the full sample of firms from 1980 to 2007. Columns (1)-(3) report the mean, median, and standard deviation for each variable. All data are obtained from Compustat and CRSP. The dataset includes all firms listed on Compustat that have non-missing price and returns data reported in the CRSP monthly file. The sample excludes all financial (SIC code 6000-6999) and utilities (SIC codes 4900-4949) firms. In addition, firms must have non-missing values for: *cash flows*, *profits*, *returns*, *volatility*, *leverage*, *payout*, *equity issuance*, *capital expenditures*, *book assets*, and *market to book*. All variables are winsorized at the 1% and 99% levels.

Variable	Mean	Median	Std Dev
Financial Constraints (KZ)	2.444	1.237	4.975
Cash Flows (%)	0.051	0.081	0.188
ROA (%)	0.097	0.119	0.197
Returns (%)	-0.016	0.038	0.522
Volatility	0.036	0.030	0.022
Tobin's Q	1.866	1.310	1.633
Leverage (%)	0.851	0.401	1.587
Asset Growth (%)	0.108	0.071	0.291
Dividends (%)	0.009	0.000	0.019
Repurchases (%)	0.010	0.000	0.029
Age (Years)	16.721	12.000	14.295
Issuance (%)	0.194	0.018	0.651
Cap Ex (%)	0.077	0.048	0.096
Payout (%)	0.390	0.000	0.484
Size (ln(Assets))(\$)	5.176	5.006	2.267
Size (ln(ME))(\$)	5.008	4.872	2.251
Fire Sales	1.107	0.009	2.591
Treatment Firm-Year	0.513	1.000	0.500
Inst Own (%)	0.246	0.113	0.292
MF Own (%)	0.084	0.023	0.118
Inst Own (HHI)	0.150	0.057	0.230
MF Own (HHI)	0.168	0.053	0.257
Observations	106223		

Table 3: Predicting Mutual Fund Flows

This table reports the forecasting regression results of mutual fund flows for the sample of U.S. equity mutual funds from 1980 to 2007. The regressions predict outflows to mutual funds j in quarter t . The dependent variable is an *outflow indicator* for each fund, equal to one if the fund receives outflows of 5% or more and zero, otherwise. Column 1 includes the independent variables that typically predict flows: $\alpha_{j,t-1}$, the monthly Carhart four-factor alpha, $Adj.Return_{j,t-1}$, the cumulative market-adjusted fund return, and lagged *capital flows* of the fund in the previous four quarters, $Flow_{j,t-1}$ through $Flow_{j,t-4}$. Column 2 includes additional fund characteristics which include $Index_j$ which is an indicator variable that denotes if the fund is index or actively managed. $Size_{j,t-1}$ is lagged quarterly *TNA* in dollars. *Fund Investment Objective* indicator variables control for a fund's investment style. The omitted category in the regression is domestic growth. Robust standard errors are clustered at the fund level. t -statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Outflow Indicator (Flow $\leq$ -5%)	
	(1)	(2)
Alpha	-2.8351*** (-7.36)	-2.8974*** (-7.65)
Adj Return (%)	-0.6291*** (-22.99)	-0.6116*** (-22.23)
Flow (%) (t-1)	-0.0690*** (-3.74)	-0.0705*** (-3.83)
Flow (%) (t-2)	-0.0265** (-2.30)	-0.0280** (-2.33)
Flow (%) (t-3)	-0.0105** (-2.00)	-0.0118** (-2.25)
Flow (%) (t-4)	-0.0005** (-2.45)	-0.0006** (-2.21)
Index Indicator		-0.0773*** (-3.73)
Size (ln(TNA))		-0.0250*** (-13.33)
Income (U.S.)		-0.0117 (-0.15)
Hedged (U.S.)		0.0604*** (3.00)
Growth & Income (U.S.)		-0.0144 (-1.61)
Large Cap (U.S.)		-0.0183 (-0.76)
Mid Cap (U.S.)		0.0291** (2.27)
Small Cap (U.S.)		0.0371*** (3.53)
Micro Cap (U.S.)		0.1028*** (3.23)
U.S. (no style)		0.2282* (1.82)
R-squared	0.091	0.112
Number of Observations	51,917	51,917
Number of Clusters	1,838	1,838
Year-Quarter FE	Yes	Yes
Cluster Variable	Fund	Fund

Table 4: Predicting Mutual Fund Manager Trades

This table reports regression results of mutual fund trading in response to large capital outflows from funds ($\geq 5\%$ outflows). The dependent variable in all specifications is the percentage change in shares in stock i held by fund j from quarters $t-1$ to t with stock split adjustments. The main independent variable of interest is the coefficient on mutual fund flows, $FLOW_{j,t}$. The main control variables reflect trading costs and other firm characteristics which include: $own_{i,j,t-1}$, the ownership share of mutual fund j in stock i , $liqcost_{i,t-1}$, the Amihud Illiquidity measure, and the average ownership share across all portfolio firms of fund j , $own_{j,t-1}$. Other control variables include: lagged annual returns ($returns_{i,t-1}$), lagged annual volatility ($volatility_{i,t-1}$), the Kaplan-Zingales measure of financial constraints ($FinConstraint_{i,t-1}$), market-to-book ($MkttoBook_{i,t-1}$), and firm size ($Size_{i,t-1}$). The coefficients are estimated using panel OLS with year-quarter fixed effects. Robust standard errors are clustered at the fund level. t -statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	$trade_{i,j,t}$	$trade_{i,j,t}$	$trade_{i,j,t}$	$trade_{i,j,t}$
	(1)	(2)	(3)	(4)
<i>Intercept</i>	0.032*** (3.420)	0.047*** (4.890)	0.021* (1.880)	0.159*** (6.930)
$FLOW_{j,t}$	0.714*** (17.790)	0.909*** (18.700)	0.839*** (9.380)	1.177*** (5.850)
$own_{i,j,t-1}$		-0.119*** (-17.560)	-0.125*** (-17.190)	-0.143*** (-17.210)
$FLOW_{j,t} \times own_{i,j,t-1}$		-0.022 (-0.330)	-0.038 (-0.520)	-0.086 (-1.070)
$liqcost_{i,t-1}$		0.000 (1.490)	0.000 (0.470)	0.001 (1.240)
$FLOW_{j,t} \times liqcost_{i,t-1}$		-41.623*** (-8.410)	-24.120*** (-6.040)	-16.690*** (-4.350)
$own_{j,t-1}$		0.123*** (8.760)	0.121*** (8.370)	0.124*** (8.280)
$FLOW_{j,t} \times own_{j,t-1}$		0.026 (0.180)	0.037 (0.260)	0.051 (0.350)
$liqcost_{j,t-1}$		-0.057 (-1.390)	-0.088** (-2.010)	-0.151*** (-3.390)
$FLOW_{j,t} \times liqcost_{j,t-1}$		-0.672** (-1.990)	-0.930** (-2.530)	-1.160*** (-3.060)
$volatility_{i,t-1}$			1.274*** (4.010)	0.473 (1.440)
$FLOW_{j,t} \times volatility_{i,t-1}$			0.605 (0.200)	-1.813 (-0.570)
$returns_{i,t-1}$			-0.039*** (-7.100)	-0.047*** (-8.440)
$FLOW_{j,t} \times returns_{i,t-1}$			-0.033 (-0.710)	-0.049 (-1.050)
$FinConstraint_{i,t-1}$				0.000 (0.510)
$FLOW_{j,t} \times FinConstraint_{i,t-1}$				0.000 (0.540)
$MkttoBook_{i,t-1}$				0.002** (2.380)
$FLOW_{j,t} \times MkttoBook_{i,t-1}$				0.007 (0.860)
$Size_{i,t-1}$				-0.014*** (-6.920)
$FLOW_{j,t} \times size_{i,t-1}$				-0.035* (-1.800)
Adjusted R2 (%)	0.021	0.032	0.034	0.036
Number of Observations	815,967	815,967	783,342	758,471

Table 5: Monthly Cumulative Average Abnormal Returns around Fire Sales

The table reports the average abnormal returns, the cumulative average abnormal returns, and test statistics for extreme fire sale firms and non-extreme fire sale firms, respectively. Cumulative average abnormal returns (*CAARs*) are measured as monthly returns in excess of the CRSP equal-weighted average return in each month. *Fire Sale* is a firm-level measure of the percentage of firm trading volume that is due to mutual fund trades from mutual funds that receive outflows of 5% or more during a given quarter. The *extreme Fire Sales* are firm-months in which firms receive the highest *Fire Sales* (top 10%) during the full sample period (1980 - 2007). Test statistics are calculated using event time fixed effects with standard errors clustered by month, giving equal weight to each monthly observation, rather than to each individual firm-month observation.

Event Time (t)	<i>Extreme Fire Sales</i>			<i>All Fire Sales</i> (excluding <i>Extreme Fire Sales</i>)		
	<i>AAR</i> (%)	<i>t</i> -statistic	<i>CAAR</i> (%)	<i>AAR</i> (%)	<i>t</i> -statistic	<i>CAAR</i> (%)
	(1)	(2)	(3)	(4)	(5)	(6)
-14	-0.224	1.590	-0.224	0.440	1.590	0.440
-13	0.055	4.970	-0.168	1.160	4.970	1.598
-12	0.389	4.550	0.222	1.078	4.550	2.667
-11	-0.354	1.160	-0.133	0.315	1.160	2.968
-10	0.081	5.320	-0.051	1.093	5.320	4.049
-9	0.471	4.400	0.420	1.048	4.400	5.076
-8	-0.494	1.110	-0.075	0.303	1.110	5.354
-7	-0.132	4.950	-0.208	0.953	4.950	6.286
-6	0.375	3.570	0.168	0.866	3.570	7.125
-5	-0.517	0.090	-0.349	0.023	0.090	7.119
-4	-0.377	3.200	-0.726	0.640	3.200	7.759
-3	0.035	2.790	-0.691	0.598	2.790	8.357
-2	-2.010	0.470	-2.701	0.105	0.470	8.462
-1	-1.629	3.120	-4.329	0.747	3.120	9.209
0	-0.802	2.500	-5.131	0.516	2.500	9.725
1	-0.614	-2.400	-5.745	-0.530	-2.400	9.195
2	-0.091	0.140	-5.836	0.029	0.140	9.224
3	0.210	0.730	-5.626	0.137	0.730	9.361
4	-0.202	-2.360	-5.828	-0.550	-2.360	8.811
5	0.097	0.890	-5.731	0.180	0.890	8.991
6	0.156	0.340	-5.576	0.065	0.340	9.057
7	-0.088	-1.680	-5.668	-0.397	-1.680	8.654
8	0.424	1.100	-5.250	0.227	1.100	8.877
9	0.249	-0.510	-5.027	-0.090	-0.510	8.784
10	-0.606	-0.830	-5.631	-0.193	-0.830	8.586
11	0.265	1.080	-5.416	0.228	1.080	8.839
12	0.734	0.000	-4.736	0.001	0.000	8.878
13	-0.618	-0.940	-5.365	-0.214	-0.940	8.675
14	0.477	1.330	-4.885	0.260	1.330	8.951
15	0.615	0.240	-4.259	0.043	0.240	9.033
16	-0.017	-1.330	-4.252	-0.319	-1.330	8.736
17	0.459	1.670	-3.774	0.307	1.670	9.105
18	0.612	0.400	-3.134	0.073	0.400	9.302
19	0.091	-0.570	-2.984	-0.139	-0.570	9.232
20	0.725	1.530	-2.155	0.311	1.530	9.595
21	0.639	-0.010	-1.452	-0.002	-0.010	9.692
22	-0.362	-0.120	-1.812	-0.028	-0.120	9.776
23	0.553	1.640	-1.186	0.313	1.640	10.180
24	0.786	0.470	-0.334	0.082	0.470	10.366

Table 6: Predicting Fire Sales

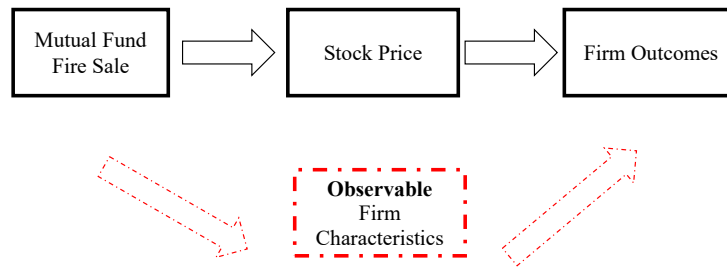
This table reports results from regressions in which an indicator variable for an individual firm's *Fire Sale* is regressed on firm characteristics within the full sample of firm-year observations (column (1)) and the *extreme Fire Sale* firm-level indicator variable is regressed on firm characteristics within the subsample of *Fire Sale* firm-year observations that receive the largest mutual fund outflows (column (2)). The *extreme fire sales* represent the largest *Fire Sales* (top 10%) during the full sample period (1980 - 2007). The *Fire Sale* is an annual measure of mutual fund trading in each firm from funds that receive outflows $\geq 5\%$ in a quarter. The independent variables include $MF\ Own(\%)_{i,t-1}$, the fraction of shares held by mutual funds, $MF\ Own(HHI)_{i,t-1}$, the concentration of mutual fund ownership, $Firm\ Size_{i,t-1}$, the natural log of book assets, $Firm\ Age_{i,t-1}$, the years from first appearance in CRSP, $Market\ to\ Book_{i,t-1}$, $Cash\ Flows_{i,t-1}$, $Returns_{i,t-1}$, and annualized monthly returns. Regressions include firm and year fixed effects. Robust standard errors are clustered at the 3-digit SIC industry level. *t*-statistics are reported in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Variables (t-1)	Fire Sale Indicator (1)	Extreme Fire Sale Indicator (2)
MF Own (%)	0.107*** (3.95)	0.617*** (15.58)
MF Own (HHI)	-0.006 (-0.85)	-0.003 (-0.13)
Size (ln(Assets))(\$)	0.076*** (12.90)	-0.032*** (-4.86)
Age (Years)	0.013*** (6.33)	-0.020*** (-4.43)
Tobin's Q	0.019*** (14.52)	-0.014*** (-3.87)
Cash Flows (%)	0.102*** (7.58)	-0.105*** (-5.23)
Returns (%)	0.016*** (4.52)	-0.063*** (-9.16)
Financial Constraints (KZ)	-0.003*** (-8.93)	0.000 (0.13)
Volatility	-1.546*** (-11.03)	-1.862*** (-6.77)
R-squared	0.716	0.382
Number of Observations	106,223	52,767
Number of Clusters	277	268
Firm FE	Yes	Yes
Year FE	Yes	Yes
Cluster Variable	3 digit SIC	3 digit SIC
Sample of Firms	Full Sample	Firm-years with Fire Sale > 0

Panel A: Valid Instrumental Variables Design



Panel B: Instrumental Variables Violation 1



Panel C: Instrumental Variables Violation 2

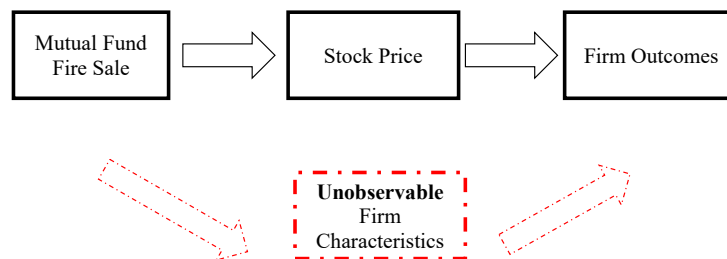
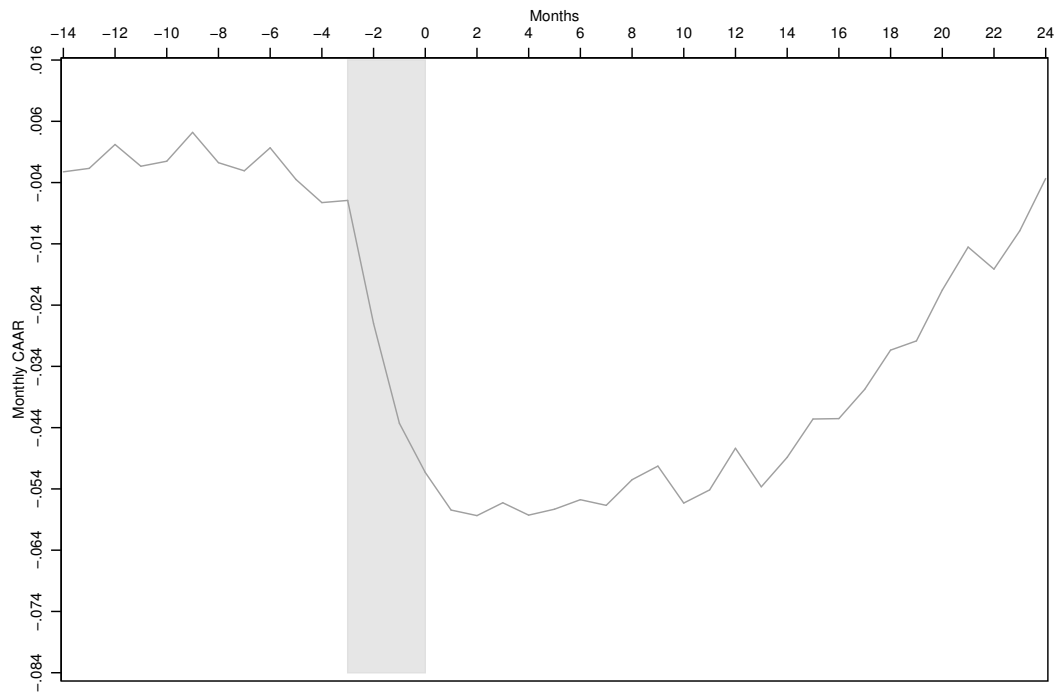
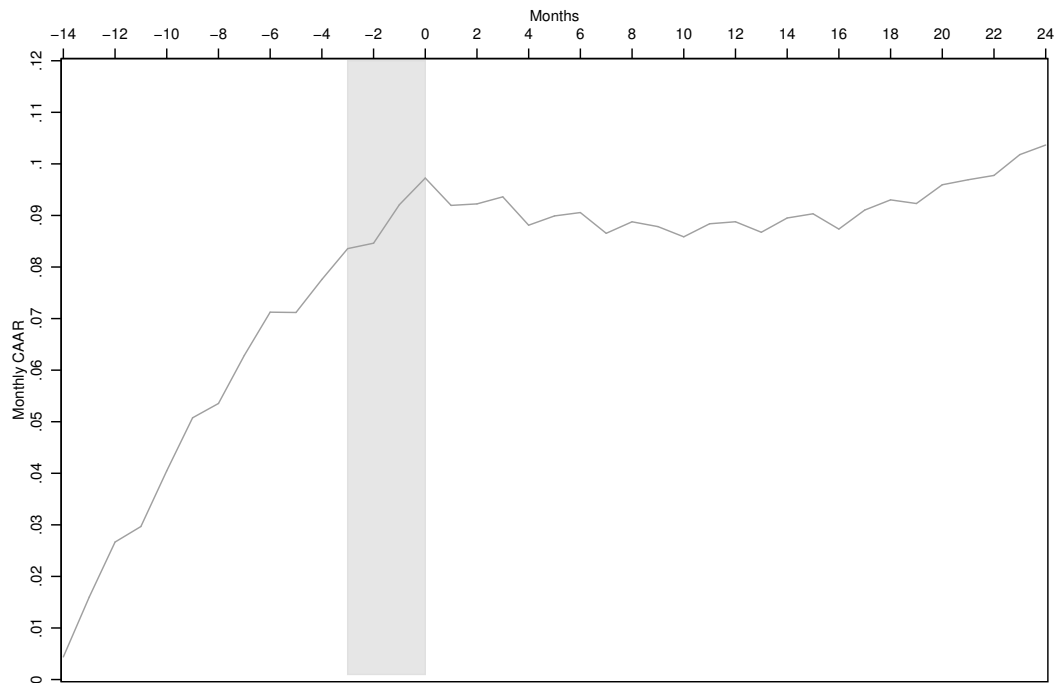


Figure 1: Instrumental Variables Design

In this table, Panels A, B, and C depict the underlying mechanisms for an optimal instrument (A) and an instrument that is flawed due to observable firm characteristics (B) or due to unobservable firm characteristics (C). In Panel B, violation 1 can be resolved by including covariates. In Panel C, violation 2 cannot be resolved.



Extreme Fire Sales



All Fire Sales - excluding Extreme Fire Sales

Figure 2: Cumulative Average Abnormal Returns

Figure 2 depicts the cumulative average abnormal returns (*CAARs*) over the 36 months surrounding a mutual fund *fire sale*. The gray bar denotes the event quarter. The *CAARs* are the difference between the firm's monthly return and the CRSP equal-weighted index returns. The *extreme fire sales* represent the largest *Fire Sales* (top 10%) during the full sample period (1980 - 2007). Panel 1a traces out the *CAARs* for the sample of *extreme fire sales*. Panel 1b includes all *fire sales*, excluding *extreme fire sales*, over the event quarter.

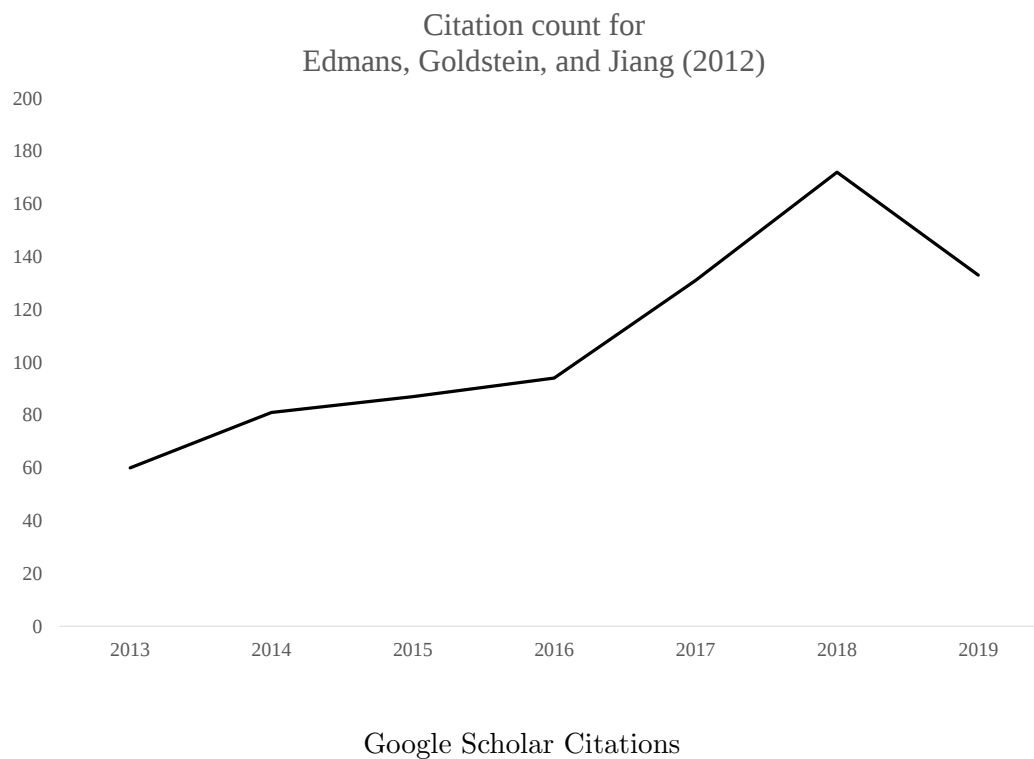


Figure 3: Edmans, Goldstein, and Jiang (2012) citation count

This figure plots the number of Google Scholar citations of Edmans, Goldstein, and Jiang (2012). The data is reported by citation count (y-axis) and year (x-axis).