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Selection Bias in Mutual Fund Fire Sales

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Abstract

Liquidity trading following mutual fund outflows creates a potentially powerful empirical setting in which stock price variation is unrelated to changes in firm fundamentals. Instrumental variables (IVs) drawn from this setting impose an additional assumption that managers sell firms in proportion to portfolio weights. I show that this assumption causes selection bias in these IVs. It misallocates large price impacts to poorly performing, illiquid firms with lower growth – firms that managers systematically avoid selling. Simulations show that selection bias doubles the magnitude of regression coefficients and precludes potential fixes. Numerous recent studies exploiting these IVs should be reevaluated.

I. Introduction

Is there a feedback loop between a firm's stock price and its financial policies? There is little doubt that firm actions affect stock prices but the less understood question is whether stock prices also affect firm actions. Finance theory suggests how such a feedback loop could arise (Chen, Goldstein, and Jiang (2007), Goldstein, Ozdenoren, and Yuan (2013)), but whether or not it exists in practice is an empirical question. Proper identification requires an exogenous shock to stock prices that separates stock prices from firm actions. A candidate instrumental variable (IV) for such a price shock is MFFLOW, which is designed to measure forced selling activity following large mutual fund outflows (Edmans, Goldstein, and Jiang (2012)).

Recent studies have used MFFLOW and variants on it as IVs exhaustively. The emerging consensus from doing so is that stock price fluctuations distort many of the most fundamental decisions that firms make. Empirical results establish that forced trading following large mutual fund outflows influences takeover attempts (Edmans et al. (2012)), R&D expenditures (Phillips and Zhdanov (2013)), corporate investment (Dessaint, Foucault, Frésard, and Matray (2019)), shareholder activism (Derrien, Kecskés, and Thesmar (2013), Norli, Ostergaard, and Schindele (2015)), analyst forecasts (Lee and So (2017)), corporate disclosures (Zuo (2016)), use of credit lines (Acharya, Almeida, Ippolito, and Perez (2014)), equity issuance

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(Khan, Kogan, and Serafeim (2012)), earnings forecasts (Lou and Wang (2018)), and option grant timing (Ali, Wei, and Zhou (2011)).

The focus of this article is to provide the literature with critical input regarding the MFFLOW measure. I construct a sample of U.S. equity mutual fund and firm-level data to reflect the data typically studied in the literature (Coval and Stafford (2007), Edmans et al. (2012)). I show that the simplifying assumptions designed to strip out endogenous selection inadvertently introduce selection bias in the MFFLOW IV. In an IV regression framework, I find that MFFLOW produces biased coefficients that overstate the effects of stock prices on firm actions. I conclude that proposed solutions, such as inserting control variables in regression specifications, are unlikely to generate consistent estimates.

MFFLOW is an IV built to measure the plausibly exogenous, negative price pressure that arises when firms experience forced selling activity from mutual funds with large outflows (e.g., outflows >5%) (Edmans et al. (2012)). It is based on the observation in Coval and Stafford (2007) that unusually large redemption requests from a mutual fund's investors force the fund manager to sell some portfolio shares, which exerts price pressure on portfolio firms. Under these conditions, stock prices fall because managers sell shares for liquidity reasons, not because managers have negative information about firm policies or fundamental value.

Edmans et al. (2012) construct the MFFLOW variable as an empirical complement to this assertion. Instead of focusing on shares that were actually sold during the quarter in which a mutual fund experiences large outflows, they make a simplifying assumption that managers sell off shares of all portfolio firms in proportion to their portfolio weights (Edmans et al. (2012)). This proportional trading assumption underlies the claim that the MFFLOW variable measures stock price fluctuations that are independent of firm fundamentals. Typically, simplifying assumptions lead to good IVs because they use some sort of policy constraint that binds, regardless of an agent's characteristics. For example, a well-known IV for educational attainment is a person's birth month. U.S. laws require children to attend school until the age of 18. This policy constraint means that some children will have a full 12 years of education, while other children, who are born in birth months between September and May, might leave school before obtaining 12 years of education. The validity of this IV rests on the assumptions that a person's birth month is exogenous to innate ability and that the policy constraint binds for all people.

The "policy constraint" in the MFFLOW setting is that mutual fund managers sell stocks in proportion to last quarter's portfolio holdings. The idea is that liquidity trading is unrelated to firm characteristics and the proportional trading assumption should ensure that MFFLOW does not pick up any firm-specific, information-based trading. If the constraint binds, all portfolio firms should experience selling activity after large outflows, on average. Instead, I find that fund managers refrain from selling illiquid or poorly performing firms following large outflow events. Hence, the "policy constraint" imposed by the proportional trading assumption applies to only specific types of firms. This is akin to the U.S. educational requirement being enforced for some groups of people and not others such that the birth month IV is correlated with the characteristics of these groups.

The assumption that managers typically adhere to a proportional trading strategy, when in fact they do not, may introduce selection bias in the MFFLOW IV. Selection bias would come from firms that are incorrectly assigned a large value of MFFLOW despite the evidence that they likely experience very little selling activity. I analyze a firm's real mutual fund trading activity to gauge how the proportional trading assumption influences the distribution of MFFLOW across different types of firms. For example, some firms may have large values of MFFLOW but low trading activity. For each firm, I compare the real trading activity from mutual funds to the *hypothetical* trading activity that comes from the proportional trading assumption. I find that the assumption assigns selling activity to firms that mutual funds do not sell – firms that are small and have negative past returns. Artificially high selling activity inflates the MFFLOW values of firms with these characteristics. An inflated MFFLOW would ascribe policy changes to shifts in stock prices, when in reality, a high MFFLOW signals poor past performance, illiquidity, size, age, and other sample selection biases that arise from the proportional trading assumption. Notably, MFFLOW is not exogenous to market prices: lower past returns predict higher values of MFFLOW.

I test whether this selection bias drives the relationship between high values of MFFLOW and large, negative price impacts. I use abnormal returns to measure the deviation of a firm's stock price from its fundamental value and compare abnormal returns of firms with real selling activity to those of firms with hypothetical selling activity. Surprisingly, I find that firms with real mutual fund selling activity (the trading that should lead to negative price pressure) have positive abnormal returns following large mutual fund outflows. In contrast, firms with hypothetical selling activity exhibit large and negative abnormal returns following large mutual fund outflows. These patterns contradict the assertion that it is mutual fund selling pressure that drives the large price reductions associated with the MFFLOW IV.

The fact that a simplifying assumption that is designed to mitigate endogeneity in fact introduces selection bias seems like a paradox. But the empirical economics, finance, and econometrics literatures have studied this problem extensively (Imbens and Angrist (1994), Heckman (1997), Rosenzweig and Wolpin (2000), and Larcker and Rusticus (2010)). Consider the birth month IV in which the simplifying assumption is that birth month measures educational attainment and is unrelated to ability. Upon further inspection, birth month is correlated with experience (through age), future educational choices, and opportunity costs to continuing education, all of which also affect future earnings (Rosenzweig and Wolpin (2000)). This seemingly innocuous assumption leads to biased estimates and Rosenzweig and Wolpin (2000) document that several studies using this IV yield opposite conclusions. For the MFFLOW IV, simplifying assumptions can lead to bias that comes from selection into treatment (not all firms have mutual fund ownership) and heterogeneous treatment effects (for the same value of MFFLOW, firms have different responses) (Imbens and Angrist (1994), Heckman (1997)).

I assess how selection bias in MFFLOW alters estimates from an IV regression of instrumented market prices on corporate policies. I construct an illustrative example in which I estimate the effect of market price (Tobin's Q) on firm investment (CAPEX), using MFFLOW as an instrument for Tobin's Q. A series of simulations reveals how correlations between MFFLOW, Tobin's Q, and CAPEX, as well as other commonly omitted variables, produce coefficients that overestimate the effect of Tobin's Q on CAPEX. Coefficients are larger and more statistically significant compared to a correctly specified IV model. I show that control variables can mitigate the bias, but only when the full set of observable and unobservable omitted variables is known, which is unlikely, and only when close proxies for these variables exist. Given the correlation between MFFLOW and a multitude of firm characteristics, omitted variables almost surely bias the regression coefficients that are estimated by using the MFFLOW IV.

I use the switching regression method (a more generalized form of the Heckman (1979) two-stage estimator) to examine how individual firm characteristics affect the magnitude of the bias in IV estimates of stock price effects on firm investment (Lee (1978), Heckman (1979), Puri (1996), and Golubov, Petmezas, and Travlos (2012)). The switching regression method "fixes" MFFLOW by removing the selection bias that comes from specific firm characteristics such as size, profitability, and returns. The results show that estimates using these alternative IVs tend to be half as large as estimates based on the biased MFFLOW measure.

Finally, I use three observable characteristics as substitutes for MFFLOW in the IV regression and find that these characteristics yield outcomes that are nearly identical to those obtained by using the MFFLOW IV. The results suggest that the correlation between MFFLOW, observable firm characteristics, and CAPEX likely drives the regression results using MFFLOW. In addition, I construct an IV using the residual variation in MFFLOW after controlling for observable firm characteristics. This residual IV captures the variation in MFFLOW that is orthogonal to firm characteristics. I find that the residual IV leads to inconsistent and statistically insignificant coefficient estimates.

The results in this article document that the proportional trading assumption introduces a selection bias into the MFFLOW IV. The magnitude of MFFLOW is driven by past prices and is correlated with observable and, most likely, unobservable firm characteristics. These firm characteristics are directly and indirectly correlated with firm outcomes, such as investment. Moreover, consistent with Wardlaw (2020), altering the MFFLOW measure to reduce selection bias means that many results in the literature disappear.

This article is complementary to the results of Wardlaw (2020) but these papers differ in terms of methodology and scope. Wardlaw (2020) decomposes MFFLOW to remove its correlation with past returns and limits its focus to the correlation between MFFLOW, realized returns, and firm fundamentals. I confirm that this specific correlation biases regression estimates, but take the analysis further. I explore the breadth of the selection bias, not only by documenting the correlation between returns and the construction of MFFLOW but also by analyzing the selection bias induced by the proportional trading assumption. Although the adjusted measures introduced by Wardlaw (2020) remove the correlation between negative past returns and MFFLOW, I document that the selection bias from the proportional trading assumption persists. It is not subsumed by the adjusted MFFLOW measures.

Viewed most broadly, this article is a contribution to the empirical methods and corporate finance literature that studies the feedback effect between stock prices and firm policy. The problems documented here are relevant, not only for the

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MFFLOW IV, but also for many empirical analyses using the mutual fund price pressure documented in Coval and Stafford (2007) as a source of exogenous variation in stock prices. In addition to Edmans et al. (2012), several identification strategies use simplifying assumptions about mutual fund flows, price pressure, and firm outcomes to derive exogenous variation in stock prices (e.g., Khan et al. (2012), Lou (2012)). The empirical finance literature has widely adopted these "price shocks" for identification. This is a dangerous practice because a good IV in one setting may not be valid in another context. There must be a clear link between the instrument and theory and a careful and limited interpretation of IV estimates (Rosenzweig and Wolpin (2000)). The results in this article raise significant doubts about many findings that are derived by using MFFLOW and other measures of exogenous variation driven from mutual fund price pressure.

The article proceeds as follows: I describe the sample in Section II and I construct the MFFLOW IV in Section III. I document the causes of selection bias in MFFLOW in Section IV. Section V illustrates the effects of selection bias in MFFLOW on estimates and conclusions drawn in an IV regression framework. Concluding remarks are in Section VI.

II. Data

I construct a data set that matches the time period and data sources used in prior studies of large mutual fund outflows (e.g., Edmans et al. (2012)). The data set spans the years 1980 to 2007 and contains 106,223 firm-year observations. Appendix B includes a detailed discussion of the data set construction.

I use the Wharton Research Data Services (WRDS) MFLinks file to merge two mutual fund level databases: the Thomson Financial CDA/Spectrum holdings database and the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund database.

Fund-level variables include total net assets (TNA), gross returns, net returns, expense ratios, and quarterly fund flows. A fund's quarterly flow is the sum of monthly asset flows into and out of the fund, net of merger assets, in each calendar quarter. Flows to fund j in quarter t represent the growth rate of the TNA under management after adjusting for the market appreciation of the mutual fund's assets ($R_{j,t}$) and new cash from fund mergers ($\text{MGN}_{j,t}$) (Chevalier and Ellison (1997), Lou (2012)). $\text{FLOW}_{j,t}$ measures the quarterly mutual fund flows scaled by TNA in the previous period.

Data from CDA/Spectrum are used to compute the number and value of shares of every firm held by each mutual fund as of the quarter end (Coval and Stafford (2007)). A fund's holdings ($h_{j,i,t} = \frac{P_{i,t} \times S_{j,i,t}}{\text{TNA}_{j,t}}$) measure the holdings of stock i, as a fraction of TNA. $P_{i,t}$ 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.

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 10-fold over the sample period and mutual fund

TABLE 1

Summary of Mutual Funds

Table 1 reports fund statistics for the mutual fund data set that spans 1980–2007 and includes U.S. equity mutual funds as of December of each year. The CRSP survivorship-bias-free mutual fund database reports a mutual fund's size, monthly returns, and fund 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	No. of Funds	TNA ($ Million)	TOTAL_EQUITY_HOLDINGS ($ Million)	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	1,070	737.25	607.60	0.058
1996	1,086	937.97	794.41	0.068
1997	1,342	1,130.29	981.85	0.079
1998	1,444	1,294.26	1,157.85	0.089
1999	1,635	1,472.73	1,359.91	0.085
2000	1,768	1,411.24	1,285.33	0.098
2001	2,005	1,072.42	989.15	0.087
2002	2,133	832.41	766.71	0.112
2003	2,195	1,102.23	999.05	0.122
2004	2,204	1,263.60	1,107.77	0.143
2005	2,244	1,408.81	1,272.50	0.143
2006	2,109	1,651.54	1,496.09	0.16
2007	2,279	1,603.55	1,454.56	0.159
Mean	1,102	783.23	688.32	0.07

ownership in the U.S. equity market grew from just 2% in 1980 to 16% in 2006. These statistics are comparable to those reported by Lou (2012).

Firm-level data include firms listed on Compustat with nonmissing price and returns data reported in the CRSP monthly file. Sample firms have nonmissing values for CASH_FLOWS, profits (ROA), RETURNS, LEVERAGE, PAYOUT, return volatility (VOLATILITY), equity issuance (ISSUANCE), capital expenditures (CAPEX), book assets (SIZE), and market-to-book (MARKET_TO_BOOK). The firm-level variables measure firm characteristics and financial policies that are potentially affected by market prices including SIZE, ROA, CASH_FLOWS, TOBINS_Q, the Kaplan–Zingales financial constraint measure (FINANCIAL_CONSTRAINTS), and the Amihud illiquidity measure (ILLIQUIDITY) (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.[1] The definitions of these variables are in Appendix A. The firm-level IV, MFFLOW, is derived from mutual fund trading and is defined in Section III.

[1]The HHI approaches 0 when a large number of mutual funds holds positions in a firm of relatively equal size and approaches its maximum of 1 when a single mutual fund controls all of the firm's shares.

TABLE 2

Summary of Firms

Table 2 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. The sample excludes all financial (SIC codes 6000–6999) and utilities (SIC codes 4900–4949) firms. All variables are winsorized at the 1% and 99% levels.

Variable	Mean	Median	Std. Dev.
FINANCIAL_CONSTRAINTS	2.444	1.237	4.975
CASH_FLOW (%)	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
TOBINS_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	16.721	12.000	14.295
ISSUANCE (%)	0.194	0.018	0.651
CAPEX (%)	0.077	0.048	0.096
PAYOUT (%)	0.390	0.000	0.484
SIZE ($)	5.176	5.006	2.267
MARKET_CAP ($)	5.008	4.872	2.251
MFFLOW	1.107	0.009	2.591
INST_OWN (%)	0.246	0.113	0.292
MF_OWN (%)	0.084	0.023	0.118
INST_HHI	0.150	0.057	0.230
MF_HHI	0.168	0.053	0.257
No. of obs.	106,223		

Table 2 reports the summary statistics for the sample of firms. 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 8% of outstanding firm shares.

III. The MFFLOW IV

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), and Khan et al. (2012)).

I follow the description in Edmans et al. (2012) to construct the MFFLOW variable. MFFLOW 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.

The flows to fund j in quarter q are defined as

$$flow_{j,q} = \mathrm{TNA}_{j,q} - \mathrm{TNA}_{j,q-1} \times \left(1 + R_{j,q}\right) - \mathrm{MGN}_{j,q},$$

$$\text{FLOW}_{j,q} = \frac{flow_{j,q}}{\text{TNA}_{j,q-1}},$$

where $flow_{j,q}$ denotes the dollar value of flows into and out of fund j in quarter q and $\text{FLOW}_{j,q}$ measures the quarterly mutual fund flows for fund j in quarter q ($flow_{j,q}$) 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)).

$$\text{HOLDINGS}_{j,i,q}: \quad h_{j,i,q} = \frac{P_{i,q} \times S_{j,i,q}}{\text{TNA}_{j,q}}$$

measures a fund's holdings of stock i, as a fraction of its TNA, where $P_{i,q}$ and $S_{j,i,q}$ are the share price of firm i in quarter q and the shares of firm i held by fund j in quarter q, respectively.

I define a subset K_q of mutual funds in period q that experienced outflows that were large in relation to their TNA ($\text{FLOW}_{j,q} \leq -5\%$). In any given period, there are $K_{N,q}$ such funds. For every fund $k \in K$ in each quarter q, I define the outflow variable:

$$\text{OUTFLOW}: \quad \phi_{k,q} = \text{TNA}_{k,q} - \left(1 + R_{k,q}\right) \times \text{TNA}_{k,q-1} - \text{MGN}_{k,q}.$$

The combination of holdings ($h_{j,i,q}$) and outflows ($\phi_{k,q}$) defines the TRADE variable, which uses the portion of the fund's previously disclosed holdings in each firm to calculate a manager's trades of each firm i.

$$\text{TRADE}_{k,i,q}: \quad T_{k,i,q} = \phi_{k,q} \times h_{k,i,q-1} = \text{FLOW}_{k,q} \times P_{i,q-1} \times S_{k,i,q-1}.$$

A firm's dollar trading volume is measured as the total trading volume for firm i in quarter q:

$$\text{TRADING\_VOLUME}: \quad V_{i,q} = P_{i,q} \times x_{i,q},$$

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

The MFFLOW variable measures the total impact of mutual fund trades on the underlying firm i in each quarter q:

$$(1) \qquad \text{MFFLOW}_{i,q} = \sum_{k=1}^{K} \frac{T_{k,i,q}}{V_{i,q}} = \sum_{k=1}^{K} \frac{\text{FLOW}_{k,q} \times P_{i,q-1} \times S_{k,i,q-1}}{V_{i,q}}.$$

The annualized $\text{MFFLOW}_{i,t}$ measure for firm i is the sum of $\text{MFFLOW}_{i,q}$ over the four quarters q of each calendar year. If firm i incurs no selling activity from mutual funds with large outflows in year t, then $\text{MFFLOW}_{i,t} = 0$. The MFFLOW variable is nonpositive, but for ease of interpretation, I adjust the variable to measure the absolute value of these shocks, so that a positive MFFLOW value is associated with a higher price impact for that firm-year observation.

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IV. Proportional Trading and Selection Bias

The MFFLOW IV is constructed to neutralize the information embedded in real trading decisions so that it can convincingly separate the price impact of mutual fund trading from firm value. The proportional trading assumption, whereby fund managers scale down the fund's shareholdings without affecting the proportion of any shares in the portfolio (e.g., Edmans et al. (2012)), bolsters the claim that MFFLOW is independent of firm characteristics and firm value by excluding real trading activity.

In this section, I analyze whether the proportional trading assumption lessens or exacerbates the link between MFFLOW and firm characteristics. The proportional trading assumption is based on the belief that all firms receive selling activity after large outflows, regardless of firm characteristics. If the assumption is incorrect, it can introduce selection bias when fund managers intentionally and systematically deviate from proportional trading during periods of distress. For example, when faced with large outflows, fund managers may refrain from selling certain types of firms, such as illiquid or poorly performing firms.

The proportional trading assumption would introduce selection bias by assigning a high MFFLOW to firms that have a low probability of experiencing selling activity (Roberts and Whited (2013)). Firms that are poorly performing (but not actually sold due to liquidity concerns, for example) would have a high MFFLOW coming from the proportional trading assumption rather than from real mutual fund trading activity. The high MFFLOW would appear to drive a large, negative effect on a firm's share price, but poor past performance would explain lower share prices. Finally, these firms may be more likely to change firm policies due to poor performance, but the policy change would be ascribed to MFFLOW.

A. Evaluating the Proportional Trading Assumption

The literature provides mixed evidence that managers trade in proportion to portfolio holdings. Lou (2012) shows that fund managers scale their portfolios proportionally when met with normal, predictable fund flows. 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), and Huang, Ringgenberg, and Zhang (2017)).

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

$$\text{(2)} \qquad \begin{aligned} \text{TRADE}_{i,j,t} = \alpha_t + \beta_1 \text{FLOW}_{j,t} + \beta_2 X + \beta_3 \text{FLOW}_{j,t} \times X \\ + \beta_4 Z + \beta_5 \text{FLOW}_{j,t} \times Z + \varepsilon_{j,t}, \end{aligned}$$

where the dependent variable, $\text{TRADE}_{i,j,t}$, 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 (2), the variable, $\text{FLOW}_{j,t}$, that is, 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 trade in proportion to portfolio holdings, β_1 will equal 1 and all other coefficients will equal 0. The vectors X and Z reflect the fund and firm characteristics that may influence a fund manager's trading decisions. X is the vector of fund-level characteristics: the ownership share of mutual fund j in stock i ($\text{OWN}_{i,j,t-1}$), the Amihud illiquidity measure to control for individual firm liquidity costs ($\text{ILLIQUIDITY}_{i,t-1}$), the portfolio-weighted average ownership share ($\text{OWN}_{j,t-1}$), and fund-level liquidity costs ($\text{ILLIQUIDITY}_{j,t-1}$). Z is a vector of firm-level characteristics that includes lagged annual returns ($\text{RETURNS}_{i,t-1}$), lagged annual volatility ($\text{VOLATILITY}_{i,t-1}$), the Kaplan–Zingales measure of financial constraints ($\text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$), Tobin's Q ($\text{TOBINS\_Q}_{i,t-1}$), and firm size ($\text{SIZE}_{i,t-1}$). 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 control for market-wide fluctuations over time. Standard errors are clustered at the fund level.[2]

The results in Table 3 show that fund managers do not sell shares in proportion to their pre-outflow portfolio holdings. The point estimate in column 1 on $\text{FLOW}_{j,t}$ is 0.71, which indicates that large outflows lead managers to liquidate only 71 cents on the dollar in proportion to portfolio weights.[3] This leaves 29 cents for the managers to trade at their discretion.

Columns 2–4 of Table 3 report the firm characteristics that fund managers target with discretionary trading. The coefficients on $\text{FLOW}_{j,t} \times \text{ILLIQUIDITY}_{i,t-1}$ imply that managers are reluctant to sell illiquid firms as outflows increase, consistent with theory (Brown et al. (2010)). The results also show that trading strategies are correlated with firm characteristics. For example, in column 4, the coefficient on $\text{OWN}_{i,t-1}$ of 0.1330 suggests that fund managers are more likely to sell firms with higher mutual fund ownership, after controlling for liquidity costs.

Tests of whether the coefficient on $\text{FLOW}_{j,t}$ differs from one ($\beta = 1$) reveal that specifications that include firm-level control variables (columns 3 and 4) exhibit proportional trading only after accounting for the strategic trading activity associated with firm characteristics. In contrast, an analysis of index fund trading, reported in Table A1 of the Appendix, shows that passive index funds exhibit proportional trading following large outflows in all specifications; that is, the test of $\beta = 1$ shows that the coefficient on $\text{FLOW}_{j,t}$ is not statistically different from one.

The assumption that managers adhere to a proportional trading strategy, when in fact they do not, may incorrectly assign a high MFFLOW to some firms despite the evidence that these firms likely experience very little selling activity. High levels of MFFLOW may be correlated with firm characteristics and would thereby introduce selection bias.

[2]The 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.

[3]In addition to being economically significant, the test that the coefficient on $\text{FLOW}_{j,t}$ differs from 1 ($\beta = 1$) in column 1 shows that this value is statistically significant at the 1% level.

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TABLE 3

Predicting Trades of Mutual Fund Managers

Table 3 reports regression results of mutual fund trading in response to large capital outflows from actively managed mutual funds (≥ 5% outflows). The dependent variable is the percentage change in shares of stock i held by fund j from quarters $t-1$ to t ($\text{TRADE}_{i,j,t}$). The main coefficient of interest is on mutual fund flows, $\text{FLOW}_{j,t}$. Control variables reflect trading costs and other firm characteristics which include: $\text{OWN}_{i,j,t-1}$, $\text{ILLIQUIDITY}_{i,t-1}$, $\text{OWN}_{j,t-1}$, $\text{RETURNS}_{i,t-1}$, $\text{VOLATILITY}_{i,t-1}$, $\text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$, $\text{TOBINS\_Q}_{i,t-1}$, and $\text{SIZE}_{i,t-1}$. Variable definitions are in Appendix A. The table reports a test of whether $\beta = 1$ and the t-statistics for this test. Specifications include 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.

	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$
	1	2	3	4
$\text{FLOW}_{j,t}$	0.7087***	0.8188***	0.8475***	1.1275***
	(16.16)	(15.51)	(8.65)	(4.75)
$\text{OWN}_{i,j,t-1}$		−0.1512***	−0.1500***	−0.1559***
		(−23.00)	(−21.57)	(−19.80)
$\text{FLOW}_{j,t} \times \text{OWN}_{i,j,t-1}$		−0.0197	−0.0074	−0.0372
		(−0.31)	(−0.11)	(−0.49)
$\text{ILLIQUIDITY}_{j,t-1}$		0.0007**	0.0011*	0.0015*
		(2.02)	(1.86)	(1.67)
$\text{FLOW}_{j,t} \times \text{ILLIQUIDITY}_{j,t-1}$		−15.6625**	−13.6829***	−13.4070***
		(−2.23)	(−2.66)	(−2.65)
$\text{OWN}_{i,t-1}$		0.1324***	0.1304***	0.1330***
		(10.42)	(10.02)	(9.80)
$\text{FLOW}_{j,t} \times \text{OWN}_{i,t-1}$		0.0826	0.0839	0.0951
		(0.68)	(0.66)	(0.73)
$\text{ILLIQUIDITY}_{i,t-1}$		−0.2643***	−0.2684***	−0.3075***
		(−4.51)	(−4.32)	(−4.74)
$\text{FLOW}_{j,t} \times \text{ILLIQUIDITY}_{i,t-1}$		−1.2277**	−1.3042**	−1.5491**
		(−2.30)	(−2.27)	(−2.55)
$\text{RETURNS}_{i,t-1}$			−0.0377***	−0.0435***
			(−6.36)	(−7.42)
$\text{FLOW}_{j,t} \times \text{RETURNS}_{i,t-1}$			−0.0385	−0.0417
			(−0.76)	(−0.85)
$\text{VOLATILITY}_{i,t-1}$			0.3519	0.1162
			(0.99)	(0.32)
$\text{FLOW}_{j,t} \times \text{VOLATILITY}_{i,t-1}$			−1.1834	−2.2589
			(−0.34)	(−0.62)
$\text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$				−0.0000
				(−0.01)
$\text{FLOW}_{j,t} \times \text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$				0.0000
				(0.00)
$\text{TOBINS\_Q}_{i,t-1}$				0.0026**
				(2.26)
$\text{FLOW}_{j,t} \times \text{TOBINS\_Q}_{i,t-1}$				0.0029
				(0.36)
$\text{SIZE}_{i,t-1}$				−0.0145***
				(−4.43)
$\text{FLOW}_{j,t} \times \text{SIZE}_{i,t-1}$				−0.0289
				(−1.32)
R^2	0.038	0.051	0.050	0.051
No. of obs.	677,070	677,070	648,185	627,461
No. of clusters	2,307	2,307	2,299	2,287
$\beta = 1$	−.291	−.181	−.153	.127
t-statistic	−6.643	−3.432	−1.558	.537

B. Linking Proportional Trading and Firm Characteristics

If the proportional trading assumption holds, all portfolio firms should experience selling activity during the event quarter from mutual funds with large outflows. Yet, the results in Section IV.A suggest that real trading activity is systematically targeted toward firm characteristics such as Tobin's Q and past returns. This result implies that there is a divergence between the "hypothetical" selling activity assigned by the proportional trading assumption and the "real" selling activity coming from mutual funds with large outflows.

I analyze whether proportional trading assigns hypothetical selling activity to firms that likely are unaffected by real trading activity. If true, the estimated selling activity for these firms would be artificially high, potentially inflating their MFFLOW measure and biasing MFFLOW toward specific types of firms.

I categorize firms based on real trading activity from mutual funds with large outflows. A firm's net trading activity is the sum of all real trading activity (buying or selling) over the quarter from funds with large outflows. For example, a firm may have 100 shares sold by some funds and 50 shares purchased by other funds during the quarter in which funds have large outflows. The firm's net trading activity would be net selling of 50 shares and this firm would be categorized as having net selling activity. Firms with net buying activity are categorized in an analogous way. I construct an annual version of this measure by assigning net selling pressure if the firm had selling pressure in any quarter of the calendar year.

The summary statistics in Table 4 show that firms which funds truly sell, that is, those with net selling activity, differ from firms with net buying activity. For example, firms with net selling activity are older (AGE), larger (SIZE), and have higher Tobin's Q (TOBINS_Q). They also have positive past returns (RETURNS). Firms that funds are reluctant to sell, that is, firms with primarily hypothetical trading, have negative past returns (RETURNS).

TABLE 4

Summary of Firms by Net Trading Activity

Table 4 presents summary statistics for firms grouped by net trading activity from 1980 to 2007. Column 1 reports the mean of each variable for firm-year observations with net selling activity. Column 2 reports the means for observations with net buying activity. A firm has net selling activity if the sum of all real trades placed by funds with 5% outflows results in more shares sold than bought in the quarter. The definition of net buying activity is analogous. All variables are winsorized at the 1% and 99% levels.

Variable	Net Selling Activity	Net Buying Activity
FINANCIAL_CONSTRAINTS	1.849	1.368
CASH_FLOWS (%)	0.083	0.051
ROA (%)	0.141	0.101
RETURNS (%)	0.053	−0.005
VOLATILITY	0.031	0.037
TOBINS_Q	2.104	1.752
LEVERAGE (%)	0.735	0.779
ASSET_GROWTH (%)	0.136	0.098
DIVIDENDS (%)	0.010	0.008
REPURCHASES (%)	0.015	0.008
AGE	20.102	16.245
ISSUANCE (%)	0.164	0.187
CAPEX (%)	0.082	0.083
PAYOUT (%)	0.434	0.353
SIZE ($)	6.101	4.520
MARKET_CAP ($)	6.198	4.326
MFFLOW	1.906	1.656
INST_OWN (%)	0.386	0.189
MF_OWN (%)	0.127	0.052
INST_HHI	0.071	0.154
MF_HHI	0.107	0.250
SELLING_ACTIVITY_INDICATOR	1.000	0.000
No. of obs.	38,483	15,507

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Proportional trading assigns both sets of firms net selling activity, when, in fact, specific types of firms do not experience net selling pressure. This increases the estimated trading in the MFFLOW measure for firms with net buying activity (e.g., smaller firms with negative past returns).[4] These characteristics, rather than MFFLOW, may ultimately drive the results from the IV estimation.

C. Linking MFFLOW and Firm Characteristics

I measure the degree to which the proportional trading assumption affects the MFFLOW variable. I test the hypothesis that observable firm characteristics are associated with the magnitude of MFFLOW. Table 5 reports summary statistics for firms with above-median and below-median values of MFFLOW. Firms with above median values of MFFLOW have lower past RETURNS, lower TOBINS_Q, lower ISSUANCE, and higher MF_OWN. This preliminary evidence suggests that the proportional trading assumption creates a correlation between the magnitude of MFFLOW and observable firm characteristics.

Edmans et al. (2012) show that the largest MFFLOW values are fundamental to the strength of the MFFLOW IV. They identify "extreme" values of MFFLOW as a subset of firm-month observations in which MFFLOW is in the top decile of quarterly values of MFFLOW over the full sample period. They document that the firms with extreme MFFLOW values exhibit a large, negative price impact

TABLE 5

Summary of Firms by Median MFFLOW

Table 5 presents summary statistics for firms grouped by median MFFLOW from 1980 to 2007. Column 1 reports the mean of each variable for firm-year observations with below median MFFLOW. Column 2 reports the means for observations with above median MFFLOW. All variables are winsorized at the 1% and 99% levels.

Variable	Below Median MFFLOW	Above Median MFFLOW
FINANCIAL_CONSTRAINTS	2.040	1.961
CASH_FLOWS (%)	0.067	0.094
ROA (%)	0.126	0.150
RETURNS (%)	0.061	0.016
VOLATILITY	0.034	0.029
TOBINS_Q	2.180	1.858
LEVERAGE (%)	0.749	0.724
ASSET_GROWTH (%)	0.138	0.118
DIVIDENDS (%)	0.010	0.010
REPURCHASES (%)	0.013	0.016
AGE	19.711	20.007
ISSUANCE (%)	0.209	0.094
CAPEX (%)	0.088	0.077
PAYOUT (%)	0.404	0.462
SIZE ($)	5.981	5.855
MARKET_CAP ($)	6.074	5.831
MFFLOW	1.058	3.103
INST_OWN (%)	0.323	0.397
MF_OWN (%)	0.096	0.137
INST_HHI	0.074	0.083
MF_HHI	0.118	0.132
No. of obs.	21,654	24,528

[4]Net buying and selling activity is based on aggregation prior to calculating the MFFLOW variable. Hence, these differences are not driven by any MFFLOW scaling conventions as discussed in Wardlaw (2020).

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following large mutual fund outflows, which should be uncorrelated with firm characteristics. I use the following probit regression model to predict whether firm characteristics are associated with the largest values of MFFLOW:

$$\begin{aligned}(3)\quad \Pr(\text{EXTREME\_MFFLOW}_{i,t}) = {} & \alpha_i + \gamma_t + \beta_1 \text{MF\_OWN} + \beta_2 \text{MF\_HHI} + \beta_3 \text{SIZE} \\ & + \beta_4 \text{AGE} + \beta_5 \text{TOBINS\_Q} + \beta_6 \text{CASH\_FLOW} \\ & + \beta_7 \text{RETURNS} + \beta_8 \text{FINANCIAL\_CONSTRAINTS} \\ & + \beta_9 \text{VOLATILITY} + \beta_{10} \text{ILLIQUIDITY} + \varepsilon_{j,t},\end{aligned}$$

where $\text{EXTREME\_MFFLOW}_{i,t}$ is an indicator variable denoting firms with the highest values of MFFLOW. Equation (3) includes TOBINS_Q, CASH_FLOWS, SIZE, AGE, past firm RETURNS, VOLATILITY, FINANCIAL_CONSTRAINTS, and ILLIQUIDITY in the year prior to the large mutual fund outflows. It also includes variables that measure the degree of mutual fund ownership of the firm (MF_OWN) and the concentration of mutual fund ownership (MF_HHI), as well as firm and year-fixed effects. Standard errors are clustered at the 3-digit SIC level.

The results reported in Table 6 confirm that firm characteristics predict the largest values of MFFLOW (column 2). A large MFFLOW is more likely among smaller and younger firms that have had relatively lower returns in the past. Firms that are more illiquid are more likely to have the largest values of MFFLOW. These firms also tend to have higher mutual fund ownership and lower cash flows and Tobin's Q. Hence, the proportional trading assumption creates selection bias such that the magnitude of MFFLOW is correlated with observable firm characteristics.

These characteristics are direct determinants of firm policies. Firms with large values of MFFLOW may change firm policies due to variation in these characteristics, rather than the price impact of MFFLOW. For example, institutional ownership drives differences in payout, corporate governance, liquidity, and investment (Grossman and Hart (1980), Shivdasani (1993), Kisin (2011), and Crane, Michenaud, and Weston (2016)). Characteristics like market-to-book ratio, size, past returns, operating profits, and asset growth have been shown to determine financial policies of firms (Miller and Rock (1985), Asquith and Mullins (1986), Fazzari, Hubbard, and Petersen (1987), Loughran and Ritter (1995), Chen, Jegadeesh, and Wermers (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), and Anton and Polk (2014)).

D. Linking MFFLOW and Firm Returns

I study the relationship between MFFLOW and firm returns to determine whether MFFLOW leads to a negative price impact on portfolio firms. I explore whether past returns are correlated with the magnitude of MFFLOW and whether these correlations might originate from the proportional trading assumption.

Edmans et al. (2012) show that high values of MFFLOW are correlated with large, negative abnormal returns. The implicit assumption is that these negative firm returns are driven by mutual fund selling activity, which is independent of a firm's

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TABLE 6

Predicting MFFLOW

Table 6 reports results from regressions in which an indicator variable for an individual firm's MFFLOW is regressed on firm characteristics. Column 1 reports the results of a regression of an indicator for firms with nonzero MFFLOW on firm characteristics using the full sample of firm-year observations. Column 2 reports results from a regression of an indicator variable for firm-year observations with Extreme MFFLOW on firm characteristics on the subsample of firms with nonzero MFFLOW. MFFLOW is an annual measure of mutual fund trading in each firm from funds that receive outflows ≥5% in a quarter. The extreme values of MFFLOW represent the largest values of MFFLOW (top 10%) during the full sample period (1980–2007). The independent variables include MF_OWN $(\%)_{i,t-1}$, the fraction of shares held by mutual funds, $\text{MF\_HHI}_{i,t-1}$, the concentration of mutual fund ownership measured by the Herfindahl–Hirschman Index (HHI), $\text{SIZE}_{i,t-1}$, the natural log of book assets, $\text{AGE}_{i,t-1}$, the years from the first appearance in CRSP, $\text{TOBINS\_Q}_{i,t-1}$, $\text{CASH\_FLOWS}_{i,t-1}$, and $\text{RETURNS}_{i,t-1}$. Regressions include firm and year-fixed effects. Robust standard errors are clustered at the 3-digit SIC industry level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	MFFLOW > 0	Extreme MFFLOW
	1	2
MF_OWN (%) ($t-1$)	0.268***	0.627***
	(9.62)	(15.76)
MF_HHI ($t-1$)	−0.045***	−0.008
	(−4.46)	(−0.40)
SIZE ($) ($t-1$)	0.062***	−0.027***
	(11.28)	(−3.91)
AGE (Years)	0.006***	−0.020***
	(3.71)	(−4.19)
TOBINS_Q ($t-1$)	0.015***	−0.011***
	(10.69)	(−3.50)
CASH_FLOWS (%) ($t-1$)	0.089***	−0.078***
	(7.25)	(−4.32)
RETURNS (%) ($t-1$)	0.025***	−0.063***
	(6.50)	(−10.30)
FINANCIAL_CONSTRAINTS ($t-1$)	−0.003***	−0.000
	(−5.42)	(−0.24)
VOLATILITY ($t-1$)	−0.507***	−2.642***
	(−3.17)	(−7.84)
ILLIQUIDITY ($t-1$)	−5.246***	4.146***
	(−16.39)	(7.56)
R^2	0.683	0.384
No. of obs.	77,434	48,251
No. of clusters	274	267
Firm FE	Yes	Yes
Year FE	Yes	Yes
Cluster variable	3-digit SIC	3-digit SIC
Sample of firms	Full sample	Firm-years with MFFLOW > 0

past returns so that these large, negative fluctuations in share price are not driven by firm value. The following analysis explores whether real selling activity drives the negative abnormal returns associated with MFFLOW rather than hypothetical selling activity arising from the proportional trading assumption.

I answer this question by comparing the abnormal returns of firms with net selling activity to those of firms with net buying activity within the subset of firms with the largest values of MFFLOW.[5] Graphs A and B of Figure 1 graph

[5] I measure cumulative abnormal monthly returns of firms around large mutual fund outflows. To be consistent with Edmans et al. (2012), I examine returns for the subset of firm-month observations in which MFFLOW is in the top 10% of its quarterly values of MFFLOW over the full sample period (i.e., the extreme MFFLOW values). I calculate abnormal monthly returns by comparing the returns of these firms to a benchmark of the CRSP equal-weighted index returns (Coval and Stafford (2007)). For 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 extreme MFFLOW and extending

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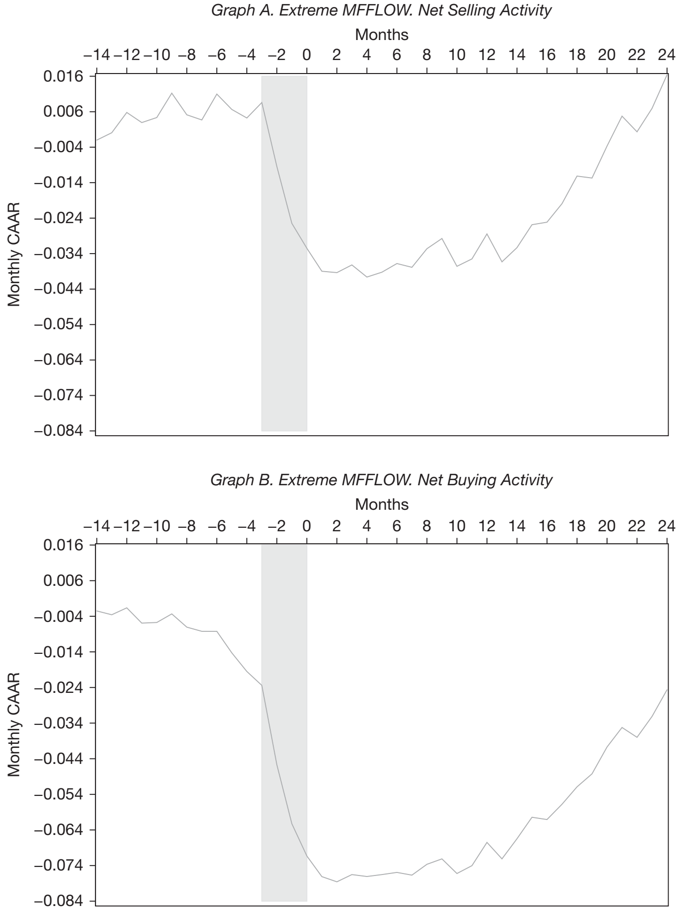
FIGURE 1

Cumulative Average Abnormal Returns (by Net Trading Activity)

Figure 1 depicts the cumulative average abnormal returns (CAARs) over the 36 months surrounding large mutual fund outflows for firms with extreme MFFLOW. Extreme MFFLOWs are the largest MFFLOW values (top 10%) over the full sample period (1980–2007). 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. Graph A (B) traces out the CAARs for firms with net selling activity (net buying activity). A firm has net selling activity if the sum of all real trades placed by funds with 5% outflows results in more shares sold than bought. The definition of net buying activity is analogous.



the abnormal returns for firms with net selling activity (Graph A) and net buying activity (Graph B). Firms with net buying activity exhibit large and negative abnormal returns when large mutual fund outflows occur (Graph A), despite the fact that mutual funds refrained from selling these firms in aggregate. In contrast, firms with net selling activity – the trading that should lead to negative

24 months after the extreme MFFLOW (Coval and Stafford (2007), Edmans et al. (2012)). There are three event months for each MFFLOW event due to the quarterly frequency of mutual fund holdings reports. I calculate t-statistics using event time fixed effects with standard errors clustered by month (Coval and Stafford (2007)).

returns – have positive abnormal returns when large mutual fund outflows occur (Graph B).

These results provide evidence that mutual fund selling pressure does not cause the negative abnormal returns associated with the MFFLOW measure. Instead, firms with hypothetical selling activity drive the negative abnormal returns. These firms have high MFFLOW and poor past returns. As a result, the MFFLOW variable erroneously attributes persistently large and negative returns to real mutual fund selling activity. Net buying and selling activity is aggregated prior to calculating the MFFLOW variable. Hence, the mechanical correlation between returns and MFFLOW documented in Wardlaw (2020) does not drive these differences.

Section IV.A shows that funds do not adhere to a proportional trading strategy. The results in Section IV.C document that the proportional trading assumption leads to selection bias in MFFLOW by creating a correlation between MFFLOW and firm characteristics – characteristics that directly determine firm policies. Section IV.D shows that selection bias drives the estimated effect of MFFLOW on firm returns. In sum, firm characteristics, and not mutual fund selling pressure, likely lead to the changes in firm policies that occur after large mutual fund outflows.

Wardlaw (2020) constructs two alternative IVs as a starting point to address the selection bias between large values of MFFLOW and past returns. I examine the link between proportional trading and the price impact of these alternative IVs using real and hypothetical trading activity. The analysis explores whether real selling activity drives the negative abnormal returns associated with FLOW_TO_STOCK (FLOW_TO_VOLUME) rather than hypothetical selling activity arising from the proportional trading assumption.[6] I compare the abnormal returns of firms with net selling activity to those of firms with net buying activity within a set of firms with the largest values of FLOW_TO_STOCK (FLOW_TO_VOLUME).

Graphs A and B of Figures 2 and 3 show the abnormal returns for firms with net selling activity (Graph A) and net buying activity (Graph B). Firms with net buying activity exhibit large and negative abnormal returns when large mutual fund outflows occur (Graph B), despite the fact that mutual funds refrain from selling these firms in aggregate. In contrast, firms with net selling activity – the trading that should lead to negative returns – have positive abnormal returns when large mutual fund outflows occur (Graph A).

Although the FLOW_TO_STOCK and FLOW_TO_VOLUME IVs correct the returns correlation between MFFLOW and past returns, the proportional trading assumption continues to drive the estimated price impact coming from the IVs. Firms with hypothetical selling activity due to the proportional trading assumption drive the negative returns patterns associated with high values of these measures following large mutual fund outflows. As a result, the variables

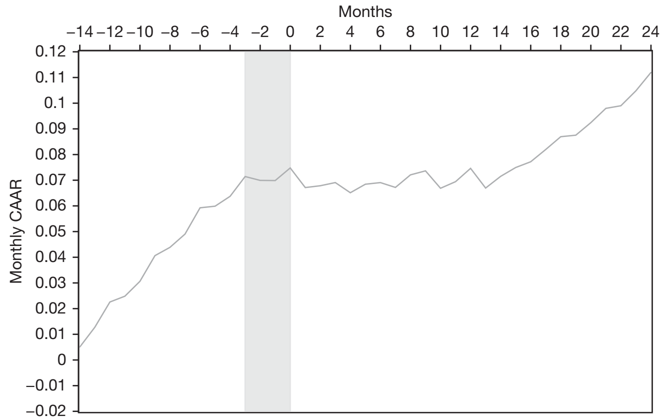
[6]I provide detailed definitions of these measures in Appendix C. FLOW_TO_VOLUME = $\sum_{k=1}^{K} \text{FLOW}_{k,t} \times S_{k,i,t-1} / \text{SHROUT}_{i,t-1}$ and FLOW_TO_STOCK = $\sum_{k=1}^{K} \text{FLOW}_{k,t} \times S_{k,i,t-1} / x_{i,t}$, where $\text{SHROUT}_{i,t-1}$ is total shares outstanding of firm i in quarter $t-1$, $x_{i,t}$ is the total shares of firm i traded in quarter t, and $S_{j,i,t}$ is the shares of firm i held by fund j in quarter t.

FIGURE 2

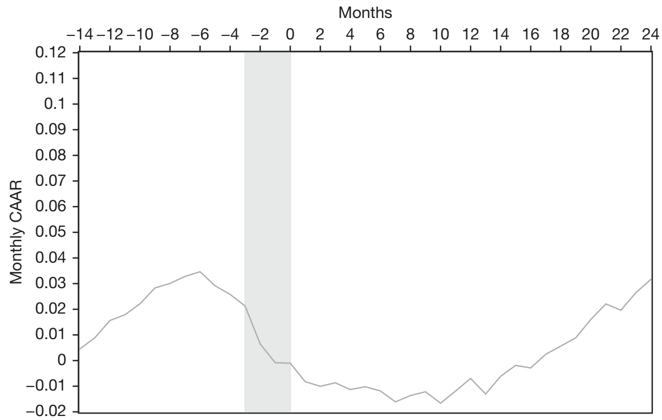
Cumulative Average Abnormal Returns: FLOW_TO_STOCK

Figure 2 depicts the cumulative average abnormal returns (CAARs) over the 36 months surrounding large mutual fund outflows for firms with extreme values of FLOW_TO_STOCK. Extreme values have the largest values of FLOW_TO_STOCK (top 10%) over the full sample period (1980–2007). FLOW_TO_STOCK is an adjusted MFFLOW measure based on shares outstanding (Wardlaw (2020)). 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. Graph A (Graph B) traces out the CAARs for firms with net selling activity (net buying activity). A firm has net selling activity if the sum of all real trades placed by funds with 5% outflows results in more shares sold than bought. The definition of net buying activity is analogous.

Graph A. Net Selling Activity - FLOW TO STOCK



Graph B. Net Buying Activity - FLOW TO STOCK



erroneously attribute persistently large and negative returns to real mutual fund selling activity. As with the MFFLOW IV, the strength of these instruments comes from hypothetical trading activity rather than real mutual fund trades.

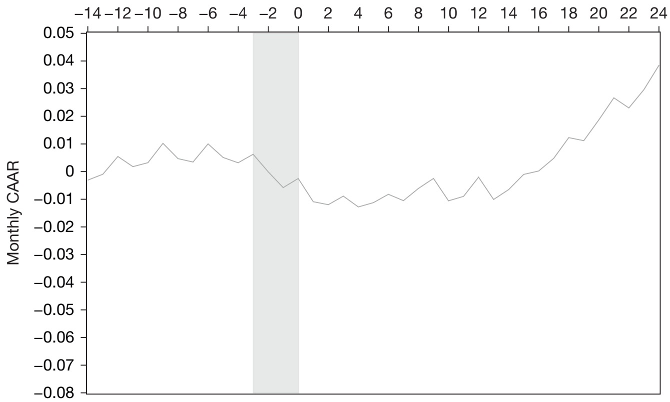
In Appendix C, I explore the relationship between these alternative IVs and the proportional trading assumption. I apply the analyses from Section IV to test for selection bias in the alternative IVs. The analysis and results show that the proportional trading assumption creates selection bias in these alternative IVs that is not subsumed by the correlation between RETURNS and MFFLOW.

FIGURE 3

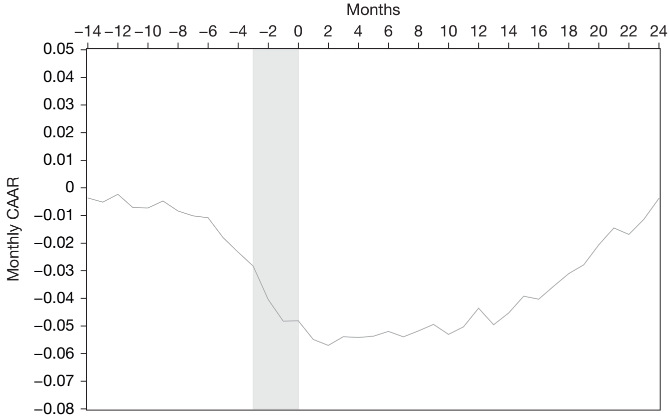
Cumulative Average Abnormal Returns: FLOW_TO_VOLUME

Figure 3 depicts the CAARs over the 36 months surrounding large mutual fund outflows for firms with extreme values of FLOW_TO_VOLUME. Extreme values have the largest values of FLOW_TO_VOLUME (top 10%) over the full sample period (1980–2007). FLOW_TO_VOLUME is an adjusted MFFLOW measure based on total shares of firm *i* traded in quarter *t* (Wardlaw (2020)). 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. Graph A (Graph B) traces out the CAARs for firms with net selling activity (net buying activity). A firm has net selling activity if the sum of all real trades placed by funds with 5% outflows results in more shares sold than bought. The definition of net buying activity is analogous.

Graph A. Net Selling Activity - FLOW TO VOLUME



Graph B. Net Buying Activity - FLOW TO VOLUME



V. Effects of Selection Bias on Firm Outcomes

In the following analysis, I highlight several channels through which selection bias leads to correlations and omitted characteristics in the relationship between MFFLOW and firm outcomes that can bias IV regression results.

A. Motivation: Investment and Seasoned Equity Offerings

Consider the role that corporate governance plays 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 also affect investment indirectly, through the link between corporate governance and project selection (Hirshleifer and Suh (1992), Shivdasani (1993)).

DeAngelo et al. (2010) show that issuers of seasoned equity offerings (SEOs) tend to have high market-to-book ratios, high pre-offer abnormal returns, and low post-offer abnormal returns. However, they document that many firms with the same observable characteristics fail to issue shares. Thus, unobservable characteristics are an important component of SEO decisions.

In an IV setting, finding covariates to "control for" every relevant firm characteristic does not mean that there are no omitted variables. For example, Edmans et al. (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."

B. Standard IVs Model: Measuring the Effect of Tobin's Q on Capital Expenditures Using MFFLOW

The following example illustrates how MFFLOW is used to measure the effects of firm value on investment in an IV regression model. I model a setting in which MFFLOW is an IV for firm value, that is, TOBINS_Q, and CAPEX measures the firm investment outcome in the following regression specification:

$$\text{(4)} \qquad \begin{aligned} \text{TOBINS\_Q}_{i,t} &= \delta_0 + \delta_1 \text{MFFLOW}_{i,t} + \beta \mathit{Controls}_{i,t} + \alpha_t + \psi_i + u_{i,t}, \\ \text{CAPEX}_{i,t} &= \beta_0 + \beta_1 \text{TOBINS\_Q}_{i,t} + \beta \mathit{Controls}_{i,t} + \tau_t + \gamma_i + \varepsilon_{i,t}, \end{aligned}$$

where $Controls_{i,t}$ are SIZE, ROA, LEVERAGE, RETURNS, and VOLATILITY and α_t and τ_t denote year fixed effects and ψ_i and γ_i denote firm fixed effects. The second stage of the regression includes standard errors clustered by firm.

Table 7 reports the results. Columns 1 and 2 report fixed-effects regression results and columns 3 and 4 report results of a first-differences model. In the first stage, the negative coefficient on MFFLOW suggests that higher mutual fund selling pressure is associated with lower TOBINS_Q – mutual fund selling reduces firm value. MFFLOW is a strong instrument with a large F-statistic. The second stage results show that TOBINS_Q, instrumented by MFFLOW, has a positive and highly statistically significant relationship with CAPEX. Higher values of TOBINS_Q translate into higher firm investment meaning that lower TOBINS_Q would render lower firm investment. These results confirm findings in the literature using MFFLOW, which show that firm value has a direct effect on firm investment.

The remainder of the analysis in this section examines how selection bias drives these baseline results.

C. IV Regression: Simulation

I use a series of simulations to explore how selection bias leads to common violations of the IV framework and how these violations affect estimates from the baseline IV regression. I model a correctly specified IV regression and then simulate

TABLE 7

Instrumental Variables Regression: MFFLOW IV

Table 7 reports the effects of TOBINS_Q on firm investment (CAPEX) using the MFFLOW instrumental variable (IV). An observation is a firm year. Columns 1 and 2 report the first- and second-stage results of the IV regression using a fixed effects model. Columns 3 and 4 report the first- and second-stage results of the IV regression using a first-differences model. The specification includes the control variables: SIZE, ROA, LEVERAGE, RETURNS, and VOLATILITY. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level and *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	MFFLOW IV			
	Fixed Effects		First Difference	
	First Stage	Second Stage	First Stage	Second Stage
	1	2	3	4
TOBINS_Q		0.0235*** (5.15)		
SIZE	−0.3346*** (−20.79)	−0.0086*** (−4.98)		
ROA (%)	0.9289*** (9.86)	0.0446*** (8.51)		
LEVERAGE (%)	−0.0177*** (−4.41)	−0.0038*** (−13.53)		
RETURNS (%)	−0.3115*** (−33.12)	0.0171*** (11.18)		
VOLATILITY	−4.8404*** (−10.05)	−0.1634*** (−5.12)		
MFFLOW IV	−0.0200*** (−14.29)			
Δ TOBINS_Q				0.0333*** (4.11)
Δ SIZE			−0.3922*** (−24.89)	−0.0117*** (−3.55)
Δ ROA			0.6875*** (10.57)	0.0081 (1.19)
Δ LEVERAGE			−0.0050 (−1.15)	−0.0051*** (−13.11)
Δ RETURNS			−0.5159*** (−54.61)	0.0222*** (5.27)
Δ VOLATILITY			0.8377* (1.85)	−0.1420*** (−5.14)
Δ MFFLOW IV			−0.0110*** (−11.58)	
F-statistic in first stage		204		134
p-value of *F*-Statistic		0.000		0.000
Partial R^2 in first stage		0.002		0.001
No. of obs.	108,971	108,971	93,615	93,615
Firm FE		Yes		Yes
Year FE		Yes		Yes

several scenarios that incorporate correlations between MFFLOW and the confounding factor, that is, TOBINS_Q, which introduce omitted variables into the definitions of MFFLOW and CAPEX.

The data-generating process for the correctly specified IV regression is

$$x_t = \gamma z_t + \rho u_t + \varepsilon_t \text{ where } \varepsilon_t \text{ iid } N\left(0, \sigma_e^2\right),$$
$$y_t = \theta + \beta x_t + u_t \text{ where } u_t \text{ iid } N\left(0, \sigma_t^2\right),$$

where x_t is the endogenous explanatory variable (TOBINS_Q), z_t is the instrument (MFFLOW), and y_t is the outcome variable (CAPEX). I simulate a single

TABLE 8

Instrumental Variables Regression: Simulation Parameters

Table 8 reports the parameter values for the simulation of a correctly specified instrumental variable (IV) regression model. The data-generating process for the IV regression is:

$$x_t = \gamma z_t + \rho u_t + \varepsilon_t \text{ where } \varepsilon_t \text{ iid } N(0, \sigma_e^2)$$
$$y_t = \theta + \beta x_t + u_t, \text{where } u_t \text{ iid } N(0, \sigma_t^2),$$

x_t is the endogenous explanatory variable (TOBINS_Q), z_t is the instrumental variable (MFFLOW), and y_t is the outcome variable (CAPEX). u_t is the single confounding variable. z_t and u_t follow a standard normal distribution. The γ controls the strength of the instrument, ρ controls the amount of correlation between x_t and the errors of the model, and σ_e^2 controls the relative variability of x_t and u_t.

	Parameter Values
β	1
σ_t	10
σ_e	0.1
γ	1
ρ	0.5
	Variable definitions
z_t = MFFLOW	rnormal(0,1)
u_t	rnormal(0,σ_t)
x_t = Q	$\gamma \times z_t + \rho \times u_t$ + rnormal(0,σ_e)
y_t = CAPEX	$\beta x_t + u_t$

confounding variable (u_t) and assume that MFFLOW (z_t) and u_t follow a standard normal distribution. TOBINS_Q (x_t) is correlated with the error (u_t) in the CAPEX (y_t) regression and MFFLOW (z_t) is the instrument, which is independent of the error, u_t.

The statistical model contains the following parameters: β,σ_e,γ, and ρ. The γ controls the strength of the instrument, ρ controls the amount of correlation between x_t and the errors of the model, and σ_e^2 controls the relative variability of x_t and u_t. The correlation between ε_t and u_t is 0. Table 8 reports these parameter values.

For each scenario, I simulate the model 1,000 times using a sample of 10,000 observations. I calculate the mean of β and the standard errors from the 1,000 iterations. Values of these measures that exceed (are less than) their true values suggest positive (negative) bias.

Column 1 in Table 9 reports the results of a correctly specified, unbiased IV simulation of CAPEX on TOBINS_Q. Consistent with the simulated initial parameters, β equals 1 with standard errors equal to 0.01. In the context of the MFFLOW example, suppose that SIZE is the omitted variable (u) in the CAPEX equation. Then TOBINS_Q would be a function of SIZE and MFFLOW would be independent of SIZE.

The remaining columns in Table 9 report the results from simulations that violate a specific condition of the correctly specified model. I simulate random variables with standard normal distributions, $rv1$, $rv2$, and $rv3$ and use these to insert omitted variables in definitions of MFFLOW and CAPEX.

The model reported in column 2 includes a correlation between MFFLOW and the error term, u. Building on the previous example, MFFLOW is now a function of SIZE. This correlation leads to a simulated coefficient that overestimates the effect of TOBINS_Q on CAPEX (β = 1.6). In column 3, the model includes two omitted variables in the error term u (e.g., SIZE and CASH_FLOWS). TOBINS_Q (x) is a

TABLE 9

Simulations of Common Violations in Instrumental Variables Regressions

Table 9 reports the results of the instrumental variables (IV) regression simulations. The data-generating process for the baseline IV regression is:

$$x_t = \gamma z_t + \rho u_t + \varepsilon_t, \text{where } \varepsilon_t \text{ iid } N(0, \sigma_e^2)$$
$$y_t = \theta + \beta x_t + u_t, \text{where } u_t \text{ iid } N(0, \sigma_t^2),$$

x_t is the endogenous explanatory variable, z_t is the instrumental variable, and y_t is the outcome variable. u_t is the confounding variable. z_t and u_t follow a standard normal distribution. Three random variables, rv1, rv2, and rv3, follow a standard normal distribution. x_t, z_t, and u_t are a function of these random variables. $x_t = \gamma \times z_t + \rho \times rv1 + N(0, 1)$ and $y_t = beta \times x_t + u_t$. Values of z_t and u_t vary across specifications. Models also vary by control variables, additional random variables, and correlation of omitted variables. These variations are noted in each column. Column 1 reports results from a correctly specified IV regression. Columns 2–8 report the results of simulations that perturb the unbiased IV regression model. Columns 6–8 report results for specifications that include correlations among random variables.

	1	2	3	4	5	6	7	8
Beta	1.000	1.400	1.501	1.000	1.150	1.535	1.458	1.311
Std. Error	0.010	0.003	0.007	0.010	0.010	0.007	0.006	0.006
Control	No	No	No	rv2	ln(1 + rv2)	No	No	No
Random variables	rv1 = *N* (0,1)	rv1 = *N* (0,1)	rv1, rv2 = *N* (0,1)	rv1, rv2 = *N* (0,1)	rv1, rv2 = *N* (0,1)	rv1, rv2, rv3 = *N*(0,1)		
Instrument	*z* = *N* (0,1)	*z* = *N* (0,1) + rv1	*z* = *N* (0,1) + rv2	*z* = *N* (0,1) + rv2	*z* = *N* (0,1) + rv2	*z* = *N*(0,1) + rv3		
Omitted variables	*u* = rv1	*u* = rv1	*u* = rv1 + rv2	*u* = rv1 + rv2	*u* = rv1 + rv2	*u* = rv1 + rv2		
Corr(rv1,rv2,rv3)						High = 0.8	Med = 0.5	Low = 0.2

function of SIZE and MFFLOW is a function of CASH_FLOWS. MFFLOW is correlated with u through CASH_FLOWS but not through SIZE. β equals 1.4 which exceeds β of the correctly specified model. Column 4 reports results of a specification that includes a control variable for CASH_FLOWS. This model recovers unbiased IV results: β equals 1.

However, it is likely that an empiricist might include a transformation of the CASH_FLOWS control variable, such as the log of CASH_FLOWS, or a scaled version of CASH_FLOWS, such as the ratio of CASH_FLOWS to a firm's book assets. Column 5 shows that one such transformation, log of CASH_FLOWS, produces a biased β of 1.15.

Columns 6–8 report results from an IV specification in which MFFLOW is indirectly correlated with $u_{i,t}$. Specifically, MFFLOW is not a direct function of omitted variables $u_{i,t}$ in CAPEX. Instead, MFFLOW is defined by variables that are correlated with $u_{i,t}$ but do not directly define u_t. For example, consider a model that includes three omitted variables: SIZE, CASH_FLOWS, and RETURNS. MFFLOW is a function of RETURNS but CAPEX is not. Instead, CAPEX is a function of SIZE and CASH_FLOWS. SIZE and CASH_FLOWS are correlated with RETURNS. The connection between MFFLOW and CAPEX is due to the correlations between SIZE, CASH_FLOWS, and RETURNS. I simulate IV estimates under various levels of correlation between these omitted variables: low correlation = 0.2; medium correlation = 0.5; and high correlation = 0.8.

In column 6, the correlation is high (0.8) and generates a biased β of 1.7. Column 7 reports results of a simulation with a medium level of correlation (0.5) between omitted variables. Again, β is biased. The results in column 8 confirm these results using a low correlation (0.2).

These simulations illustrate how commonly omitted variables and correlations among variables lead to biased estimates. It is possible to fix the bias by controlling for all of the omitted variables with the correct transformations. However, the multitude of omitted variables highlighted in Section IV makes it unlikely that a model will include the full set of omitted variables with the correct proxies. As a result, omitted observable and unobservable variables probably bias the regression coefficients in the MFFLOW IV.

D. Adjusting MFFLOW Using the Switching Regression Method

Next, I measure the magnitude of the bias in coefficient estimates coming from correlations between firm characteristics and the MFFLOW variable. If MFFLOW is a function of a random variable and firm characteristics and I can perfectly control for firm characteristics then MFFLOW is a good instrument (see column 4 in Table 9).

However, suppose that a firm characteristic, such as size, has a nonlinear effect on MFFLOW but I use a linear control. This creates an omitted factor in size, coming from the nonlinear transformation, which may also be correlated with $u_{i,t}$ in the CAPEX regression. Hence, the firm size proxy will not fully control for the endogenous relationship between firm size, MFFLOW, and $u_{i,t}$ in the IV regression (see column 5 in Table 9).

In this section, I use the switching regression method to measure the bias that a particular firm characteristic introduces into the IV results (Lee (1978), Heckman (1979), Puri (1996), and Golubov et al. (2012)). The method is a more generalized form of the Heckman (1979) two-stage estimator to correct for selection bias. The switching regression method "fixes" the bias in MFFLOW that comes from one specific characteristic. I perform the switching regression analysis in four steps and use firm size (SIZE) as an example in the following discussion.

In the first step, I apply the Heckman (1979) two-stage estimator to correct for selection bias. Specifically, I calculate terciles of SIZE and assign firms in the top tercile to the "large" subsample and firms in the bottom tercile to the "small" subsample. Then, I run a probit regression in which firm characteristics predict whether a firm is in the "large" subsample (column 1 in Table 10).

The Heckman (1979) two-stage estimator includes the inverse Mills ratio (IMR), which is a control variable for endogeneity, as an additional regressor in the second-stage equation.[7] When this term is included as a right-hand-side variable, an OLS regression that measures the effect of firm size on MFFLOW provides a consistent estimate of MFFLOW with respect to firm size.

In the second step, I regress MFFLOW on SIZE and IMR using a subsample of small firms and of large firms separately. Columns 2 and 3 in Table 10 report the results from this analysis. The statistically significant coefficient on IMR shows that there is endogeneity with respect to firm size.

[7]To construct the IMR, I use the linear prediction from the probit regression model to calculate the density function and cumulative distribution function of the normal distribution. The IMR is the density function scaled by the cumulative distribution function. The IMR adjusts for self-selection by correcting for the nonzero mean of the error terms.

TABLE 10

Switching Regression Method: Firm Size Example

Table 10 reports results from the switching regression method. Columns 1–4 report the output of each step of the analysis using firm size (SIZE) as an example. Column 1 reports the results of a probit regression in which firm characteristics predict whether a firm is "large," where "large" firms are those in the top tercile of the size distribution. Columns 2 and 3 report the results of a regression of MFFLOW on firm characteristics for the subsample of large firms and small firms, respectively. Inverse Mills Ratio (IMR) is calculated from the linear prediction of the probit model. Column 4 reports instrumental variables (IV) regression results using "adjusted MFFLOW" as the IV. "Adjusted MFFLOW" is a predicted MFFLOW based on the combination of "large" firm coefficients (column 2) with "small" firm data and "small" firm coefficients (column 3) with "large" firm data. Standard errors are clustered at the firm level and t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Probit (SIZE)	MFFLOW – Large Firms	MFFLOW – Small Firms	Adj. MFFLOW IV (2nd Stage)
	1	2	3	4
TOBINS_Q ($t-1$)	−0.1474***	−0.1125***	−0.2024***	0.0052
	(−29.58)	(−7.98)	(−6.72)	(1.18)
FINANCIAL_CONSTRAINTS ($t-1$)	0.0374***	0.0225	0.0565***	
	(6.09)	(1.59)	(4.51)	
MF_OWN (%) ($t-1$)	7.2653***	0.8134***	20.0544***	
	(82.90)	(4.58)	(12.09)	
MF_HHI ($t-1$)	−1.2501***	0.1669*	−1.2805***	
	(−47.79)	(1.94)	(−5.09)	
AGE	0.0286***	0.0221***	0.0485***	
	(50.77)	(6.31)	(6.23)	
CASH_FLOWS (%) ($t-1$)	−0.5649***	0.3427*	−0.3711**	
	(−5.69)	(1.88)	(−2.29)	
VOLATILITY ($t-1$)	−43.7972***	0.4877	−49.2829***	−0.2278***
	(−95.17)	(0.27)	(−5.64)	(−5.69)
LEVERAGE ($t-1$)	0.0769***	−0.0683	0.0145	−0.0043***
	(4.02)	(−1.55)	(0.42)	(−11.04)
ROA ($t-1$)	1.1933***	−0.1364	0.7389***	0.0484***
	(13.23)	(−0.63)	(2.69)	(12.96)
RETURNS (%) ($t-1$)	0.0224*	−0.1002***	0.0353**	0.0122***
	(1.78)	(−4.42)	(2.09)	(7.22)
SIZE ($) ($t-1$)		−0.0394	0.0761**	
		(−1.28)	(2.44)	
IMR		−0.0151	1.2565***	
		(−0.26)	(5.50)	
No. of obs.	76,654	37,936	38,718	70,625
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	No	Yes
F-statistic in first stage				108
p-value of F-statistic				0.000
Pseudo R^2	0.542			
Partial R^2 in first stage				0.004

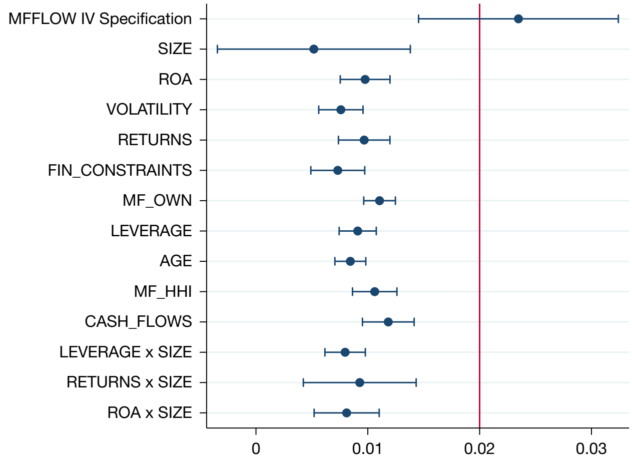
Next, I use the coefficients from these subsample regressions to calculate an "adjusted" MFFLOW variable that corrects for bias coming from SIZE. I predict MFFLOW by combining the coefficients from the regression on large firms with the data for small firms. Likewise, I use coefficients from the small firm analysis to calculate MFFLOW based on data for the large firm subsample. The final measure of MFFLOW reflects the "pure effects" of SIZE on MFFLOW without the error due to endogenous firm size.

In the final step, I run the IV regression of CAPEX on TOBINS_Q using the adjusted MFFLOW as the IV. In column 4, the coefficient on instrumented TOBINS_Q is smaller (0.0045) than the original estimate of 0.02 (see column 2 in Table 7) and statistically insignificant. This result suggests that the bias in MFFLOW coming from firm size overestimates the effect of TOBINS_Q on CAPEX.

FIGURE 4

Instrumental Variables Coefficients from Switching Regressions

Figure 4 reports coefficients from the second stage of an instrumental variables (IV) regression of CAPEX on TOBINS_Q, using "adjusted MFFLOW" as the IV. The switching regression method provides an adjusted MFFLOW IV for TOBINS_Q that corrects for bias in the IV. The results are reported for each firm characteristic: SIZE, ROA, VOLATILITY, RETURNS, FINANCIAL_CONSTRAINTS, MF_OWN, LEVERAGE, AGE, MF_HHI, CASH_FLOWS, and the combinations of LEVERAGE and SIZE, RETURNS and SIZE, and ROA and SIZE. The method uses a probit regression and an OLS model on subsamples of firms to construct an unbiased, "adjusted MFFLOW." Bars represent the 95% confidence intervals for the coefficient estimates.



I repeat this procedure for each of the following firm characteristics: SIZE, ROA, VOLATILITY, RETURNS, FINANCIAL_CONSTRAINTS, MF_OWN, LEVERAGE, AGE, MF_HHI, CASH_FLOWS, LEVERAGE and SIZE, RETURNS and SIZE, and ROA and SIZE.

Figure 4 plots the range of β_1 coefficient estimates from the second stage of these IV regressions. Each estimate is the coefficient on TOBINS_Q using the adjusted MFFLOW as the IV. The results show that the unbiased coefficients are roughly half the size of the coefficient on TOBINS_Q using the biased MFFLOW IV.

E. Alternative IVs

I explore how alternative IVs affect regression estimates. First, I use observable firm characteristics as substitutes for MFFLOW in the IV regression. Second, I use an alternative IV that captures the variation in MFFLOW that is orthogonal to observable firm characteristics.

1. Adjusting MFFLOW: Observable Characteristics as IVs

I analyze how the regression results might change if observable firm characteristics substitute for MFFLOW. Specifically, I use three observable characteristics as alternative IVs: a firm's share of institutional ownership (INST_OWN), a firm's share of mutual fund ownership (MF_OWN), and the log of trading volume (TRADING_VOLUME). The analysis illustrates how these observable characteristics, and potentially associated unobservable characteristics, change the results.

TABLE 11

Instrumental Variables Regression: Firm Characteristic IVs

Table 11 reports the effects of TOBINS_Q on firm investment (CAPEX) using alternative instrumental variables (IVs). The analysis uses the following observable firm characteristics as alternative instruments for TOBINS_Q: mutual fund ownership (MF_OWN), institutional ownership (INST_OWN), and trading volume (TRADING_VOLUME). Columns 1 and 2 report the first and second stages of the IV regression using MF_OWN as the instrumental variable. Columns 3 and 4 (5 and 6) report the first- and second-stage regressions using INST_OWN (TRADING_VOLUME). For reference, columns 7 and 8 report the first- and second-stage regressions using the MFFLOW IV. The specification includes the control variables: SIZE, ROA, LEVERAGE, RETURNS, and VOLATILITY and firm and year fixed effects. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level and *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Mutual Fund Ownership IV		Institutional Ownership IV		Trading Volume IV		MFFLOW IV	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
	1	2	3	4	5	6	7	8
TOBINS_Q		0.0214***		0.0205***		0.0206***		0.0235***
		(5.10)		(5.08)		(16.71)		(5.15)
SIZE	−0.3584***	−0.0093***	−0.3681***	−0.0096***	−0.5257***	−0.0095***	−0.3346***	−0.0086***
	(−22.24)	(−5.77)	(−22.64)	(−6.11)	(−32.42)	(−10.21)	(−20.79)	(−4.98)
ROA (%)	0.9155***	0.0465***	0.9112***	0.0474***	0.6687***	0.0466***	0.9289***	0.0446***
	(9.74)	(9.15)	(9.70)	(9.72)	(7.46)	(14.54)	(9.86)	(8.51)
LEVERAGE (%)	−0.0153***	−0.0038***	−0.0152***	−0.0039***	−0.0042	−0.0038***	−0.0177***	−0.0038***
	(−3.83)	(−13.91)	(−3.79)	(−13.95)	(−1.06)	(−14.30)	(−4.41)	(−13.53)
RETURNS (%)	−0.3049***	0.0165***	−0.3054***	0.0162***	−0.3231***	0.0161***	−0.3115***	0.0171***
	(−32.39)	(11.91)	(−32.51)	(12.02)	(−34.57)	(24.96)	(−33.12)	(11.18)
VOLATILITY	−4.3538***	−0.1729***	−4.2592***	−0.1774***	−7.4862***	−0.1770***	−4.8404***	−0.1634***
	(−9.08)	(−5.51)	(−8.87)	(−5.79)	(−16.05)	(−6.99)	(−10.05)	(−5.12)
MF_OWN (%)	1.1097***							
	(12.00)							
INST_OWN (%)			0.5290***					
			(12.37)					
ln(TRADING_ VOLUME)					0.3615***			
					(38.89)			
MFFLOW IV							−0.0200***	
							(−14.29)	
F-stat. in 1st stage		144		153		1,512		204
p-value of *F*-stat.		0.000		0.000		0.000		0.000
Partial R^2 in 1st stage		0.004		0.004		0.066		0.002
No. of obs.	108,971	108,971	108,971	108,971	108,584	108,584	108,971	108,971
Firm FE		Yes		Yes		Yes		Yes
Year FE		Yes		Yes		Yes		Yes

Table 11 reports the regression results. Columns 1–6 report the first- and second-stage results using the alternative IVs. For ease of comparison, columns 7 and 8 report results using the original MFFLOW variable. The results in columns 1–6 show that these observable firm characteristics yield nearly identical results to those using MFFLOW. Coefficients on TOBINS_Q (between 0.0205 and 0.0214) are similar in magnitude to the baseline coefficient of 0.0235 on TOBINS_Q (column 8) and are statistically significant at the 1% level.

Fang, Tian, and Tice (2014) and Bena, Ferreira, Matos, and Pires (2017) show that these variables are direct determinants of CAPEX. The results suggest that the correlation between MFFLOW and these observable firm characteristics may drive the regression results rather than the variation in MFFLOW that is orthogonal to CAPEX.

2. Adjusting MFFLOW: Residuals as an Alternative IV

Empirical specifications using MFFLOW include control variables for the observable firm characteristics that predict MFFLOW (e.g., Edmans et al. (2012), Phillips and Zhdanov (2013), and Zuo (2016)). In this section, I use the residuals from a regression of MFFLOW on observable firm characteristics to test whether the residual variation in MFFLOW is a good alternative IV.

I predict MFFLOW using the firm characteristics from Table 7: SIZE, ROA, LEVERAGE, RETURNS, and VOLATILITY. The residuals from this regression should reflect the variation in MFFLOW that is orthogonal to firm fundamentals. I use these residuals to define an alternative IV, RESIDUALS.

Table 12 reports the results using the RESIDUALS IV. Columns 1 and 2 report the first- and second-stage regression results and columns 3 and 4 report the first- and second-stage regression results using the MFFLOW IV, for comparison. The first stage regressions, reported in columns 1 and 3, show that both instruments predict TOBINS_Q. However, the coefficient on RESIDUALS is smaller and less statistically significant than the coefficient on MFFLOW. The second stage results in columns 2 and 4 show that both the MFFLOW IV and the RESIDUALS IV have a positive coefficient on TOBINS_Q. However, the RESIDUALS coefficient is 50% larger and is not a statistically significant determinant of CAPEX (t-statistic = 0.94). The higher coefficient suggests that additional correlations exist between the residual variation and CAPEX that introduces bias when using the RESIDUALS IV.

TABLE 12

Instrumental Variables Regression: Residuals IV

Table 12 reports the effects of TOBINS_Q on firm investment (CAPEX) using an instrumental variable (IV) specification with regression residuals as an alternative IV. Residual terms from a regression of MFFLOW on firm characteristics define an alternative instrumental variable, RESIDUALS, for firm value (TOBINS_Q). Columns 1 and 2 report the first and second stages of the IV regression using RESIDUALS. Columns 3 and 4 report the first and second stages of an IV regression using the MFFLOW IV. The specification includes the control variables: SIZE, ROA, LEVERAGE, RETURNS, and VOLATILITY and firm and year fixed effects. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level and t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	RESIDUALS IV		MFFLOW IV	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	1	2	3	4
TOBINS_Q	0.0364	(0.94)	0.0235***	(5.15)
SIZE	−0.3379*** (−20.85)	−0.0041 (−0.32)	−0.3346*** (−20.79)	−0.0086*** (−4.98)
ROA (%)	0.9388*** (9.92)	0.0317 (0.87)	0.9289*** (9.86)	0.0446*** (8.51)
LEVERAGE (%)	−0.0167*** (−4.17)	−0.0036*** (−5.04)	−0.0177*** (−4.41)	−0.0038*** (−13.53)
RETURNS (%)	−0.3098*** (−32.90)	0.0211* (1.75)	−0.3115*** (−33.12)	0.0171*** (11.18)
VOLATILITY	−4.7078*** (−9.74)	−0.1026 (−0.56)	−4.8404*** (−10.05)	−0.1634*** (−5.12)
RESIDUALS IV	−0.0025* (−1.77)			
MFFLOW IV			−0.0200*** (−14.29)	
F-stat. in 1st stage		3		204
p-value of F-stat.		0.076		0.000
Partial R^2 in 1st stage		0.000		0.002
No. of obs.	107,965	107,965	108,971	108,971
Firm FE		Yes		Yes
Year FE		Yes		Yes

This outcome is consistent with the findings from the simulations in Section V.C. Hence, the residual variation in MFFLOW that is orthogonal to CAPEX is not a strong or reliable instrument for TOBINS_Q.

VI. Conclusion

Studies that use MFFLOW or its variants as an IV to measure exogenous changes in stock price find that stock mispricing affects corporate decision-making. Hence, incorrect market prices can distort crucial aspects of real economic outcomes. This result has enormous efficiency implications for the economy at large. It implies that incorrect stock prices influence the current organization of financial markets in the U.S. and the mechanism that allocates some $17 trillion in savings.

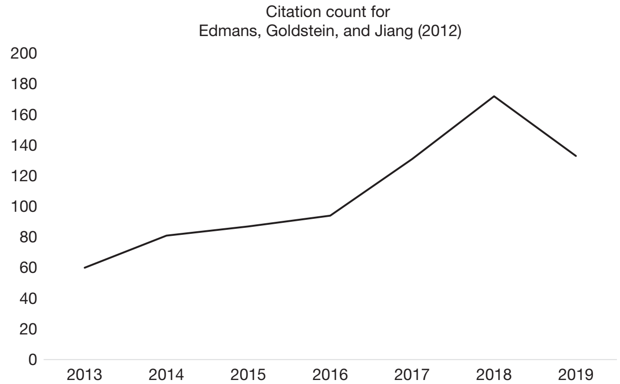
The empirical finance literature has given considerable weight to MFFLOW as an exogenous shock to stock prices. Figure 5 illustrates its impact with citation trajectories for articles that use MFFLOW, or its variants. The magnitude of the citation count is large and the trajectory of citations is growing, by 40% per year in recent years. This growth rate predicts that the lifetime impact of MFFLOW will be considerably higher than what it is now.

I investigate whether the MFFLOW IV has a selection bias problem. I identify that the proportional trading assumption is a key driver of selection bias. In response to large outflows, fund managers do not employ a proportional trading strategy. Instead, they systematically avoid selling shares of firms with specific characteristics. This trend biases MFFLOW such that the magnitude of MFFLOW is correlated with observable firm characteristics. Firms with large values of MFFLOW are illiquid, smaller, and younger and have lower past returns, cash flows, and Tobin's Q. The divergence between mutual fund trades that originate from mutual fund trading and hypothetical trades that originate from the proportional trading assumption leads to correlations between MFFLOW and firm characteristics.

FIGURE 5

Edmans, Goldstein, and Jiang (2012) Citation Count

Figure 5 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).



In addition, I document that hypothetical trades drive the correlation between MFFLOW and large, negative price impacts whereas real trading activity is associated with positive future price impacts. These results contradict the assumption that MFFLOW measures the negative price impacts induced by mutual fund trading pressure. In sum, the magnitude of MFFLOW is predictable and correlates with firm characteristics.

I use several empirical approaches to quantify the impact of selection bias on IV estimates. The results of simulations demonstrate how selection bias distorts these estimates and how control variables might mitigate these distortions. A switching regression analysis shows that the biased MFFLOW IV doubles the magnitude of coefficient estimates compared to estimates using an unbiased IV. Analyses using alternative IVs indicate that observable, and likely unobservable, variables drive the magnitude and statistical significance of the results.

I assert that these differences cannot be controlled for using additional covariates. There are unobservable factors that systematically correlate with firm outcomes. I show that although the alternative measures introduced in Wardlaw (2020) may mitigate bias that stems from the correlation between MFFLOW and past returns, they do not resolve the selection bias introduced by the proportional trading assumption.

Given the widespread use of MFFLOW and the economic implications of findings using this measure, it is essential to understand whether MFFLOW is a valid IV. I conclude that it is not. The consequence of this finding is that a growing body of empirical results should be reexamined. The challenge is to find a new identification strategy that can convincingly measure the effects of market prices on firm policy.

Appendix A. Variable Definitions

AAR: Firm returns compared to CRSP equal-weighted index returns in each event month.

AGE: Years from a firm's first appearance in CRSP.

ASSET_GROWTH: log(book assets(#6)) − log(lagged book assets(#6)).

CAAR: AAR over the period of 12 months before an outflow of 5% or more through 24 months after the outflow.

CAPEX: Capital expenditures (#128)/lagged book assets (#6).

CASH_FLOWS: (income before extraordinary items (#21) + depreciation (#14))/lagged Book assets(#6).

DIVIDENDS: Dividends(#21)/lagged book assets(#6).

FINANCIAL_CONSTRAINTS: Kaplan–Zingales measure of financial constraints.

FLOW: (Total net assets − lagged total net assets × fund returns − MGN)/lagged total net assets.

FLOW_TO_STOCK: FLOW × lagged shares of firm i held by fund j/lagged shares outstanding of firm i.

FLOW_TO_VOLUME: FLOW × lagged shares of firm i held by fund j/total shares of firm i traded.

TRADE: FLOW × lagged end of quarter share price × lagged shares of firm i held by fund j.

TABLE A1

Predicting Trades of Index Fund Managers

Table A1 reports regression results of mutual fund trading in response to large capital outflows from passive, index mutual funds ($\geq$ 5% outflows). The dependent variable is the percentage change in shares of stock i held by fund j from quarters $t-1$ to t ($\text{TRADE}_{i,j,t}$). The main coefficient of interest is on mutual fund flows, $\text{FLOW}_{j,t}$. Control variables reflect trading costs and other firm characteristics which include: $\text{OWN}_{i,j,t-1}$, $\text{ILLIQUIDITY}_{i,t-1}$, $\text{OWN}_{j,t-1}$, $\text{RETURNS}_{i,t-1}$, $\text{VOLATILITY}_{i,t-1}$, $\text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$, $\text{TOBINS\_Q}_{i,t-1}$, and $\text{SIZE}_{i,t-1}$. Variable definitions are in Appendix A. The table reports a test of whether $\beta = 1$ and the t-statistics for this test. Specifications include 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.

	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$	$\text{TRADE}_{i,j,t}$
	1	2	3	4
$\text{FLOW}_{j,t}$	1.0409***	1.1397***	1.1944***	1.0982***
	(9.42)	(9.05)	(10.37)	(4.96)
$\text{OWN}_{i,j,t-1}$		1.6200	1.5679	1.8525
		(0.74)	(0.69)	(0.77)
$\text{FLOW}_{j,t} \times \text{OWN}_{i,j,t-1}$		35.2424	35.0293	37.8065
		(0.87)	(0.86)	(0.90)
$\text{ILLIQUIDITY}_{j,t-1}$		−0.0013	0.0058	0.0090
		(−0.03)	(0.14)	(0.21)
$\text{FLOW}_{j,t} \times \text{ILLIQUIDITY}_{j,t-1}$		−7.8496	−0.4383	−1.0955
		(−0.56)	(−0.05)	(−0.12)
$\text{OWN}_{i,t-1}$		−3.7935	−3.7192	−3.9758
		(−1.56)	(−1.52)	(−1.58)
$\text{FLOW}_{j,t} \times \text{OWN}_{i,t-1}$		−48.1745	−47.5859	−49.9467
		(−1.27)	(−1.26)	(−1.27)
$\text{ILLIQUIDITY}_{i,t-1}$		−33.8667**	−33.3690**	−31.3908**
		(−2.28)	(−2.22)	(−2.10)
$\text{FLOW}_{j,t} \times \text{ILLIQUIDITY}_{i,t-1}$		−19.7431	−19.3134	−18.2462
		(−1.50)	(−1.45)	(−1.37)
$\text{RETURNS}_{i,t-1}$			−0.0094	−0.0026
			(−0.32)	(−0.09)
$\text{FLOW}_{j,t} \times \text{RETURNS}_{i,t-1}$			0.0046	0.0425
			(0.04)	(0.32)
$\text{VOLATILITY}_{i,t-1}$			−0.3717	−0.3677
			(−0.49)	(−0.51)
$\text{FLOW}_{j,t} \times \text{VOLATILITY}_{i,t-1}$			−3.5475	−4.1461
			(−0.88)	(−0.96)
$\text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$				−0.0000
				(−0.51)
$\text{FLOW}_{j,t} \times \text{FINANCIAL\_CONSTRAINTS}_{i,t-1}$				−0.0001
				(−0.38)
$\text{TOBINS\_Q}_{i,t-1}$				0.0046***
				(2.92)
$\text{FLOW}_{j,t} \times \text{TOBINS\_Q}_{i,t-1}$				0.0328***
				(3.05)
$\text{SIZE}_{i,t-1}$				0.0032
				(0.58)
$\text{FLOW}_{j,t} \times \text{SIZE}_{i,t-1}$				0.0017
				(0.11)
R^2	0.396	0.403	0.403	0.403
No. of obs.	32,175	32,175	31,478	30,633
No. of clusters	36	36	36	36
$\beta = 1$	0.041	0.14	0.194	0.098
t-statistic	0.37	1.109	1.688	0.443

HOLDINGS: Share price of firm i in quarter t $\times$ shares of firm i held by fund j in quarter t/total net assets of fund j.

INST_OWN: Fraction of a firm's total shares outstanding owned by institutional investors.

INST_HHI: Herfindahl–Hirschman Index of the concentration of institutional ownership of a firm's shares outstanding.

ILLIQUIDITY: Illiquidity measure per Amihud (2002); yearly average of the square root of (Price × Vol)/Return.

ISSUANCE: (Change in common equity (#60) + change in deferred taxes (#74) − change in retained earnings (#36))/lagged common equity (#60).

LEVERAGE: (Long-term debt (#9) + current liabilities (#34) − cash (#1))/(assets (#6)).

MARKET_CAP: ln(price (#199) × shares outstanding (#25) at fiscal year end).

MFFLOW: Abs(trading volume from mutual funds with outflows of 5% or more)/total trading volume.

MF_OWN: Fraction of a firm's total shares outstanding owned by mutual funds.

MF_HHI: Herfindahl–Hirschman Index of the concentration of mutual fund ownership of shares outstanding.

MGN: Increase in *TNA* caused by a fund merger.

$\text{OWN}_{i,j,t-1}$: Percentage of all shares outstanding of firm i held by fund j in quarter $t-1$.

$\text{OWN}_{j,t-1}$: Portfolio weighted average ownership share of fund j.

PAYOUT: (Dividends (#21) + repurchases (#115) − sale of common and preferred stock (#108)) / lagged book assets (#6); 0 if numerator is 0 or missing, and 1 if numerator > 0 and denominator = 0.

REPURCHASES: (Repurchases (#115) − sale of common and preferred stock (#108))/lagged book assets (#6).

RETURNS: Cumulative monthly stock returns over the prior year (CRSP monthly file).

ROA: Gross operating income (#13)/lagged book assets (#6).

SIZE: ln(book assets (#6)).

TNA: Total net assets of a fund in millions of dollars.

TOBINS_Q: (Price (#199) × shares outstanding (#25) + long-term debt + short-term debt)/(long-term debt + short-term debt + book equity).

TRADING_VOLUME: End of quarter share price × total shares of firm traded in the quarter.

VOLATILITY: Standard deviation of daily stock returns over the past year.

Appendix B. Data Set Construction

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)).

Firm-level data consist of firms with share codes 10 or 11, listed on Compustat with nonmissing price and returns data reported in the CRSP monthly file. I exclude all financial (SIC 6000–6999) and utilities (SIC 4000–4949) firms 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 multishare class fund characteristics (e.g., investment objective codes) are set equal to the value of the share class with the largest TNA.

A fund's quarterly flow is 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. To calculate the increase in TNA caused by a merger in quarter t, $\mathrm{MGN}_{j,t}$, 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 1 month before to 5 months after its last NAV report date and calculate the merger-adjusted flow for each of the months in this 6-month window. I then select the month with the smallest absolute percentage flow as the event month (Lou (2012)).

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 TNAs do not differ by more than a factor of two (i.e., $0.5 < \mathrm{TNA}_{\mathrm{CDA}}/\mathrm{TNA}_{\mathrm{CRSP}} < 2$) (Coval and Stafford (2007)). In addition, I require a minimum fund size of \$1 million (Coval and Stafford (2007)).

Appendix C. Alternative MFFLOW Instrumental Variables

Wardlaw (2020) points to a mechanical correlation between past returns and MFFLOW as the source of selection bias in the MFFLOW instrumental variable (IV). This selection bias comes from the definition of the MFFLOW variable in which MFFLOW is calculated as a direct function of past returns. Specifically, consider the definition of MFFLOW in Section III. Wardlaw (2020) decomposes the

MFFLOW variable into three parts: the returns portion, the turnover portion, and the flows portion and offers two variations on the MFFLOW measure as a starting point to resolve the correlation between MFFLOW and past returns. The alternative IVs exclude the returns portion and focus on the flows portion. These measures are FLOW_TO_STOCK and FLOW_TO_VOLUME. Using the notation from Sections II and III: FLOW_TO_STOCK $= \sum_{k=1}^{K} \text{FLOW}_{k,t} \times S_{k,i,t-1} / \text{SHROUT}_{i,t-1}$ and FLOW_TO_VOLUME $= \sum_{k=1}^{K} \text{FLOW}_{k,t} \times S_{k,i,t-1} / x_{i,t}$, where $\text{SHROUT}_{i,t-1}$ is total shares outstanding of firm i in quarter $t-1$ and $x_{i,t}$ is the total shares of firm i traded in quarter t.

Although these alternative IVs may resolve one source of selection bias, my results provide evidence that the proportional trading assumption introduces another source of selection bias. I assess whether the proportional trading assumption introduces selection bias that is unique or is subsumed by the FLOW_TO_STOCK and FLOW_TO_VOLUME measures.

I use the methods from Section IV to identify selection bias in these alternative IVs coming from the proportional trading assumption.

First, I examine whether the magnitude of these alternative IVs is correlated with observable firm characteristics. Table A2 (A4) reports summary statistics for firms with above median and below median values of FLOW_TO_STOCK (FLOW_TO_VOLUME). Firms with above median values of FLOW_TO_STOCK have higher ROA, CASH_FLOWS, and ASSET_GROWTH. They are younger and have higher institutional ownership.

TABLE A2

Summary of Firms by Median FLOW_TO_STOCK

Table A2 presents summary statistics for firms grouped by the median of the FLOW_TO_STOCK instrumental variable (IV) from 1980 to 2007. FLOW_TO_STOCK is an adjusted MFFLOW measure based on shares outstanding (Wardlaw (2020)). Column 1 reports the mean of each variable for firm-year observations with below median FLOW_TO_STOCK. Column 2 reports the means for observations with above median FLOW_TO_STOCK. All data are obtained from Compustat and CRSP. All variables are winsorized at the 1% and 99% levels.

	FLOW_TO_STOCK	
Variable	Below Median	Above Median
FINANCIAL_CONSTRAINTS	2.011	1.981
CASH_FLOWS (%)	0.066	0.094
ROA (%)	0.122	0.152
RETURNS (%)	0.033	0.040
VOLATILITY	0.032	0.031
TOBINS_Q	1.972	2.040
LEVERAGE (%)	0.773	0.703
ASSET_GROWTH (%)	0.110	0.143
DIVIDENDS (%)	0.012	0.008
REPURCHASES (%)	0.012	0.016
AGE (Years)	21.034	18.810
ISSUANCE (%)	0.159	0.139
CAPEX (%)	0.084	0.081
PAYOUT (%)	0.480	0.396
SIZE ($)	5.855	5.946
MARKET_CAP ($)	5.822	6.030
MFFLOW	2.057	6.091
INST_OWN (%)	0.280	0.427
MF_OWN (%)	0.074	0.153
INST_HHI	0.088	0.072
MF_HHI	0.143	0.112
Observations	21,056	25,398

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TABLE A3

Predicting FLOW_TO_STOCK

Table A3 reports results from regressions in which an indicator variable for an individual firm's FLOW_TO_STOCK instrumental variable (IV) is regressed on firm characteristics. Column 1 reports results of a regression of an indicator for firms with nonzero FLOW_TO_STOCK on firm characteristics using the full sample of firm-year observations. Column 2 reports results from a regression of an indicator variable for firm-year observations with Extreme FLOW_TO_STOCK on firm characteristics on the subsample of firms with nonzero FLOW_TO_STOCK. FLOW_TO_STOCK is an adjusted MFFLOW measure based on shares outstanding (Wardlaw (2020)). The extreme values represent the largest values of FLOW_TO_STOCK (top 10%) during the full sample period (1980–2007). The independent variables include $\text{MF\_OWN}_{i,t-1}$, the fraction of shares held by mutual funds, $\text{MF\_HHI}_{i,t-1}$, the concentration of mutual fund ownership measured by the Herfindahl–Hirschman Index (HHI), $\text{SIZE}_{i,t-1}$, the natural log of book assets, $\text{AGE}_{i,t-1}$, the years from first appearance in CRSP, $\text{TOBINS\_Q}_{i,t-1}$, $\text{CASH\_FLOWS}_{i,t-1}$, and $\text{RETURNS}_{i,t-1}$. Regressions include firm and year-fixed effects. Robust standard errors are clustered at the 3-digit SIC industry level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	FLOW_TO_STOCK > 0	Extreme FLOW_TO_STOCK
	1	2
MF_OWN (%) ($t-1$)	0.264***	0.902***
	(9.63)	(18.24)
MF_HHI ($t-1$)	−0.029***	−0.011
	(−2.79)	(−0.55)
SIZE ($) ($t-1$)	0.063***	0.004
	(11.54)	(0.56)
AGE (Years)	0.006***	−0.019***
	(3.54)	(−4.51)
TOBINS_Q ($t-1$)	0.015***	0.011***
	(10.68)	(5.92)
CASH_FLOWS (%) ($t-1$)	0.085***	0.084***
	(7.22)	(2.95)
RETURNS (%) ($t-1$)	0.026***	0.014**
	(6.94)	(2.54)
FINANCIAL_CONSTRAINTS ($t-1$)	−0.002***	−0.001
	(−5.20)	(−0.65)
VOLATILITY ($t-1$)	−0.487***	−1.115***
	(−3.10)	(−3.59)
ILLIQUIDITY ($t-1$)	−5.320***	2.037***
	(−16.52)	(3.72)
R^2	0.684	0.409
No. of obs.	77,434	48,587
No. of clusters	274	267
Firm FE	Yes	Yes
Year FE	Yes	Yes
Cluster variable	3-digit SIC	3-digit SIC
Sample of firms	Full sample	Firm-years with MFFLOW > 0

These results document that the proportional trading assumption creates a correlation between the magnitude of FLOW_TO_STOCK (FLOW_TO_VOLUME) and firm characteristics – characteristics that directly determine firm policies.

I use a probit regression model to determine whether firm characteristics predict the largest values of FLOW_TO_STOCK (FLOW_TO_VOLUME). The results reported in Tables A3 and A5 confirm that firm characteristics predict the largest values of these alternative IVs (column 2).

Large values of FLOW_TO_STOCK are more likely among smaller, younger firms with lower TOBINS_Q, CASH_FLOWS, and RETURNS and equity with higher ILLIQUIDITY. Hence, the proportional trading assumption creates selection bias in these alternative IVs such that the magnitude of these measures is correlated with observable firm characteristics. This evidence suggests that removing the returns correlation does not resolve selection bias coming from the proportional trading assumption.

TABLE A4

Summary of Firms by Median FLOW_TO_VOLUME

Table A4 presents summary statistics for firms grouped by the median of the FLOW_TO_VOLUME instrumental variable (IV) from 1980 to 2007. FLOW_TO_VOLUME is an adjusted MFFLOW measure based on total shares of firm *i* traded in quarter *t* (Wardlaw (2020)). Column 1 reports the mean of each variable for firm-year observations with below median FLOW_TO_VOLUME. Column 2 reports the means for observations with above median FLOW_TO_VOLUME. All data are obtained from Compustat and CRSP. All variables are winsorized at the 1% and 99% levels.

	FLOW_TO_VOLUME	
Variable	Below Median	Above Median
FINANCIAL_CONSTRAINTS	2.026	1.971
CASH_FLOWS (%)	0.065	0.095
ROA (%)	0.125	0.151
RETURNS (%)	0.044	0.030
VOLATILITY	0.034	0.029
TOBINS_Q	2.204	1.839
LEVERAGE (%)	0.743	0.729
ASSET_GROWTH (%)	0.141	0.115
DIVIDENDS (%)	0.010	0.010
REPURCHASES (%)	0.013	0.016
AGE (Years)	19.565	20.086
ISSUANCE (%)	0.210	0.094
CAPEX (%)	0.088	0.077
PAYOUT (%)	0.401	0.463
SIZE ($)	5.966	5.858
MARKET_CAP ($)	6.072	5.821
MFFLOW	1.020	3.120
INST_OWN (%)	0.322	0.396
MF_OWN (%)	0.095	0.137
INST_HHI	0.074	0.084
MF_HHI	0.117	0.134
Observations	21,688	24,657

Finally, I examine the link between proportional trading and the price impact of these alternative IVs using real and hypothetical trading activity as discussed in Section IV.D. The analysis explores whether real selling activity drives the negative abnormal returns associated with FLOW_TO_STOCK (FLOW_TO_VOLUME) rather than hypothetical selling activity arising from the proportional trading assumption. I compare the abnormal returns of firms with net selling activity to those of firms with net buying activity within a set of firms with the largest values of FLOW_TO_STOCK (FLOW_TO_VOLUME).

Graphs A and B of Figures 2 and 3 graph the abnormal returns for firms with net selling activity (Graph A) and net buying activity (Graph B). Firms with net buying activity exhibit large and negative abnormal returns when large mutual fund outflows occur (Graph A), despite the fact that mutual funds refrain from selling these firms in aggregate. In contrast, firms with net selling activity – the trading that should lead to negative returns – have positive abnormal returns when large mutual fund outflows occur (Graph B).

Although the FLOW_TO_STOCK and FLOW_TO_VOLUME IVs correct the returns correlation between MFFLOW and past RETURNS, the proportional trading assumption continues to drive the estimated price impact coming from the IVs. Firms with hypothetical selling activity due to the proportional trading assumption drive the negative returns patterns associated with high values of these measures following large mutual fund outflows. As a result, the variables erroneously attribute persistently large and negative returns to real mutual fund selling activity.

TABLE A5

Predicting FLOW_TO_VOLUME

Table A5 reports results from regressions in which an indicator variable for an individual firm's FLOW_TO_VOLUME instrumental variable (IV) is regressed on firm characteristics. Column 1 reports the results of a regression of an indicator for firms with nonzero FLOW_TO_VOLUME on firm characteristics using the full sample of firm-year observations. Column 2 reports results from a regression of an indicator variable for firm-year observations with extreme FLOW_TO_VOLUME on firm characteristics on the subsample of firms with nonzero FLOW_TO_VOLUME. FLOW_TO_VOLUME is an adjusted MFFLOW measure based on total shares of firm *i* traded in quarter *t* (Wardlaw (2020)). The extreme values represent the largest values of FLOW_TO_VOLUME (top 10%) during the full sample period (1980–2007). The independent variables include $MF\_OWN_{i,t-1}$, the fraction of shares held by mutual funds, $MF\_HHI_{i,t-1}$, the concentration of mutual fund ownership measured by the Herfindahl–Hirschman Index (HHI), $SIZE_{i,t-1}$, the natural log of book assets, $AGE_{i,t-1}$, the years from the first appearance in CRSP, $TOBINS\_Q_{i,t-1}$, $CASH\_FLOWS_{i,t-1}$, and $RETURNS_{i,t-1}$. Regressions include firm and year-fixed effects. Robust standard errors are clustered at the 3-digit SIC industry level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	FLOW_TO_VOLUME > 0	Extreme FLOW_TO_VOLUME
	1	2
MF_OWN (%) (*t* – 1)	0.264***	0.644***
	(9.63)	(15.19)
MF_HHI (*t* – 1)	−0.029***	−0.001
	(−2.79)	(−0.05)
SIZE ($) (*t* – 1)	0.063***	−0.023***
	(11.54)	(−3.46)
AGE (Years)	0.006***	−0.023***
	(3.54)	(−4.87)
TOBINS_Q (*t* – 1)	0.015***	−0.014***
	(10.68)	(−4.14)
CASH_FLOWS (%) (*t* – 1)	0.085***	−0.060***
	(7.22)	(−3.54)
RETURNS (%) (*t* – 1)	0.026***	−0.039***
	(6.94)	(−6.93)
FINANCIAL_CONSTRAINTS (*t* – 1)	−0.002***	−0.000
	(−5.20)	(−0.22)
VOLATILITY (*t* – 1)	−0.487***	−2.956***
	(−3.10)	(−8.24)
ILLIQUIDITY (*t* – 1)	−5.320***	4.764***
	(−16.52)	(8.63)
R^2	0.684	0.390
No. of obs.	77,434	48,587
No. of clusters	274	267
Firm FE	Yes	Yes
Year FE	Yes	Yes
Cluster variable	3-digit SIC	3-digit SIC
Sample of firms	Full sample	Firm-years with MFFLOW > 0

These results provide evidence that selection bias due to the proportional trading assumption is not subsumed by the potential solution in Wardlaw (2020). Selection bias leads to a correlation between the magnitudes of the IVs and firm characteristics. Moreover, the strength of these IVs comes from hypothetical trading activity rather than real mutual fund trades. Proportional trading introduces additional selection bias that the FLOW_TO_STOCK and FLOW_TO_VOLUME measures do not mitigate.

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