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

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Abstract

I propose a new method to isolate a plausibly exogenous component of mutual fund flows in order 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 aggregated 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

JEL Codes: G12; G23; G31

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1 Introduction

What is the price impact of mutual fund flow-induced fire sales? Current answers to this question rely on the correlation between quarterly mutual fund flows and the contemporaneous returns of the stocks in their portfolios (e.g. Edmans et al., 2012). But this correlation could be 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. This paper shows the relevance of this reverse causality problem, proposes a new method to isolate a component of mutual fund flows that is plausibly exogenous to stock returns and uses that method to revisit classic questions in empirical finance research.

From a policy maker's perspective, the price impact of mutual fund flow-induced fire sales is important for financial stability regulation; from a researcher's perspective, it is important because it is the state-of-the-art nonfundamental shock to stock prices. Using flow-induced trading, Coval and Stafford (2007), Duffie (2010), Greenwood and Thesmar (2011), Ben-Rephael et al. (2012), Jotikasthira et al. (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. Moreover, instrumenting stock returns with flow-induced fire sales, Edmans et al. (2012), Khan et al. (2012), Derrien et al. (2013), Phillips and Zhdanov (2013), Norli et al. (2014), Lee and So (2017), Bonaime et al. (2018), Dessaint et al. (2018), Eckbo et al. (2018) and Lou and Wang (2018) find that market misvaluation distorts corporate decisions.

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. I trace out retail investors' high-frequency purchase/redemption responses to mutual fund returns and find strong evidence for high-frequency return chasing. I also show that both mutual fund portfolio conditions are empirical facts.

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.

To address this reverse causality problem, I propose a solution inspired by the literature on the real effects of monetary policy. This literature 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 construct high-frequency surprise mutual fund flows that are orthogonal to past and contemporaneous mutual fund returns. I then construct the low-frequency instrument from aggregated daily surprise flows. This means 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. Using the new instrument, the estimated price impact of fire sales shrinks by around two thirds 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 et al., 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 0.1% return. But a 1% demand shock induced by the most extreme mutual fund flows triggers a 1% return. I also find fire sales have larger price impacts than fire purchases. 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 1st and 100th percentiles. This is much more extreme than e.g. in Coval and Stafford (2007), who use flows in the 1st and 10th decile.

Next, 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 under-valuation causes underinvestment. Using the new instrument, the estimated coefficient is 80% smaller and statistically insignificant. While this does not imply the absence of market feedback effects, it does indicate that equity markets are likely less distortive than suggested.

Finally, if the price impact of fire sales is not as large as previously suggested, why do simple flow-based trading strategies generate sizable alpha (Coval and Stafford, 2007; Lou, 2012)? I show that implementable strategies do not. Predicting fund flows out-of-sample and taking into account that portfolio holdings become public after a two-month delay, flow-based trading strategies fail to generate alpha beyond momentum. This is not driven by the quality of the fund flow prediction models. Even strategies based on machine learning predictions of mutual fund flows do not consistently generate alpha; expected flows are priced.

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. Broadly, the market feedback effect literature uses flows very uniformly, closely following Edmans et al. (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 that is the center of this paper. 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. This paper starts off where Wardlaw (2020) concludes. 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 et al., 2007; Rakowski and Wang, 2009; Rakowski, 2010; Ben-Rephael et al., 2011) by relating fund flows and returns to fund portfolios, by expanding the prediction horizon, by investigating the predictability of high-frequency fund flows using machine learning techniques 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 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 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 shock. However, starting with Edmans et al. (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 et al., 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 make trading decisions daily and 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.

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. In addition, it is well known that retail investors chase past mutual fund performance (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 observe mutual fund returns after markets close and only react 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, the mutual fund return is the portfolio weight-weighted mean of stock returns

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

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:

$$\begin{aligned}
& flow_{i,t} = \eta_t && (5)\\
& + \sum_{l=0}^{L} \alpha_l w_{i,t-l}(n) r_{t-l}(n) && \text{Reverse causality}\\
& + \sum_{l=0}^{L} \alpha_l \sum_{m \neq n} w_{i,t-l}(m) \beta(m)' f_{t-l} && \text{Endogeneity}\\
& + \sum_{l=0}^{L} \alpha_l \sum_{m \neq n} w_{i,t-l}(m) \epsilon_{i,t-l} && \text{IV: shocks to other stocks}\\
& + u_{i,t}. && \text{IV: surprise flows}
\end{aligned}$$

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.

Note that, if there is no within-quarter return chasing, $\alpha_l = 0$ for all $0 \leq l < 65$[1], the critique does not apply; however, I show this is strongly rejected empirically. Also, if portfolio weights are small, this direct dependence 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

[1]65 is the maximum number of business days in a quarter.

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. Therefore, if retail investors chase high-frequency returns, the instrument is only valid if most mutual funds hold the market. Yet, if they held the market, there would be no cross-sectional shock to begin with. When funds that hold the market sell to meet redemptions, these demand shocks are proportional to market values and hence collinear with time fixed effects. If retail investors chase high-frequency returns, the instrument is either invalid or weak.

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, namely the part of flows that is orthogonal to past and contemporaneous mutual fund returns. Surprise flows are generated by random liquidity shocks to retail investors. I use this term to construct the new instrument. 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. 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

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

I obtain daily surprise flows as the residuals of a regression estimate of equation 2. I include 65 lags, corresponding to the maximum number of business days in a quarter. 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. A concern may be that the flow-return relation could be nonlinear (Chevalier and Ellison, 1997). However, since Spiegel and Zhang (2013), the literature acknowledges the flow-return relation as linear.

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. This leaves 2987 mutual funds in the last cross-section. Out of these, I can match 2466 to Morningstar data. With ten years of daily data, this yields about six million observations. For comparison with the literature, I construct quarterly mutual fund flows and returns using CRSP. I also use mutual fund characteristics from CRSP and require a minimum fund size of $10 million.

3.2 Portfolio Holdings Data

The Thomson Reuters Mutual Fund Holdings database provides quarterly fund-level portfolios from 1980 to 2017. The sources for this database are SEC mandated disclosures in Forms N-30D, N-Q and N-CSR as well as voluntary disclosures. Thomson Reuters provides the file date. I merge to this date when constructing instruments for returns. However, mutual fund holdings typically become publicly available after a two-month delay. Hence, when constructing trading strategies, I lag portfolio holdings by one quarter to ensure a trader could have used them. I merge the Thomson Reuters holdings data with CRSP mutual fund data using MFLinks.

3.3 Stock 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 et al. (2017). I restrict the sample to US ordinary common stocks that trade on the NYSE, AMEX or Nasdaq, have non-missing return data and have at least 1% mutual fund ownership.

3.4 Summary Statistics

Panel A of Table 1 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 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 \$200 billion; for Morningstar, they are \$150 billion. Overall, high-frequency Morningstar data cover about three quarters of the low-frequency CRSP data.

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 B indicates that both mutual fund portfolio conditions hold. Panel B 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. There are about 4000 stocks in the cross-section. Hence, 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 6 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). Figure 3 shows that retail investors do indeed chase high-frequency mutual fund returns. I report results from a regression of daily mutual fund flows on lags of flows and returns. 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 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 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 over the next 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 with a p-value of 0.8. This is 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 mutual fund flows. Flows are highly autocorrelated. A 10% flow today predicts a 7% flow over the next 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. All estimated coefficients are highly statistically significant. Overall, this exercise shows that retail investors engage in high-frequency 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 investors chasing return. However, if mutual fund managers had a crystal ball, they could trade prior to flows, which would 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 2.

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 flow-induced trading on lags of flow-induced trading and stock returns. 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 over the next 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 et al. (2012), Khan et al. (2012), Lou (2012), Jotikasthira et al. (2012) and Dessaint et al. (2018). I replicate the graph from Edmans et al. (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 stops at exactly the onset of the event. This is additional evidence that the reverse causality problem is relevant. 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.

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. In Table 2, I compare flow-induced trading, the traditional instrument which is subject to the reverse causality critique, to surprise flow-induced trading, the new instrument. I show regressions of quarterly stock returns on different versions of the instrument. I include time fixed effects and controls and cluster standard errors by time. This regression estimates the price impact of forced trading and is the first stage of the common instrumental variable regression of a corporate outcome on returns. In column 1, 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 3, 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 0.38 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 to the new, corrected instrument. In column 5, the coefficient drops to 0.13, but remains weakly statistically significant. Demand is more elastic. A 1% demand shock triggers a 0.13% instead of a 0.38% return. The F-statistic of this regression is 3.2, meaning the instrument is weak. In column 7, I regress the old on the new instrument and find an R^2 of 92%. Even though the traditional and the new instrument are almost identical, the new instrument estimates a drastically lower price impact because it avoids the reverse causality problem. Columns 2, 4 and 6 show the conclusions do not change when controlling for common risk factors. Overall, correcting the reverse causality problem shows that markets are deeper than suggested.

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 et al. (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.[2] In blue, I depict the mapping from Edmans et al. (2012) which is standard in the market feedback effect literature and only uses flows less than -5%. Both mappings can be written as

$$\tilde{g}(flow_{i,q}) = \begin{cases} flow_{i,q} & \text{if } flow_{i,q} \leq \alpha_L \text{ or } flow_{i,q} \geq \alpha_H \\ 0 & \text{if } \alpha_L < flow_{i,q} < \alpha_H. \end{cases} \tag{7}$$

The exact cutoffs in Coval and Stafford (2007) and Edmans et al. (2012) are arbitrary. Therefore, I estimate the price impact of surprise flow-induced fire sales for 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 fire sales 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 vs. new instruments 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, the estimated coefficients are large and strongly statistically significant in all specifications.

Using the new instrument and the fire sale kernels from the literature, the estimates are consistently smaller and less statistically significant. As before, this is because the new instrument mitigates the reverse causality problem. 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 performs on par with the traditional instrument. When including controls, the estimated coefficient is 1 and the t-statistic is 6. Using the optimal fire sale kernel, the demand shock is a strong instrument. Finally, using 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.

How does the new fire sale kernel achieve this performance? The heatmaps in Figure 6 report coefficient estimates and F-statistics for the grid search 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 cutoff, α_H, is on the x-axis,

[2] 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 et al. (2012) the literature recognizes that actual trades are endogenous. Hence, I update the Coval and Stafford (2007) measure to reflect this.

and the negative cutoff, $-\alpha_L$, is on the y-axis. 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%.

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[3] 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 0.1% return, but a 1% demand shock induced by the most extreme mutual fund flows triggers a 1% return. In addition, the coefficient estimates are largest on the right edge of panel (a), i.e. when dropping all positive flows. This means fire sales have larger price impacts than fire purchases.

For instrument strength in the right panel, a second force is in 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 $\alpha_L = -0.375$ and $\alpha_H = 0.825$ maximize instrument strength. These cutoffs correspond to the 1st and 99th percentiles of the fund flow distribution, which is much more extreme than e.g. in Coval and Stafford (2007), who use flows in the 1st and 10th decile. Overall, the new fire sale kernel makes the instrument strong because it focuses on more extreme flows.

Naturally, testing $(1/0.025)^2 = 1600$ specifications raises data mining concerns. However, a t-statistic of 6 is highly unlikely under the null, even with 1600 tests. As an upper bound, a Bonferroni correction raises the 1% critical t-value to 4.5. In addition, this multiple testing concern is mitigated by the fact that the tests are highly correlated and economically motivated. 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.

4.5 Application: the Market Feedback Effect on Investment

Does the reverse causality problem matter in applications? The 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. Edmans et al., 2012). I focus on investment, which is the most studied outcome in this literature. I follow the convention of dropping financial firms (SIC code 6000-6999) in this section. To test for

[3]there are flows > 1; but for $\alpha_H = 1$, I drop all positive flows to show this extreme.

market feedback effects, I start with a Q-theory regression of the investment rate on log Tobin's Q, control variables, and time and firm fixed effects

$$\frac{I_t(n)}{K_t(n)} = \alpha_t + \alpha(n) + \beta Q_t(n) + \gamma' X_t(n) + \epsilon_t(n). \tag{8}$$

Stock returns are approximately first differences of log Tobin's Q. Hence, I estimate

$$\frac{I_t(n)}{K_t(n)} = \alpha_t + \alpha(n) + \beta_1 r_t(n) + \beta_2 Q_{t-1}(n) + \gamma' X_t(n) + \epsilon_t(n), \tag{9}$$

a regression of the investment rate on returns. I can now instrument returns, instead of Tobin's Q, with flow-induced trading. This is preferable because the reverse causality problem is more severe when instrumenting Tobin's Q than when instrumenting returns. As illustrated in Figure 2, the reverse causality problem is created by cumulating daily stock returns and fund flows over a quarter which hides their high-frequency temporal order. Tobin's Q cumulates the entire return history, which makes the same issue more severe. In addition, this specification allows me to control for lagged Tobin's Q. This alleviates the potential endogeneity concern that the entire return history affects the instrument and also drives investment via Tobin's Q.

Table 4 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 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 decrease 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 0.02

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.

4.6 Application: Mutual Fund Flow-Based Trading Strategies

Mutual fund flow-induced fire sales have price impact. Hence, a trader who anticipates fund flows could front-run mutual funds and generate excess returns. Coval and Stafford (2007) and Lou (2012) find strategies that implement this logic generate sizable alpha. However, if the fire sale results are partially driven by reverse causality, why are simple flow-based trading strategies so profitable? Taking expectations of equation 1 gives the trading signal

$$\mathbb{E}FIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n)\mathbb{E}[g(flow_{i,q})]}{SharesOutstanding_{q-1}(n)}. \tag{10}$$

Note that $\mathbb{E}[g(flow_{i,q})] = g(\mathbb{E}[flow_{i,q}])$ for the $g()$ I consider. I construct high minus low, long-short trading strategies from decile portfolios.[4] The trading signal has three degrees of freedom: how to compute the expected value of flows, how to map flows into fire sales and which denominator to choose.

4.6.1 Predicting Mutual Fund Flows

Coval and Stafford (2007) estimate a cross-sectional predictive regression of quarterly flows on eight lags of fund flows and returns. Lou (2012) estimates a cross-sectional predictive regression of flows on mutual fund CAPM alpha over the previous twelve months.[5] Both papers then use the estimated models to predict flows in-sample. Here, to determine whether expected flows are priced, I investigate whether implementable flow-based trading strategies generate alpha. To ensure the strategies are implementable, I avoid two sources of look-ahead bias. First, I predict flows using their models but recursively out-of-sample. Their models contain time fixed effects. But it is impossible to estimate time fixed effects for out-of-sample data from in-sample data. Hence, I use the mean estimated time fixed effect

[4]The trading strategies using the Edmans et al. (2012) fire sale kernel are exceptions, since half of all stocks have a trading signal of 0 because none of the funds holding them is predicted to receive extreme outflows. Hence, instead of a decile portfolio, the long portfolio contains all stocks with a zero signal.

[5]As Lou (2012)'s prediction model only uses one predictor, expected flows have little variation, and as mean flows are positive, many time periods do not have a single fund with negative expected flows. This creates problems in conjunction with the fire sale mappings. E.g., with the Edmans et al. (2012) mapping, most time periods contain only zero signals. Hence, when using the Lou (2012) flow prediction model, I apply two remedies. First, I predict cross-sectionally demeaned flows; second, I lower the Edmans et al. (2012) threshold from -5% to 0%.

instead. Second, portfolio holdings data typically become available after a two-month delay. Accordingly, I lag portfolio holdings to ensure a trader could have used them.

The main question is whether market prices fully reflect predictable fund flows. To answer this, one should use the best possible prediction model. Hence, I also construct machine learning mutual fund flow predictions. As neural nets are the most powerful machine learning models, I construct the trading signal using neural net fund flow predictions. I compare neural nets' performance to two benchmarks: a penalized regression, an elastic net, as a simple benchmark and a random forest as a more sophisticated benchmark. I list all model details in the machine learning appendix. For data availability reasons, the literature runs low-frequency mutual fund flow prediction exercises. In addition, I also examine high-frequency flow predictability because this is the prediction problem that is relevant for fund managers. Figure 7 reports performance in terms of out-of-sample R^2. In the high-frequency prediction problem, moving from elastic nets to random forests to neural nets, the R^2 increases from 8 to 15 to 17%. In the low-frequency prediction problem, performance increases from 11 to 17 to 22%. Neural nets perform best.

Of course, the two prediction problems are not comparable. The daily prediction problem is harder, because noise cancels out over the quarter. To make the two approaches comparable, I also report R-squareds from regressions of daily flows on the low-frequency predictions. This measures how informative the low-frequency predictions are for day-to-day cash management.[6] R-squareds are about 2%, much lower than in the daily prediction problem. Unsurprisingly, mutual fund managers should exploit high-frequency data and neural nets for cash management.

4.6.2 Trading Strategy Performance

Three ways to construct expected flows, five ways to map flows into fire sales and two candidate denominators produce 30 trading strategies, the performance of which I document in Table 5.[7] I show results for all possible combinations to show they are not driven by particular choices. I report quarterly average returns, Sharpe ratios and 3- (Fama and French, 1993), 5- (Fama and French, 2015) and 6-factor alphas (Fama and French, 2018) for equal- and value-weighted portfolios. First, in panel A, constructing expected flows as in Coval and Stafford (2007) gives quarterly average return, Sharpe ratios and alphas of zero. Next, in panel B, constructing expected fund flows as in Lou (2012) gives quarterly average return and 3- and 5-factor alphas of about 0.8%. However, momentum explains these excess returns. Naturally, funds that hold high-momentum stocks receive inflows because investors

[6] I do not make this comparison by aggregating the daily predictions to avoid look-ahead bias.

[7] and in appendix Table A2 for shares outstanding as the alternative denominator

chase past performance, and high-momentum stocks outperform. The pattern is qualitatively the same across the different flow transformations and for value-weighted portfolios.

Implementable versions of the flow-based trading strategies from the literature do not generate alpha with respect to a 6-factor model. However, this could be because the flow prediction models lack power. To test this, I construct the trading signal using fund flows predicted by neural nets. Panel C reports trading strategy performance. The results are qualitatively the same as in panel A. The strategies generate 0 returns. Hence, I conclude that expected flows are priced.

5 Conclusion

Based on evidence from mutual fund flows, an extensive literature finds equity markets are shallow and distort corporate decisions. This paper argues these findings are partially 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 shrinks by two thirds. Equity markets are deeper than suggested. Also, estimates of market feedback effects are smaller and noisier. Markets are less distortive than suggested. Finally, implementable flow-based trading strategies do not generate alpha beyond momentum. Expected mutual fund flows are priced.

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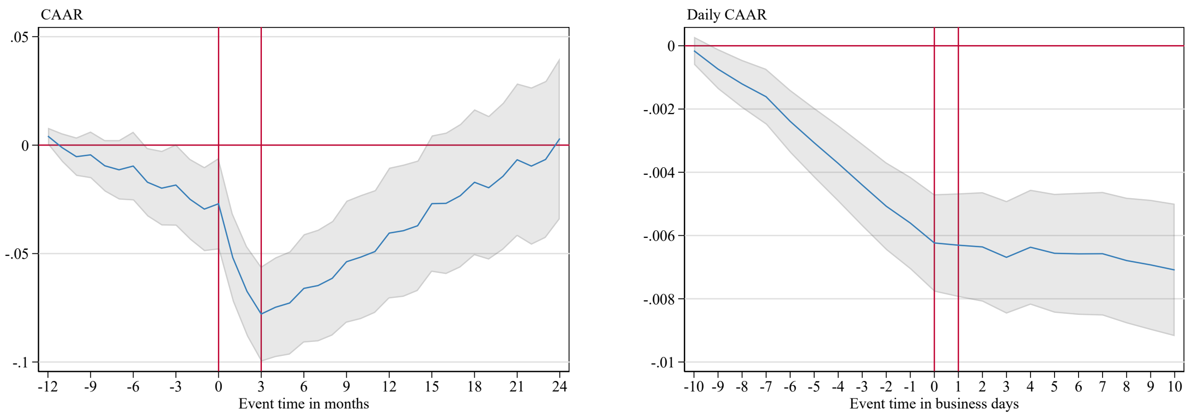
Figures

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 et al. (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 et al. (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

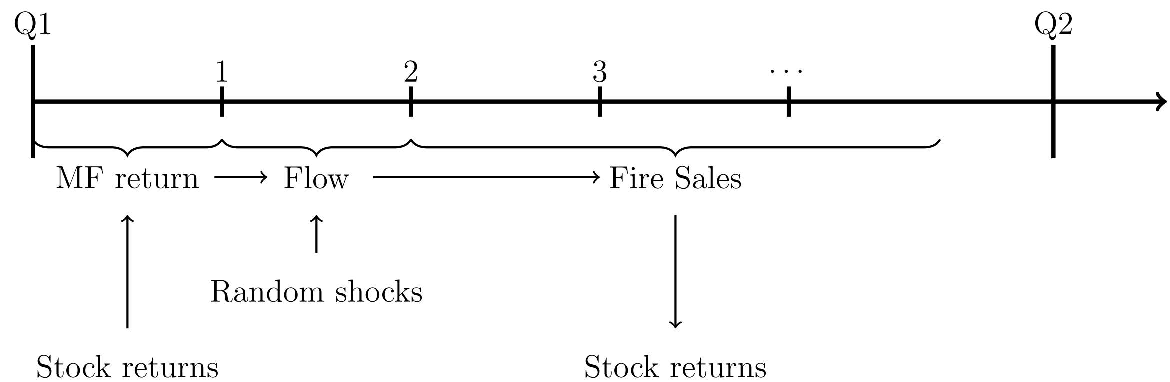
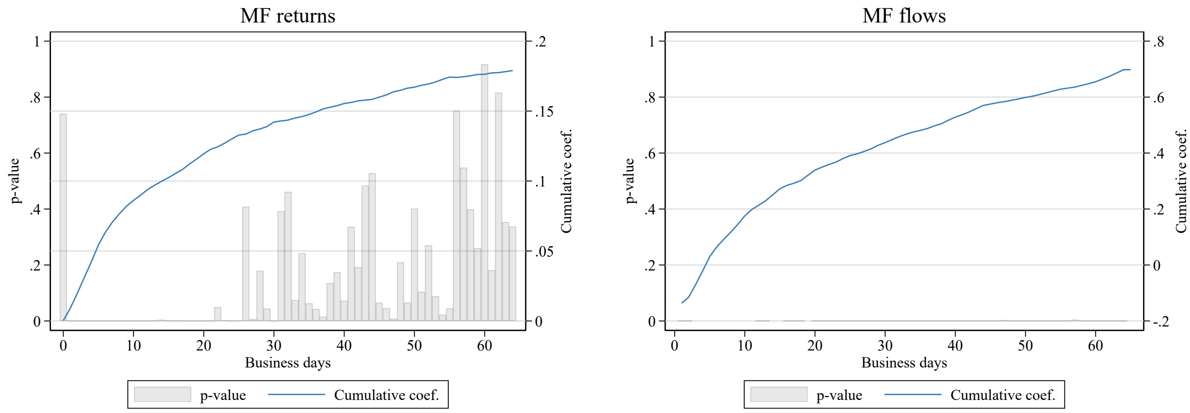


Illustration of the relationship between mutual fund flows and stock returns. I show events along a daily time series. Q1 and Q2 denote the beginning of a quarter. Mutual fund flows force mutual funds to trade which may have price impact. Flows can come from two sources. First, they may be generated 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

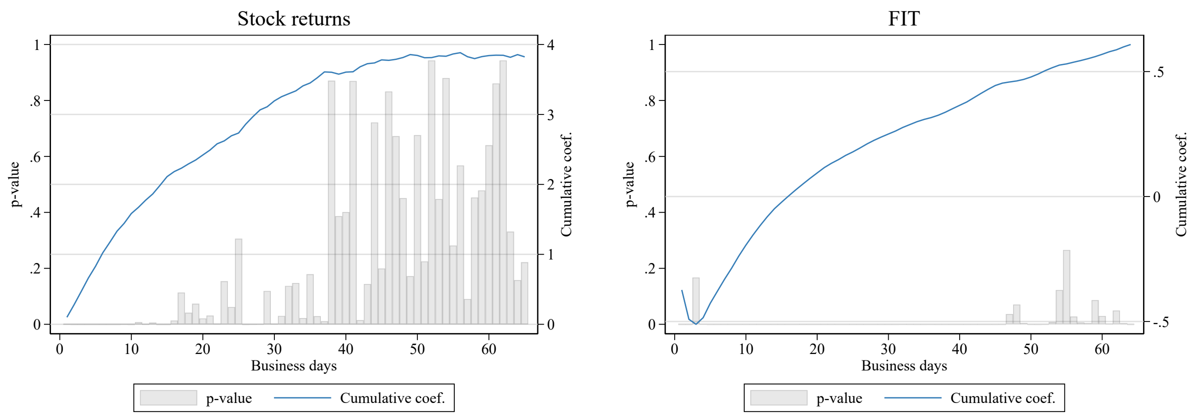


(a) Cum. coef. on lags of MF returns

(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. 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 sample excludes index mutual funds. The number of observations is 5,305,467. The R^2 is 0.0414. The within-R^2 is 0.0387. 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

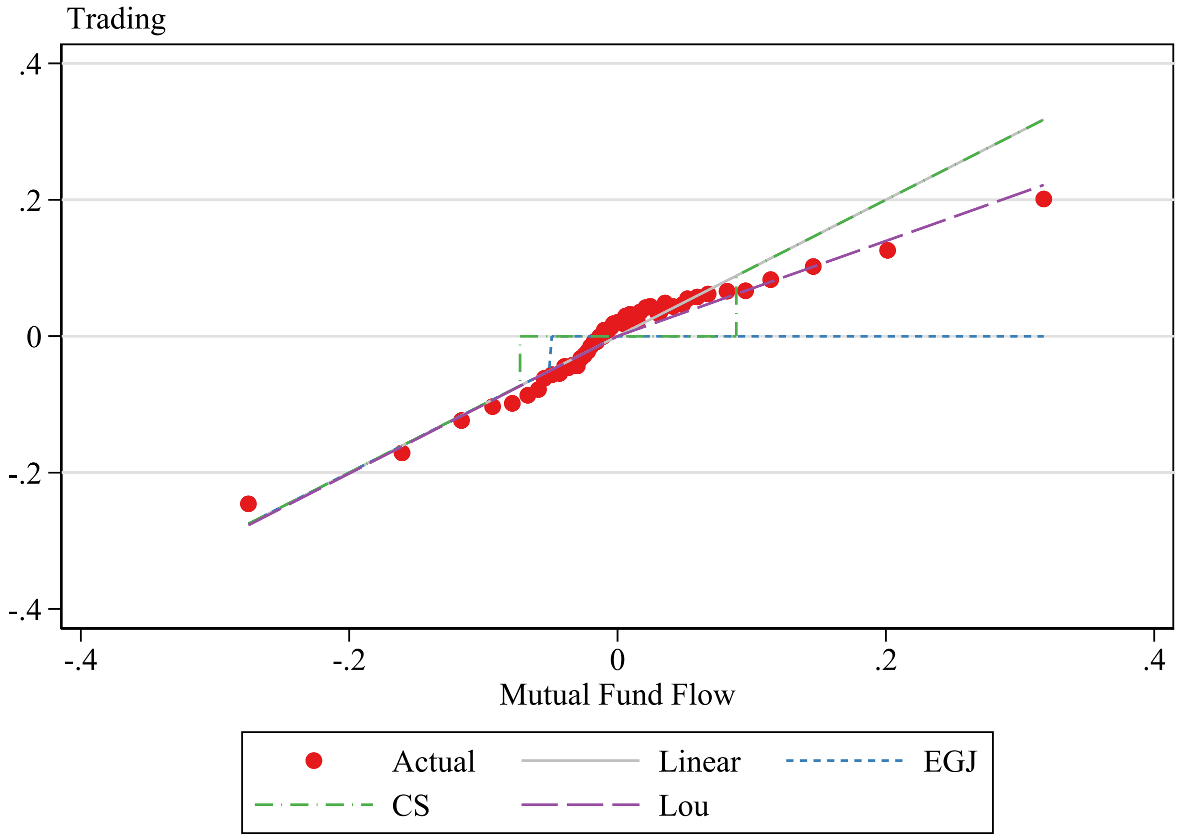


(a) Cum. coef. on lags of stock returns

(b) Cum. coef. on lags of FIT

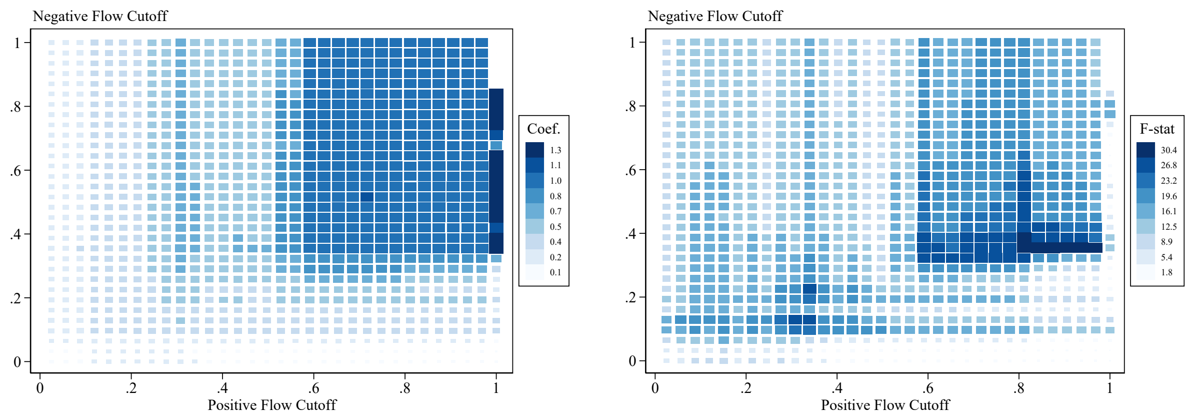
This figure shows the results from a cross-sectional, predictive regression of daily flow-induced trading (FIT) on lags of stock returns and FIT. This is the analogue to the regression in figure 3 at the stock level, rather than the mutual fund level. For ease of interpretation, daily FIT is normalized 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 et al. (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

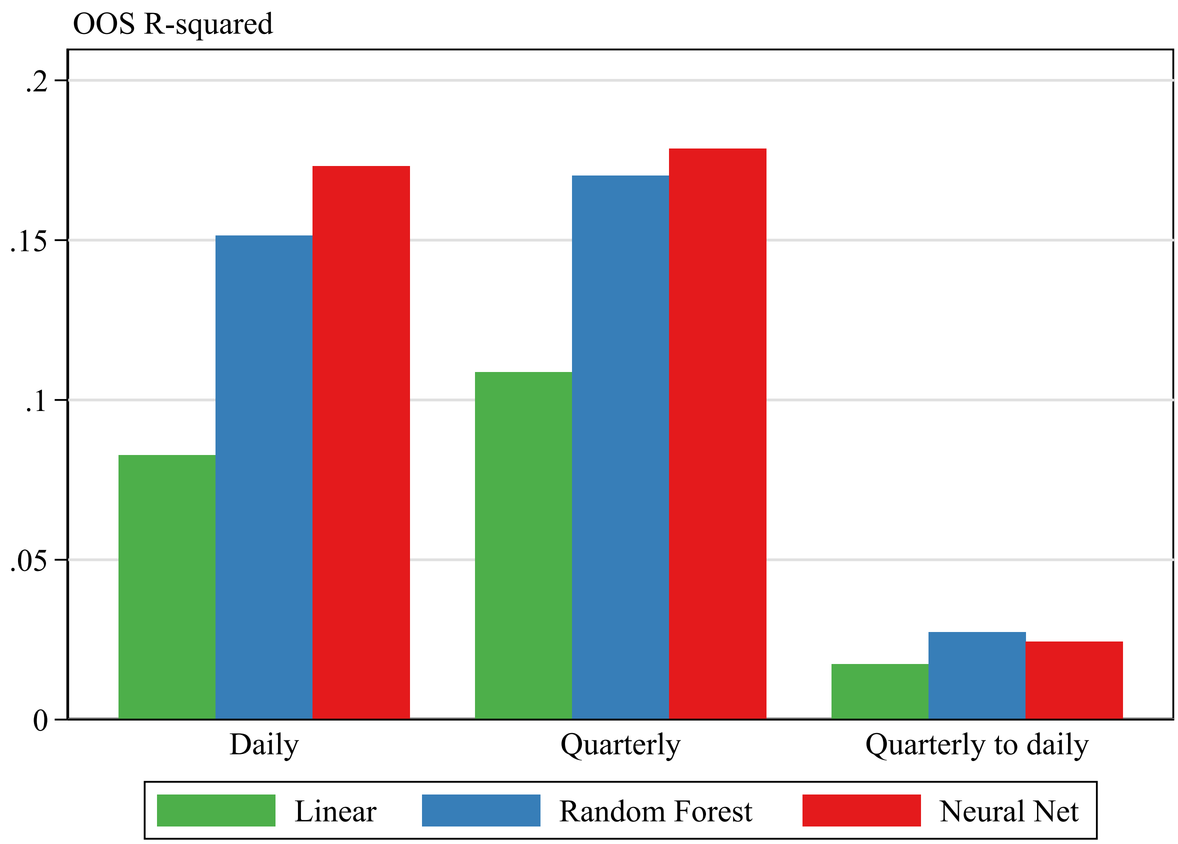


(a) Estimated coefficients

(b) F-statistics

The two heatmaps report coefficient estimates and 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 7. The x-axis gives the positive cutoff, the y-axis gives the negative cutoff; i.e. for each (x,y), I only use extreme surprise flows that are either greater than x or less than -y. For x=1, I drop all positive 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.

Figure 7: Performance of Mutual Fund Flow Prediction Models



This figure shows predictive performance in terms of out-of-sample R-squared for different mutual fund flow prediction models, including elastic net regressions, random forests and neural nets. Hyperparameters are chosen optimally by cross-validation. See the machine learning appendix for details. The first three bars compare performance for the prediction of daily mutual fund flows and the middle bars for the prediction of quarterly flows. The last three bars compare the two approaches, reporting R-squareds for regressions of daily mutual fund flows on the respective quarterly predictions. The sample is 2008 to 2017 because of the availability of 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	3769	3190	113	99	3.1	2.1	221	122
2009	3516	2961	173	156	4.0	2.7	166	121
2010	3408	2862	224	201	4.4	3.0	192	130
2011	3288	2742	216	189	4.2	2.8	199	136
2012	3212	2673	247	210	4.7	3.0	210	125
2013	3260	2707	287	241	5.9	3.8	231	152
2014	3392	2835	286	244	6.3	4.1	230	161
2015	3565	2976	246	205	6.0	3.9	244	164
2016	3547	2958	246	206	6.3	4.2	256	176
2017	2987	2463	278	222	6.7	4.1	234	150

Panel B: 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	2.0	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). The sample is 2008 to 2017 because the daily mutual fund flow data from Morningstar start in 2008. Panel B shows the cross-sectional distribution of mutual fund portfolio characteristics corresponding to a standard 6-factor asset pricing model 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***					
	(0.0351)	(0.0332)					
FIT			0.382***	0.370***			
			(0.0806)	(0.0643)			
SFIT					0.128*	0.103*	0.967***
					(0.0716)	(0.0525)	(0.0132)
Controls	No	Yes	No	Yes	No	Yes	No
F-statistic	71.75	74.83	22.52	33.07	3.212	3.831	5325.0
R-squared	0.196	0.207	0.245	0.247	0.243	0.246	0.925
N	409146	409146	108562	108562	108562	108562	110117

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 * 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	0.382***	0.370***	0.128*	0.103*
	(4.746)	(5.751)	(1.792)	(1.957)
Lou (2012)	0.447***	0.430***	0.114	0.082
	(4.802)	(5.621)	(1.394)	(1.356)
Edmans et al. (2012)	0.516***	0.480***	0.172*	0.120
	(3.996)	(4.340)	(1.796)	(1.590)
Coval, Stafford (2007)	0.421***	0.418***	0.209**	0.196***
	(4.632)	(5.645)	(2.713)	(3.451)
Optimal Flow Cutoffs	0.923***	1.033***	0.812***	0.935***
	(4.743)	(5.400)	(5.306)	(5.992)
Panel B: FIT scaled by shares outstanding				
Flows	2.831***	2.804***	0.156	0.054
	(5.786)	(6.235)	(0.281)	(0.131)
Lou (2012)	2.498***	2.723***	-0.464	-0.335
	(4.704)	(5.561)	(-0.765)	(-0.686)
Edmans et al. (2012)	1.337*	1.900***	-1.078	-0.636
	(1.866)	(3.101)	(-1.324)	(-0.927)
Coval, Stafford (2007)	3.812***	3.763***	1.637**	1.492***
	(5.694)	(6.498)	(2.496)	(3.524)
Optimal Flow Cutoffs	14.356***	15.346***	12.176***	13.446***
	(5.410)	(5.719)	(7.696)	(7.185)

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 et al. (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: Application: the Market Feedback Effect on Investment

	OLS	IV		
	Dep. var.: Investment	FIT(CRSP)	FIT	SFIT
ret	0.0433***	0.0954***	0.103**	0.0167
	(0.00112)	(0.0164)	(0.0440)	(0.0472)
Lagged Log Tobin's Q	0.0233***	0.0238***	0.0171***	0.0174***
	(0.000686)	(0.000728)	(0.00122)	(0.00146)
F-statistic		67.78	32.23	22.28
N	339929	331703	86350	86350

This table shows regressions of the investment rate on returns, lagged Tobin's Q and control variables. In the first column, I show the results of an OLS regression. Column 2 uses the traditional instrument constructed using CRSP data, which is subject to the reverse causality critique. In column 3, I run 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 run the IV regression using the new, optimal, corrected 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 the 6-factor asset pricing model, excluding investment, because investment is the dependent variable. All regressions include firm and time fixed effects. I report standard errors clustered by time in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

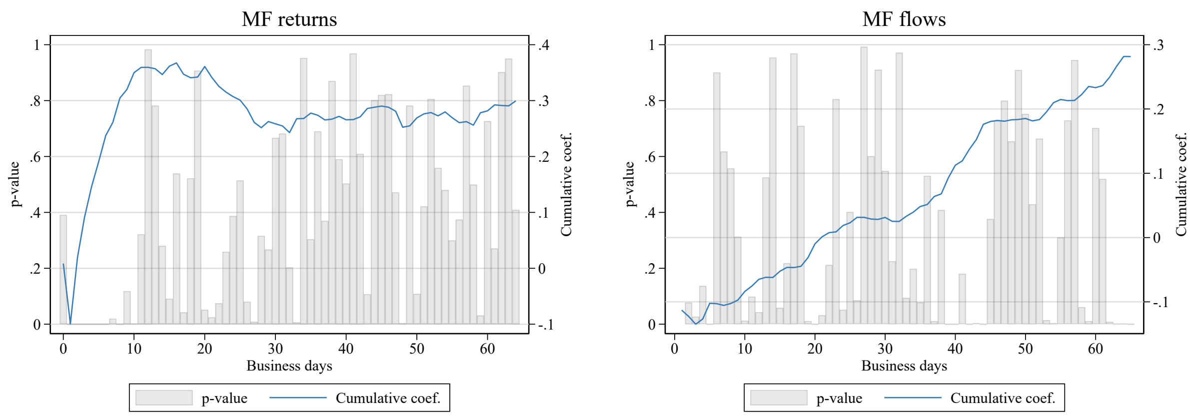
Table 5: Application: Mutual Fund Flow-Based Trading Strategies

	EW					VW				
	$\mathbb{E}r_t$	SR	3F	5F	6F	$\mathbb{E}r_t$	SR	3F	5F	6F
Panel A: Expected flows as in Coval and Stafford (2007)										
Flows	0.02	0.01	0.39	0.43	-0.70	-0.01	-0.00	0.41	0.90	-0.06
			(0.70)	(0.87)	(0.79)			(0.76)	(0.88)	(0.84)
Lou (2012)	-0.03	-0.01	0.40	0.46	-0.71	0.20	0.07	0.73	1.27	0.12
			(0.70)	(0.87)	(0.78)			(0.83)	(1.00)	(0.87)
Edmans et al. (2012)	0.01	0.01	0.22	0.38	0.07	-0.41	-0.24	-0.24	0.06	-0.45
			(0.56)	(0.71)	(0.78)			(0.57)	(0.66)	(0.63)
Coval, Stafford (2007)	-0.01	-0.01	0.32	0.32	-0.73	-0.43	-0.18	0.01	0.56	-0.40
			(0.65)	(0.81)	(0.74)			(0.70)	(0.81)	(0.73)
Optimal Flow Cutoffs	-0.21	-0.11	0.00	0.02	-0.74	-0.52	-0.29	-0.42	0.13	-0.53
			(0.52)	(0.63)	(0.61)			(0.58)	(0.67)	(0.64)
Panel B: Expected flows as in Lou (2012)										
Flows	0.86	0.30	1.16	0.85	-0.82	0.35	0.11	0.63	0.65	-1.25*
			(0.78)	(0.98)	(0.81)			(0.90)	(1.01)	(0.75)
Lou (2012)	0.77	0.27	1.05	0.78	-0.92	0.21	0.06	0.44	0.45	-1.50*
			(0.78)	(0.99)	(0.80)			(0.91)	(1.02)	(0.76)
Edmans et al. (2012)	0.80	0.29	1.11	0.73	-0.79	0.62	0.19	0.79	0.67	-1.15
			(0.75)	(0.98)	(0.84)			(0.92)	(1.12)	(0.82)
Coval, Stafford (2007)	0.09	0.03	0.65	0.29	-0.74	-0.14	-0.04	0.49	0.14	-0.99
			(1.18)	(1.25)	(1.04)			(1.33)	(1.31)	(1.02)
Optimal Flow Cutoffs	0.60	0.22	0.73	1.33	-0.27	0.46	0.19	0.52	1.14	0.03
			(0.86)	(0.88)	(0.78)			(0.80)	(0.79)	(0.72)
Panel C: Expected flows from Neural Net										
Flows	0.24	0.09	0.59	0.26	-1.11	0.01	0.00	0.35	0.81	-0.45
			(0.82)	(0.87)	(0.84)			(0.94)	(1.09)	(1.19)
Lou (2012)	0.23	0.09	0.59	0.36	-0.99	0.04	0.01	0.31	0.79	-0.42
			(0.82)	(0.87)	(0.85)			(0.89)	(0.99)	(1.08)
Edmans et al. (2012)	0.30	0.16	0.57	1.29*	0.80	-0.49	-0.22	-0.16	0.77	-0.07
			(0.64)	(0.67)	(0.76)			(0.77)	(0.74)	(0.83)
Coval, Stafford (2007)	0.26	0.11	0.53	0.53	-0.62	0.33	0.11	0.47	1.04	-0.37
			(0.71)	(0.80)	(0.79)			(0.94)	(1.10)	(1.12)
Optimal Flow Cutoffs	1.07	0.50	1.27*	1.92*	1.29	0.14	0.07	0.22	0.86	0.24
			(0.75)	(1.03)	(1.07)			(0.69)	(0.77)	(0.79)

Performance of implementable, fund flow-based, long-short trading strategies constructed from decile portfolios sorted by different versions of expected flow-induced trading (FIT). I show quarterly mean returns, annualized Sharpe ratios and quarterly 3, 5, 6-factor alphas for equal and value-weighted portfolios. Expected FIT is scaled by shares observed. Holdings data are lagged by one quarter. Expected flows are constructed rolling out-of-sample, and from panel A to C, using the prediction model from Coval and Stafford (2007), Lou (2012) and neural nets. In each panel, I show results for the different mappings of flows into trading. The sample is 1980 to 2017. I report robust standard errors in parentheses. ***, **, 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. 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 665,404. The R^2 is 0.0296. The within-R^2 is 0.0238. The sample is 2008 to 2017 because of the availability of 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	26394751	26394751	26394751	26394751	26394751	26394751

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 $\times$ time in parentheses. The sample is 1980 to 2017. ***, **, and * denote significance at the 1%, 5% and 10% levels.

Table A2: Application: Mutual Fund Flow-Based Trading Strategies
FIT scaled by shares outstanding

	EW					VW				
	$\mathbb{E}r_t$	SR	3F	5F	6F	$\mathbb{E}r_t$	SR	3F	5F	6F
Panel A: Expected flows as in Coval and Stafford (2007)										
Flows	-0.31	-0.14	-0.02	-0.48	-1.50**	-0.28	-0.11	0.35	0.71	-0.25
			(0.62)	(0.79)	(0.70)			(0.72)	(0.84)	(0.81)
Lou (2012)	-0.28	-0.13	0.04	-0.41	-1.48**	-0.39	-0.14	0.19	0.73	-0.31
			(0.64)	(0.80)	(0.70)			(0.77)	(0.89)	(0.85)
Edmans et al. (2012)	0.07	0.04	0.34	0.60	0.26	-0.52	-0.30	-0.25	0.14	-0.37
			(0.55)	(0.69)	(0.74)			(0.57)	(0.65)	(0.64)
Coval, Stafford (2007)	-0.11	-0.05	0.23	0.24	-0.84	0.00	0.00	0.54	1.12	0.08
			(0.58)	(0.74)	(0.65)			(0.69)	(0.83)	(0.72)
Optimal Flow Cutoffs	-0.16	-0.09	0.06	0.16	-0.57	-0.46	-0.26	-0.30	0.27	-0.36
			(0.51)	(0.63)	(0.63)			(0.54)	(0.61)	(0.59)
Panel B: Expected flows as in Lou (2012)										
Flows	0.38	0.16	0.55	0.32	-1.16*	0.52	0.19	0.66	0.81	-0.70
			(0.65)	(0.77)	(0.60)			(0.74)	(0.83)	(0.62)
Lou (2012)	0.39	0.16	0.54	0.33	-1.13*	0.57	0.22	0.75	0.89	-0.53
			(0.65)	(0.77)	(0.60)			(0.72)	(0.81)	(0.62)
Edmans et al. (2012)	1.06	0.44	1.44**	1.51*	0.27	0.99	0.33	1.36	1.50	0.16
			(0.67)	(0.85)	(0.76)			(0.89)	(1.17)	(0.83)
Coval, Stafford (2007)	-0.42	-0.14	0.02	-0.25	-1.16	-0.68	-0.22	-0.32	-0.26	-1.08
			(1.01)	(1.05)	(0.85)			(1.05)	(1.06)	(0.90)
Optimal Flow Cutoffs	0.47	0.17	0.62	1.21	-0.38	0.31	0.13	0.37	0.93	-0.10
			(0.85)	(0.86)	(0.79)			(0.80)	(0.81)	(0.76)
Panel C: Expected flows from Neural Net										
Flows	-0.08	-0.04	0.37	0.29	-0.99	0.61	0.23	0.86	1.48	0.41
			(0.71)	(0.77)	(0.68)			(0.83)	(0.93)	(0.93)
Lou (2012)	0.06	0.03	0.49	0.56	-0.65	0.50	0.19	0.81	1.47	0.40
			(0.70)	(0.75)	(0.69)			(0.84)	(0.92)	(0.93)
Edmans et al. (2012)	0.26	0.14	0.53	1.33*	0.87	-0.04	-0.02	0.15	1.00	0.45
			(0.65)	(0.68)	(0.77)			(0.73)	(0.70)	(0.78)
Coval, Stafford (2007)	0.16	0.08	0.47	0.58	-0.50	0.50	0.19	0.61	1.34	0.28
			(0.68)	(0.73)	(0.72)			(0.83)	(0.93)	(0.91)
Optimal Flow Cutoffs	0.95	0.44	1.10	1.77*	1.14	-0.07	-0.03	0.07	0.76	0.03
			(0.75)	(1.03)	(1.07)			(0.72)	(0.81)	(0.82)

Performance of implementable, fund flow-based, long-short trading strategies constructed from decile portfolios sorted by different versions of expected flow-induced trading (FIT). I show quarterly mean returns, annualized Sharpe ratios and quarterly 3, 5, 6-factor alphas for equal and value-weighted portfolios. Expected FIT is scaled by shares outstanding. Holdings data are lagged by one quarter. Expected flows are constructed rolling out-of-sample, and from panel A to C, using the prediction model from Coval and Stafford (2007), Lou (2012) and neural nets. In each panel, I show results for the different mappings of flows into trading. The sample is 1980 to 2017. I report robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

C Machine Learning Details

I use machine learning techniques to predict mutual fund flows. Here, I describe the selected prediction models and training scheme. I implement the prediction exercises using tensorflow and scikit-learn (Martin Abadi et al., 2015; Pedregosa et al., 2011). At each point in time, a trader could only have used past information. Hence, to prevent look-ahead bias, I adopt a recursive training, validation and testing scheme. To construct $t+1$ expected values, I train models using data from time 0 to t. I choose hyperparameters using 3-fold cross-validation, except for when training neural nets. To save computing resources, I use simple validation when choosing neural net hyperparameters. In the training step, I randomly sample 50 sets of hyperparameters from a large grid and train one model for each set. The validation step then selects the model that performs best on validation data. Finally, I report performance for the out-of-sample test on $t+1$ data. I retrain annually.

For each task, I compare the performance of three types of models. First, I use a simple penalized regression, an elastic net, as a benchmark. I sample penalization rates of 2^N for $N \sim U(-10, 10)$, a uniform distribution. I sample the mixing parameter from $N \sim U(0, 1)$. The second model is a random forest. Constrained by computational resources, I use 250 trees in a forest. I sample from a maximum depth of 1 to 50, a minimum fraction of observations per leaf of 2^{-N} for $N \sim U(5, 20)$ and a fraction of features to consider from $U(0.05, 0.5)$. Lastly, I use neural nets with L fully connected layers and H hidden neurons each and minimize a MSE loss function. I sample L from 1 to 5, H is 2^N with N sampled from 3 to 8. I use the Adam optimizer (Kingma and Ba, 2017) with a learning rate of 2^{-N} with N sampled from 7 to 14, a dropout rate (Srivastava et al., 2014) from $U(0, 0.5)$, an L1 penalization rate on all parameters of 0 or 10^{-N} with N sampled from 1 to 10, the same for an L2 penalty, a batch size of 2^N with N sampled from 6 to 12, a patience from 0 to 10 (I use early stopping) and an activation function of either ReLU or ELU. Unmentioned hyperparameters are scikit-learn or tensorflow defaults.

In the quarterly mutual fund flow prediction exercise, the predictors are past quarterly flows and excess returns for the past 3 years. Excess returns mean cross-sectionally demeaned returns. In the daily mutual fund flow prediction exercise, the predictors are past daily flows and daily excess returns for the past quarter and monthly flows and monthly excess returns from one quarter ago to 3 years ago. In both exercises, I also include market returns of analogous frequencies, an index fund dummy and dummies for the 9 Morningstar styles (a three by three matrix assigning a size and a value characteristic to a mutual fund). I also include cross-sectionally normalized (and hence stationary) fund size. All predictor variables are normalized using in-sample statistics.