Identifying the Price Impact of Fire Sales Using High-Frequency Surprise Mutual Fund Flows*

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Abstract

This paper proposes a new method to isolate a plausibly exogenous component of mutual fund flows to estimate the price impact of fire sales. The method addresses a potential reverse causality problem: instead of mutual fund outflows inducing fire sales, which drive down prices, poor stock returns reduce mutual fund returns, which in turn trigger outflows. The solution is to construct a new instrument from high-frequency surprise flows. Using surprise flows to reexamine important findings in the literature, I find equity markets are deeper and less distortive than suggested.

Keywords: Mutual Fund Flows; Fire Sales; Price Pressure; Market Feedback Effects

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1 Introduction

What is the price impact of mutual fund flow-induced fire sales? From a policy maker's perspective, this question is important for financial stability regulation; from a researcher's perspective, it is important because fund flow-induced trading generates the state-of-the-art natural experiment for changes in asset prices. Since Edmans, Goldstein, and Jiang (2012), researchers use fire sales triggered by contemporaneous fund flows as an instrument for stock returns and find that market misvaluation distorts corporate decisions (e.g. Khan, Kogan, and Serafeim, 2012; Derrien, Kecskes, and Thesmar, 2013; Phillips and Zhdanov, 2013; Norli, Ostergaard, and Schindele, 2014; Lee and So, 2017; Bonaime, Gulen, and Ion, 2018; Dessaint et al., 2018; Eckbo, Makaew, and Thorburn, 2018; Lou and Wang, 2018). Moreover, using flow-induced trading, Coval and Stafford (2007), Duffie (2010), Greenwood and Thesmar (2011), Ben-Rephael, Kandel, and Wohl (2012), Jotikasthira, Lundblad, and Ramadorai (2012), Lou (2012), Anton and Polk (2014) and Li (2019) show that price pressure effects are large, arbitrage capital is slow-moving and fund flows explain returns of stocks, factors and asset classes, as well as return volatility and comovement.

While mutual fund flow-induced trading provides the best available natural experiment for changes in asset prices, the literature acknowledges that fund flows may not be exogenous to firm fundamentals because retail investors chase past performance (e.g. Edmans, Goldstein, and Jiang, 2012). In particular, the contemporaneous correlation between quarterly fund flows and the returns of the stocks in their portfolios could be driven by reverse causality: instead of outflows inducing fire sales, which drive down prices, poor stock returns reduce mutual fund returns, which in turn trigger outflows. As only low-frequency fund flows are easily observable and as fund flows and stock returns occur simultaneously from a low-frequency perspective, this issue is largely unexamined and unsolved. Therefore, this paper obtains high-frequency fund flows, investigates the relevance of the reverse causality problem, proposes a new method to isolate a component of flows that is plausibly exogenous to stock returns and uses that method to revisit classic empirical finance questions.

To begin, I show that the standard regression of stock returns on mutual fund flow-induced fire sales suffers from reverse causality if retail investors chase within-quarter mutual fund returns and mutual funds hold few stocks and/or stocks with correlated factor loadings. Empirically, I show that these conditions are met. In particular, while it is well known that retail investors chase past performance at low frequency (e.g. Chevalier and Ellison, 1997), I trace out retail investors' high-frequency purchase/redemption responses to mutual fund returns and find strong evidence for within-quarter return chasing.

In addition, I demonstrate the importance of the reverse causality issue at the stock instead of the mutual fund level. The literature typically examines the price impact of mutual fund flow-induced fire sales using the quarterly event study depicted in Figure 1, on the left. In the event quarter, when mutual funds that hold a stock receive extreme outflows, stock prices crash, followed by a slow recovery. But increasing the event study frequency to daily, as in the right panel, stock prices crash before the event; returns precede flows. Consistent with this interpretation, I also show that daily stock returns strongly Granger cause daily flow-induced trading in calendar time.

In addition to high-frequency return chasing, low-frequency return chasing can also be problematic. Fundamental shocks may drive future corporate decisions and fund flows via returns. However, this endogeneity issue is easier to mitigate because researchers can control for past stock returns. I therefore emphasize the reverse causality issue.

I propose a solution inspired by the literature on the real effects of monetary policy, which also faces a reverse causality issue. At low frequency, instead of monetary policy affecting economic activity, the Fed may respond to changes in economic conditions. A popular solution is to extract monetary policy surprises using high-frequency data and then aggregating the high-frequency surprises to low frequency (Cochrane and Piazzesi, 2002; Gorodnichenko and Weber, 2016; Nakamura and Steinsson, 2018). Analogously, I isolate high-frequency *surprise flows* which I aggregate to quarterly surprise mutual fund flows. I then construct surprise flow-induced trading as a new instrument for stock returns.

Fund flows come from two sources: retail investor trades in response to new information and trades in response to random liquidity shocks (e.g., retail investors may redeem mutual fund shares to make a down payment on a mortgage). The former gives rise to the identification concerns, the latter, surprise flows, are orthogonal to firm fundamentals. If researchers can isolate surprise flows, they can construct a valid instrument for returns. In this paper, I extract surprise flows by orthogonalizing high-frequency mutual fund flows with respect to contemporaneous fund returns and with respect to a long history of mutual fund returns and flows. This means, when instrumenting stock returns using surprise flow induced trading, I only attribute stock returns that occur after mutual fund flows to the demand shock. Hence, the only threats to identification are omitted variables that trigger flows today and returns tomorrow, a much weaker concern.

I use surprise flows to reevaluate important findings in the literature. There are two competing forces when comparing the price impact of flow-induced trading to surprise flow-induced trading. First, the price impact of surprise flow-induced trading is not inflated by the reverse causality mechanism. But second, fund managers likely trade more drastically in response to surprise flows than in response to expected flows because they have less time to execute trades. Therefore, which force dominates, is an empirical question. I find that using the new instrument, the estimated price impact of fire sales shrinks by around one third compared to existing estimates but is still economically and statistically significant; mutual fund flow-induced fire sales have price impact, but equity markets are deeper than previously suggested.

Many papers drop modest fund flows because they may not trigger a fast trading response that moves prices (e.g. Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012). Because the choice of cutoff value is arbitrary, I estimate the price impact of surprise flow-induced fire sales for all combinations of negative and positive cutoffs. I find more extreme fund flows trigger more drastic fire sales that result in larger price impacts. Using all mutual fund flows, a 1% demand shock triggers a 0.2% return. But a 1% demand shock induced by the most extreme mutual fund flows triggers a 1% return. Further, in the spirit of the causal inference using machine learning literature (Mullainathan and Spiess, 2017), choosing optimal flow cutoffs that maximize the strength of the instrument generates a strong instrument. The optimal cutoffs focus on extreme flows in the bottom 7.5% and the top 5% of the flow distribution. This is similar to, but more extreme than in Coval and Stafford (2007), who use flows in the 1st and 10th decile.

Finally, I use surprise flows to reevaluate the standard market feedback effect regression of investment on returns instrumented with flow-induced trading. IV regressions using the traditional instrument find strong, positive market feedback effects, meaning that undervaluation causes underinvestment. Using the new instrument, the estimated coefficient is close to zero and statistically insignificant, indicating that equity markets are likely less distortive than suggested.

The reverse causality issue highlighted in this paper does not necessarily invalidate existing research findings. Many papers provide additional evidence unaffected by this critique. Hence, only the particular evidence involving fund flows should be reevaluated. A good example is Anton and Polk (2014), who also show unaffected evidence from the 2003 mutual fund flow scandal. The literature also highlights the stock price reversal that follows fire sale events as evidence for temporary price pressure (e.g. Coval and Stafford, 2007). While stock price reversal does suggest that the abnormal returns generated by flow-induced trading are at least partially the result of price pressure, it cannot show the absence of the reverse causality mechanism. In addition, the stock price reversal pattern may be explained by risk factor loadings (Wardlaw, 2020).

Further, the market feedback effect literature uses flows very uniformly, closely following Edmans, Goldstein, and Jiang (2012). Outside this literature, papers use flows more heterogeneously, often making the reverse causality problem more subtle. For example, Greenwood and Thesmar (2011) relate stock return volatility to flow volatility and Anton and Polk (2014) relate stock return comovement to the absolute value of flows to mutual funds that hold both stocks. But the reverse causality issue still applies in higher moments. Volatile stock returns imply volatile mutual fund returns which cause volatile flows. And when two stocks crash, funds that hold both stocks suffer bad returns and, consequently, outflows. In addition, both papers lag the explanatory flow variable, but this does not fully eliminate the concern because higher moments of returns are persistent.

This paper is related to Berger (2019), who finds the instrument as constructed in the market feedback effect literature implies unbalanced treatment and control groups, indicative of selection bias. To solve this issue she proposes testing for market feedback effects in a homogeneous subsample. While this approach improves the test, it does not address the reverse causality problem at the center of this paper. Further, eliminating the reverse causality issue by taking surprise flows addresses the Berger (2019) concern: past returns and firm characteristics predict flow-induced trading, but not surprise flow-induced trading.

Also, Wardlaw (2020) documents a mechanical issue in the standard construction of the instrument in the market feedback effect literature. The standard instrument contains the lagged stock price in the numerator (dollar portfolio position) and the stock price in the denominator (dollar trading volume). Therefore, the instrument for returns mechanically contains returns. Only the market feedback effect literature is subject to this critique, because papers outside this literature do not typically scale the demand shock by dollar trading volume. I demonstrate that even the Wardlaw (2020) corrected instrument suffers from an economic problem that applies more widely. I then propose a solution and use the improved instrument in applications.

This paper focuses on the price impact of mutual fund flow-induced fire sales, but also contributes to the literature examining high-frequency fund flows (Edelen and Warner, 2001; Greene, Hodges, and Rakowski, 2007; Rakowski and Wang, 2009; Rakowski, 2010; Ben-Rephael, Kandel, and Wohl, 2011) by relating high-frequency fund flows and returns to fund portfolios, by expanding the prediction horizon and by using a new, larger panel dataset.

2 Empirical Strategy

I illustrate a simplified version of the environment in Figure 2. Stock returns form mutual fund returns which become public information after markets close and potentially trigger mutual fund flows the next day. Flows are also determined by random liquidity needs of retail investors. Redemptions and purchases settle after markets close. Mutual funds absorb these flows with their cash position and trade over the next days to rebalance it. This forced trading may cause stock returns. Note that this description is stylized and events may fall closer together for sophisticated agents. Now, cumulating daily flows and returns over a quarter hides their temporal ordering so that quarterly flows and returns seem to happen contemporaneously, no matter which happens first at the daily frequency. Hence, the impact of flow-induced trading on stock prices cannot be inferred from the contemporaneous quarterly correlation.

2.1 Mutual Fund Flow-Induced Trading

There are N firms, indexed by n. Stocks are held by I investors, indexed by i. I denote the time in days by t and the time in quarters by q. I make this distinction because the literature works with quarterly data, while retail investors observe and could potentially chase daily mutual fund returns. The goal is to test whether mutual fund flow-induced trading has a causal effect on asset prices. This is the price impact of fire sales, as well as the first stage in an instrumental variable regression of a corporate outcome on stock returns that tests for market feedback effects.

Mutual funds receive net dollar flows, $Flow_{i,q}$. They hold $A_{i,q}$ in assets under management (AuM), so relative flows are $flow_{i,q} = Flow_{i,q}/A_{i,q-1}$. Flows are shocks to the liability side and force funds to adjust the asset side. The ensuing trades are the demand shocks. However, starting with Edmans, Goldstein, and Jiang (2012), the literature recognizes that actual trades are endogenous. Hence, they construct hypothetical flow-induced trading

$$FIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n) g(flow_{i,q})}{SharesOutstanding_{q-1}(n)}. \tag{1}$$

The numerator is the net amount of shares mutual funds buy or sell to accommodate flows. $g()$ maps flows into relative changes in held shares that move prices. I call $g()$ the fire sale kernel. For example, if funds keep portfolio weights constant and the demand elasticity is constant, $g()$ is simply the identity; in response to a 10% outflow, funds sell 10% of each portfolio position, resulting in a price impact proportional to the fraction of outstanding shares held by the fund. The market feedback effect literature uses the identity, except they drop flows greater than -5%, arguing that flows>-5% do not force funds to trade quickly and likely do not generate large price impacts. Outside of this literature, researchers use different fire sale kernels. In the empirical part, I start by using the identity as the simplest benchmark but then examine all relevant candidates. The measure is scaled by shares outstanding to make it a relative demand shock. The literature also uses different denominators. In addition to shares outstanding, common choices are total shares held by mutual funds (e.g. Lou, 2012) and trading volume (e.g. Edmans, Goldstein, and Jiang, 2012). However, since the Wardlaw (2020) critique, using trading volume is no longer state-of-the-art. Hence, I only examine the first two.

I now turn from quarterly to daily frequency, because retail investors can make trading decisions daily and can use daily mutual fund returns to inform those decisions. This is because mutual funds publish their net asset value once a day, after markets close, and retail orders settle at that price. Of course, most retail investors review their portfolios infrequently and also base their investment decisions on long-term performance metrics. But this behavior does not give rise to the reverse causality problem. Instead, I ask whether the fraction of retail investors who do review their portfolio on any given day take within-quarter fund returns into account when making purchase/redemption decisions, because this is the potential source of reverse causality.

2.2 Decomposition of the Mutual Fund Flow Instrument

Where do mutual fund flows come from? First, retail investors face liquidity shocks. They may redeem mutual fund shares to make a down payment on a mortgage. This is the original idea behind the fund flow instrument. Random retail redemptions are exogenous to firm fundamentals but change asset prices by triggering fire sales. But in addition, it is well known that retail investors chase past mutual fund performance (e.g Chevalier and Ellison, 1997). In a Berk and Green (2004) model, retail investors chase past performance because they use realized mutual fund returns, $MFret_{i,t}$, to update their beliefs about the ability of the mutual fund manager. I write this as

$$flow_{i,t} = \eta_t + \sum_{l=0}^{L} \alpha_l MFret_{i,t-l} + u_{i,t}, \tag{2}$$

where I allow for macro shocks to flows. Retail investors may react to information beyond returns. For example, they may redeem shares in response to redemptions by other retail investors because of strategic complementarities (e.g. Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017). For ease of notation, I omit these terms here, but include them later in the empirical part.

Retail investors observe mutual fund returns after markets close and can therefore only react to the exact fund return the next day. Yet, sophisticated retail investors may be able to infer the contemporaneous return and react the same day. Hence, to be conservative, I also allow for contemporaneous return chasing, i.e. the sum starts at zero. Next, for a stylized mutual fund that only holds equities, neither incurs trading costs nor receives lending revenues and only trades at the end of each quarter, the mutual fund return is the portfolio weight-weighted mean of stock returns

$$MFret_{i,t} = \sum_{n=1}^{N} w_{i,t-1}(n) r_t(n). \tag{3}$$

I make this simplification for ease of notation. Stock returns follow a linear asset pricing model. They are driven by factor returns, f_t, and idiosyncratic shocks

$$r_t(n) = \beta(n)' f_t + \epsilon_t(n). \tag{4}$$

Substituting equations 3 and 4 into equation 2, I decompose mutual fund flows into the following components:

$$\begin{aligned} flow_{i,t} &= \eta_t \\ &+ \sum_{l=0}^{L} \alpha_l w_{i,t-1-l}(n) r_{t-l}(n) \\ &+ \sum_{l=0}^{L} \alpha_l \sum_{m \neq n} w_{i,t-1-l}(m) \beta(m)' f_{t-l} \\ &+ \sum_{l=0}^{L} \alpha_l \sum_{m \neq n} w_{i,t-1-l}(m) \epsilon_{i,t-l} \\ &+ u_{i,t}. \end{aligned} \tag{5}$$

This decomposition shows why quarterly flow-induced trading is not exogeneous to contemporaneous quarterly stock returns. $FIT_q(n)$ is a function of the daily flows that fall into quarter q, and the first term above contains daily stock returns that fall into quarter q. This means the instrument for returns depends on returns, a reverse causality problem.

In addition, the first term implies that $FIT_q(n)$ depends on stock returns that occurred before the current quarter. While this is not a problem in the regression of stock returns on flow-induced trading, it does create an endogeneity problem in the market feedback effect regression of a corporate outcome on stock returns instrumented with flow-induced trading. Longer-term stock returns may be the result of fundamental shocks that influence corporate decisions in the future. Hence, both, the corporate outcome and the instrument may be driven by the fundamental shock, an endogeneity problem. Yet, while this endogeneity concern is generated by the same economic mechanism as the reverse causality issue, it is easier to mitigate because researchers can control for past stock returns. I therefore emphasize the reverse causality issue.

Note that if retail investors do not chase returns, $\alpha_l = 0$, these critiques do not apply. However, this is strongly rejected empirically. It is well known that retail investors chase low-frequency returns (e.g. Chevalier and Ellison, 1997) and in this paper, I show that retail investors chase within-quarter returns. Also, if portfolio weights are small, the direct dependence of the instrument on the stock return itself is weak. But that does not mean that constructing the instrument excluding concentrated mutual funds solves the problem, because the second term is also problematic. The instrument depends on the systematic mutual fund return. Hence, if factor loadings are correlated within a portfolio, then factor returns drive both: they drive stock returns directly and they drive flows via mutual fund returns. Most stocks in the portfolio of a value fund load on HML. Accordingly, high HML returns at the beginning of a quarter cause high returns for the stocks in the portfolio, meaning high mutual fund returns that trigger inflows later in the quarter. Together, the first two terms show the instrument is invalid if retail investors chase within-quarter mutual fund returns and portfolios are concentrated and/or contain stocks with correlated factor loadings.

Terms three and four are exogenous to stock returns and can be used to construct demand shocks. Term three contains flows triggered by mutual fund returns stemming from idiosyncratic returns of other stocks in the portfolio. Say a fund receives outflows because it had poor returns due to a fire at GM's factory in a foreign country. This flow could be used to instrument the return of Goldman Sachs. In practice, these shocks are difficult to identify, because they depend on the asset pricing model. Hence, I do not use them in this paper.

Term four contains surprise flows, flows generated by random liquidity shocks to retail investors. I use this term to construct the new instrument. Specifically, I aggregate daily surprise flows to quarterly surprise flows and substitute flows with surprise flows when constructing the instrument. This gives surprise flow-induced trading

$$SFIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n) g(surpriseflow_{i,q})}{SharesOutstanding_{q-1}(n)}, \tag{6}$$

where

$$surpriseflow_{i,q} = \frac{\sum_{t \in q} u_{i,t} A_{i,t-1}}{A_{i,q-1}}. \tag{7}$$

I extract daily surprise flows as the residuals of a cross-sectional regression motivated by equation 2. Daily mutual fund flows are the dependent variable. The independent variables are, first, 65 lags of mutual fund returns, including the contemporaneous fund return. 65 is the the maximum number of business days in a quarter. This solves the reverse causality problem outlined above. However, when using the flow instrument to test for market feedback effects on corporate decisions, additional variables may raise endogeneity concerns, as discussed above. I address this by adding control variables to equation 2. In addition to the 65 daily fund return lags, I include 65 daily fund flow lags and quarterly fund return and flow lags from one quarter to three years ago. I also estimate the regression separately for active and index mutual funds because the main return chasing motive, using returns to update beliefs about the fund manager's ability as in Berk and Green (2004), does not apply to index funds. This accounts for the finding in Dannhauser and Pontiff (2019) that the difference between active and index mutual funds explains a large share of the heterogeneity in the flow-return relation. By construction, surprise flows are orthogonal to past and contemporaneous mutual fund returns. This implies that I only attribute stock returns that occur after mutual fund flows to the demand shock. Hence, the only threats to identification are omitted variables that trigger flows today and returns tomorrow, a much weaker concern.

In future work, potential additional concerns about the endogeneity of fund flows can be addressed in this step. Any measure of surprise flows that isolates random liquidity needs of retail investors can be used to construct instruments that are exogenous to firm fundamentals.

3 Data

3.1 Mutual Fund Data

All data I use are standard with one exception: daily mutual fund flows and returns from Morningstar. I use the Morningstar variables *daily return index*, *estimated fund level net flow (comprehensive) (daily)* and *fund size - comprehensive (daily)* to construct daily flows and returns. The data become reliably available starting in July 2008, which dictates the start of my sample. When an exercise requires high-frequency Morningstar data, the sample is July 2008 to December 2017. Whenever it does not, I use the common 1980 to 2017 sample. I restrict the sample to equity mutual funds that are in the MFLinks database. These are the funds that I can match with CRSP mutual fund characteristics and Thomson Reuters portfolios. The availability of MFLinks data prescribes the end of my sample. I merge Morningstar and MFLinks using share class cusips. Then, I collapse the data from the share class to the portfolio level by taking size-weighted means where necessary. There are about 3500 mutual funds in the average cross-section. Out of these, I can match about 2900 to daily Morningstar data. With ten years of daily data, this yields over six million observations. For comparison with the literature, I also construct quarterly mutual fund flows, returns and characteristics using CRSP.

I make minor modifications to the mutual fund flow data. First, I require a minimum fund size of \$10 million. Next, a small number of observations show extreme spikes in assets under management that only last one day. I assume these are data entry mistakes. Therefore, I replace fund size with its lagged value where it implies last and next period flows with an absolute value greater than 25% with opposite signs. This leaves a few daily flows with an absolute value greater than 25%, less than 0.1% of observations. I set these outliers to missing because many of these are likely data errors. For the same reason, I set quarterly flows less than -100% or greater than 200% to missing. Lastly, a small number of daily observations is missing. As I estimate regressions with 65 daily lags, one missing observation would eliminate 65 observations. To avoid this loss of information, I fill missing lags with their cross-sectional mean.

3.2 Portfolio Holdings Data

The Thomson Reuters Mutual Fund Holdings database provides quarterly fund-level portfolios starting in 1980. The sources for this database are SEC mandated disclosures in Forms N-30D, N-Q and N-CSR as well as voluntary disclosures. I merge the Thomson Reuters holdings data with CRSP mutual fund data using MFLinks. I merge to the Thomson Reuters file date.

3.3 Stock Level Data

Stock data are from CRSP. Accounting data are from the CRSP/Compustat Merged Fundamentals Quarterly and Annual databases. Specifically, I use the stock characteristics corresponding to a standard 6-factor asset pricing model (Fama and French, 2018), beta, log market equity, log Tobin's Q, profitability, investment and momentum as the standard control variables because they are the most prominent sources of variation in the cross-section of expected returns. To construct market beta, I take the 1-month T-bill rate and the market return from Kenneth French's website. I winsorize characteristics at the 1 and 99% levels as in Green, Hand, and Zhang (2017). I restrict the sample to US ordinary common stocks that trade on the NYSE, AMEX or Nasdaq, have non-missing returns and have at least 1% mutual fund ownership. When testing for market feedback effects, I also follow the convention of dropping financial firms (SIC code 6000-6999).

3.4 Summary Statistics

While the literature typically uses low-frequency fund flows from CRSP, I obtain high-frequency fund flows from Morningstar because CRSP does not provide high-frequency flows.[1] Table 1 compares Morningstar to CRSP data. Panel A reports summary statistics for each year-end quarter where Morningstar data are available, from 2008 to 2017. I compare Morningstar and CRSP data in terms of number of funds, median fund total net assets, total net assets and total absolute fund flows. In an average cross-section, the CRSP sample contains about 3500 funds and the Morningstar sample about 2900. By construction, the Morningstar data are a strict subsample. The number of funds decreases by about 10% after the financial crisis. Median total net assets increase from \$110 to \$280 million. They are similar but lower for Morningstar data. Total TNA increase from \$3 to \$7 trillion for CRSP and from \$2 to \$4.5 trillion for Morningstar data. Flows are more stable over time, meaning that relative flows decrease over time. For CRSP, total quarterly absolute fund flows are about \$220 billion; for Morningstar, they are about \$150 billion. Overall, high-frequency Morningstar data cover about three quarters of the low-frequency CRSP data.

Next, Panel B shows fund level instead of aggregate summary statistics. It summarizes the distribution of mutual fund flows and returns at the daily and quarterly frequency, as indicated by (D) and (Q). Daily flows and returns are centered around zero with a standard deviation of about 1%. Quarterly flows are centered around zero with a standard deviation of 19%. Quarterly returns are centered around the quarterly equity premium with a standard deviation of 9%. Returns are largely uncorrelated in the time series, so the ratio of the

[1] CRSP provides daily fund returns and net asset values. However, CRSP does not provide daily total net assets which are necessary to compute fund flows

quarterly and the daily standard deviation is about the square root of the number of business days in a quarter. In contrast to that, flows are autocorrelated, so the ratio is larger.

The previous section shows that the standard regression of stock returns on flow-induced trading suffers from reverse causality if there is within-quarter mutual fund return chasing and portfolios are concentrated and/or contain stocks with correlated factor loadings. Panel C indicates that both mutual fund portfolio conditions hold. Panel C summarizes the distribution of mutual fund portfolio characteristics for the last cross-section in my sample, 2017 Q4. The number of stocks in a portfolio varies substantially. From the 5th percentile, to the median, to the 95th percentile, mutual funds hold 11, 64 and 497 stocks, respectively. Comparing this to the about 4000 stocks in the cross-section, this means most mutual funds hold concentrated portfolios. Below, I show the distribution of portfolio characteristics that correspond to a standard 6-factor asset pricing model (Fama and French, 2018). Portfolio characteristics are the portfolio weight-weighted mean of the characteristic across all stocks in a portfolio. Again, there is substantial dispersion. The median fund has a market beta of 1.1. This is as in Frazzini and Pedersen (2014), who argue mutual funds use high market exposure because they are leverage-constrained. From the 5th to the 95th percentile, mutual fund betas vary from 0.9 to 1.4. Mutual funds also choose differential exposure to firm size. From the 5th percentile, to the median, to the 95th percentile, mutual funds hold stocks with market values of \$2, \$88 and \$220 billion, respectively. The wide dispersion in mean portfolio characteristics across mutual funds suggests mutual funds hold stocks with correlated factor loadings. Of course, this is not a formal test. I report the results of a formal test in appendix Table A1. Mutual fund portfolio position level regressions of stock characteristics on the portfolio weight-weighted mean of the same characteristic over all other stocks in the same portfolio strongly reject that factor loadings are uncorrelated within portfolios.

4 Results

4.1 Mutual Fund Flows and Mutual Fund Returns

Equation 5 shows that the standard regression of stock returns on flow-induced trading suffers from reverse causality if there is within-quarter mutual fund return chasing (and portfolios are either concentrated or contain stocks with correlated factor loadings; both are empirical facts as shown in the previous section). While it is well known that retail investors chase past performance at low frequency (e.g. Chevalier and Ellison, 1997), I trace out retail investors' high-frequency purchase/redemption responses to mutual fund returns. Figure 3 shows that retail investors do indeed chase within-quarter mutual fund returns. I report results for the regression that extracts daily surprise flows, as described in section 2, a regression of daily mutual fund flows on lags of daily flows and returns. I include 65 lags, the maximum number of business days in a quarter. The regression also controls for quarterly fund return and flow lags from one quarter to three years ago and for time fixed effects. Standard errors are clustered by time because, similar to returns, flows are correlated in the cross-section. I estimate the regression separately for active and index mutual funds because the main return chasing motive, using returns to update beliefs about the fund manager's ability as in Berk and Green (2004), does not apply to index funds. I show the active fund results here and the index fund results in appendix Figure A1. I plot cumulative coefficients in blue and display the p-values of each coefficient as gray bars.

The left panel of Figure 3 shows the cumulative coefficients on daily past mutual fund returns. The cumulative coefficients trace out a concave impulse response and reach 0.2; a 10% mutual fund return triggers a 2% mutual fund flow within one quarter. For the first 20 business day lags all coefficients are highly statistically significant. After that, they remain positive but are less precisely estimated. The coefficient on the contemporaneous mutual fund return is insignificant. This is likely because retail investors only observe the contemporaneous return after markets close and only react to it the next day. On the right, I show the cumulative coefficients on past daily mutual fund flows. Flows are highly autocorrelated. A 10% flow today predicts a 6% flow within one quarter. Yet, curiously, flows feature a one-day reversal, so that a 10% inflow today predicts a 1% outflow tomorrow, but all other coefficients are positive.

Appendix Figure A1 shows the analogous results for index mutual funds. Puzzlingly, but consistent with Dannhauser and Pontiff (2019), I find that index fund flows are more elastic to past performance than active fund flows. A 10% index mutual fund return triggers a 3% in comparison to a 2% mutual fund flow within one quarter. However, the estimates are much less precise because less than 15% of observations correspond to index funds. Overall, this exercise shows that retail investors engage in within-quarter return chasing, meaning the reverse causality issue is relevant.

Of course, this empirical argument's limitation is that it could itself be subject to a reverse causality critique. I attribute the fact that mutual fund returns predict future mutual fund flows to retail investor return chasing. However, if mutual fund managers had a crystal ball, they could trade prior to flows, which could generate the same empirical pattern. Yet, to overturn the reverse causality critique, this anticipatory trading must be the only reason for the observed predictive pattern and fund managers would need to engage in anticipatory trading far in advance, up to one quarter. Further, the following subsection shows that most of the flow-induced cumulative abnormal returns realize before extreme flows. Therefore, anticipatory trading needs to be far greater than reactive trading. This is unlikely, though, since most flows are unpredictable, as indicated by the 4% R^2 of the flow predictive regression reported in Figure 3.

4.2 Flow-Induced Trading and Stock Returns

In Figure 4, I show the corresponding analysis at the stock level instead of the mutual fund level. I report results from a regression of daily flow-induced trading on daily lags of flow-induced trading and stock returns. Daily FIT is constructed as in equation 1, except at the daily instead of the quarterly frequency. I find the same pattern as in the previous figure. Looking at the graph on the left, the cumulative coefficients on stock returns are positive and highly statistically significant for the first 20 lags. For ease of interpretation, I normalize FIT. The cumulative coefficients reach 4; a 10% stock return predicts an additional 0.4 standard deviations of FIT within one quarter. Stock returns Granger cause the instrument, which is additional evidence for the relevance of the reverse causality issue. Looking at the graph on the right, FIT is autocorrelated because flows are autocorrelated.

The literature typically illustrates the impact of flow-induced trading in event time instead of calendar time. One graph is ubiquitous: an event study around flow-induced fire sale events. Prominent examples that show a version of the graph include Coval and Stafford (2007), Duffie (2010), Edmans, Goldstein, and Jiang (2012), Khan, Kogan, and Serafeim (2012), Lou (2012), Jotikasthira, Lundblad, and Ramadorai (2012) and Dessaint et al. (2018). I replicate the graph from Edmans, Goldstein, and Jiang (2012) in the left panel of Figure 1. The definition of the event is that FIT falls into the bottom decile of the full sample distribution. They compute abnormal returns by deducting the CRSP equal-weighted return. I add Fama-MacBeth standard errors following Coval and Stafford (2007). In the literature, the typical interpretation of the graph is that there is no significant pre-event trend, prices crash by about 5% during the event quarter and prices recover from the fire sale over the following two years. Together, these observations are taken as evidence that flow-induced fire sales drive asset prices away from fundamentals.

Wardlaw (2020) already shows that correcting a mechanical mistake attenuates the empirical pattern in the left panel of Figure 1. This paper highlights a different issue. In the right panel of Figure 1, I show the result of the event study at the daily level, after making the Wardlaw (2020) correction. The event window is now one month instead of three years. The high-frequency event study shows that prices crash before the event. In fact, the price collapse largely stops at exactly the onset of the event. This is additional evidence that the reverse causality problem is relevant.[2]

The reverse causality problem can explain several nuances in the popular graph on the left of Figure 1. First, there is a pre-event trend. Stock returns over the last year form mutual fund returns over the last year which trigger flows. Second, the return during the event quarter is convex because stock returns on the first days of a quarter have more time to trigger flows than stock returns that occur at the end of the quarter. If the causality ran from flows to returns, we would expect the opposite. Stock returns on the first days of the quarter can only be driven down by flows from these first days, while stock returns during the end of the quarter follow many days of extreme flows. Finally, as pointed out by Wardlaw (2020), the price reversal does not stop at a CAAR of 0. The "recovery" is largely a relic of how abnormal returns are constructed. The sample of stocks held by mutual funds has higher average returns than the CRSP equal-weighted return and event stocks have size and value exposure.

4.3 The New Instrument - Surprise Flow-Induced Trading

As managers make corporate decisions at low frequency, market feedback effect regressions require a low-frequency instrument. Accordingly, I now turn from daily to quarterly frequency. The low-frequency instruments are constructed as described in equation 1 for the traditional instrument and as described in equations 6 and 7 for the new instrument. Table 2 estimates the price impact of fund flow-induced fire sales using the traditional and the new instrument. There are two competing forces when comparing the price impact of flow-induced trading to surprise flow-induced trading. First, the price impact of surprise flow-induced trading is not inflated by the reverse causality mechanism. But second, fund managers likely trade more drastically in response to surprise flows than in response to expected flows because they can liquidate positions in anticipation of expected flows but, by

[2] In the daily event study the CAAR is an order of magnitude smaller than in the quarterly event study. This is because the daily shock is about an order of magnitude smaller than its quarterly analogue. Hence, the implied elasticities are similar.

definition, not in anticipation of surprise flows. Therefore, which force dominates, is an empirical question. Table 2 reports results for regressions of quarterly stock returns on different versions of the instrument, controls and time fixed effects. As stock returns are highly correlated in the cross-section but not in the time series, I cluster standard errors by time. This regression is also the first stage of the common instrumental variable regression of a corporate outcome on returns.

In column 2, I construct FIT as in the literature. The estimated coefficient is 0.3 and highly statistically significant. It suggests a 1% demand shock triggers a 0.3% return. In column 4, I change my data source from CRSP to Morningstar but use the same object. I show this intermediate step to ensure the results are not driven by the change in data source and sample period. Now the coefficient is 0.37 and highly statistically significant, but less precisely estimated. This is because I lose over 70% of observations as there are only 10 years of Morningstar data in comparison to 37 years of CRSP data.

While the regressions in columns 1 to 4 are subject to the reverse causality critique, the following regressions employ the new, corrected instrument. In column 6, the coefficient drops to 0.23, but remains statistically significant. Demand is more elastic. A 1% demand shock triggers a 0.23% instead of a 0.37% return. The Kleibergen and Paap (2006) F-statistic of this regression is 5, meaning the instrument is weak. Columns 1, 3 and 5 show the conclusions do not change when not controlling for common risk factors. Overall, correcting the reverse causality problem indicates that markets are deeper than suggested. In column 7, I regress the old on the new instrument. By construction, the two variables are highly correlated. The estimated coefficient is 1.2 with a standard error of 0.07 and the R^2 is 52%.

4.4 Which Mutual Fund Flows Trigger Fire Sales/Purchases?

When constructing flow-induced trading, I need to map mutual fund flows into trades that move prices. This is the purpose of $g()$ in equation 1. The literature proposes several candidate mappings which I illustrate in Figure 5. This figure also shows mutual funds' actual trading response to flows in red; I show position-weighted mean trading, the relative change in shares held, for 50 mutual fund flow bins. The mapping used in the analysis above corresponds to the gray 45 degree line, which is the simplest option. This mapping assumes mutual funds keep portfolio weights constant, scaling their entire portfolio up or down in response to flows. This is a rough approximation to mutual funds' actual trading behavior, but the actual trading response is stronger for outflows than for inflows. Naturally, mutual funds sell stocks they own, but they may initiate new positions. Lou (2012) accommodates this by scaling inflows and outflows with the empirically observed slopes. I show the resulting mapping in purple. By construction, it is a closer fit to realized trading.

However, as the goal is to construct a nonfundamental shock to asset prices, realized trading is not necessarily the relevant target. While modest flows trigger trades in the medium run, these trades can be smoothed using a fund's cash position to minimize price impact. Hence, only large flows that force funds to trade quickly trigger fire sales and thus have significant price impact. This is the reasoning in Coval and Stafford (2007) and Edmans, Goldstein, and Jiang (2012). I show the fire sale kernel from Coval and Stafford (2007) in green. They only use flows in the extreme deciles of the mutual fund flow distribution.[3] In blue, I depict the mapping from Edmans, Goldstein, and Jiang (2012) which is standard in the market feedback effect literature and only uses flows less than -5%. Both mappings can be written as

$$\tilde{g}(flow_{i,q}) = \begin{cases} flow_{i,q} & \text{if } flow_{i,q} \leq \alpha_L \text{ or } flow_{i,q} \geq \alpha_H \\ 0 & \text{if } \alpha_L < flow_{i,q} < \alpha_H. \end{cases} \tag{8}$$

The exact cutoffs in Coval and Stafford (2007) and Edmans, Goldstein, and Jiang (2012) are arbitrary. Therefore, I estimate the price impact of surprise flow-induced fire sales for

[3]As Coval and Stafford (2007) use actual trades instead of hypothetical trades, their exact measure is not nested by equation 1. However, starting with Edmans, Goldstein, and Jiang (2012) the literature recognizes that actual trades are endogenous. Hence, I update the Coval and Stafford (2007) measure to reflect this.

all combinations of negative and positive cutoffs. This allows me to select the optimal $\tilde{g}()$. I pick the negative and positive flow cutoffs to maximize instrument strength. I pick them separately because there is no reason flows should map into forced trading symmetrically.

The construction of flow-induced trading contains many degrees of freedom. Hence, I report results for all combinations in Table 3. There are two choices, the fire sale kernel and the denominator. For each combination, I show the same quarterly, cross-sectional return regressions as in Table 2, for the traditional versus the new instrument and excluding and including controls. I report t-statistics in parentheses to allow the reader to quickly determine instrument strength and statistical significance. Using the traditional instrument in the left two columns, the estimated coefficients are large and strongly statistically significant in all specifications.

The two columns on the right report results for the new instrument. Using the fire sale kernels from the literature, the estimates tend to be smaller and are consistently less statistically significant. Though when focusing on extreme flows using the Edmans, Goldstein, and Jiang (2012) or Coval and Stafford (2007) fire sale kernel and scaling FIT by shares observed in Panel A, the estimated price impact is similar. Among the fire sale kernels from the literature, the Coval and Stafford (2007) mapping performs best, but the new, optimal fire sale kernel performs substantially better. In fact, it almost performs on par with the traditional instrument in terms of t-statistic.[4] When including controls, the estimated coefficient is 0.6 and the t-statistic is 5. Using the optimal fire sale kernel, the demand shock is a strong instrument. Finally, scaling FIT by shares outstanding in panel B instead of shares held by mutual funds gives qualitatively the same results, except the estimates are an order of magnitude larger than in panel A because the denominator is an order of magnitude larger. The new, optimal instrument is even stronger in panel B, with a t-statistic of 7.

How does the new fire sale kernel achieve this performance? The heatmaps in Figure 6 report coefficient estimates and Kleibergen and Paap (2006) F-statistics for the grid search

[4] Note that the coefficient estimates using the traditional versus the new instrument cannot be compared when using optimal fire sale kernels, because the optimal flow cutoffs are different.

that picks the optimal cutoffs. Every grid cell corresponds to one quarterly cross-sectional regression of stock returns on surprise flow-induced trading and control variables. The positive percentile cutoff is on the x-axis and the negative percentile cutoff is on the y-axis. So the (0.9, 0.1) value corresponds to the Coval and Stafford (2007) fire sale kernel. The squares' color and size indicate the magnitude of the coefficient estimates or F-statistics corresponding to the respective grid cell. I use a grid with a step size of 2.5%.

I flip the y-axis to make the graph more intuitive. Now the regression corresponding to the bottom left does not drop any flows. It is the same as in Table 2; accordingly, the coefficient and F-statistic are small. The top right is the opposite extreme: I drop all flows and therefore obtain missing estimates by construction. From the bottom left to the top right, the focus on extreme flows increases, as do the coefficient estimates in the left panel. More dramatic fund flows trigger more drastic fire sales that result in larger price impacts. Using all flows, a 1% demand shock triggers a 0.2% return, but a 1% demand shock induced by the most extreme mutual fund flows triggers a 1% return.

For instrument strength in the right panel, a second force is at play. While focusing on more extreme flows increases the price impact of the ensuing fire sales, it also decreases the number of experiments. Hence, there is an interior optimum. I find choosing flows in the bottom 7.5% and the top 5% maximizes instrument strength. These cutoffs are similar to, but more extreme than in Coval and Stafford (2007), who use flows in the bottom and top 10%. Looking at the summary statistics in Table 1, the bottom 7.5% and the top 5% of the fund flow distribution correspond to fund flows of about -10% and 27%. This choice shares qualitative similarities with Edmans, Goldstein, and Jiang (2012) who use flows less than -5%. The negative cutoff is broadly similar and the effect of inflows and outflows is asymmetric. Inflows need to be substantially larger than outflows to induce a strong trading response that impacts asset prices. This is because funds have to sell stocks they own to accommodate outflows, but they may use inflows to initiate new positions. Appendix Figure A2 demonstrates that the results are qualitatively the same when scaling surprise flow-induced trading by shares outstanding instead of by total shares held by mutual funds. Overall, the new fire sale kernel makes the instrument strong because it focuses on more extreme flows.

Naturally, testing $(0.5/0.025)^2 = 400$ specifications raises data mining concerns. This is why the analysis above reports both: results from the data mined instrument and results from instruments as constructed in the literature. In addition, the t-statistics of 5 and 7 are highly unlikely under the null, even with 400 tests. As a very conservative upper bound, a Bonferroni correction raises the 1% critical t-value to 4.2. Further, this multiple testing concern is mitigated by the fact that the tests are highly correlated and economically motivated. Finally, when the goal is to construct an instrument, there is no good alternative: either the instrument is constructed as in the literature but weak or the instrument is data mined but strong. Overall, even though correcting the reverse causality problem weakens the instrument, choosing the optimal fire sale kernel yields a strong instrument. I use this instrument below in subsection 4.6.

4.5 Robustness

The new instrument is constructed from high-frequency surprise flows instead of from low-frequency flows and hence not driven by retail investor return chasing. While this is true by construction, I illustrate it further in Table 4. The table reports regressions of different versions of the instrument on lags of stock returns and control variables. Column 1 uses the traditional instrument constructed using CRSP data. Naturally, the coefficients on the four lags of stock returns are positive and statistically significant. Column 2 also uses the traditional instrument, but now constructed using Morningstar data. I show this intermediate step to clarify that the results are not driven by the change in data source. Again, returns predict the instrument. The last column uses the new, corrected instrument. Now the coefficients on lagged stock returns have mixed signs and are statistically insignificant. As expected, stock returns do not predict the corrected instrument.

In addition, the instrument is uncorrelated with firm characteristics, mitigating the concerns raised in Berger (2019). All five firm characteristics corresponding to a Fama and French (2015) 5-factor asset pricing model, market beta, size, Tobin's Q, profitability and investment, predict the traditional, but not the corrected instrument. [5]

Next, the literature highlights the stock price reversal that follows fire sale events as evidence for temporary price pressure (e.g. Coval and Stafford, 2007). However, Wardlaw (2020) finds the reversal pattern is explained by risk factor loadings. I examine whether flow-induced trading and surprise flow induced-trading are followed by price reversal in Table 5, where I show cross-sectional, predictive regressions of stock returns on lags of different versions of flow-induced trading, controlling for risk factors and time fixed effects. Column 1 uses the traditional instrument constructed using CRSP data. The coefficients on the four lags of flow-induced trading have mixed signs and are statistically insignificant. This confirms the finding in Wardlaw (2020). Once accounting for risk factor loadings and time fixed effects, there is no stock price reversal.

Column 2 also uses the traditional instrument, but now constructed using Morningstar data. I show this intermediate step to clarify that the results are not driven by the change in data source. The results are qualitatively the same. The last column uses the new, corrected instrument. Again, the results are qualitatively the same. I do not find evidence for stock price reversal. However, this does not suggest the absence of price pressure effects. In fact, the index/additions deletions literature finds no reversals in response to asset demand shocks (e.g. Chang, Hong, and Liskovich, 2015). Therefore, the absence of price reversals suggests that mutual fund fire sales have permanent price impact.

4.6 Application: the Market Feedback Effect on Investment

Does the reverse causality problem matter in applications? Since, Edmans, Goldstein, and Jiang (2012), an extensive literature asks whether nonfundamental variation in asset prices

[5] I do not include momentum because momentum is close to collinear with the lagged returns. Momentum is not exactly collinear with the four lagged quarterly returns because it omits the most recent month.

has a causal effect on corporate decisions. This literature tests for market feedback effects with instrumental variable regressions of a corporate outcome on Tobin's Q or stock returns instrumented with mutual fund flow-induced fire sales (e.g. Khan, Kogan, and Serafeim, 2012; Derrien, Kecskes, and Thesmar, 2013; Phillips and Zhdanov, 2013; Norli, Ostergaard, and Schindele, 2014; Lee and So, 2017; Bonaime, Gulen, and Ion, 2018; Dessaint et al., 2018; Eckbo, Makaew, and Thorburn, 2018; Lou and Wang, 2018). Here, I focus on investment, which is the most studied outcome in this literature (e.g. Derrien, Kecskes, and Thesmar, 2013; Dessaint et al., 2018; Lou and Wang, 2018).

When instrumenting Tobin's Q instead of stock returns, the literature typically sums flow-induced trading by year (e.g. Dessaint et al., 2018) to create a strong instrument. However, that makes the reverse causality problem harder to overcome. The issue is created by cumulating daily stock returns and fund flows which hides their high-frequency temporal order. Cumulating the instrument over the year and cumulating stock returns over their entire history, as Tobin's Q implicitly does, extends the source of the issue from within-quarter to within-year return chasing. Hence, I instrument quarterly returns, not Tobin's Q. A Q-theory regression of the investment rate on log Tobin's Q, control variables, and time and firm fixed effects can be written as

$$\frac{I_q(n)}{K_q(n)} = \alpha_q + \alpha(n) + \beta Q_q(n) + \gamma' X_q(n) + \epsilon_q(n), \tag{9}$$

where quarterly time is denoted as q for consistency with section 2. First differences of log Tobin's Q are approximately log returns. Hence, I estimate

$$\frac{I_q(n)}{K_q(n)} = \alpha_q + \alpha(n) + \beta_1 r_q(n) + \beta_2 Q_{q-1}(n) + \gamma' X_q(n) + \epsilon_q(n), \tag{10}$$

a regression of the investment rate on returns. I can now instrument returns with flow-induced trading and control for lagged Tobin's Q. Table 6 reports the estimation results. In all specifications, naturally, the coefficient on lagged Tobin's Q is positive and statistically significant. The first column shows OLS regression results. The coefficient on returns is 0.04 and highly statistically significant. However, this is not very insightful. When investment opportunities improve, firms experience great returns and invest. This is why the literature instruments returns. In column 2, I use the traditional instrument that is subject to the reverse causality critique. It is constructed as in the literature, using CRSP data. The coefficient goes up to 0.1 and is highly statistically significant. If this were a valid instrument, a 10% stock return would cause an absolute increase of 1% in the investment rate. In comparison to the median quarterly investment rate of about 5%, this is a very large effect.

The next column reports results for the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to ensure the results are not driven by the change in data source. The coefficient remains the same, but standard errors increase. This is because I lose over 70% of observations, as there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. In the last column, I estimate the IV regression using the new, strong instrument, SFIT. The coefficient decreases to close to zero and standard errors increase to 0.05. Using the corrected instrument, I fail to detect market feedback effects. This does not imply the absence of market feedback effects; but it suggests equity markets are likely less distortive than suggested.

I report results for several robustness checks in the appendix. First, Table A2 shows the results are qualitatively the same at the annual instead of the quarterly frequency. Second, Table A3 indicates the results are insensitive to omitting the control variables. Third, I scale surprise flow-induced trading by shares outstanding instead of total shares held by mutual funds in Table A4. Again, when instrumenting returns with surprise flow-induced trading, I do not find evidence for a market feedback effect on investment, neither at the quarterly nor at the annual level and neither including nor excluding control variables. Lastly, in the main analysis, I follow the asset pricing convention of clustering standard errors by time because returns are highly correlated in the cross-section, but close to uncorrelated in the time series. Table A5 demonstrates that this is conservative. First stage F-statistics increase massively and second stage standard errors generally decrease when clustering by firm instead of by time, but are virtually unchanged when double clustering by firm and time instead of by time.

5 Conclusion

Based on evidence from mutual fund flows, an extensive literature finds equity markets are shallow and distort corporate decisions. This paper investigates to what extent these findings are driven by reverse causality: instead of mutual fund outflows inducing fire sales, which drive down prices, poor stock returns reduce mutual fund returns, which in turn trigger outflows. I show this critique applies if retail investors chase within-quarter mutual fund returns and mutual funds hold few stocks and/or stocks with correlated factor loadings. Empirically, I show these conditions are met. The reverse causality issue also becomes intuitively apparent when increasing the frequency of the standard event study from quarterly to daily; returns precede flows. The solution is to construct a new instrument for returns from high-frequency surprise mutual fund flows. Correcting the instrument, the estimated price impact of mutual fund flow-induced fire sales and estimates of market feedback effects are smaller and noisier. Markets are deeper and less distortive than suggested.

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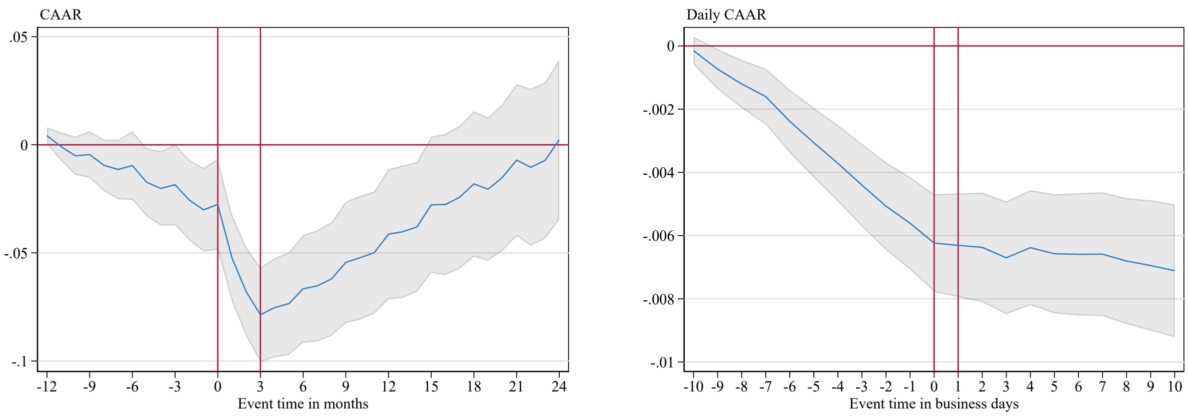
Figures

Figure 1: Quarterly versus Daily Mutual Fund Flow-Induced Fire Sale Event Study



(a) Standard, low-frequency event study

(b) New, high-frequency event study

The left graph replicates the event study in Edmans, Goldstein, and Jiang (2012). An event is a stock level observation in which flow-induced trading (FIT) is in the bottom decile of its full sample distribution. The event lasts one quarter, from months 0 to 3. The authors compute cumulative average abnormal returns (CAAR) by deducting the CRSP equal-weighted index return and plot CAARs from one year before to two years after event onset. The sample is 1980 to 2017. The right figure is the analogue at the daily level, except that it takes into account the Wardlaw (2020) critique, meaning FIT is constructed as in equation 1 and CAARs are computed by demeaning returns cross-sectionally. Daily fund flows are an order of magnitude smaller than quarterly fund flows. To accomodate this while staying close to Edmans, Goldstein, and Jiang (2012), I define extreme outflows as flows less than -0.5% instead of -5% and use the bottom 1st percentile instead of the bottom decile. The results are robust with respect to these choices. The time is in business days, so the event window is one month. The sample is 2008 to 2017 because of the availability of daily Morningstar data.

Figure 2: Illustration of the Reverse Causality Problem

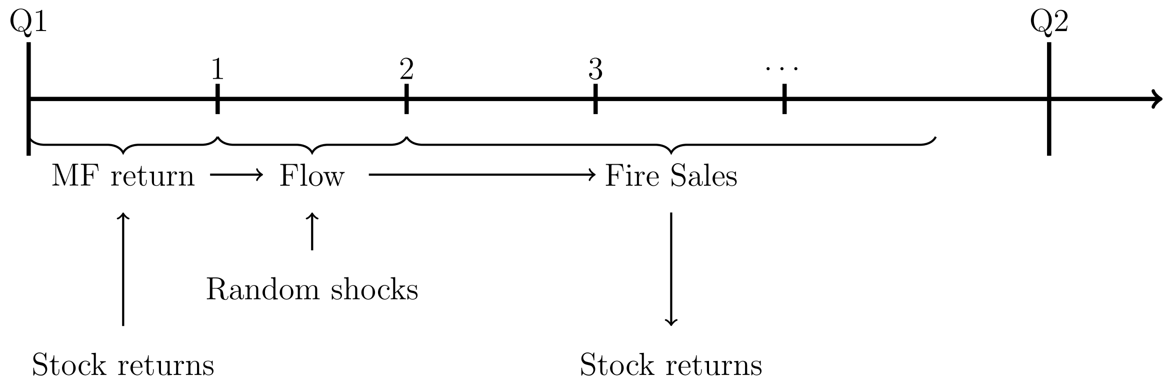
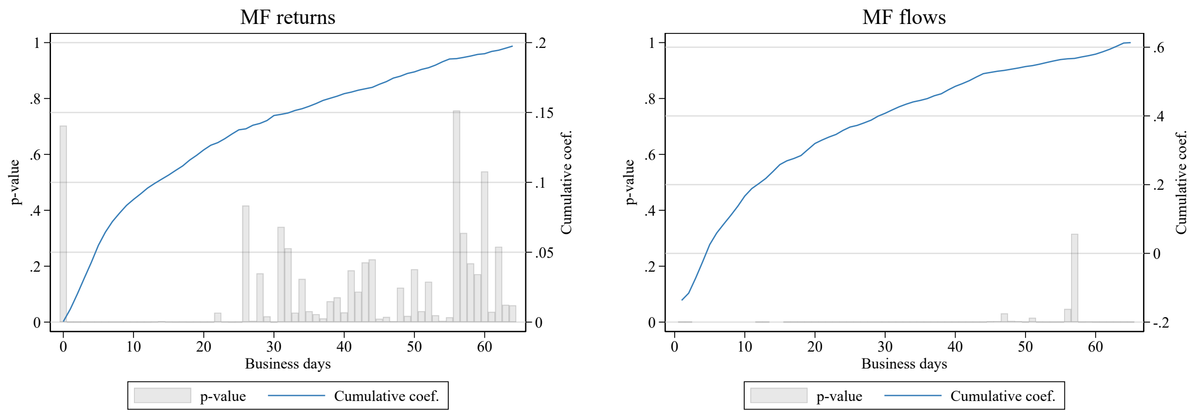


Illustration of the relationship between mutual fund flows and stock returns. I show events along a daily time series. Q1 and Q2 denote the beginning of a quarter. Mutual fund flows force mutual funds to trade which may have price impact. Flows can come from two sources. First, they may be generated by retail investors' random liquidity needs. In this case, the flow happens first, followed by stocks returns. Second, fund flows can result from performance chasing, and past performance is the result of the past returns of stocks in the mutual fund portfolio. In this case, stock returns happen first, followed by fund flows. As cumulating daily fund flows and stock returns over the quarter hides this temporal order, the impact of flow-induced trading on stock prices cannot be inferred from the contemporaneous, quarterly correlation.

Figure 3: Regression of Daily Mutual Fund Flows on Lags of Flows and Returns

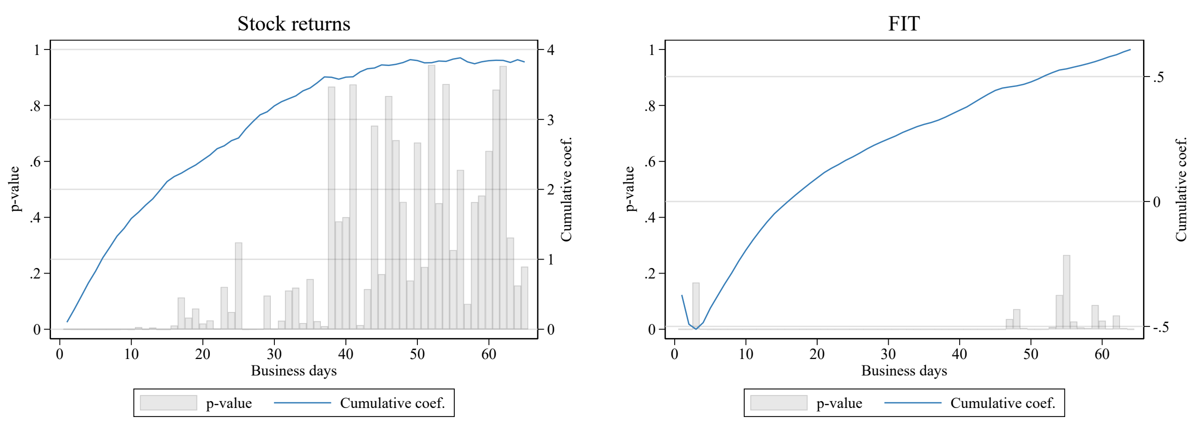


(a) Cum. coef. on lags of MF returns

(b) Cum. coef. on lags of MF flows

This figure shows the results from a cross-sectional, predictive regression of daily mutual fund flows on lags of daily mutual fund returns and lags of daily mutual fund flows. It also controls for quarterly fund return and flow lags from one quarter to three years ago. I include time fixed effects and cluster standard errors by time. I include 65 daily lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient as gray bars. The sample excludes index mutual funds. The number of observations is 5,352,989. The R^2 is 0.0430. The within-R^2 is 0.0404. The sample is 2008 to 2017 because of the availability of daily Morningstar data.

Figure 4: Regression of Daily Flow-Induced Trading on Lags of FIT and Stock Returns

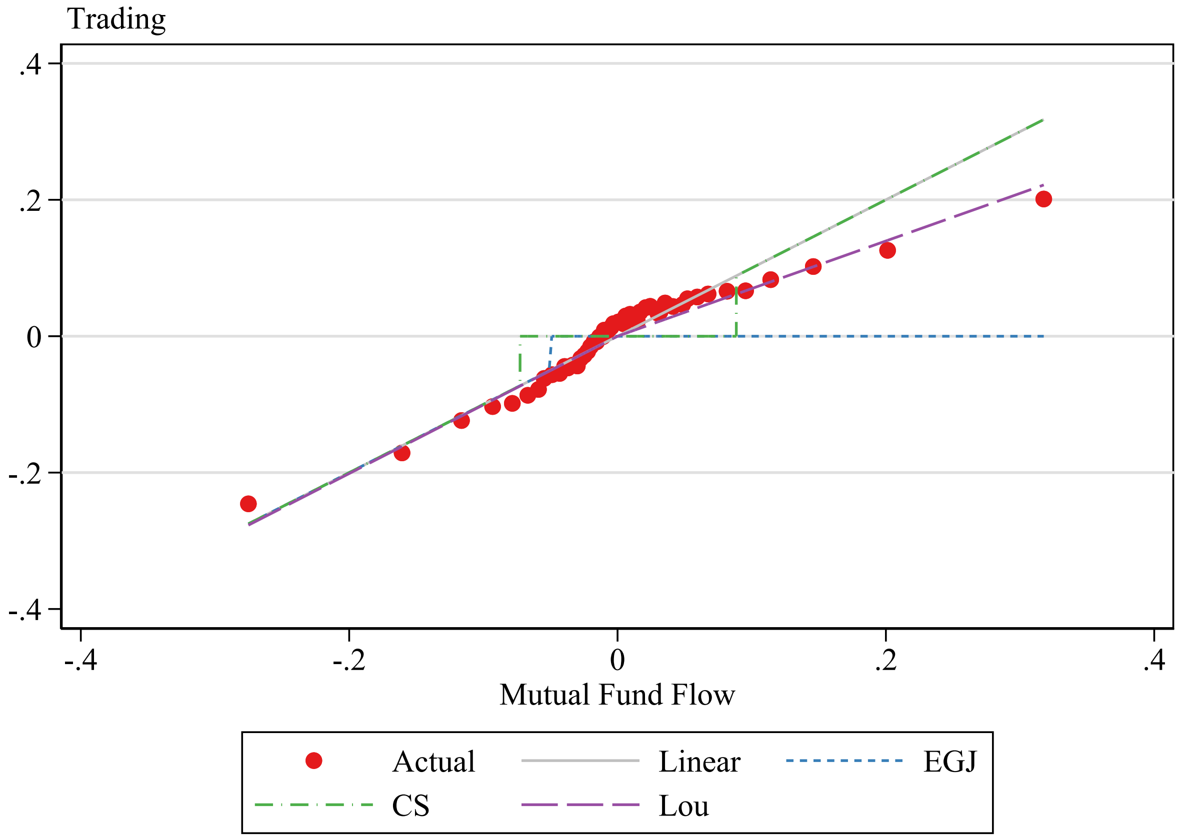


(a) Cum. coef. on lags of stock returns

(b) Cum. coef. on lags of FIT

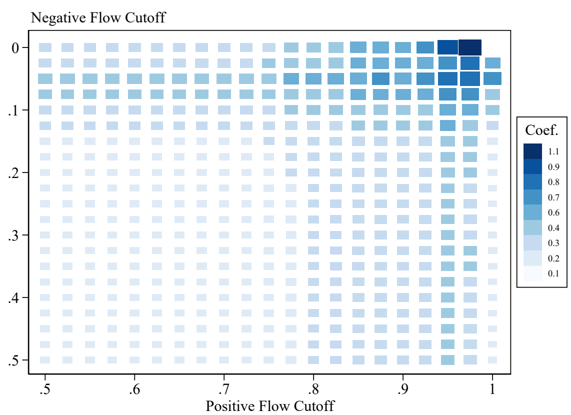
This figure shows the results from a cross-sectional, predictive regression of daily flow-induced trading (FIT) on lags of stock returns and FIT. This is the analogue to the regression in figure 3 at the stock level, rather than the mutual fund level. For ease of interpretation, daily FIT is normalized in the cross-section. I include time fixed effects and cluster standard errors by time. I include 65 lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient as gray bars. The number of observations is 5,664,001. The R^2 is 0.2279. The within-R^2 is 0.1398. The sample is 2008 to 2017 because of the availability of daily Morningstar data.

Figure 5: Mutual Fund Trading in Response to Mutual Fund Flows

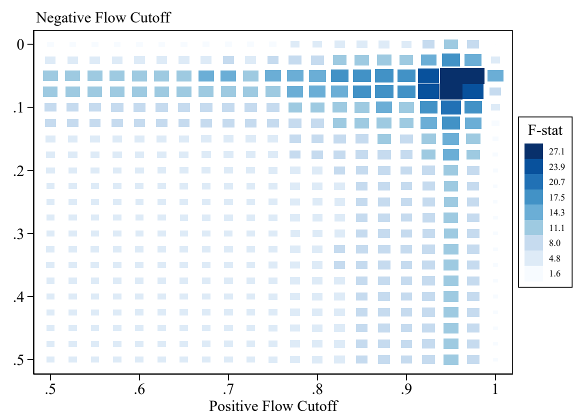


This figure shows how mutual funds trade in response to flows. Trading is the relative change in shares held. In red, I show demeaned position-weighted mean trading, for 50 mutual fund flow bins. I also plot four mappings of flows into trading from the literature. A basic approach is to use the identity which assumes mutual funds keep portfolio weights constant in response to flows. This corresponds to the grey 45 degree line. Following Edmans, Goldstein, and Jiang (2012), the market feedback effect literature makes this choice, except it discards flows greater than -5%. This is depicted in blue. Finally, I also show the mappings used in Coval and Stafford (2007) in green and Lou (2012) in purple. The sample is 1980 to 2017.

Figure 6: Regressions of Quarterly Stock Returns on Surprise Flow-Induced Trading for Different Flow Cutoffs



(a) Estimated coefficients



(b) F-statistics

The two heatmaps report coefficient estimates and Kleibergen and Paap (2006) F-statistics for quarterly cross-sectional regressions of stock returns on surprise flow-induced trading and control variables. Surprise flow-induced trading is constructed for all combinations of positive and negative flow cutoffs, according to equation 8. The x-axis gives the positive percentile cutoff, the y-axis gives the negative percentile cutoff; i.e. for each (x,y), I only use extreme surprise flows that are either in the top x or the bottom y percentile. The y-axis is reversed so that the bottom left corner drops all flows and the top right corner keeps all flows. The color and size of the squares indicate the magnitude of the F-statistic or estimated coefficient corresponding to the respective grid cell. Note that the heatmap values are not exact because they bin grid cells. I use a grid with a step size of 2.5%. The control variables are the 5 Fama French characteristics and momentum. The sample is 2008 to 2017 because constructing surprise flows requires daily Morningstar data.

Tables

Table 1: Summary Statistics

Panel A: CRSP versus Morningstar mutual fund coverage over time

	No. Funds		Median TNA ($M)		Total TNA ($T)		Total Flows ($B)	
Year	CRSP	Morningstar	CRSP	Morningstar	CRSP	Morningstar	CRSP	Morningstar
2008	3805	3221	110	97	3.1	2.1	220	121
2009	3533	2975	176	156	4.0	2.7	166	122
2010	3413	2866	224	201	4.4	3.0	199	137
2011	3328	2778	210	185	4.2	2.8	198	135
2012	3229	2690	244	206	4.7	3.0	212	126
2013	3287	2729	280	238	5.9	3.8	235	160
2014	3438	2877	275	231	6.3	4.1	232	164
2015	3604	3015	238	196	6.0	3.9	258	180
2016	3576	2986	241	199	6.3	4.2	268	189
2017	3417	2842	284	241	7.1	4.5	249	164

Panel B: Distribution of mutual fund flows and returns

	p5	p10	p25	p50	p75	p90	p95	sd
Flows (D)	-0.3	-0.2	-0.1	-0.0	0.0	0.2	0.4	1.1
Returns (D)	-1.9	-1.2	-0.4	0.1	0.5	1.2	1.8	1.3
Flows (Q)	-13.0	-8.0	-3.8	-1.0	3.2	13.4	27.4	19.1
Returns (Q)	-14.0	-8.7	-0.8	2.8	6.4	11.5	14.5	8.5

Panel C: Distribution of mutual fund portfolio characteristics in 2017 Q4

	p5	p10	p25	p50	p75	p90	p95	sd
# Stocks held	11.0	22.0	36.0	64.0	114.0	342.0	497.0	302.1
Market beta	0.9	0.9	1.0	1.1	1.2	1.3	1.4	0.2
Market equity	2.2	2.8	11.6	88.2	158.4	200.3	222.1	79.9
Tobin's Q	2.1	2.5	3.5	5.2	6.7	8.5	9.3	2.3
Profitability	23.4	31.6	42.1	51.1	57.1	62.4	65.6	13.5
Investment	2.4	4.0	6.5	9.4	13.2	16.7	19.1	6.0
Momentum	6.5	10.5	15.2	20.8	27.1	32.7	35.8	9.7

Panel A shows equity mutual fund summary statistics for each last quarter of a year, with CRSP and Morningstar data shown separately. I report the number of funds, their median total net assets (in million USD), the sum of their total net assets (in trillion USD) and the sum of absolute dollar mutual fund flows over the quarter (in billion USD). Panel B summarizes the distribution of mutual fund flows and returns at the daily and quarterly frequency, as indicated by (D) and (Q). For panels A and B, the sample is 2008 to 2017 because the daily mutual fund flow data from Morningstar start in 2008. Panel C shows the cross-sectional distribution of mutual fund portfolio characteristics corresponding to a standard 6-factor asset pricing model (Fama and French, 2018) and the number of stocks held. Portfolio characteristics are the portfolio weight-weighted mean of the characteristic across all stocks in a portfolio. I show these statistics for the last cross-section in my sample, 2017 Q4.

Table 2: Regressions of Quarterly Returns on (Surprise) Flow-Induced Trading

	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret	(7) FIT
FIT(CRSP)	0.297***	0.287***					
	(0.0352)	(0.0332)					
FIT			0.381***	0.369***			
			(0.0818)	(0.0652)			
SFIT					0.266**	0.232**	1.215***
					(0.112)	(0.105)	(0.0662)
Controls	No	Yes	No	Yes	No	Yes	No
F-statistic	71.22	74.33	21.71	31.96	5.638	4.896	336.3
R-squared	0.197	0.207	0.245	0.247	0.243	0.246	0.515
N	409203	409203	108597	108597	108597	108597	110157

This table shows regressions of quarterly stock returns on different versions of flow-induced trading (FIT) and control variables. In columns 1 and 2, I construct FIT as in the literature. In columns 3 and 4, I change the data source from CRSP to Morningstar but use the same object. I show this intermediate step to clarify that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. In columns 5 to 7, I switch to the new, corrected instrument. The samples are 1980 to 2017 in columns 1 and 2, and 2008 to 2017 in columns 3 to 7, because of the availability of daily Morningstar data. The control variables are the 5 Fama French characteristics and momentum. All regressions include time fixed effects. I report standard errors clustered by time in parentheses and Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table 3: Regressions of Quarterly Returns on (Surprise) Flow-Induced Trading

	Flows		Surprise Flows	
	No Controls	Controls	No Controls	Controls
Panel A: FIT scaled by shares observed				
Flows	0.381***	0.369***	0.266**	0.232**
	(4.659)	(5.654)	(2.374)	(2.213)
Lou (2012)	0.448***	0.432***	0.291**	0.235*
	(4.782)	(5.591)	(2.318)	(1.973)
Edmans et al. (2012)	0.522***	0.487***	0.584***	0.493***
	(4.043)	(4.391)	(3.212)	(2.825)
Coval, Stafford (2007)	0.419***	0.416***	0.476***	0.452***
	(4.520)	(5.499)	(3.733)	(3.634)
Optimal Flow Cutoffs	0.385***	0.375***	0.664***	0.634***
	(4.926)	(6.235)	(5.071)	(5.106)
Panel B: FIT scaled by shares outstanding				
Flows	2.777***	2.751***	-0.106	-0.348
	(5.568)	(6.149)	(-0.075)	(-0.262)
Lou (2012)	2.461***	2.690***	-1.196	-0.979
	(4.605)	(5.522)	(-0.719)	(-0.620)
Edmans et al. (2012)	1.360*	1.928***	0.050	1.000
	(1.892)	(3.129)	(0.018)	(0.388)
Coval, Stafford (2007)	3.732***	3.688***	3.127*	2.976*
	(5.406)	(6.258)	(1.952)	(1.902)
Optimal Flow Cutoffs	4.073***	3.826***	7.788***	7.873***
	(5.863)	(6.987)	(7.074)	(7.123)

This table shows regressions of quarterly stock returns on different versions of flow-induced trading (FIT) and control variables. Columns 1 and 2 use mutual fund flows; columns 3 and 4 use surprise mutual fund flows to construct FIT. The regressions in columns 1 and 3 do not include control variables, while the other regressions do. The control variables are the 5 Fama French characteristics and momentum. In each panel, I show results for different mappings of flows into trading: the identity, following Lou (2012), following Edmans, Goldstein, and Jiang (2012), following Coval and Stafford (2007) and the new, optimal mapping. The samples are 1980 to 2017 in columns 1 and 2, and 2008 to 2017 in columns 3 and 4, because of the availability of daily Morningstar data. All regressions include time fixed effects. Standard errors are clustered by time. I report t-statistics in parentheses to allow the reader to quickly determine instrument strength and statistical significance. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table 4: Predicting (Surprise) Flow-Induced Trading

	(1) FIT(CRSP)	(2) FIT	(3) SFIT
L.ret	0.252***	0.319***	0.0978
	(0.0679)	(0.0651)	(0.0596)
L2.ret	0.139***	0.133*	-0.0586
	(0.0449)	(0.0677)	(0.0484)
L3.ret	0.102**	0.0835	-0.0269
	(0.0496)	(0.0709)	(0.0358)
L4.ret	0.124**	0.0920*	-0.0183
	(0.0506)	(0.0540)	(0.0334)
Market beta	-0.0798***	-0.134***	-0.0169
	(0.0198)	(0.0153)	(0.0124)
Log Market equity	0.0936***	0.0355	0.0227
	(0.0218)	(0.0212)	(0.0189)
Log Tobin's Q	-0.0741***	-0.0754***	-0.000531
	(0.0221)	(0.0178)	(0.0138)
Profitability	-0.0188	-0.0617*	0.000697
	(0.0393)	(0.0319)	(0.0190)
Investment	-0.302***	-0.484***	-0.0488
	(0.0524)	(0.0426)	(0.0410)
R-squared	0.195	0.128	0.0742
N	335551	100824	100824

This table shows regressions of different versions of flow-induced trading (FIT) on lagged stock returns and control variables. Column 1 uses the traditional instrument constructed using CRSP data, which is subject to the reverse causality critique. In column 2, I estimate the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to clarify that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. In the last column, I estimate the regression using the new, optimal, corrected instrument. The control variables are the characteristics corresponding to the 6-factor asset pricing model, excluding momentum, because momentum is close to collinear with lagged returns. All regressions include time fixed effects. I report standard errors clustered by time in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table 5: Predicting Returns with (Surprise) Flow-Induced Trading

	(1) ret	(2) ret	(3) ret
L.FIT(CRSP)	0.0115		
	(0.0513)		
L2.FIT(CRSP)	-0.0223		
	(0.0632)		
L3.FIT(CRSP)	-0.0856		
	(0.113)		
L4.FIT(CRSP)	-0.0619		
	(0.0612)		
L.FIT		0.0493	
		(0.0739)	
L2.FIT		0.0520	
		(0.120)	
L3.FIT		-0.108	
		(0.0893)	
L4.FIT		0.102	
		(0.0992)	
L.SFIT			-0.0751
			(0.101)
L2.SFIT			0.199*
			(0.103)
L3.SFIT			-0.0901
			(0.114)
L4.SFIT			0.159
			(0.118)
R-squared	0.206	0.156	0.156
N	332148	88380	88380

This table shows regressions of quarterly stock returns on lags of different versions of flow-induced trading (FIT) on lagged stock returns and control variables. In Column 1, FIT is the traditional instrument constructed using CRSP data, which is subject to the reverse causality critique. In column 2, I estimate the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to clarify that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. In the last column, I estimate the regression using the new, optimal, corrected instrument. The control variables are the characteristics corresponding to the 6-factor asset pricing model. All regressions include time fixed effects. I report standard errors clustered by time in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

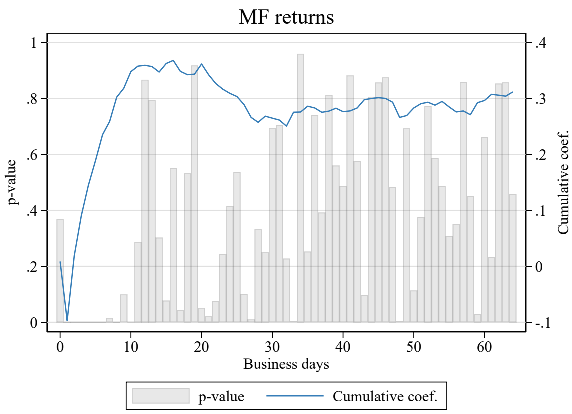
Table 6: Application: the Market Feedback Effect on Investment

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.0430***	0.0977***	0.0961**	-0.0191
	(0.00114)	(0.0174)	(0.0446)	(0.0472)
L.Log Tobin's Q	0.0233***	0.0239***	0.0160***	0.0165***
	(0.000690)	(0.000728)	(0.00120)	(0.00148)
F-statistic		61.91	20.21	13.49
N	331742	331742	86378	86378

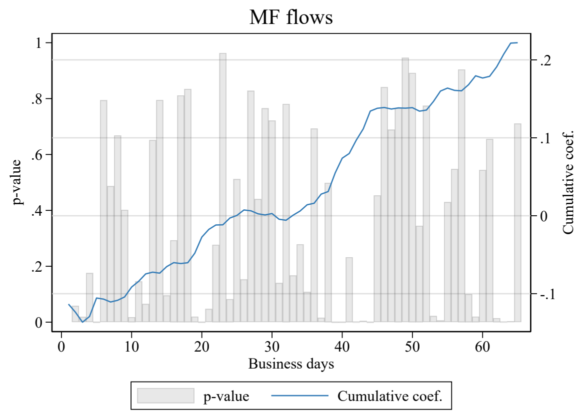
This table shows regressions of the investment rate on returns, lagged Tobin's Q and control variables. The first column shows results for an OLS regression. In columns 2 to 4, returns are instrumented with different versions of flow-induced trading, all of which are constructed using the optimal flow cutoffs. Column 2 uses the traditional instrument constructed using CRSP data. In column 3, I estimate the same regression, except that FIT is now constructed using Morningstar data. This intermediate step clarifies that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. The last column uses the corrected, optimal instrument. The investment rate is the change in non-cash assets divided by lagged non-cash assets. The control variables are the characteristics corresponding to a 6-factor asset pricing model. All regressions include firm and time fixed effects. I report standard errors clustered by time in parentheses and Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.

A Figures

Figure A1: Regression of Daily Mutual Fund Flows on Lags of Flows and Returns
Index Funds Only



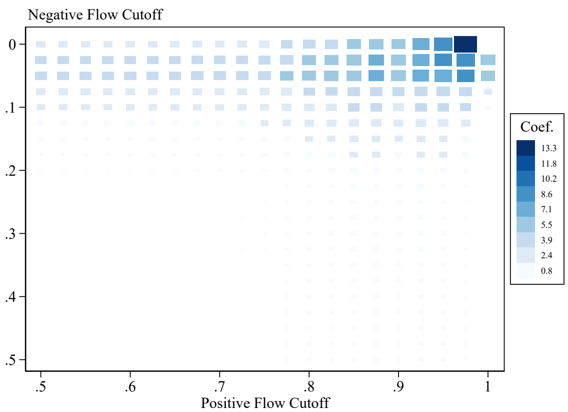
(a) Cum. coef. on lags of MF returns



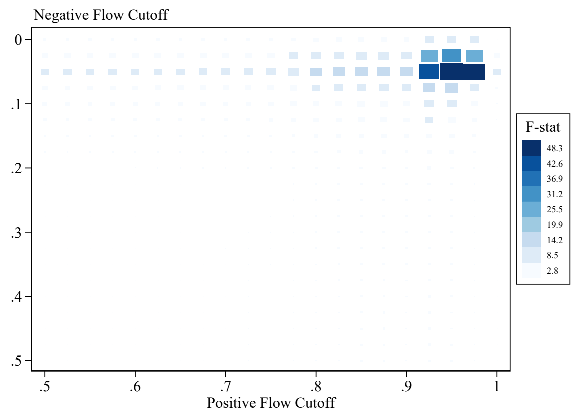
(b) Cum. coef. on lags of MF flows

This figure shows the results from a cross-sectional, predictive regression of daily mutual fund flows on lags of daily mutual fund flows and returns. This is the regression for index mutual funds. It also controls for quarterly fund return and flow lags from one quarter to three years ago. I include time fixed effects and cluster standard errors by time. I include daily 65 lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient as gray bars. The number of observations is 670,962. The R^2 is 0.0302. The within-R^2 is 0.0245. The sample is 2008 to 2017 because of the availability of daily Morningstar data.

Figure A2: Regressions of Quarterly Stock Returns on Surprise Flow-Induced Trading for Different Flow Cutoffs - Scaled by Shares Outstanding



(a) Estimated coefficients



(b) F-statistics

The two heatmaps report coefficient estimates and Kleibergen and Paap (2006) F-statistics for quarterly cross-sectional regressions of stock returns on surprise flow-induced trading and control variables. The difference to Figure 6 is that surprise flow-induced trading is constructed by scaling by shares outstanding instead of total shares held by mutual funds. Surprise flow-induced trading is constructed for all combinations of positive and negative flow cutoffs, according to equation 8. The x-axis gives the positive percentile cutoff, the y-axis gives the negative percentile cutoff; i.e. for each (x,y), I only use extreme surprise flows that are either in the top x or the bottom y percentile. The y-axis is reversed so that the bottom left corner drops all flows and the top right corner keeps all flows. The color and size of the squares indicate the magnitude of the F-statistic or estimated coefficient corresponding to the respective grid cell. Note that the heatmap values are not exact because they bin grid cells. I use a grid with a step size of 2.5%. The control variables are the 5 Fama French characteristics and momentum. The sample is 2008 to 2017 because constructing surprise flows requires daily Morningstar data.

B Tables

Table A1: Do Mutual Funds Hold Stocks with Correlated Characteristics?

	(1) Beta	(2) MV	(3) Q	(4) Profit	(5) Investment	(6) Momentum
PF mean (other)	0.654***	1.068***	0.863***	0.852***	0.736***	0.744***
	(0.00197)	(0.00372)	(0.00177)	(0.00275)	(0.00196)	(0.00226)
R-squared	0.0405	0.421	0.126	0.0998	0.0560	0.0562
N	26394754	26394754	26394754	26394754	26394754	26394754

This table shows regressions at the mutual fund portfolio position level. I regress the respective stock characteristic on the portfolio weight-weighted mean of the same characteristic over all other stocks in the same portfolio. The characteristics are market beta, market value, log Tobin's Q, profitability, investment and momentum, corresponding to a 6-factor asset pricing model. All regressions include time fixed effects. I report standard errors clustered by mutual fund × time in parentheses. The sample is 1980 to 2017. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table A2: Application: the Market Feedback Effect on Investment - Annual

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.126***	0.508***	0.359***	0.152
	(0.00931)	(0.166)	(0.100)	(0.129)
L.Log Tobin's Q	0.0724***	0.0849***	0.0528***	0.0485***
	(0.00494)	(0.00676)	(0.00809)	(0.00942)
F-statistic		15.21	22.35	18.50
N	82963	82963	24102	24102

This table shows regressions of the investment rate on returns, lagged Tobin's Q and control variables. The analysis in this table is the same as in table 6, except at the annual instead of the quarterly frequency. In the first column, I show the results of an OLS regression. In columns 2 to 4, returns are instrumented with different versions of flow-induced trading, all of which are constructed using the optimal flow cutoffs.. Column 2 uses the traditional instrument constructed using CRSP data. In column 3, I estimate the same regression, except that FIT is now constructed using Morningstar data. This intermediate step clarifies that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. The last column uses the corrected, optimal instrument. The investment rate is the change in non-cash assets divided by lagged non-cash assets. The control variables are the characteristics corresponding to a 6-factor asset pricing model. All regressions include firm and time fixed effects. I report standard errors clustered by time in parentheses and Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table A3: Application: the Market Feedback Effect on Investment - No Controls

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.0425***	0.122***	0.121**	-0.0155
	(0.00131)	(0.0180)	(0.0484)	(0.0479)
L.Log Tobin's Q	0.0313***	0.0338***	0.0264***	0.0209***
	(0.000764)	(0.00103)	(0.00246)	(0.00259)
F-statistic		65.42	15.28	10.14
N	331742	331742	86378	86378

This table shows regressions of the investment rate on returns and lagged Tobin's Q. The analysis in this table is the same as in table 6, except that I omit control variables. In the first column, I show the results of an OLS regression. In columns 2 to 4, returns are instrumented with different versions of flow-induced trading, all of which are constructed using the optimal flow cutoffs.. Column 2 uses the traditional instrument constructed using CRSP data. In column 3, I estimate the same regression, except that FIT is now constructed using Morningstar data. This intermediate step clarifies that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. The last column uses the corrected, optimal instrument. The investment rate is the change in non-cash assets divided by lagged non-cash assets. The control variables are the characteristics corresponding to a 6-factor asset pricing model. All regressions include firm and time fixed effects. I report standard errors clustered by time in parentheses and Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table A4: Application: the Market Feedback Effect on Investment
- FIT Scaled by Shares Outstanding

	Quarterly		Annual	
	Investment	Investment	Investment	Investment
ret	-0.0435	-0.0405	0.0838	0.103
	(0.0448)	(0.0459)	(0.139)	(0.128)
Log Tobin's Q	0.0198***	0.0165***	0.0454**	0.0475***
	(0.00250)	(0.00157)	(0.0185)	(0.0104)
Controls	No	Yes	No	Yes
F-statistic	22.47	21.83	24.99	28.46
N	86378	86378	24102	24102

This table shows regressions of the investment rate on returns, lagged Tobin's Q and control variables. Stock returns are instrumented with the optimal surprise flow-induced trading instrument. The analysis in this table is the same as in column four of table 6, except that flow-induced trading is scaled by shares outstanding instead of total shares held by mutual funds. The investment rate is the change in non-cash assets divided by lagged non-cash assets. The control variables are the characteristics corresponding to a 6-factor asset pricing model. All regressions include firm and time fixed effects. I report standard errors clustered by time in parentheses and Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table A5: Application: the Market Feedback Effect on Investment - Alternative Clustering

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.0430***	0.0959***	0.0882**	-0.0191
	(0.000835)	(0.00949)	(0.0388)	(0.0601)
L.Log Tobin's Q	0.0233***	0.0238***	0.0160***	0.0165***
	(0.000608)	(0.000622)	(0.00113)	(0.00115)
F-statistic		1109.4	68.00	39.92
N	331742	331742	86378	86378

(a) Standard errors clustered by firm

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.0430***	0.0959***	0.0882**	-0.0191
	(0.00119)	(0.0162)	(0.0404)	(0.0525)
L.Log Tobin's Q	0.0233***	0.0238***	0.0160***	0.0165***
	(0.000817)	(0.000850)	(0.00139)	(0.00163)
F-statistic		68.81	18.47	13.56
N	331742	331742	86378	86378

(b) Standard errors double clustered by firm and time

This table shows regressions of the investment rate on returns, lagged Tobin's Q and control variables. The analysis in this table is the same as in table 6, except that standard errors are clustered by firm in panel (a) and double clustered by time and firm in panel (b). In the first column, I show the results of an OLS regression. In columns 2 to 4, returns are instrumented with different versions of flow-induced trading, all of which are constructed using the optimal flow cutoffs.. Column 2 uses the traditional instrument constructed using CRSP data. In column 3, I estimate the same regression, except that FIT is now constructed using Morningstar data. This intermediate step clarifies that the results are not driven by the change in data source. The number of observations decreases because there are only 10 years of Morningstar data in comparison to 37 years of CRSP data. The last column uses the corrected, optimal instrument. The investment rate is the change in non-cash assets divided by lagged non-cash assets. The control variables are the characteristics corresponding to a 6-factor asset pricing model. All regressions include firm and time fixed effects. I report Kleibergen and Paap (2006) F-statistics in the table footer. ***, **, and * denote significance at the 1%, 5% and 10% levels.