Asset Fire Sales or Assets on Fire?

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Abstract

Using high frequency data and machine learning methods, I propose a new method to isolate a plausibly exogenous component of mutual fund flows and use it as an instrument to revisit classic empirical questions in Finance because previous methods are vulnerable to a reverse causality critique.

The idea that mutual fund flows induce fire sales which drive asset prices away from fundamentals has been fruitful. Based on this idea the Asset Pricing literature finds markets are inefficient and fragile and the Corporate Finance literature shows market misvaluation distorts real outcomes. First, I argue these findings are partially driven by reverse causality. Assets on fire reduce mutual fund returns which trigger outflows. Empirically, this becomes apparent when increasing the frequency of the standard event study from quarterly to daily; returns precede flows. Second, I suggest a solution. In contrast to quarterly flows, an instrument constructed from daily surprise flows is exogenous to fundamentals. Also, this instrument can be strengthened by training machine learning models to predict how mutual funds trade in response to flows. Third, I use surprise flows to reevaluate important findings in the literature. Overall, while I confirm most findings qualitatively, the new estimates imply that equity markets are more efficient, less fragile and less distortive than suggested.

Keywords: Mutual Fund Flows; Fire Sales; Market Feedback Effects; Return Predictability; Trading Predictability; Machine Learning; Neural Nets

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1 Introduction

Coval and Stafford [2007] find mutual fund flow induced fire sales can move asset prices far away from fundamentals for a long time. Since this seminal idea, mutual fund flow demand shocks have been widely used in Asset Pricing and Corporate Finance.

The Asset Pricing literature finds markets are inefficient and fragile. Flow induced fire sales have large price impact; this price impact takes two years to reverse suggesting that arbitrage capital is very slow-moving; flow-based trading strategies generate sizeable alpha and mutual fund flows explain returns of stocks, factors and asset classes as well as return volatility and comovement [Coval and Stafford, 2007, Duffie, 2010, Lou, 2012, Lee and So, 2017, Li, 2019, Ben-Rephael et al., 2012, Greenwood and Thesmar, 2011, Anton and Polk, 2014].

The Corporate Finance literature instruments stock returns with mutual fund flows to show that market misvaluation distorts real outcomes. If flow-induced fire sales drive asset prices away from fundamentals, this allows researchers to study the direct market feedback effect of asset prices on real outcomes. The literature finds that undervaluation triggers takeovers and reduces investment [Edmans et al., 2012, Derrien et al., 2013, Phillips and Zhdanov, 2013, Norli et al., 2014, Bonaime et al., 2018, Eckbo et al., 2018, Lou and Wang, 2018, Dessaint et al., 2018, Khan et al., 2012].

In this paper I show that these results are partially driven by reverse causality, suggest a solution and use the new instrument to revisit classic empirical questions in Finance.

First, I show that the regression of stock returns on flow-induced trading suffers from an economic reverse causality problem. Instead of mutual fund outflows inducing fire sales which drive down prices, assets on fire reduce mutual fund returns which trigger outflows. Empirically, the literature typically shows the quarterly event study depicted in figure 1 at the top. In the event quarter, i.e. when the mutual funds that hold a stock receive extreme outflows, stock prices crash followed by a slow recovery. But increasing the frequency of the event study to daily in the bottom graph, stock prices crash before the event; returns precede flows. Similarly, daily stock returns strongly granger cause daily flow induced trading in calendar, instead of event time. Also, the reverse causality problem explains finer patterns observed in the standard quarterly event study. There is a small pre-event trend. And cumulative abnormal returns are convex during the event quarter because returns at the beginning of a quarter have more time to trigger flows.

Next, I suggest a solution. The source of the reverse causality problem is the dependence of quarterly mutual fund flows on mutual fund returns within the same quarter. To solve this, I construct daily surprise flows that are orthogonal to past and contemporaneous mutual fund returns. I then construct the instrument from daily surprise flows. This implies that I only attribute stock returns that occur after mutual fund flows to the demand shock. Hence, the only threat to identification are omitted variables that trigger flows today and returns tomorrow, a much weaker concern because it violates market efficiency. Of course, an alternative approach is to use events such as the 2003 mutual fund trading scandal as in Anton and Polk [2014]. However, that confines the analysis to 2003. When constructing the instrument the researcher maps flows into trading. However, he cannot use the actual trading of the fund because trading is endogenous. Hence, he has to choose a mechanical mapping of flows into trading. The Corporate Finance literature typically assumes mutual funds scale their whole portfolio proportionally. This corresponds to keeping portfolio weights constant. For the first surprise flow instrument I suggest, I assume the same. But in practice, we know that mutual fund liquidations are nonlinear, heterogeneous and depend on stock characteristics. For example, mutual funds preferentially liquidate liquid assets [Lou, 2012, Berger, 2019]. Hence, I train neural networks to predict how flows map into trading allowing for arbitrary nonlinearity, heterogeneity across mutual funds and interactions with characteristics. The resulting instrument is stronger because it captures the resulting demand shock more precisely.

Lastly, I reevaluate important findings in the literature. Using the new instrument, the price impact of mutual fund fire sales is about a third the previous estimate, but still economically and statistically significant. The new estimate implies a demand elasticity of 3 instead of 1. This means I qualitatively confirm that mutual fund flow induced fire sales have price impact, but find that equity markets are deeper than suggested.

I also reevaluate the standard market feedback regression of investment on returns instrumented with flow induced trading. IV regressions using the old instruments suggest strong market feedback effects. Using the new instrument, I only find weak evidence for market feedback effects. While this does not suggest the absence of market feedback effects, it does suggest that equity markets are less distortive than suggested.

Finally, if the price impact of fire sales in equity markets is not as large, why do simple flow-based trading strategies generate sizable alpha? I show that they do not. Most flow-based trading strategies fail to generate alpha once constructed out-of sample. The remaining strategies construct expected flows using only one predictor, 12-month fund alpha, as in Lou [2012]. But that means these strategies are analytically identical to copycatting strategies, they simply buy stocks held by winner mutual funds and sell stocks held by loser funds. Together, that means markets are more efficient than suggested - it is difficult to beat the market by exploiting the predictability of mutual fund flows.

However, a new, sophisticated, out-of-sample, flow-based trading strategy is profitable.

It is constructed in two steps. First, I train neural nets to predict mutual fund flows. Second, just as in the construction of the machine learning enhanced instrument, I train neural nets to predict trading. The new strategy generates an annual alpha of 10%. Hence, I confirm that the predictability of mutual fund flows is exploitable.

Not all papers that use flow induced fire sales are affected in the same way. Many provide additional, unaffected evidence. Hence, the reverse causality problem only means the particular evidence involving fund flows has to be reevaluated. A good example is Anton and Polk [2014] who also show unaffected evidence from the 2003 mutual fund flow scandal. Broadly, the Corporate Finance literature uses flows very uniformly, closely following Edmans et al. [2012]. The Asset Pricing literature uses 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 of mutual funds that hold both stocks. Note that the reverse causality problem still applies in higher moments. Volatile stock returns imply volatile mutual fund returns which cause volatile flows. And when two stocks crash, funds who hold both stocks suffer bad returns and outflows. In addition, both papers lag the explanatory flow variable. But this does not eliminate the concern because higher moments of returns are persistent.

This paper is related to Berger [2019]. She finds the instrument as constructed in the Corporate Finance literature implies unbalanced treatment and control groups, suggestive of selection bias. To solve this problem she suggests to test for market feedback effects in a homogeneous subsample. While this improves the test, it neither demonstrates nor solves the reverse causality problem. Also, Wardlaw [2018] documents a mechanical problem in the standard Corporate Finance construction of the instrument. The usual instrument implicitly contains the lagged stock price in the numerator (dollar portfolio position) and the stock price in the denominator (dollar trading volume). This means the instrument for returns mechanically contains returns. He finds that removing the offending term makes the instrument weak. Only Corporate Finance, not Asset Pricing, is subject to this critique, because Asset Pricing does not typically scale the demand shock by dollar trading volume. This paper starts off where Wardlaw [2018] concludes. First, I show that the corrected instrument is strong when eliminating an arbitrary restriction. When constructing the instrument, the Corporate Finance literature ignores mutual fund flows greater than -5% to focus on the flows that are most likely to result in fire sales. Dropping this restriction makes the instrument strong. Then, I address the economic reverse causality problem. This problem applies to both, Corporate Finance and Asset Pricing. Finally, I suggests a new instrument and use it in Corporate Finance and Asset Pricing applications.

2 Empirical Strategy

I illustrate the environment in figure 2. Stock returns form mutual fund returns. Mutual fund returns 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 flows and returns over the quarter hides their temporal ordering. Quarterly flows and returns happen contemporaneously, no matter which happens first at the daily frequency. Hence, the impact of flow induced trading on stock prices can not be inferred from the contemporaneous, quarterly correlation.

2.1 The Mutual Fund Flow Instrument - Problem and Solution

There are N firms, indexed by n. Stocks are held by I investors, indexed by i. I denote the time in days as t and the time in quarters as 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. In Asset Pricing, this is the price impact of fire sales. In Corporate Finance, this is the first stage in an instrumental variable regression of a corporate outcome on stock returns that tests for market feedback effects.

2.1.1 The Demand Shock - Mutual Fund Flow Induced Trading

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. They force funds to adjust the asset side. This generates the demand shock

$$F\tilde{I}T_q(n) = \frac{\sum_{i=1}^{I} \Delta Shares_{i,q}(n)}{SharesOutstanding_{q-1}(n)}. \quad (1)$$

The numerator is the net amount of shares mutual funds buy or sell. The measure is scaled by shares outstanding to make it a relative demand shock; so its price impact should be its product with the inverse demand elasticity. However, starting with Edmans et al. [2012] the literature recognizes that actual trades, $\Delta Shares_{i,q}(n)$, are endogenous. Hence, they construct hypothetical flow induced trading

$$FIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n) g(flow_{i,q})}{SharesOutstanding_{q-1}(n)}, \tag{2}$$

where $\frac{\Delta Shares_{i,q}(n)}{Shares_{i,q-1}(n)} = g(flow_{i,q}) + v_{i,q}(n)$. If funds keep portfolio weights constant, $g()$ is simply the identity. This is the state-of-the-art instrument for returns in the Corporate Finance literature after taking into account the Wardlaw [2018] critique and dropping the restriction to ignore flows greater than -5%. This is the central object in this paper.

I now change the frequency from quarterly to daily, because mutual funds compute and publish their net asset value once a day, after markets close. Retail orders also settle at that price. That means retail investors make trading decisions daily and use daily mutual fund returns $MFret_{i,t}$ to inform that decision.

2.1.2 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. Apart from that, it is a well known empirical fact 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 to update their beliefs about the ability of the mutual fund manager. I write this as

$$flow_{i,t} = \eta_t + \sum_{l=0}^{L} [\alpha_l MFret_{i,t-l}] + u_{i,t}, \tag{3}$$

where I also allow for macro shocks to flows. Next, the mutual fund return is simply the portfolio weight weighted mean of stock returns.

$$MFret_{i,t} = \sum_{n=1}^{N} w_{i,t}(n) r_t(n). \tag{4}$$

And stock returns follow a linear asset pricing model. They are driven by factor returns, f, and idiosyncratic shocks.

$$r_t(n) = \beta(n)' f_t + \epsilon_t(n). \tag{5}$$

Now, substituting equations 4 and 5 into equation 3, I decompose mutual fund flows

$$\begin{aligned}
flow_{i,t} &= \eta_t && (6)\\
&+ \sum_{l=0}^{L}[\alpha_l w_{i,t-l}(n) r_{t-l}(n)] && \text{Reverse Causality}\\
&+ \sum_{l=0}^{L}[\alpha_l \sum_{m\neq n} w_{i,t-l}(m)\beta(m)' f_{t-l}] && \text{Endogeneity}\\
&+ \sum_{l=0}^{L}[\alpha_l \sum_{m\neq n} w_{i,t-l}(m)\epsilon_{i,t-l}] && \text{IV: Shocks to other stocks}\\
&+ u_{i,t}. && \text{IV: Surprise flows}
\end{aligned}$$

This shows the problem in the regression of quarterly stock returns on quarterly flow induced trading. $FIT_q(n)$ depends on the daily flows $flow_{i,t}$ that fall into quarter q; and the first term above contains daily stock returns that fall into quarter q. That means the instrument for returns depends on returns, a reverse causality problem. Yet, if there is no within-quarter return chasing, $\alpha_l = 0$, the critique does not apply. But I show that empirically, $\alpha_l > 0$.

Also, if portfolio weights are small, this direct dependence is weak. However, that does not mean that constructing the instrument excluding concentrated mutual funds solves the problem. This is 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. So 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.

Terms three and four are exogenous to firm fundamentals and can be used to construct demand shocks. Term three contains flows that were triggered by mutual fund returns that stem from idiosyncratic returns of other stocks in the portfolio. Say a fund receives outflows because it had bad returns because GM's factory in China burned down. 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 the new instrument I propose.

Term four contains surprise flows; the part of flows that is orthogonal to past and contemporaneous mutual fund returns which I interpret as 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 threat to identification are omitted variables that trigger flows today and returns tomorrow, a much weaker concern because it violates market efficiency. Precisely, I aggregate daily surprise flows to quarterly surprise flows and substitute flows with surprise flows in the construction of the instrument

$$SFIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n) g(surpriseflow_{i,q})}{SharesOutstanding_{q-1}(n)}, \tag{7}$$

surprise flow induced trading. I start with using the identity for $g()$ and then extend my analysis to more flexible mappings. In practice, I obtain daily surprise flows as the residuals of a regression of daily mutual fund flows on contemporaneous and lagged mutual fund returns and lagged mutual fund flows. I also include time fixed effects. This is the high frequency analogue to the standard flow predictive regression as e.g. in Coval and Stafford [2007]. I include 65 lags, corresponding to the maximum number of business days in a quarter.

2.2 Prediction Models

This paper involves two prediction tasks. Predicting trading to construct the instrument and a trading strategy and predicting flows to construct the strategy. The literature restricts these prediction tasks to simple regression models. In this paper, I will also explore more powerful prediction models. Here, I describe the machine learning architecture and training scheme I use.

2.2.1 Machine Learning Architecture

I choose neural networks because of their universal function approximator property Hornik [1991]. I visualize the computational graph in figure 8. It takes two types of inputs. First, predictor variables that feed directly into the neural network. Second, an ID that identifies the fund. This is a categorical variable, so I cannot feed it into the model directly. However, say each institution has a latent K-dimensional type. Then, I map each ID into a K-dimensional vector which I can feed into the network. The institution type is latent. Hence, I find its elements during training. This is an embedding, the state-of-the-art method to treat words in natural language processing. The two types of inputs then feed into a standard feed-forward neural network. The output is the prediction for trading or flows.

The neural net architecture loosely follows Gu et al. [2018]. I use $L \in \{1, 2, 3\}$ fully connected hidden layers. Each layer contains 32 neurons. The hidden layers use the ELU activation function. The output layer uses the identity. Note that the particular functional form of the neural network is unimportant. The only reason to choose it is that it can approximate any continuous, smooth function of its inputs [Hornik, 1991].

2.2.2 Training and Regularization

I train the model by minimizing a loss function over the network parameters and latent institution types. Neural networks contain many trainable parameters creating the danger of overfitting. To combat overfitting, the machine learning literature developed several regularization techniques. Here, I use five techniques that are current best practice. I minimize the MSE using stochastic gradient descent (SGD) using the Adam optimizer [Kingma and Ba, 2017]. I use Batch Normalization layers before and dropout layers after the activation functions [Srivastava et al., 2014]. I use Early Stopping, L2 penalization and ensemble many trained neural nets. For all implementation details, see the appendix.

2.2.3 Training, Validation and Testing

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 my predictor at time t, I use data from time 0 to t and split them into a training and a validation sample by randomly splitting the list of dates until t into an 80% and a 20% list. This allows me to train the model on the most recent information, while validating using data from different time periods. I then use the model to make predictions for the testing period. The process has three steps. First, I train 15 different model architectures, one for each combination of network depth and L2 penalization rate. In the second step, I select the five architectures that achieve the lowest validation mean squared error for my ensemble. Third, I use the selected ensemble to make predictions in the next time period, the testing data.

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 at the daily frequency starting in July 2008. This dictates the sample length. When an excercise requires high frequency Morningstar data, the sample is July 2008 to December 2017. Whenever it does not, I use the standard sample January 1980 to December 2017. I restrict the sample to mutual funds (i.e. I drop ETFs and ETNs) that are in the MFLinks database. These are the funds that I can match with CRSP mutual fund characteristics and Thomson Reuters portfolios. I merge Morningstar and MFLinks using the share class cusip. Then, I collapse the data from the share class to the portfolio level by taking size weighted means where necessary. This leaves about 5500 mutual funds in the last cross-section. Out of these, I can match 4500 to Morningstar data. With ten years of daily data, this gives about ten million observations. For comparison with the literature, I also construct quarterly mutual flows and returns from CRSP. I also take mutual fund characteristics from CRSP, e.g. an index fund indicator.

3.2 Portfolio Holdings Data

The Thomson Reuters Mutual Fund Holdings database provides fund level portfolios. The sources for this database are SEC mandated disclosures in Forms N-30D, N-Q and N-CSR and voluntary disclosures. I merge the Thomson Reuters Mutual Fund data with CRSP Mutual Fund data using MFLinks. Holdings data are available from 1980 Q1 to 2017 Q4 at a quarterly frequency. Mutual fund and portfolio holdings data together allow me to construct the key object in this paper, flow induced trading

$$FIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n) flow_{i,q}}{SharesOutstanding_{q-1}(n)}. \tag{8}$$

This is the same as equation 2 using the identity to map flows into trading as a baseline. The Corporate Finance literature drops flows greater than -5%, i.e. 80% of all observations, in the construction of this instrument, arguing that these are the flows that are most likely to force trading. I eliminate this restriction because the value of -5% is arbitrary. Also, since the Wardlaw [2018] critique, the cutoff makes the instrument weak. In figure 3, I report the F-statistic of the regression of stock returns on the instrument for each possible cutoff value for flows. I include time fixed effects and cluster standard errors by time. The vertical line designates the cutoff used in the literature. Since the Wardlaw [2018] critique and using the -5% cutoff, the instrument is weak. However, this is due to the cutoff. Figure 3 shows that removing the cutoff makes the instrument strong, with an F-statistic over 100.

3.3 Stock Data

Stock data are from CRSP, accounting data are from Compustat North America Fundamentals Annual and Quarterly. The stock characteristics of interest correspond to a five-factor asset pricing model plus momentum [Fama and French, 2015]. I use these 6 characteristics, beta, log market equity, log Tobin's Q, profitability, investment and momentum as the standard control variables. In most regressions, I also include time fixed effects and cluster standard errors by time. 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% level as in Green et al. [2017]. I restrict the sample to US ordinary common stocks that trade on the NYSE, AMEX and Nasdaq and have non-missing price and accounting data.

3.4 Summary Statistics

Figure 4 shows summary statistics. In the top left graph, I plot total mutual fund AuM over time for the CRSP and the Morningstar sample. At the end of the sample, CRSP data cover 12 trillion USD in mutual fund AuM. By construction, the Morningstar data are a strict subsample. At any point, it covers about 80% of AuM. In the top right graph, I show the sum of absolute dollar mutual fund flows over time. On average, retail investors reallocate 400 billion dollars in assets per quarter. This results in sizable shocks. The bottom graphs show the distribution of the daily and the quarterly demand shock. Demand shocks are centered around zero. A large quarterly demand shock is 1%; a large daily demand shock is 0.1% of shares outstanding. The shocks are smaller here than in previous papers, because they are scaled by shares outstanding, as suggested in Wardlaw [2018]. Previous papers typically use trading volume or shares held in the holdings data sample [Coval and Stafford, 2007, Edmans et al., 2012].

4 Results

4.1 Mutual Fund Returns and Flows

Equation 7 shows that the standard Corporate Finance and Asset Pricing 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 of which is an empirical fact [Koijen and Yogo, 2018]). Figure 5 shows that investors do indeed chase daily returns. It shows the results from a regression of daily mutual fund flows on lags of daily mutual fund returns and itself. I include time fixed effects and cluster standard errors by time. I include up to 66 lags, the maximum number of business days in a quarter. The regression corresponds to equation 3. 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 manger'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 the appendix. I plot cumulative coefficients in blue and display the p-values of each coefficient in grey bars.

On the left, I show the cumulative coefficient on past mutual fund returns. The cumulative coefficient reaches 0.13. This means a 10% mutual fund return triggers a 1.3% mutual fund flow over the next quarter. For the first 40 lags, most coefficients are highly statistically significant. After that, the coefficient estimates remain positive but are less precisely estimated. The coefficient on the contemporaneous mutual fund return is insignificant with a p-value of 0.6. This is because retail investors only observe the contemporaneous return after markets close and can only react to it on the next day.

On the right, I show the cumulative coefficient on past mutual fund flows. Flows are highly autocorrelated. A 10% flow today translates to a 7% flow over the next quarter. All estimated coefficients are highly statistically significant. Overall, this exercise shows that retail investors engage in high-frequency return chasing meaning the reverse causality problem applies.

4.2 Stock Returns and Flow Induced Trading

4.2.1 In Event Time

The success of mutual fund flow induced trading as a shock to stock returns is largely tied to one graph; an event study around flow induced fire sale events. In Corporate Finance, prominent examples that show a version of the graph include Edmans et al. [2012], Khan et al. [2012] and Dessaint et al. [2018]. In Asset Pricing, prominent examples include Coval and Stafford [2007], Duffie [2010], Lou [2012] and Jotikasthira et al. [2012]. I show a replication of the graph from Edmans et al. [2012] at the top of figure 1. The definition of the event is that FIT falls into the bottom decile of the full sample distribution. Edmans et al. [2012] 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 first, there is no significant pre-event trend; second, prices crash by about 5% during the event quarter; third, prices recover from the fire sale over the following two years. Together, this is taken as evidence that mutual fund flow induced fire sales drive asset prices away from fundamentals.

But one quarter is a long time in financial markets. At the bottom, I show the result of an event study at the daily level. I show two weeks before and after the event. Now, prices crash before the event. In fact, exactly with the onset of the event, the price collapse stops. This is evidence for the reverse causality problem. Stock returns cause flows. 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 elasticities are similar.

The reverse causality problem can explain several nuances in the popular graph at the top. 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. This is because stock returns on the first days of a quarter have more time to trigger flows than stock returns during the end of the quarter. If the causality ran from flows to returns, we would expect the opposite. Stock returns on the first days can only be driven down by flows from these first days. Stock returns during the end of the quarter follow many days of extreme flows. Finally, the price reversal does not stop at a CAAR of 0. As pointed out by Wardlaw [2018], the recovery is mostly a relic of the construction of abnormal returns. The sample of stocks held by mutual funds has higher average returns than the CRSP equal weighted return and event stocks have size, value and momentum exposure.

4.2.2 In Calendar Time

The literature typically analyzes the impact of flow induced trading in event time. However, it is simpler to run the analysis in calendar time. In figure 6, I show the results of a regression of FIT on lags of stock returns and itself. It is the analogue to the regression in figure 5 at the stock, instead of the mutual fund level. Looking at the graph on the left, the cumulative coefficient on stock returns is positive and highly statistically significant for the first ten lags. For ease of interpretation, I normalize daily FIT in the cross-section. The cumulative coefficient reaches 3. That means a 10% stock return predicts an additional 0.3 standard deviations of FIT over the next quarter. Stock returns predict the instrument. This finding corresponds to the daily event study. Stock returns precede flows suggesting that stock returns cause flows. Looking at the graph on the right, FIT is autocorrelated. This comes with no surprise because as documented earlier, flows are autocorrelated.

4.3 The New Instrument - Surprise Flow Induced Trading

The decomposition of mutual fund flows in equation 7 shows that flows depend on stock returns, making the traditional instrument invalid. However, surprise flows do not, allowing the construction of a valid instrument. I construct daily surprise flows as the residuals from the regression depicted in figure 6 that I discuss above. Daily surprise flows are orthogonal to past and contemporaneous returns by construction. This means the only threat to identification here are omitted variables that trigger flows today and returns tomorrow, a much weaker concern because it violates market efficiency.

4.3.1 The Mapping of Mutual Fund Flows into Trading

To construct FIT, I need to map mutual fund flows into trading. For the first new instrument, I simply use the identity. However, this is not a good mapping empirically. In figure 7, I plot how mutual funds actually trade in response to flows. In red, I show mean trading, the relative change in shares held, for 20 mutual fund flow bins. Mean trading falls below the 45 degree line. This is because mutual funds initiate new positions. It is also highly nonlinear. So far, the literature has not used this fact. To illustrate this, I plot four mappings that have been used in the literature. A basic approach is to use the identity. This assumes mutual funds keep portfolio weights constant in response to flows. This corresponds to the grey 45 degree line. The Corporate Finance literature makes this choice, except it discards flows greate than -5%. This is depicted in blue. Finally, I also show the mappings used in Coval and Stafford [2007] and Lou [2012]. Overall, none of these approaches are close to the observed relationship between flows and trading.

In addition, we know that trading depends on other variables. For example, mutual funds preferentially liquidate liquid assets when they receive large flows [Lou, 2012, Berger, 2019]. I illustrate this on the right side of figure 7. Again, I show mean trading for 20 flow bins, but now I separate liquid from illiquid stocks as defined by belonging to the top or bottom size decile portfolio. In response to large flows, funds preferentially trade liquid assets. For example, in response to a 25% inflow, funds increase liquid positions by almost 20% and illiquid positions by only 10%. Liquidity is not the only consideration. For example, funds should also take into account tax considerations that depend on the holding time and return. The relationship may also be heterogeneous. For example, retirement eligible funds may worry less about tax considerations.

With this in mind, I argue there is no need to restrict the mapping of flows into trading to any particular functional form. Hence, I machine learn $g()$, allowing for dependence on other variables, arbitrary nonlinearity, heterogeneity and interactions. The other variables are stock liquidity (log market equity), the holding time and the holding period return until the end of the previous quarter. I describe the neural net architecture and training scheme in an earlier section.

4.3.2 The Old vs. the New Instrument

Table 1 shows regressions of quarterly stock returns on different versions of the instrument. I include time fixed effects and cluster standard errors by time. This regression is important in Asset Pricing, because it estimates the price impact of forced trading, i.e. the inverse demand elasticity. And the regression is important in Corporate Finance because it is the first stage in an instrumental variable regression of a corporate outcome on returns.

In column one, I construct FIT as in the literature. The estimated coefficient is 0.89 and highly statistically significant. So the corresponding demand elasticity is about 1. In column two, I change my data source from CRSP to Morningstar, but use the same object. I show this intermediate step to make clear that my finding is not driven by the change in data source. The new coefficient is 0.86 and highly statistically significant, but less precisely estimated. This is because I lose two thirds of my observations because I only have ten years of Morningstar data in comparison to 37 years of CRSP data.

The regressions in columns 1 and 2 are subject to the reverse causality critique. Now, I switch to the new, corrected instrument. In column 3, the coefficient drops to 0.37, but remains statistically significant. Demand is more elastic. Correcting the reverse causality problem increases the estimated demand elasticity from 1 to 3. The F-statistic of this regression is 12.2. Hence, in a Corporate Finance context this suggests weak instrument concerns. In column four, I use the new, corrected and machine learning enhanced instrument. The coefficient goes up to 0.47 and the F-statistic increases to 20. It is not a weak instrument and I use it in the applications that follow. Overall, correcting the reverse causality problem shows that markets are deeper than suggested.

4.4 Corporate Finance Application

Does the reverse causality problem matter in applications? The Corporate Finance literature tests for market feedback effects with instrumental variable regressions of a corporate outcome on stock returns instrumented with mutual fund flow induced trading. Here, I focus on the corporate outcome that is most prevalent in this literature, investment. Investment is CAPX divided by lagged property, plant and equipment, as in Dessaint et al. [2018].

In table 2, I show regressions of changes in investment over the next quarter on returns in this quarter. In the first column, I show the results of a plain OLS regression. I include time fixed effects and cluster standard errors by firm. The coefficient is 0.035 and highly statistically significant. However, this is not very insightful. Naturally, when investment opportunities improve, firms experience great returns and invest more. This is why the literature instruments returns. In column two, I use the old instrument that is subject to the reverse causality critique. It is constructed as in the literature, using CRSP data. The coefficient goes up to 0.07 and is highly statistically significant. If this were a valid instrument, a 10% stock return would cause an absolute increase of 0.7% in the investment rate. At a median investment rate of about 10%, this would be a 7% relative increase. Note that if the quality of the investment opportunity set is the key omitted variable, it is surprising that the coefficient increases in the IV regression. This suggests that the old instrument does not solve the endogeneity problem.

In the next column, I run the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to make clear that my finding is not driven by the change in data source. The coefficient remains the same, but standard errors increase. This is because I lose two thirds of my observations because I only have ten years of Morningstar data in comparison to 37 years of CRSP data.

In the last column, I run the IV regression using the new, strong instrument, SFIT^{ML}. The coefficient decreases to 0.03 and standard errors become large. The control variables in all four regressions are the six standard firm characteristics plus twelve lags of returns. I include lagged returns because while $\text{SFIT}_q^{ML}(n)$ is exogeneous to changes in fundamentals over quarter q making the fire sale regression valid, $\text{SFIT}_q^{ML}(n)$ is correlated with returns over past quarters. These past returns may also be correlated with future changes in investment. Hence, I control for them. An alternative approach would be to construct $\text{SFIT}_q^{ML}(n)$ by purging daily flows of their dependence of returns that fall outside the same quarter. However, that would make the fire sale regression less powerful.

Appendix table A1 shows the same analysis, but controlling for firm fixed effects instead of taking first differences of investment. The results are qualitatively the same. Overall, the coefficient remains positive after correcting the instrument, suggesting that there may be market feedback effects. However, standard errors are so large that it is harder to show them empirically. Hence, the evidence that equity markets are distortive is weaker than suggested.

4.5 Asset Pricing Application

If the fire sale results are driven by reverse causality, then why do simple flow-based trading strategies generate sizable alpha? Here, I show that they either do not generate alpha out-of-sample, or they do so because they are copycatting strategies in disguise. That means markets are more efficient than suggested. However, I also show that a new, sophisticated flow-based strategy does generate alpha, confirming the qualitative finding that the predictability of flows is exploitable. Taking expectations of equation 2 gives the trading signal

$$\mathbb{E}FIT_q(n) = \frac{\sum_{i=1}^{I} Shares_{i,q-1}(n)\mathbb{E}[g(flow_{i,q})]}{SharesOutstanding_{q-1}(n)}. \tag{9}$$

And $\mathbb{E}[g(flow_{i,q})] \approx g(\mathbb{E}[flow_{i,q}])$ which is exact for the $g()$ I consider in this section. All trading strategies in this paper are high minus low, long-short trading strategies constructed by sorting stocks into decile portfolios.

4.5.1 Simple Mutual Fund Flow Based Trading Strategies

The trading signal has two degrees of freedom. First, how to compute the expected value of flows. Coval and Stafford [2007] compute expected flows from a predictive regression of quarterly flows on many lags of fund returns and itself. They find an in-sample R^2 of 36%. Lou [2012] computes expected flows from a predictive regression of flows on mutual fund alpha over the last twelve months. He finds an in-sample R^2 of 4.5%. Coval and Stafford [2007] and Lou [2012] then use the estimated models to predict flows in sample. Here, I predict flows out-of-sample using a rolling prediction scheme.

The second degree of freedom is the choice of $g()$. I consider four choices. First, the identity. Second, the identity but ignoring flows greater than -5% as is standard in the Corporate Finance literature. Third, Coval and Stafford [2007] use an indicator function for whether flows fall into the top decile minus and indicator function for whether flows fall into the bottom decile. Forth, Lou [2012] fits linear regressions of trading on flows, for positive and negative flows separately.

This gives eight simple flow-based trading strategies. I document their performance in table 3. Constructing expected returns as in Coval and Stafford [2007] gives annual expected returns and three factor alphas of about 5%. However, momentum explains these excess returns. The pattern is qualitatively the same across the different flow transformations.

Again, constructing expected returns as in Lou [2012] gives about 5% annual expected returns and three factor alpha. However, now momentum does not explain these excess returns. The four and six factor alphas are now around 6%. This is puzzling - the worse flow prediction model constructs more profitable portfolios. Looking at this trading signal more closely gives

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

where I substitute in the prediction model and take the identity to map flows into trading.

I also drop the estimated constant and coefficient in the flow prediction model because the trading strategy is invariant to it. Equation 10 shows that the trading strategy is analytically equivalent to a copycatting strategy. It simply buys the stocks held by winner funds and sells stocks held by loser funds. It may seem surprising that copycatting strategies generate alpha, given that mutual fund managers are broadly considered not to have skill Carhart [1997]. Indeed, in a predictive regression of mutual fund returns on 12-month alpha, the coefficient is insignificant. However, once I set up a regression that is closer to the copycatting trading strategy, bad performance is persistent. For the table and details, see the appendix. Overall, simple flow-based trading strategies either do not generate alpha out-of-sample, or they do so because they are copycatting strategies in disguise.

4.5.2 Sophisticated Mutual Fund Flow Based Trading Strategies

Does this evidence mean that expected flows are perfectly priced? Or are the trading strategies not powerful enough? Here, I maximize power. First, instead of predicting flows from a linear regression, I machine learn flows using ensembles of neural networks. Second, instead of mapping flows into trading linearly and homogeneously, I train ensembles of neural networks to learn how mutual funds trade in response to flows. I allow this mapping to depend on the identity of the mutual fund, stock liquidity (log market equity), the holding time and the holding period return until the end of the previous quarter. So the neural networks can exploit arbitrary nonlinearity, interactions and heterogeneity. The reasoning here is the same as in the construction of the enhanced instrument above.

I show alphas and factor loadings of this new, sophisticated flow-based strategy in table 4. The strategy trades quarterly with the arrival of new holdings data which is why I show quarterly alphas. In columns one to five, I consider five standard factor models. The annualized alpha ranges from 8 to 12 %. It is statistically significant with standard errors of about 1%. Most factor loadings are statistically insignificant, except for a negative loading on the profitability factor. Depending on the model, the strategy also loads negatively on the market return. In the last column, I include the return of the copycat portfolio as a factor. The estimated coefficient is close to zero with a t-statistic of -0.25. This shows that this strategy is different from the strategy in Lou [2012].

Overall, markets are efficient enough to make simple flow-based strategies unprofitable. However, sophisticated flow-based strategies still generate alpha.

5 Conclusion

Based on evidence from mutual fund flows, the Asset Pricing literature finds markets are inefficient and fragile and the Corporate Finance literature shows market misvaluation distorts real outcomes. First, I argue these findings are partially driven by reverse causality. Instead of mutual fund outflows inducing fire sales which drive down prices, assets on fire reduce mutual fund returns which trigger outflows. Empirically, this becomes apparent when increasing the frequency of the standard event study from quarterly to daily; returns precede flows.

Second, I suggest a solution. Orthogonalizing daily mutual fund flows with respect to contemporaneous and past daily mutual fund returns, I construct daily surprise flows. I then construct the instrument from daily surprise flows. This implies that I only attribute stock returns that occur after mutual fund flows to the demand shock. Hence, the only threat to identification are omitted variables that trigger flows today and returns tomorrow, a much weaker concern because it violates market efficiency. Also, this instrument can be strengthened by training machine learning models to predict how mutual funds trade in response to flows.

Third, I use surprise flows to reevaluate important findings in the literature. Correcting flow induced trading for reverse causality, demand elasticity estimates increase from 1 to 3. Equity markets are deeper than suggested. In Corporate Finance, correcting the instrument makes the estimates of market feedback effects smaller and noisier. Markets are less distortive than suggested. In Asset Pricing, simple flow-based trading strategies that are not copycatting strategies do not generate alpha out of sample. However, sophisticated, machine learning, flow-based trading strategies generate an annual alpha of 10%. Markets are more efficient than suggested.

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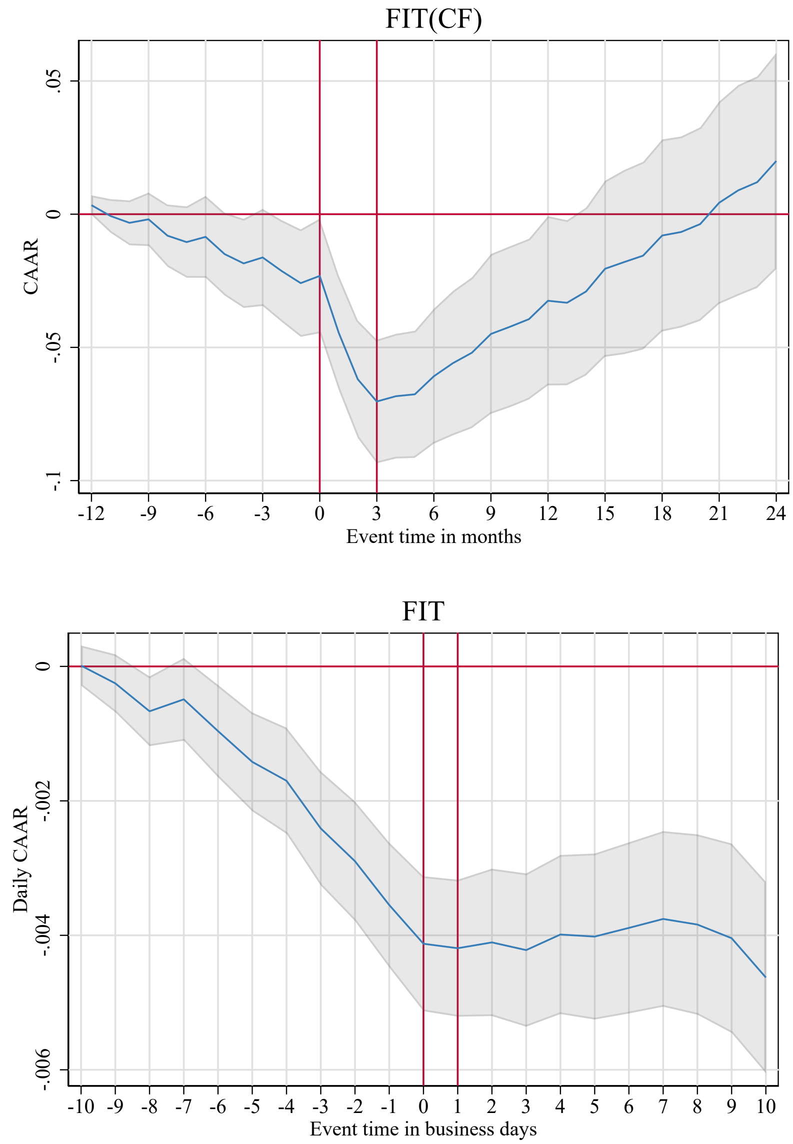
Graphs

Figure 1: Does the Mutual Fund Outflow Induced Trading Event Cause the Price Crash? Quarterly vs. Daily Event Study



The top figure is a replication of the event study in Edmans et al. [2012]. An event is a firm-month observation in which FIT falls in the bottom decile of its full sample distribution. The event lasts one quarter, from 0 to 3. They 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 the onset of the event. The sample is 1980 Q1 to 2017 Q4. The bottom figure is the analogue at the daily level, except that it takes into account the Wardlaw [2018] critique and uses the bottom 1st percentile, because large daily shocks are much rarer than large quarterly shocks. The time is in business days, so I show the month around the event. The sample is July 2008 to December 2017, because of the availability of daily Morningstar data.

Figure 2: Timeline of Flow Induced Trading

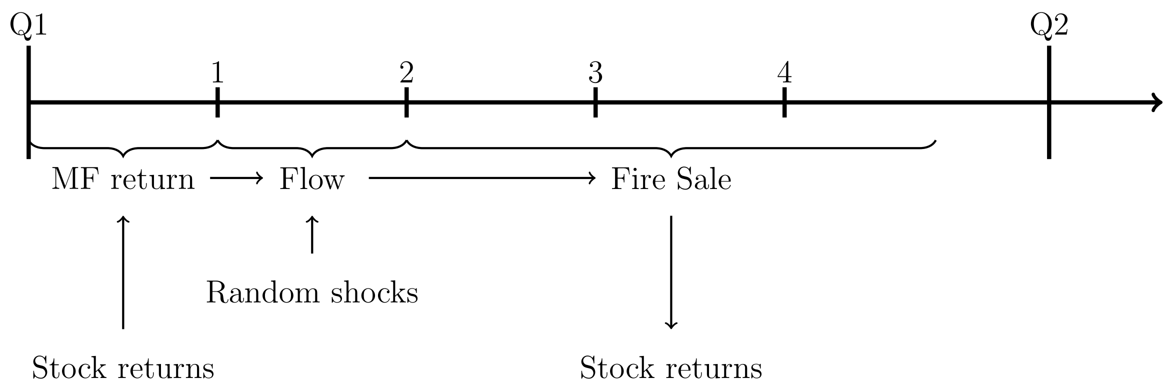
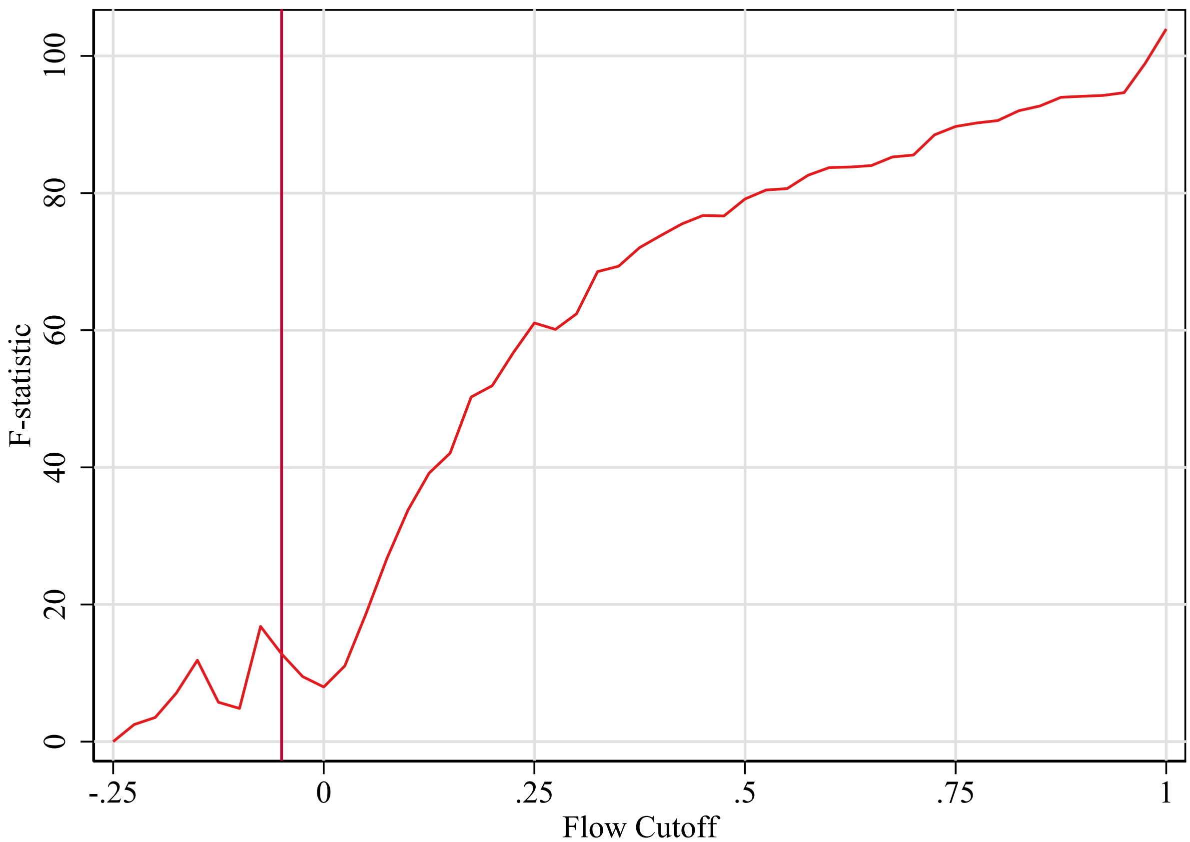


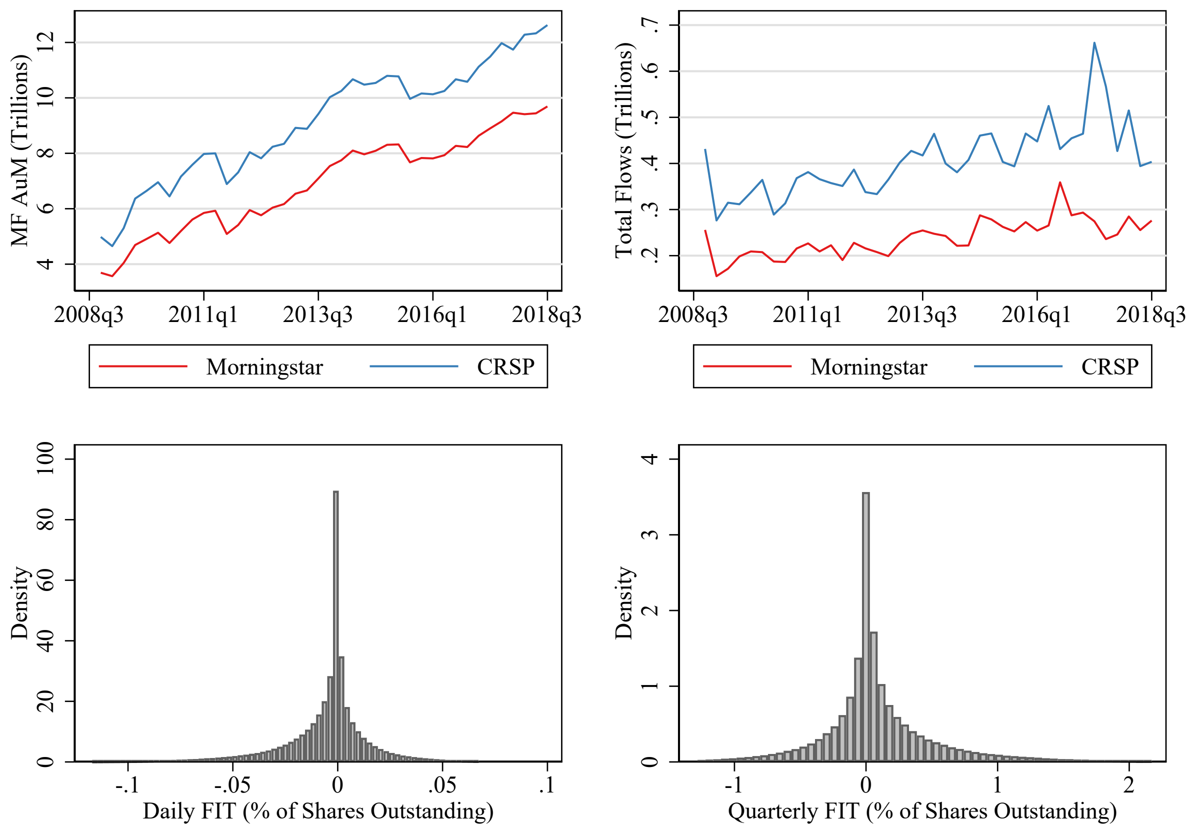
Illustration of the relationship between mutual fund flows and stock returns. I show events along a daily time series. Q1 and Q2 denote the beginning and the end of a quarter. Mutual fund flows force mutual funds to trade which has price impact. But flows can come from two sources. First, they may be generated by random liquidity needs of retail investors. In this case, the flow happens first, followed by stocks returns. Second, they can be a result of performance chasing, and past performance is the result of the past returns of the stocks in the mutual fund portfolio. In this case, stock returns happen first, followed by fund flows. Now, taking quarterly flows and stock returns hides this temporal ordering. Quarterly flows and returns happen contemporaneously, no matter which happens first at the daily frequency. Hence, the impact of flow induced trading on stock prices can not be inferred from the contemporaneous, quarterly correlation.

Figure 3: Instrument Strength by Flow Cutoff



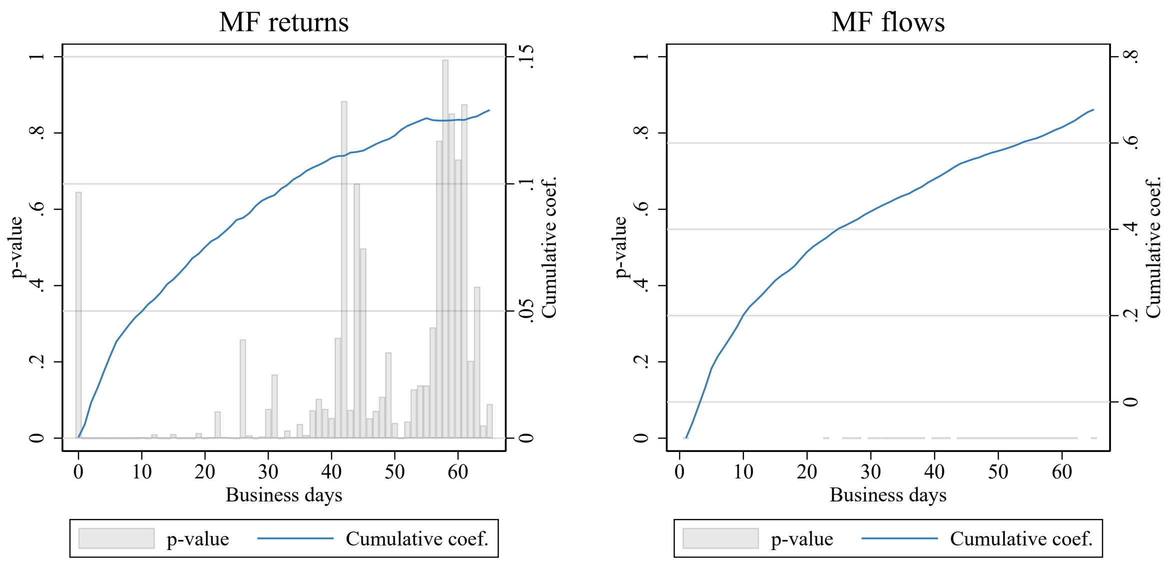
Strength of the Wardlaw [2018] instrument by flow cutoff. When constructing flow induced trading, the Corporate Finance literature drop flows greater than -5%, indicated by the red, vertical line. Here, I regress quarterly stock returns on FIT for any cutoff and report the corresponding F-statistics. The regressions include time fixed effects and standard errors are clustered by time. For the left and right most F-statistic, I drop all or no flow, respectively. The sample is 1980 Q1 to 2017 Q4.

Figure 4: Summary Statistics



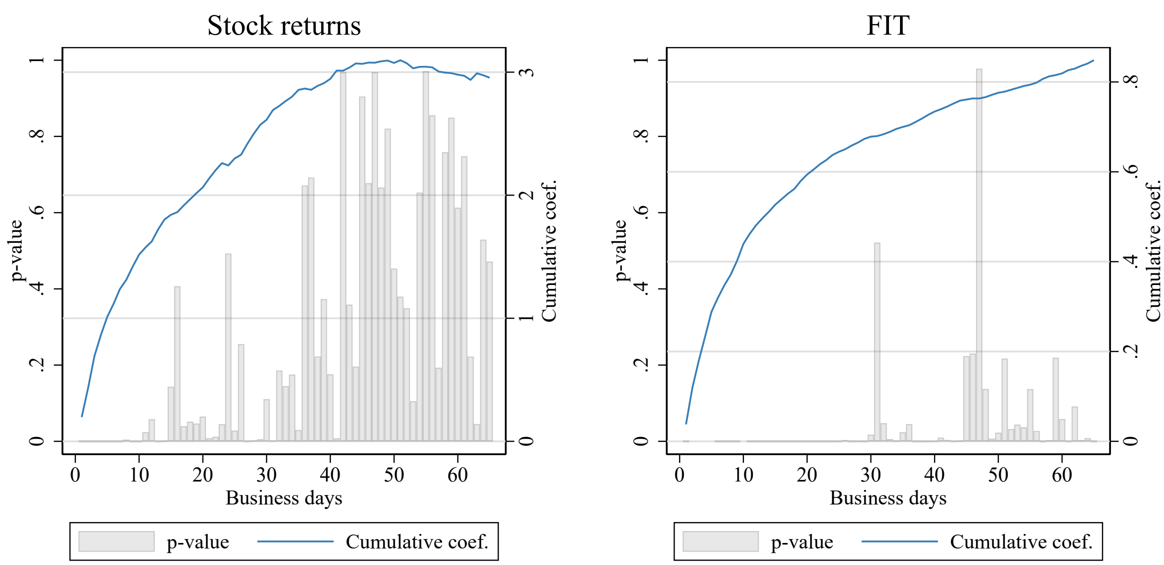
Summary statistics. In the top left graph, I plot total mutual fund AuM over time for the CRSP and the Morningstar sample. In the top right graph, I show the sum of absolute dollar mutual fund flows over time. The bottom graphs show the distribution of the daily and the quarterly demand shock, mutual fund flow induced trading. The shocks are smaller here than in previous papers, because they are scaled by shares outstanding, as suggested in Wardlaw [2018]. Previous papers typically use trading volume or shares held in the holdings data sample [Coval and Stafford, 2007, Edmans et al., 2012]

Figure 5: Results of Regression of Daily Mutual Fund Flows on Fund Returns and Itself



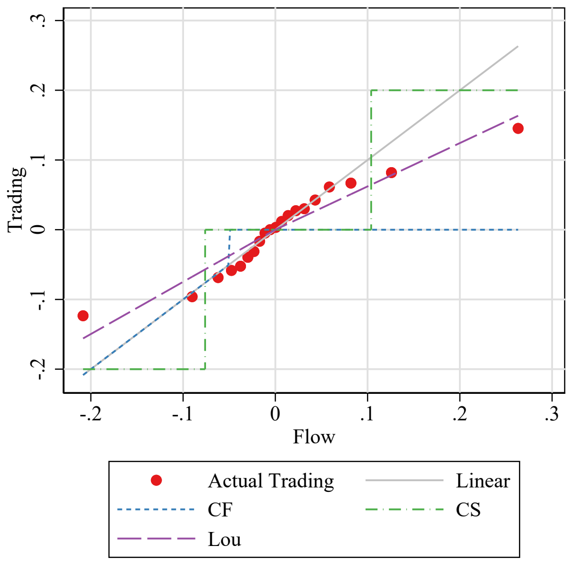
This figure shows the results from a regression of daily mutual fund flows on lags of daily mutual fund returns and itself. The regression corresponds to equation 3. This is the regression for active mutual funds. As for most regressions in this paper, I include time fixed effects and cluster standard errors by time. I include up to 66 lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient in grey bars. The number of observations is 9,263,282. The R^2 is 0.0419. The within-R^2 is 0.0395. The sample is July 2008 to December 2017.

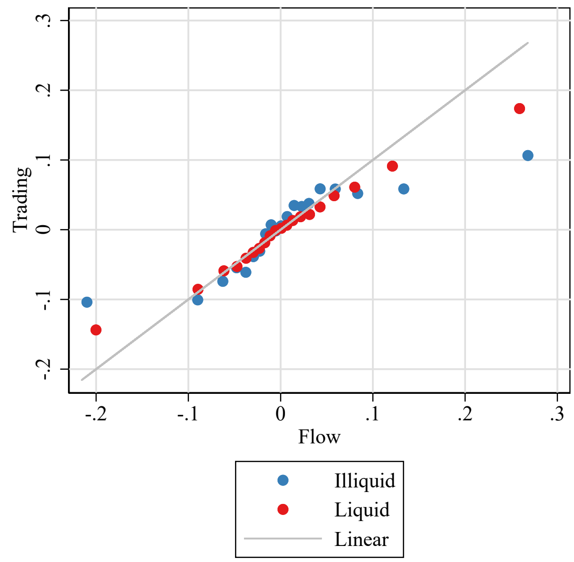
Figure 6: Results of Regression of Daily Flow Induced Trading on Stock Returns and Itself



This figure shows the results of a regression of flow induced trading on lags of stock returns and itself. It is the analogue to the regression in figure 5 at the stock, instead of the mutual fund level. For ease of interpretation, daily FIT is normalized in the cross-section. As for most regressions in this paper, I include time fixed effects and cluster standard errors by time. I include up to 66 lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient in grey bars. The number of observations is 8,489,076. The R^2 is 0.1222. The within-R^2 is 0.1221. The sample is July 2008 to December 2017.

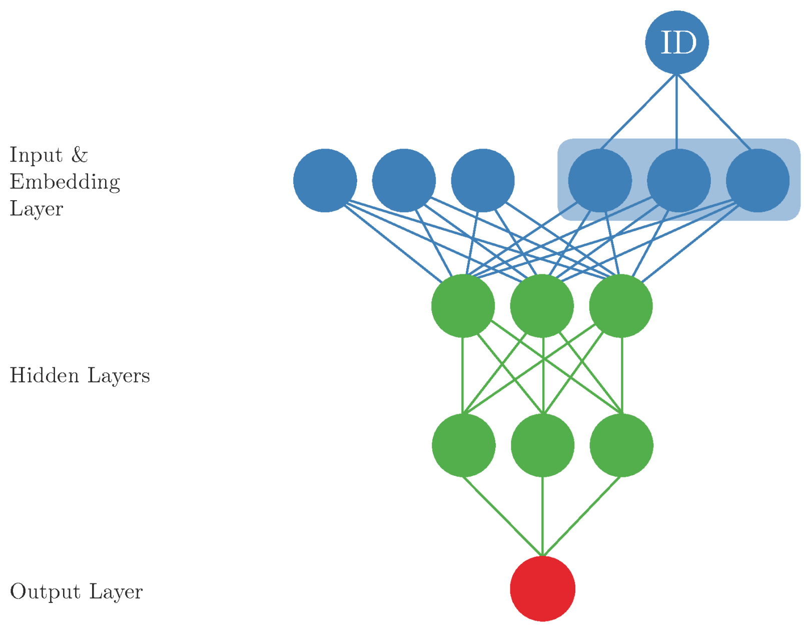
Figure 7: Mutual Fund Trading in Response to Mutual Fund Flows





This figure plots how mutual funds trade in response to flows. Trading is the relative change in shares held. In red, I show mean demeaned trading, the relative change in shares held, for 20 mutual fund flow bins. It also plots four mappings of flows into trading that have been used in the literature. A basic approach is to use the identity. This assumes mutual funds keep portfolio weights constant in response to flows. This corresponds to the grey 45 degree line. The Corporate Finance literature makes this choice, except it discards flows greate than -5%. This is depicted in blue. Finally, I also show the mappings used in Coval and Stafford [2007] and Lou [2012]. On the right side, I show mean trading for 20 flow bins, but now I separate liquid from illiquid stocks as defined by belonging to the top or bottom size decile portfolio. The sample is 1980 Q1 to 2017 Q4.

Figure 8: Machine Learning Architecture



The computational graph of the prediction model that I use to predict flows and trading. It takes two types of inputs. First, predictor variables that feed directly into the neural network. Second, an ID that identifies the financial institution. This is a categorical variable, so I cannot feed it into the model directly. However, say each institution has a latent K-dimensional type. Then, I map each institution ID into a K-dimensional vector which I can feed into the network. The institution type is latent. Hence, I find its elements during training. This is an embedding, the state-of-the-art method to treat words in natural language processing. The two types of inputs then feed into a standard feed-forward neural network. The output is the predicted value.

Tables

Table 1: Regressions of Quarterly Returns on Flow-induced Trading

	(1)	(2)	(3)	(4)
	r_t	r_t	r_t	r_t
FIT^{CRSP}	0.890***			
	(0.101)			
FIT		0.856***		
		(0.126)		
SFIT			0.373***	
			(0.107)	
SFIT^{ML}				0.473***
				(0.106)
N	555160	143194	143194	139596
F	77.6	46.2	12.2	19.9
R-squared	0.206	0.244	0.240	0.243

This table shows regressions of quarterly stock returns on different versions of flow induced trading. In column one, I construct FIT as in the literature. In column two, I change my data source from CRSP to Morningstar, but use the same object. I show this intermediate step to make clear that my finding is not driven by the change in data source. The number of observations decreases because I only have ten years of Morningstar data in comparison to 37 years of CRSP data. In column 3, I switch to the new, corrected instrument. In column four, I use the new, corrected and machine learning enhanced instrument. All regressions include time fixed effects. I report standard errors clustered by firm in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table 2: Corporate Finance Application: Is There a Market Feedback Effect on Investment? First Differences Estimator

	OLS	IV		
	Dep. var.: Investment	FIT^{CRSP}	FIT	SFIT^{ML}
r_t	0.0347***	0.0728***	0.0788***	0.0293
	(0.00154)	(0.0116)	(0.0257)	(0.415)
Controls	Yes	Yes	Yes	Yes
R-squared	258045	258035	81449	81440
r2	0.0136	0.00904	0.0150	0.0215

This table shows regressions of changes in investment over the next quarter on returns in this quarter. Investment is CAPX over lagged property plant and equipment as in Dessaint et al. [2018]. In the first column, I show the results of a plain OLS regression. In column two, I use the old instrument that is subject to the reverse causality critique. It is constructed as in the literature, using CRSP data. In the next column, I run the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to make clear that my finding is not driven by the change in data source. The number of observations decreases because I only have ten years of Morningstar data in comparison to 37 years of CRSP data. In the last column, I run the IV regression using the new, corrected and machine learning enhanced instrument. The control variables correspond to a 6-factor asset pricing model. They are beta, log market equity, log Tobin's Q, profitability, investment and momentum. I also include twelve lags of the returns. All regressions include time fixed effects. I report standard errors clustered by firm in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table 3: Key Performance Measures of Simple Flow-Based Portfolios

E[flow]	Transformation	Er	3F α	4F α	5F α	6F α
CS	linear	4.0	4.7	-.7	2.3	-1.4
		(17.57)	(3.10)	(2.91)	(3.93)	(3.26)
	CF	3.2	3.1	2.5	1.2	1.0
		(12.07)	(2.03)	(2.61)	(2.31)	(2.63)
	CS	5.2	5.0	-.2	2.4	-1.3
		(17.18)	(3.03)	(2.94)	(3.97)	(3.30)
	Lou	3.8	4.5	-.9	2.2	-1.6
		(17.56)	(3.10)	(2.88)	(3.92)	(3.23)
Lou	linear	4.4	5.7	5.2	7.3	6.7
		(17.87)	(2.60)	(3.03)	(2.84)	(3.10)
	CF	2.2	1.7	1.9	-.8	-.8
		(14.14)	(2.55)	(2.51)	(2.36)	(2.28)
	CS	6.2	7.6	6.3	8.9	7.7
		(17.35)	(2.52)	(2.79)	(2.70)	(2.91)
	Lou	4.4	5.6	5.1	7.3	6.6
		(17.80)	(2.59)	(3.01)	(2.81)	(3.07)

Key performance measures for a set of portfolios; mean returns (Er) with standard deviation in parenthesis below, and the three, four, five and six-factor alpha with standard errors in parenthesis below. All measures are annualized (standard errors are annualized to maintain the correct t-statistic). In the first panel, expected flows are constructed as in Coval and Stafford [2007]. In the second panel, expected flows are constructed as in Lou [2012]. In each panel, I show results for four different mappings of flows into trading. The identity, the identity but dropping flows greater than -5% as is standard in the Corporate Finance literature, the mapping from Coval and Stafford [2007] and the mapping from Lou [2012]. The sample is 1980 Q1 to 2017 Q4.

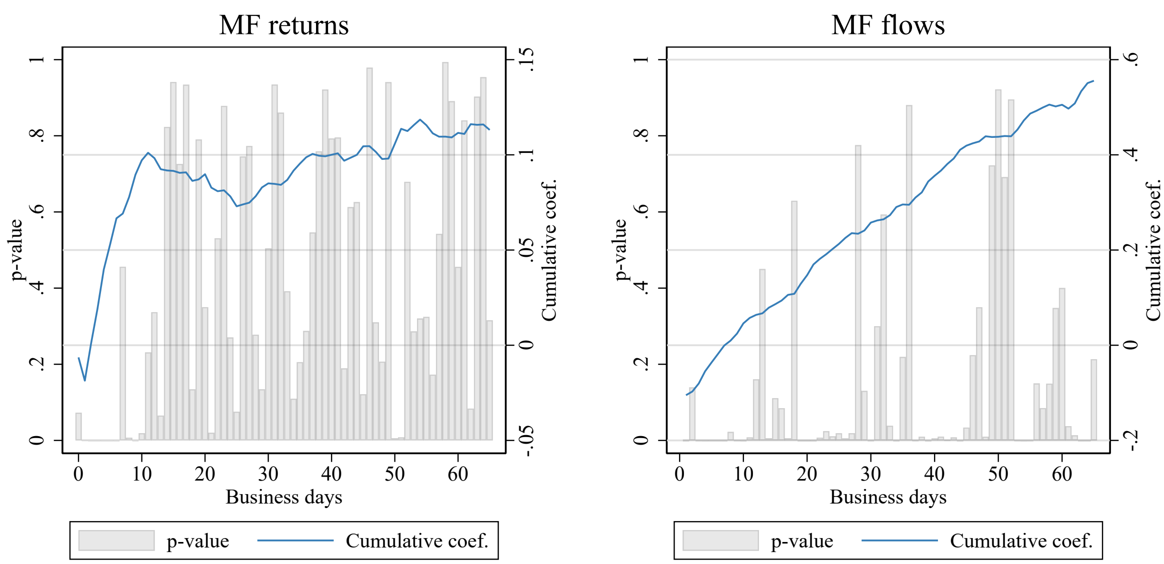
Table 4: Alphas and Factor Loadings of Machine Learning Flow-based Trading Strategy

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.0231**	0.0204**	0.0226**	0.0274***	0.0293***	0.0295**
	(0.0101)	(0.00908)	(0.0101)	(0.0100)	(0.0110)	(0.0114)
MKT	-0.0868	-0.141	-0.187	-0.325	-0.365*	-0.346*
	(0.161)	(0.161)	(0.173)	(0.207)	(0.214)	(0.200)
HML		0.104	0.0662	0.102	0.0200	-0.00522
		(0.197)	(0.199)	(0.295)	(0.289)	(0.276)
SMB		0.320	0.292	0.127	0.0935	0.0946
		(0.320)	(0.311)	(0.310)	(0.306)	(0.302)
MOM			-0.110		-0.126	-0.117
			(0.163)		(0.164)	(0.161)
RMW				-0.601**	-0.587**	-0.598**
				(0.272)	(0.270)	(0.282)
CMA				0.431	0.500	0.492
				(0.391)	(0.397)	(0.403)
Copycat						-0.0556
						(0.201)
R-squared	0.00702	0.0356	0.0468	0.110	0.124	0.126

I report alphas and factor loadings for five different factor models. The CAPM, the Fama-French 3-factor model, the Carhart 4-factor model, the Fama-French 5-factor model, and the Fama-French 5-factor model plus momentum. The Copycat return is the strategy from Lou [2012], but constructed out-of-sample. The sample is the second half of the full 1980 Q1 to 2017 Q4 sample. The first half is used for initial training. I report robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

A Graphs

Figure A1: Results of Regression of Daily Mutual Fund Flows on Past Daily Fund Returns - Index Funds Only



This figure shows the results from a regression of daily mutual fund flows on lags of daily mutual fund returns and itself. The regression corresponds to equation 3. This is the regression for index mutual funds. As for most regressions in this paper, I include time fixed effects and cluster standard errors by time. I include up to 66 lags, the maximum number of business days in a quarter. I plot cumulative coefficients in blue and display the p-values of each coefficient in grey bars. The number of observations is 765,005. The R^2 is 0.0339. The within-R^2 is 0.0269. The sample is July 2008 to December 2017.

B Tables

Table A1: Corporate Finance Application: Is There a Market Feedback Effect on Investment? Fixed Effects Estimator

	OLS	IV		
	Dep. var.: Investment	FIT^{CRSP}	FIT	SFIT^{ML}
r_t	0.0465***	0.0415***	0.0474***	0.0407
	(0.00120)	(0.00999)	(0.0183)	(0.0681)
Controls	Yes	Yes	Yes	Yes
R-squared	257814	257804	81336	81327
r2	0.159	0.159	0.186	0.186

This table shows regressions of investment over the next quarter on returns in this quarter. Investment is CAPX over lagged property plant and equipment as in Dessaint et al. [2018]. In the first column, I show the results of a plain OLS regression. In column two, I use the old instrument that is subject to the reverse causality critique. It is constructed as in the literature, using CRSP data. In the next column, I run the same regression, except that FIT is now constructed using Morningstar data. I show this intermediate step to make clear that my finding is not driven by the change in data source. The number of observations decreases because I only have ten years of Morningstar data in comparison to 37 years of CRSP data. In the last column, I run the IV regression using the new, corrected and machine learning enhanced instrument. The control variables correspond to a 6-factor asset pricing model. They are beta, log market equity, log Tobin's Q, profitability, investment and momentum. I also include twelve lags of the returns. All regressions include time and firm fixed effects. I report standard errors clustered by firm in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table A2: Is Mutual Fund Performance Persistent?

	Conventional		As Traded	
	Inst. ret_{t+1}	Inst. ret_{t+1}	Inst. ret_{t+1}	Inst. ret_{t+1}
Alpha_t	0.0970		0.00291	
	(0.0945)		(0.00227)	
Alpha_t * $1\{\text{Alpha}_t <0\}$		0.129		0.00686**
		(0.117)		(0.00284)
Alpha_t * $1\{\text{Alpha}_t >0\}$		0.0738		0.000514
		(0.155)		(0.00336)
R-squared	0.696	0.696	0.773	0.774
N	317432	317432	317432	317432

This table shows the results of predictive regressions of quarterly mutual fund returns on mutual fund alpha over the past 12 months. In columns 3 and 4, I run the regressions to resemble the corresponding trading strategy. First, I weight observations by fund size because funds enter proportionally to their size in the trading signal in equation 10. Second, I normalize alpha cross-sectionally, because trading strategies only use the ordering, not the actual value of the trading signal. The sample is 1980 Q1 to 2017 Q4. All regressions include time fixed effects. I report standard errors clustered by time in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

C Machine Learning Details

First, I minimize MSE using stochastic gradient descent (SGD). Instead of computing the gradient from the full sample, each iteration of the optimization routine only uses a small, random subset of the training data, a mini-batch. Also, I use the Adam optimizer, which features learning rate decay and momentum [Kingma and Ba, 2017]. Second, I terminate training once the validation loss increases. This is called Early Stopping. Third, I add a Batch Normalization layer before the nonlinearity [Ioffe and Szegedy, 2015]. This layer centers inputs and scales them to unit variance across the mini-batch. With Batch Normalization, neural networks train faster and generalize better to new data. Forth, after this, I add a dropout layer with a 25% dropout rate [Srivastava et al., 2014]. At each iteration, I randomly select 25% of the neurons and set their output to zero. This prevents the model from learning complex co-adaptations and forces it to learn robust patterns that tend to generalize better. The original paper suggests a dropout rate between 0 and 50%. So I choose the midpoint.

Fifth, I apply L2 penalization. This encourages small parameters. Lastly, I use an ensemble of five neural networks and average their predictions. Neural net optimization routines typically converge to local minima. Hence, averaging predictions from multiple models makes the final prediction more stable and leads to better forecasts in practice. Here, the neural nets make different forecasts because they have slightly different architectures, start at different initial weights and the dropout layers shut down different neurons in each iteration. In practice, the predictions from different models have a correlation coefficient of 0.9.

Implementing machine learning algorithms requires making a set of choices. First, non-key hyperparameters; I validate over L2 penalization rates 10^n, for n from 3 to 7. Setting the L2 penalization rate too high sets most weights to 0 and makes the model predict the mean for all observations. Setting it too low means it loses its purpose. The validation algorithm choses 10^{-5} most often. Hence, these rates strike a balance between the two extremes.

I set early stopping patience to ten, allowing a maximum of ten epochs in which the validation loss increases before terminating training. I then reload the parameters that produced the minimum validation loss. Further,I choose an embedding size of 10. I choose mini-batch size of 2^8. Where possible, I use tensorflow defaults. I use the ELU activation function default of 1 for alpha and use the Adam optimizer defaults, e.g. an initial learning rate of 0.001.

Second, transfer learning; Instead of starting training from randomly initialized weights at every time period, I initialize the weights from the last trained models, except the initial time periods. However, the architectures change over time because the number of financial institutions in the embedding layer grows. To address this issue, I take all parameters from the old model and fill in the embedding for the missing institutions in the new model with the median of the trained embedding of the old model. I do the same in the testing step. When an institution appears for the first time, I use the median embedding values to fill in the missing (i.e randomly initialized, but untrained) embedding values for the new institutions.

Third, parallelization. To increase speed, whenever I train many models to predict the same outcome, I add them into one graph, next to each other. That means, in the model selection step, I add all 15 models (3 depths x 5 L2 penalization rates) into one graph. This has the advantage, that I only need to hold the training data in memory once. It also allows me to train many models on a single GPU. Otherwise, to achieve similar performance, I would need an order of magnitude more power.

Fourth, feeding data into the optimization routine. At the beginning of each epoch, I reshuffle the data. Shuffling data serves the same purpose as mini-batching. By training the model on ever new sets of data, it is less likely that the optimization algorithm gets stuck in local minima that fit training data well, but generalize poorly out of sample.