Self-Inflated Funds*

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Abstract

When funds with illiquid portfolios grow rapidly without rebalancing into more liquid assets, they generate self-inflated returns via their own price impact. Investors chase these returns, triggering a positive feedback loop that inflates both fund size and asset prices. We introduce a simple measure – fund illiquidity – that captures a fund's potential for return inflation. Using daily ETF data, we estimate price impact, decompose returns, and show that investors chase both fundamental and self-inflated returns. We find that inflated funds underperform in the long run and that stock-level ownership by inflated funds predicts negative long-term returns.

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1 Introduction

The collapse of Archegos Capital Management[1] prominently showed how trading concentrated, illiquid positions can let a fund's own price impact drive its returns. Market participants seem unable to identify whether realized returns come from price impact as opposed to fundamental determinants. Is this a pathology of a few extreme funds, or does it reflect a broader force that distorts capital allocation and asset prices more generally? We show that the negative feedback loop between non-fundamental returns and outflows (Falato et al., 2021; Darmouni et al., 2022), or more generally, between returns and funding liquidity (Brunnermeier and Pedersen, 2009), is not confined to distressed debt markets and fire sales. It also operates in reverse: positive returns attract inflows, which generate further returns via price impact, and trigger additional inflows. This positive feedback loop inflates funds and generates persistent distortions in capital allocation and asset prices.[2]

Our key insight is that the positive feedback loop stems from three choices made by funds and their investors. First, portfolio liquidity varies enormously across funds. Second, the majority of funds choose not to elastically rebalance towards more liquid assets as they grow. As a result of the inelastic liquidity choice, fast-growing funds exert *excess* price pressure on the securities they hold – more than they would if they adjusted their portfolios towards more liquid assets within their investable universe. Third, investors do not distinguish between self-inflated returns and other return sources in their allocation choices — flows chase raw returns regardless of their source. Together, these behaviors enable the positive feedback loop, amplify price impact, inflate stock prices and fund NAVs, and predict long-run underperformance. We introduce "fund illiquidity" as a simple, transparent measure of a fund's potential to incite these feedback loops. Because it is easy to compute, quantifies funds' potentially distortive price impact, and significantly predicts their long-run collapse, we advocate that it be disclosed in regulatory filings and fund prospectuses.

We start by formalizing and theoretically motivating our new concept, fund illiquidity, the key catalyst for self-inflated funds. It measures how much of the underlying volume a fund buys if it proportionally invests a 1% inflow, in excess of what it would have bought under the cheapest to liquidate ("most liquid") feasible portfolio within its universe. Fund illiquidity can be decomposed as

[1] Inside Archego's Epic Meltdown (WSJ, 2021). Other prominent examples include the collapse of LTCM in 1998 and the Janus Twenty Fund in 2020.

[2] The title of this paper does *not* imply that concentrated funds deliberately push up prices to attract capital in the short term. Rather, flow-induced price impact arises because fund managers do not adjust portfolio liquidity elastically when receiving large inflows, allowing *investors* to inflate returns through their own flows.

the product of portfolio illiquidity and fund size. Following Pástor et al. (2020), portfolio illiquidity measures the extent to which a portfolio is tilted towards illiquid securities within the fund's asset universe. Portfolio illiquity alone is insufficient to generate large price impact, it is the combination of size and portfolio illiquidity, that leads to inflated funds.

Our definition of fund illiquidity allows separating our mechanism from ordinary return chasing for individual assets, styles, or sectors, where price impact is often difficult to disentangle from company fundamentals. In illiquid funds, there is a structural misalignment between investor intent (as captured by portfolio weights) and realized price impact (as captured by the liquidity of the underlying).[3] While positive feedback loops from extrapolative beliefs (Barberis et al., 2015) are likely a general feature of financial markets, inflated funds are special: They can emerge endogenously, without relying on hot themes or sectors, simply from the excess price impact of flows into an illiquid rather than the most liquid feasible portfolio within the *same* subset of assets.

We construct fund illiquidity and portfolio illiquidity for all ETFs and mutual funds in the US. Our main analysis focuses on ETFs for which security-level holdings and flows are available daily which allows us to accurately estimate their daily price impact.[4] However, because total assets in mutual funds — particularly active ones — far exceed those in active ETFs, we later extend our analysis to this larger segment. A substantial subset of small-cap, thematic, and strategy ETFs – which initially held illiquid portfolios and subsequently received large inflows – exhibit high fund illiquidity. Among mutual funds, fund illiquidity is even more pronounced: for many funds, a 1% inflow results in excess buying of over 10% of average daily volume, relative to the most liquid feasible portfolio in their universe.

What drives fund illiquidity and how do some funds become so illiquid? We show that fund illiquidity rises mainly because funds grow without elastically shifting toward more liquid portfolios. Fund growth explains 90% of the variation in fund illiquidity. We estimate the elasticity of portfolio illiquidity with respect to fund size both in the time-series and the cross-section. Liquidity choice is highly inelastic: a 1% increase in size leads to less than a 0.07% decline in portfolio illiquidity. Importantly, this inelasticity is not limited to ETFs that may be constrained by illiquid sector benchmarks, but also applies to ETFs that do not report any benchmark at all. The inelastic response means inflows

[3]While broad index funds or single-stock ETFs can become overvalued, they cannot become *inflated* under our definition. Flows into, e.g., single-stock ETFs or broad index ETFs may move prices, but the impact aligns with investor intent and is not distortive. In contrast, illiquid funds concentrate flows into securities that cannot absorb them without large price moves, creating a wedge between portfolio weights and realized price impact.

[4]The arbitrage mechanism for physically replicating ETFs ensures that flows are (almost) perfectly invested in the specified arbitrage basket on the day they occur. Furthermore, it allows estimating return-chasing behaviour at a high frequency.

mechanically increase fund illiquidity over time. While Pástor et al. (2020) document a significantly negative relationship between portfolio illiquidity and fund size in the cross-section, this paper is the first to document that funds' liquidity choice is inelastic with respect to their size in the time series. Furthermore, we directly link this inelasticity to fund illiquidity, which increases endogenously with large fund flows.

Linking fund illiquidity to returns requires an estimate of the price impact of ETF flows on the underlying assets. We propose a novel difference-in-difference estimator for the price impact of ETF trades based on the fact that self-inflated returns are driven by the interaction of fund illiquidity and flows. Across various specifications, we find that ETFs buying 1% of daily volume pushes stock prices up by 5-10 basis points, which is in line with previous studies (e.g., Brokmann et al. (2015); Frazzini et al. (2018); Bouchaud et al. (2018)). While the novel estimator is a contribution of this paper, our results do not hinge on this estimate. Plugging in a price impact estimate from existing studies leaves all results unchanged. In line with Ben-David et al. (2018), we confirm that ETFs can have a significant impact on their underlying securities. Furthermore, we find that self- and co-inflated returns have an economically meaningful impact on the cross-sectional variation in ETF returns, which can therefore lead to fund flows chasing these returns.

We then decompose past fund returns into an inflated component and a "fundamental" component. Because many funds hold overlapping portfolios, we also estimate *co-inflated returns* as the component of a fund's return driven by the trades of other illiquid funds with overlapping holdings.[5] Total inflated returns are the sum of self-inflated and co-inflated components. Quite strikingly, the flow-performance relationship is not confined to the fundamental component of fund returns. Instead, investors significantly chase the inflated component of fund returns. This holds for various models of price impact. Furthermore, a placebo decomposition using randomly generated price impact does not yield significant impact chasing. Importantly, we find that the weight investors place on more distant fund returns decays exponentially.[6] Therefore, even a completely reverting price impact in the long run (Ben-David et al., 2022a) can still lead to significantly inflated funds because flows chase returns at a high frequency. Regardless of the interpretation of why investors chase past price impact this has important implications for the wealth distribution of managed funds. Illiquid funds with high

[5]Several studies investigate spillover of flows on co-held assets. See, e.g., Greenwood and Thesmar (2011), Falato et al. (2021), Girardi et al. (2021), but not the positive feedback loop arising from these spillover effects.

[6]Consistent with Barber et al. (2016) and Dannhauser and Pontiff (2019), who show that flows respond most to the first monthly lag. We find the strongest response to the more recent daily returns.

price impact receive higher flows, making them more illiquid and hence increasing the future potential impact on their holdings.

Last, we examine the long-term performance of inflated funds – funds that grew without rebalancing into more liquid assets. To this end, we extend our analysis to mutual funds, which are both larger and span a much longer sample – making fund inflation more likely and long-run reversals easier to detect. Among mutual funds that strongly outperformed the market, those with high fund illiquidity exhibit sharp and statistically significant reversals. Fund illiquidity robustly predicts lower future long-run returns, even after controlling for portfolio illiquidity, past flows, and past performance. Furthermore, the negative relationship between fund illiquidity and long-run returns becomes monotonically stronger for funds with better past performance. Because fund performance is driven by underlying holdings, the negative returns of inflated funds should translate into negative returns for the stocks they own. We show that stocks heavily owned by inflated funds exhibit significantly negative long-run returns. Sorting stocks by inflated ownership, we find no short-run return predictability but strong long-run reversals: stocks with inflated ownership exceeding 5% show significantly negative returns of up to -30% over the following three years. Importantly, the negative long-run returns do not appear for stocks owned by ordinary funds receiving high inflows, or stocks owned by funds with high realized returns, but are specific to ownership by inflated funds.

This paper is the first to show that funds' inelastic liquidity choice can lead to inflated funds and *positive* feedback loops that distort capital allocation and asset prices. In negative feedback loops (Darmouni et al., 2022), the sale of illiquid assets is often unavoidable as no other assets are available. In contrast, the existence of positive feedback loops is less obvious: funds could, in principle, shift toward more liquid assets upon receiving large inflows, thereby avoiding further price inflation. Instead, we show that funds' liquidity choice is inelastic, enabling positive feedback loops. We leave the question of why funds do not adjust toward more liquid securities as they grow to future research. One possibility is that running large, inflated funds – even temporarily – generates high fees and is easier than delivering sustained "fundamental" returns. This would be consistent with evidence that ETFs are often launched into hot themes, which subsequently underperform (Ben-David et al., 2023).

Related Literature.

We contribute to the literature on fund fragility and amplification dynamics driven by the negative feedback loop of flows and returns during fire sales (Coval and Stafford, 2007; Brunnermeier and

Pedersen, 2009; Ellul et al., 2011; Mitchell and Pulvino, 2012; Chernenko and Sunderam, 2020; Falato et al., 2021; Darmouni et al., 2022). Our paper is the first to provide explicit evidence that similar feedback loops arise from *positive* shocks: initial gains lead to inflows, which generate further price impact, inflating both funds and their underlying holdings. Lou (2012) and Coval and Stafford (2007) show that reinvested inflows affect prices positively, but they do not provide evidence for the full feedback loop, which requires investors to chase their own price impact. Falato et al. (2021) provides empirical evidence for the downside, i.e., negative feedback loops. We are the first to provide explicit evidence for the upside, i.e., positive feedback loops. Thus, the feedback between returns and flows is not confined to distressed markets (Shleifer and Vishny, 2011), but is a general phenomenon that distorts capital allocation as investors systematically chase flow-driven returns. We argue that studying the positive feedback loop is as important as the fire sale channel but has received considerably less attention in the literature: It inflates funds and asset prices, concentrates firm ownership in potentially fragile holders, distorts capital allocation, and exposes investors to low long-run returns.

Second, we contribute to the literature on the liquidity choice of managed funds (Chen et al., 2010; Pástor et al., 2020; Koont et al., 2022). While Lou (2012) shows that funds reinvest flows in more liquid portfolio constituents to minimize price impact, we show that overall portfolio liquidity choice is *inelastic* with respect to fund size. This leads to funds having *excess* impact relative to the most liquid feasible portfolio, given their benchmark. While the price impact initially inflates the funds' own returns, we show that inflated funds collapse in the long-run, after periods of strong outperformance.

Third, our mechanism connects directly to the large literature on mutual fund performance and investor flows (Jensen, 1968; Carhart, 1997; Pástor and Stambaugh, 2002; Cohen et al., 2005; Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Building on Berk and Green (2004), who argue that skilled managers attract flows until their own price impact erodes alpha, there is a large literature that regresses fund flows on past returns and alphas (Huang et al., 2007; Berk and Van Binsbergen, 2016; Barber et al., 2016; Goldstein et al., 2017; Jiang and Zheng, 2018; Dannhauser and Pontiff, 2019; Jin et al., 2022). Although our findings may appear to contradict Berk and Green (2004), they in fact build on and extend the core mechanism linking scale and skill. In line with (Berk and Green, 2004; Pástor et al., 2015; Berk and Van Binsbergen, 2015), we show that fund growth lowers *expected* returns via price impact. However, it positively affects *realized* returns during the transition period. This mismatch between realized and expected returns (Pástor et al., 2022) can lead to long-lived misallocations of flows, inflating illiquid funds and generating excessive fee income unrelated to managerial skill (Song, 2020). More recently, Ben-David et al. (2022b) provide strong evidence that households chase raw returns and Morningstar ratings rather than alpha, implying naive performance chasing rather than bayesian learning. Building on this, we show that investors not only chase unadjusted performance but also do not distinguish stock-picking skill from the price impact caused by their own flows. While the literature often assumes that return chasing applies to any type of return – fueling both positive and negative feedback loops – we provide direct empirical evidence that investors indeed chase both fundamental and price impact–driven returns. This offers important corroborating evidence for the positive feedback loops in this paper and for the fire sale literature more broadly.

Fourth, our paper relates to the large literature investigating the price impact of non-fundamental demand shocks in financial markets (Shleifer, 1986; Harris and Gurel, 1986; Wurgler and Zhuravskaya, 2002; Chen et al., 2004; Greenwood, 2005; Chang et al., 2015; Pavlova and Sikorskaya, 2023; Greenwood et al., 2023), and in particular, the price impact of mutual fund flows (Coval and Stafford, 2007; Lou, 2012; Edmans et al., 2012; Ben-Rephael et al., 2011; Schmickler, 2020; Ben-David et al., 2021). It is sometimes difficult to determine whether mutual fund flows are pure "noise", i.e., they are unrelated to the funds' underlying holdings, or whether they specifically target the fund's underlying holdings (i.e., the fund acts merely as a pass-through for households' fundamental beliefs). Our novel difference-in-difference estimator separately controls for the informational or preference component of flows, allowing us to distinguish between the intended price impact – determined by the fund's portfolio weights – and the (perhaps) unintended impact, which is shaped by the liquidity of the underlying holdings rather than the portfolio weights. This helps address a challenge in the flow-driven trading literature, where the informational component of flows is difficult to disentangle from the uninformed "noise" component. We also relate to the growing literature on *quantifying* the price impact of institutional demand shocks structurally (Koijen and Yogo, 2019; Bretscher et al., 2022; Koijen et al., 2020; Haddad et al., 2021; Gabaix and Koijen, 2021). We contribute to this literature by estimating the impact of institutional demand shocks at a daily frequency. We find similar overall magnitudes and provide a direct link to price impact estimates at a higher frequency (Chacko et al., 2008; Tóth et al., 2011; Frazzini et al., 2018; Bouchaud et al., 2018; Kyle and Obizhaeva, 2016). We furthermore show that a square root specification and scaling demand shocks by (past) trading volume, as opposed to shares outstanding, statistically dominates at a daily frequency.

Last, this paper is related to the growing literature studying the rise of exchange-traded funds

(ETFs) and the relationship between ETF flows and returns (Ben-David et al., 2018; Glosten et al., 2021; Ben-David et al., 2023; Box et al., 2021; Dannhauser and Pontiff, 2019; Brown et al., 2021; Davies, 2022; Broman, 2022, 2016). On the one hand, ETFs may improve price discovery in the underlying basket securities by offering investors superior liquidity. On the other hand, the liquidity of ETFs may attract a new clientele, which introduces non-fundamental volatility in the underlying basket securities. In this paper, we follow Ben-David et al. (2018) and Davies (2022) and argue that the nature of ETFs – a liquid vehicle that tracks a potentially illiquid basket of securities – can cause considerable price distortions in the underlying securities. We additionally show that illiquid portfolio tilts cause *excess* price impact relative to the most liquid portfolio the funds could hold, given their benchmark, and that this has economically meaningful effects on the cross-section of fund returns. Building on Ben-David et al. (2021) and Ben-David et al. (2022a), we furthermore show that it is not only *aggregate* positive feedback trading that affects style-level returns, but that positive feedback trading at the individual fund level can lead to self-inflated returns, if funds hold illiquid portfolios. While Ben-David et al. (2023) show that many specialized ETFs underperform by launching into overvalued themes, the funds we study are different: their own trading drives the outperformance, leading to predictable long-run underperformance. In line with Broman (2022) and Ben-David et al. (2021) who show that the flow-specific characteristics, such as ratings-chasing or positive feedback trading, are impounded in the underlying securities the funds hold, we find that inflated funds lead to inflated ownership, which predicts negative subsequent returns at the stock level.

The remainder of this paper is structured as follows. Section 2 describes the ETF and mutual fund data and provides summary statistics. Section 3 provides an analytical expression for self-inflated fund returns and introduces the concepts of fund illiquidity and portfolio illiquidity. Section 4 describes fund illiquidity in the cross-section of US mutual funds and ETFs, and estimates the elasticity of portfolio illiquidity with respect to fund size. Section 5 estimates the price impact of flow-induced trades. Section 6 tests whether investors chase past self-inflated returns. Section 7 estimates the long-run returns of inflated funds and stocks with high self-inflated ownership. Section 8 concludes.

2 Data

We obtain daily holdings of all ETFs in the US from 2017 to 2024 from ETF Global. The holdings data include the daily shareholdings of each ETF provider in the underlying securities, as well as the

ETFs' daily shares outstanding. This allows us to construct a host of daily portfolio-level variables, such as flows, liquidity of the underlying portfolio, and flow-induced trades. Security prices and characteristics for common ordinary shares traded on the NYSE, AMEX and NASDAQ are from CRSP and Compustat. We restrict our sample to U.S. equity ETFs with (on average) at least $1 million in assets under management and 20 cross-sectional positions. Our main analysis focuses on ETF data, for which daily holdings are available. We split ETFs into different categories, such as broad equity, thematic, sector etc.[7] We furthermore use a broader classification into *passive* and *active* ETFs, based on whether the fund explicitly reports a benchmark index that it seeks to track.[8] Table 1 provides summary statistics of the ETF data.

Our sample consists of 699 passive and 447 active ETFs with a total of 1,266,506 ETF-day observations. The average active ETF has $430 million in assets under management, holds 160 stocks in its portfolio, and receives an average daily inflow of 0.61% relative to assets. We supplement the daily ETF data with quarterly holdings and flows for US mutual funds from the CRSP Survivorship-Bias-Free database. We focus on domestic equity mutual funds with at least 20 cross-sectional positions, for which total dollar holdings constructed from SEC filings are at least 50% of their reported total net assets. Table C.6 in the Appendix provides summary statistics of the mutual fund data, which consists of 1743 active and 9935 passive mutual funds and 286,080 fund-quarter observations.

3 Fund Illiquidity and Inflated Fund Returns

In this section, we define the concept of fund illiquidity and show that inflated fund returns arise from the product of fund flows and fund illiquidity. Stocks are indexed by n with price $P_{n,t}$, return $r_{n,t+1}$, and average daily dollar volume $V_{n,t}$. Funds, indexed by i, have assets $A_{i,t}$ and portfolio weights $w_{i,n,t}$. The portfolio return is $R_{i,t+1} = \sum_n r_{n,t+1}$. Dollar flows are $F_{i,t+1}$, and relative flows $f_{i,t} = F_{i,t+1}/A_{i,t}$. Flow-induced demand for stock n is $w_{i,n,t}F_{i,t+1}$, reflecting reinvestment of flows in proportion to existing weights. For simplicity of exposition, we omit the fund-level indicator i when there is no ambiguity.

[7]We use ETF Global's *Category* label and further split ETFs by the more narrowly defined *Focus* label if a given focus has more than 50 unique ETFs.

[8]While the majority of ETFs attempt to replicate a rules-based index, they often follow proprietary benchmarks developed by the ETF provider. The distinction between *active* and *passive* ETFs is therefore not clear-cut. We therefore generally include both types of ETFs and sometimes single out ETFs that track broad equity indices such as the S&P500, or Russell 1000. To this end, we use ETFGs category label "Broad Equity".

Table 1: **Summary Statistics Daily ETF Data**.
The table reports summary statistics of the sample of daily ETF data from 2017 to 2024. We split the sample into passive (benchmarked) ETFs and active (not benchmarked) ETFs. AUM is the total net asset value of the ETF. Fund illiquidity $\mathcal{I}$, portfolio illiquidity $\mathcal{I}_p$, and relative fund size $\mathcal{S}$ are defined in Section 3.

(a) Passive ETFs: (N=699)

	Mean	Std	Min	Q1	Median	Q3	Max
AUM ($ Billion)	4.13	20.64	0.00	0.08	0.40	1.58	530.67
Daily Flow (% AUM)	0.09	1.93	-10.00	-0.41	0.08	0.55	10.00
Daily Flow ($ Million)	3.43	203.40	-4988.93	-6.10	1.81	9.85	4970.78
Daily Flow Volatility (%)	1.14	1.60	0.00	0.23	0.57	1.36	65.94
Number of Stocks	245.55	365.25	11.00	47.00	97.00	327.00	3751.00
Fund Illiquidity $\mathcal{I}$	0.27	0.70	0.00	0.01	0.05	0.21	17.03
Portfolio Illiquidity I_p	2.31	5.45	0.00	0.41	0.84	2.09	444.66
Fund Size $\mathcal{S}$	0.15	0.44	0.00	0.00	0.02	0.09	10.41

(b) Active ETFs: (N=447)

	Mean	Std	Min	Q1	Median	Q3	Max
AUM ($ Billion)	0.43	1.81	0.00	0.02	0.06	0.19	33.80
Daily Flow (% AUM)	0.61	2.57	-10.00	-0.26	0.43	1.44	10.00
Daily Flow ($ Million)	4.01	31.55	-1376.06	-0.96	1.53	4.60	1216.38
Daily Flow Volatility (%)	1.41	2.05	0.00	0.28	0.70	1.69	56.81
Number of Stocks	160.87	246.87	6.00	40.00	75.00	176.00	2448.00
Fund Illiquidity $\mathcal{I}$	0.09	0.35	0.00	0.00	0.01	0.03	6.44
Portfolio Illiquidity I_p	4.88	10.39	0.00	0.77	1.60	4.22	423.25
Fund Size $\mathcal{S}$	0.02	0.08	0.00	0.00	0.00	0.01	2.49

3.1 Price Impact

Trading a given dollar amount D in a stock causes price impact. We assume that a fund's price impact is greater when trading a larger fraction of n's volume. The main results in the paper remain unchanged when we scale demand shocks by other measures of liquidity such as float-adjusted market cap. Following the literature on transaction costs (see e.g., Chacko et al. (2008), Frazzini et al. (2018), Tóth et al. (2011), Kyle and Obizhaeva (2016)) we model price impact as

$$\text{Price Impact}_{n,t}(D) = \theta_\eta \left(\frac{D}{V_{n,t}} \right)^\eta \tag{1}$$

The price impact (expressed as a return) is proportional to dollar trade relative to supply. We allow for non-linearity η in the relationship between trade size and price impact. A large empirical literature estimates the price impact of trades at a high frequency and finds a square-root impact $\eta \approx 0.5$.[9] Figure C.9 in the Appendix shows that square-root price impact strongly dominates the linear model for our data on daily ETF trades. For expositional purposes, we use $\eta = 1$ in the main text which leads to algebraically simpler expressions, and write $\theta \equiv \theta_1$ henceforth. Modeling price impact as concave ($\eta < 1$) leaves the *qualitative* results of the paper unchanged. Empirically, Brokmann et al. (2015); Frazzini et al. (2018) find that trading 1% of daily volume leads to an average price impact of around 10 basis points, i.e., $\theta \approx 0.1$, a number that we confirm in our regressions using ETF trades (see section 5).

3.2 Fund Illiquidity and Portfolio Illiquidity

We define fund illiquidity as the product of portfolio illiquidity and effective size. To this end, note that the dollar position of a fund in stock n is given by $w_{n,t}A_t$. Following Pástor et al. (2020), we define portfolio illiquidity as proportional to the excess liquidation cost of that portfolio, assuming linear impact:

$$I_{p,t} = \sum_{n=1}^{N} \frac{w_{n,t}^2}{v_{n,t}} - 1 \tag{2}$$

where $v_{n,t}$ is the weight of stock n in a volume-weighted benchmark portfolio $v_{n,t} = \frac{V_{n,t}}{\sum_{n=1}^{N} V_{n,t}}$, given the fund's current asset universe N. Empirically, $v_{n,t}$ are close to market-cap weights as dollar volume $V_{n,t}$ and market capitalization are 90% correlated in the cross-section.[10] Portfolio illiquidity $I_{p,t}$ lies between 0 and ∞ and measures the extent to which a fund tilts away from the cheapest portfolio to liquidate. If a fund is precisely liquidity weighted, then $w_{n,t} = v_{n,t}$ and $I_{p,t} = 0$. With a slight abuse of language, we will call such a portfolio the "most liquid", given the fund's trading universe. In this sense, single stock ETFs are not illiquid funds: since $w_{n,t} = v_{n,t} = 1$, their portfolio illiquidity is $I_{p,t} = 0$. The

[9]See Bouchaud et al. (2018) for a detailed literature summary. The literature on flow-induced trading at a quarterly frequency (see e.g., Lou (2012)) typically assumes a linear specification $\eta = 1$ and scales dollar trades by market cap as opposed to dollar volume. Formally, the linear price impact specification in, e.g., Lou (2012), Pavlova and Sikorskaya (2023), Koijen and Yogo (2019) is given by $\text{Price Impact}_{n,t}(D) = \theta \frac{D}{M_{n,t}}$ where $M_{n,t}$ is the market capitalization of n. However, Chaudhry and Li (2025) find that even at a quarterly frequency price impact tends to be concave.

[10]See Appendix C.9. Defining portfolio illiquidity with respect to market capitalization weights as opposed to volume weights leaves all results unchanged. However, scaling by volume instead of market cap when estimating the price impact of dollar trades leads to statistically more precise impact estimates. Pástor et al. (2020) define portfolio *liquidity* $L = \left(\sum_{n=1}^{N} \frac{w_{n,t}^2}{v_{n,t}}\right)^{-1}$ as opposed to *illiquidity*. Since our focus is on the excess price impact of funds on their underlying holdings – which is proportional to $I_{p,t}$ – we work with the illiquidity measure $I_{p,t} = L_t^{-1} - 1$ rather than L_t.

price impact of flows into single stock ETFs cannot be separated from the preferences and beliefs of the investors, and therefore the fundamentals of the company. Only for illiquid funds this is possible, as the price impact is different from portfolio weights, and can be separated from investor intent.

We define *fund illiquidity* $\mathcal{I}_t$ as the simple product of portfolio illiquidity and effective fund size

$$\mathcal{I}_t = I_{p,t} \cdot \mathcal{S}_t. \tag{3}$$

where effective fund size $\mathcal{S}_t = \frac{A_t}{V_t}$ is given by the fund's assets under management A_t relative to the total liquidity of its current holdings $V_t = \sum_{n=1}^{N} V_{n,t}$.[11] The next section provides a simple micro-foundation for fund illiquidity as the product of size and portfolio illiquidity, showing that it naturally emerges from the price impact of flow-induced trades in excess of the most liquid feasible portfolio given the fund's universe.

Fund illiquidity measures the potential distortive effects a fund can have on its own portfolio when it receives inflows. Funds that hold illiquid portfolios (high $I_{p,t}$) and receive high inflows ($\mathcal{S}_t$ increases) can have large impacts on their underlying holdings. Note that because portfolio illiquidity $I_{p,t}$ is defined in excess of the volume-weighted benchmark, a fund with weights close to volume weights (e.g., market-cap weighted funds) has $I_{p,t} = 0$ and hence zero fund illiquidity ($\mathcal{I}_t = 0$) regardless of their size. As a result, broad index funds that track value-weighted benchmarks – such as the SPDR S&P 500 ETF (SPY) – have low fund illiquidity, even if their flows materially affect market prices. SPY's impact on the S&P 500 index is not "distortive": it is explicitly used by investors to take directional bets on the index, and its flow-driven trading is aligned with that intent. According to our definition, such a fund is not illiquid. This however does not mean that flows into the S&P 500 index cannot create the type of feedback loop we are discussing here. Our definition of fund illiquidity allows us to cleanly identify impact-induced effects using the *distortionary effects* that arise from the composition of illiquid funds.

Similarly, a triple-leveraged single-stock ETF may exert substantial pressure on its underlying, yet its fund illiquidity is zero because its flows and exposures are perfectly aligned. In contrast, a fund that tilts toward illiquid stocks – say, by allocating 5% of its portfolio to a thinly traded security – can

[11] Alternatively, one could define effective size relative to the total market capitalization of the fund's holdings and compute portfolio illiquidity using market-cap weights instead of volume weights. This changes only the scale of the variables, not the results. One could also scale $\mathcal{S}_t$ by flow volatility σ_f to account for variation in percent flows across funds. Empirically, however, while the volatility of dollar flows σ_F varies greatly across funds, the volatility of percent flows σ_f is relatively stable.

exert a large impact on that stock even though the overall allocation appears small. Fund illiquidity captures this kind of distortion: it measures how misaligned a fund's price impact is with the likely preferences of its investors, who typically interpret portfolio weights – not trading impact – as their effective exposures.

3.3 Self-Inflated Fund Returns

The price impact of flow-induced trading is a realized return on the existing positions of the fund. Let $w^x_{n,t} = w_{n,t} - v_{n,t}$ denote the weights held in excess of the most liquid portfolio, conditional on the fund's current universe. Setting $\eta = 1$, the stock-specific price impact of a flow-driven trade in excess of the most liquid portfolio is given by $\theta \frac{F_t w^x_{n,t-1}}{V_{n,t}}$. We define the self-inflated fund return as the flow-induced fund return in excess of what it would have been if the fund held the most liquid portfolio given its universe. Formally

$$R^{\mathcal{I}}_t = \theta \sum_n w_{n,t-1} \frac{F_t w^x_{n,t-1}}{V_{n,t}} \tag{4}$$

Rearranging and plugging in the expression for fund illiquidity (4) the self-inflated fund return simplifies to:

$$R^{\mathcal{I}}_t = \theta f_t \mathcal{I}_{t-1} \tag{5}$$

The self-inflated fund return $R^{\mathcal{I}}_t$ is given by the relative flow in the fund f_t, interacted with fund illiquidity $\mathcal{I}_{t-1}$, scaled by price impact θ. The more illiquid the fund's positions are relative to the underlying supply, the greater the potential impact of a 1% flow in the fund. Recall that fund illiquidity is driven by fund size and portfolio illiquidity. When funds attract significant inflows, they inelastically adjust their portfolio liquidity, leading to steadily increasing $\mathcal{I}_{t-1}$ and an elevated potential for self-inflated fund returns. When $\eta \neq 1$, for example under concave price impact, the self-inflated return becomes $R^{\mathcal{I}}_t = \theta_\eta (f_t \tilde{\mathcal{I}}_{t-1})^\eta$.[12]

3.4 Co-Inflated Fund Returns

Many funds hold overlapping portfolios. When holdings overlap, flow-driven trades of one fund affect the returns of other funds with overlapping holdings. Fund returns caused by flow-induced trades of other ETFs are not *self*-inflated but *co*-inflated. We define co-inflated returns as returns caused by

[12] Fund illiquidity $\tilde{\mathcal{I}}_t = \mathcal{S}_t \cdot \tilde{I}_{p,t}$ should be slightly adjusted to account for the nonlinear impact with $\tilde{I}_{p,t} = \left(\sum_n (\frac{w^x_{n,t}}{v_{n,t}})^\eta w_{n,t}\right)^{1/\eta}$. In the presence of outflows ($f_t < 0$), which is the empirically relevant case, the expression becomes $R^{\mathcal{I}}_t = \theta_\eta \ \mathrm{sign}(f_t)(|f_t|\tilde{\mathcal{I}}_t)^\eta$.

flow-induced trades of *other* ETFs. We re-introduce the fund subscript i here to distinguish between own and co-inflated returns. Formally, for a fund i, the co-inflated return is defined as

$$R^{\mathcal{C}}_{i,t} = \theta \sum_{j \neq i} f_{j,t} \mathcal{I}_{ji,t-1} \tag{6}$$

where $\mathcal{I}_{ji,t}$, defined in Appendix A, is the co-illiquidity between i and j, measuring the portfolio overlap of two funds and the extent to which this overlap is concentrated in illiquid positions. Appendix A shows that $R^{\mathcal{I}}_{i,t} + R^{\mathcal{C}}_{i,t}$ is equal to the weighted average price impact from total flow-induced trading by all funds in excess of their respective liquid benchmarks. When $\eta \neq 1$, the co-inflated return is $R^{\mathcal{C}}_t = \theta_\eta \sum_{j \neq i} (f_{j,t} \tilde{\mathcal{I}}_{ji,t-1})^\eta$.[13]

4 Fund Illiquidity in the Cross-Section of Mutual Funds and ETFs

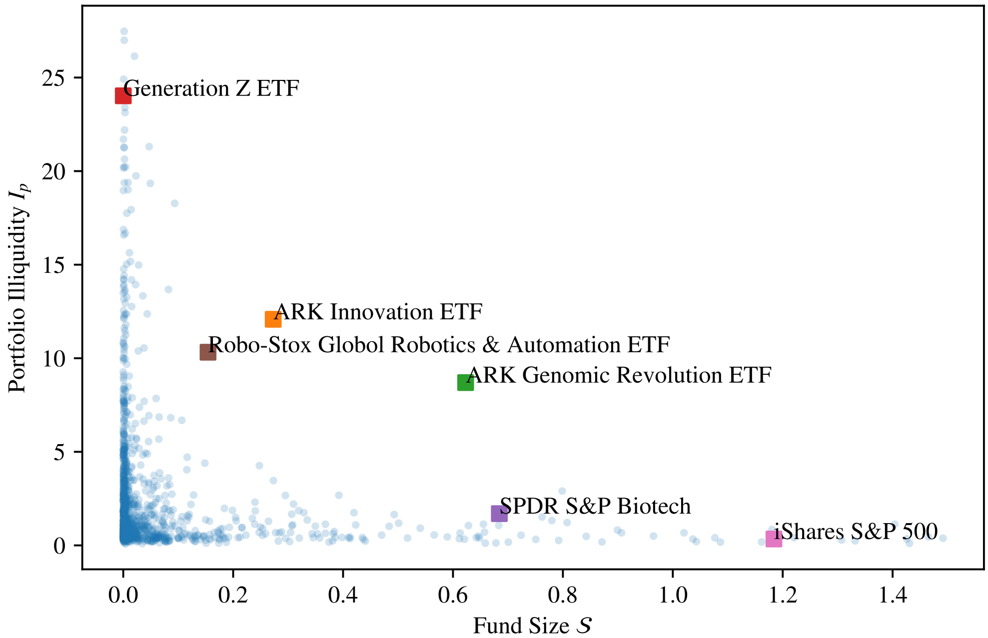
4.1 Portfolio Illiquidity and Fund Size

We construct portfolio illiquidity, fund size, and fund illiquidity for all equity ETFs and mutual funds in the US. We focus on ETFs, for which we have daily holdings data, and report all mutual fund results (based on quarterly filings) in the appendix. Figure 1 plots the portfolio illiquidity and effective size $\mathcal{S}_t$ for all US equity ETFs in our sample. Appendix Figure C.10 repeats the exercise for all equity mutual funds in the US. For both ETFs and mutual funds, there is considerable cross-sectional variation in fund illiquidity with $\mathcal{I}_t > 1$ for many mutual funds.[14] In line with the findings in Pástor et al. (2020), the largest ETFs hold liquid portfolios. They give investors exposure to broad equity indices and have little impact on the cross-section of their holdings as they do not hold concentrated illiquid positions. On the other end of the spectrum, there are specialized ETFs (such as the Generation Z ETF) that hold illiquid portfolios and allow investors to get exposure to specific segments of the market. These ETFs are typically small relative to the stocks they hold. Hence, regardless of their objective, the majority of ETFs located close to the axes have low fund illiquidity ($\mathcal{I}_t \approx 0$). However, there are also many ETFs located towards the center of the figure, which implies a high fund illiquidity and potentially large impacts on their underlying portfolio constituents. Figure 2 plots average illiquidity by fund type along with the total assets managed by each group. Small cap, strategy and thematic ETFs are the most illiquid fund types with a combined assets under management of over 600 billion

[13] See Appendix A for details.

[14] See Tables 1 and C.6 for the distributions of $\mathcal{S}_t$, $I_{p,t}$, and $\mathcal{I}_t$ for the cross-section of US ETFs and mutual funds.

Figure 1: **Portfolio Illiquidity versus Effective Size**.
The figure plots the portfolio illiquidity $I_{p,t}$ and effective size $\mathcal{S}_t$ for each ETF in our sample, averaged over time. Each dot represents a single ETF. Portfolio illiquidity (on the y-axis) $I_{p,t} = \sum_n w_{n,t}^2/v_{n,t} - 1$ measures the average deviation from liquid positions. Effective size (on the x-axis) $\mathcal{S}_t = A_t/V_t$ is total assets relative to the total liquidity of the underlying securities. The labeled dots represent illustrative examples.

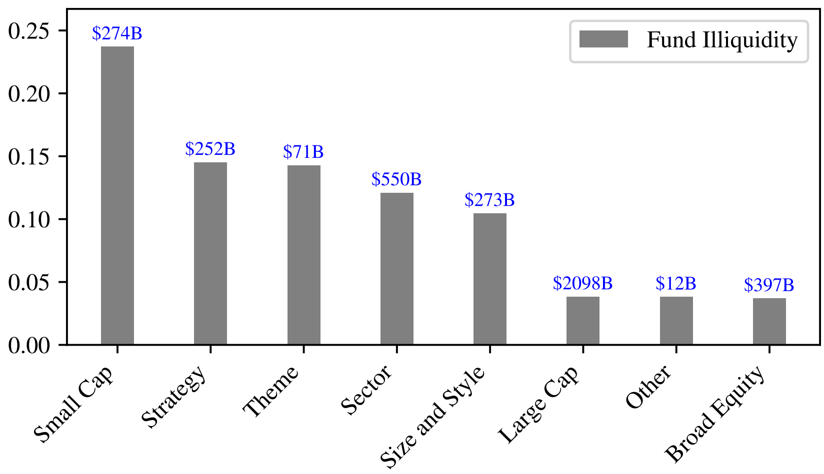


as of May 2024. Large cap funds and broad equity funds manage over $2.5 trillion but are relatively liquid according to our measure of fund illiquidity. Appendix Table C.7 lists the ten most illiquid ETFs and mutual funds in the U.S. The most illiquid ETF is the iShares Core S&P Small-Cap ETF, with a fund illiquidity of 8.3. In other words, a 1% inflow results in trades amounting to 8.3% more daily volume than would be required under the most liquid portfolio given the asset universe.

4.2 What Drives Fund Illiquidity?

Before estimating the exact link between fund returns, flows, and fund illiquidity (see next section), we examine the drivers of fund illiquidity. In order to assess what drives the cross-section of fund illiquidity, we first conduct a simple variance decomposition of changes in fund illiquidity. Let $\Delta \log \mathcal{I}_t = \log \mathcal{I}_t - \log \mathcal{I}_0$ denote the change in fund illiquidity from the time when fund i first appears in our sample. $\Delta \log A_t$, $\Delta \log V_t$, $\Delta \log I_{p,t}$ are defined accordingly. We can decompose changes in log fund illiquidity

Figure 2: **Fund Illiquidity by ETF Type**. The figure shows the average fund illiquidity $\mathcal{I}_t$ for each ETF type. Blue labels indicate the total assets managed by each group (in billion dollars) as of May 2024.



into changes in portfolio illiquidity, assets under management, and liquidity of the underlying assets.

$$\Delta \log \mathcal{I}_t = \Delta \log I_{p,t} + \underbrace{\Delta \log A_t - \Delta \log V_t}_{\Delta \log \mathcal{S}_t} \tag{7}$$

Panel a) of Table 2 presents the results. For both benchmarked (passive) and non-benchmarked (active) ETFs, changes in fund size account for the vast majority of the variation in fund illiquidity, while changes in portfolio illiquidity contribute little. As funds grow, they do not meaningfully adjust their portfolios toward more liquid assets, allowing fund illiquidity to rise with size. To further investigate the limited liquidity adjustments as funds grow, Panel b) of Table 2 estimates the relationship between fund size and portfolio illiquidity, i.e., how elastically funds respond in their liquidity choice as their assets grow. We regress quarterly changes in portfolio illiquidity $\log I_{p,t}$ onto changes in assets. The estimated coefficient is -0.075, indicating that a 1% increase in assets leads to only a 0.075% decrease in portfolio illiquidity – or equivalently, a 0.925% increase in fund illiquidity. This limited response is not driven by over-differencing. In the time-series specification with ETF fixed effects, the coefficient remains similar at -0.063. Appendix Table C.8 confirms the inelastic liquidity adjustment for the subsample of active ETFs and alternative fixed effects specifications, with estimates ranging from -0.05 to -0.095.

Finally, the analysis accounts for extensive-margin adjustments by controlling for changes in underlying liquidity V_t, defined as the total volume of stocks held by the fund. If inflows lead funds to add liquid stocks, this is captured by V_t. To test whether this masks stronger liquidity adjustments, we regress the combined change in portfolio illiquidity and underlying liquidity, $\Delta \log I_{p,t} + \Delta \log V_t$, on changes in assets $\Delta \log A_t$.[15]. The coefficient remains nearly unchanged at –0.089, confirming that liquidity adjustments remain limited even after accounting for extensive margin responses.

Table 2: **What Drives Fund Illiquidity?**
Panel (a) decomposes the variance of changes in fund illiquidity $\Delta \log \mathcal{I}_t$ into changes in portfolio illiquidity $\Delta \log I_{p,t}$, changes in assets $\Delta \log A_t$, and changes in underlying liquidity $\Delta \log V_t$. Panel (b) regresses quarterly changes and levels of portfolio illiquidity $\log I_{p,t}$ on quarterly changes and levels of assets, controlling for liquidity, expense ratio and flow volatility. Standard errors are double clustered at the day and fund level.

(a) Variance Decomposition $\Delta\mathcal{I}$

All Funds	$\Delta \log \mathcal{I}_p$	0.12	(0.01)
	$\Delta \log A$	0.84	(0.02)
	$-\Delta \log V$	0.04	(0.01)
Active Funds	$\Delta \log \mathcal{I}_p$	0.10	(0.02)
	$\Delta \log A$	0.89	(0.02)
	$-\Delta \log V$	0.01	(0.02)
Passive Funds	$\Delta \log \mathcal{I}_p$	0.14	(0.02)
	$\Delta \log A$	0.83	(0.02)
	$-\Delta \log V$	0.03	(0.01)

(b) Inelastic Portfolio Illiquidity I_p

	$\Delta \log I_p$ (1)	$\log I_p$ (2)
$\Delta \log A$	-0.075*** (0.016)	
$\Delta \log V$	0.850*** (0.037)	
$\log A$		-0.063*** (0.015)
$\log V$		0.535*** (0.046)
Log Expense Ratio	-0.005 (0.005)	0.014 (0.036)
Flow Volatility	0.125 (0.238)	-0.028 (0.285)
Date FE	x	-
ETF FE	-	x
Observations	21748	22834
R^2	0.341	0.917
R^2 Within	0.277	0.188

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

These results build on Pástor et al. (2020), who document a positive relationship between assets under management and portfolio liquidity in the cross-section of mutual funds.[16] While funds do shift toward more liquid securities as they grow in the time series, the adjustment in portfolio liquidity is too limited to offset the resulting increase in fund illiquidity. Regardless of the exact magnitude, the

[15] See Appendix Table C.8

[16] Pástor et al. (2020) report a cross-sectional coefficient of 0.15. We find a somewhat weaker relationship in the time series, both using first differences and controlling for fund fixed effects.

evidence highlights that the fund's liquidity choice is *inelastic*. Funds do not meaningfully counteract the effects of inflows by rebalancing toward more liquid stocks, leading to sharp increases in fund illiquidity as they grow.

5 Estimating Self-Inflated Returns

Recall that self-inflated fund returns are given by $R_t^{\mathcal{I}} = \theta f_t \mathcal{I}_{t-1}$, i.e., their economic magnitude is critically driven by the price impact θ. The difficulty in estimating price impact lies in the fact that trades likely contain information about the underlying fundamentals or risk exposures. They are correlated with unobserved variation in prices (the error term), which leads to biased price impact estimates. The empirical literature on low-frequency price impact has therefore carefully constructed exogenous variation in demand from index inclusions (Shleifer, 1986), mutual fund flows (Lou, 2012), and dividend reinvestments (Hartzmark and Solomon, 2022). Building on this literature, we estimate high-frequency price impact from flow-driven trades by ETFs.

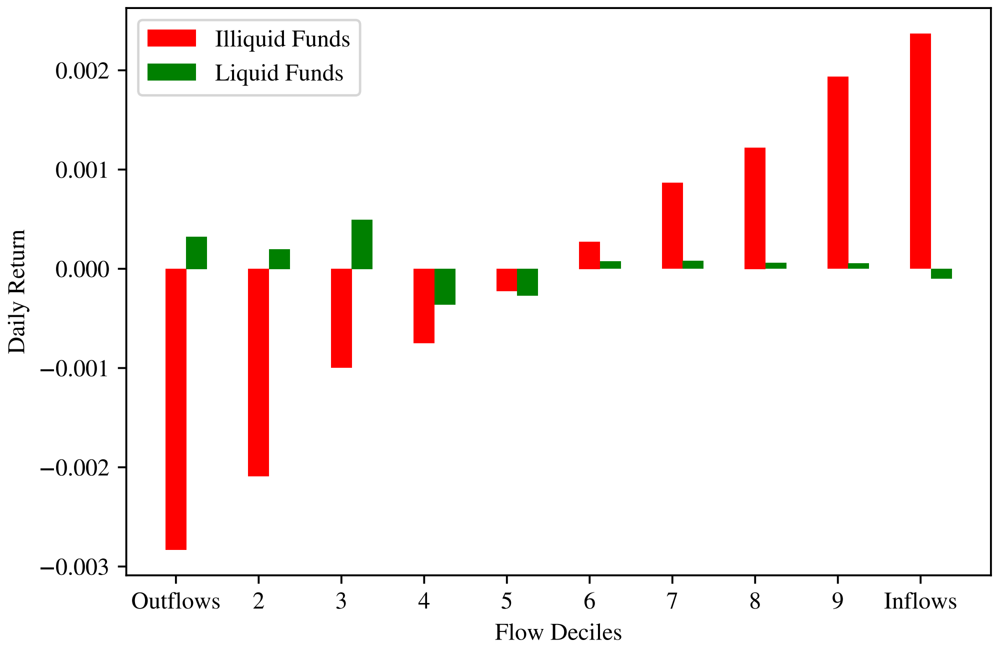
5.1 Reinvested ETF Flows at the Daily Frequency

While the exchange-traded nature of ETFs slightly alters the construction of flows and flow-driven trading (see Appendix B for details), the underlying mechanics of flow-driven trading in mutual funds and ETFs are identical. The main difference comes from the fact that for ETFs, the flow-induced trading is effectively done by third parties – authorized participants (APs). The availability of *daily* holdings for ETFs allows us to assess the exact extent to which flows are reinvested in the existing portfolios. For each ETF in our sample, we regress changes in its stock holdings onto flows over the panel of stock-day observations for each ETF. Appendix Figure B.8 reports the flow-scaling coefficient for all active and passive ETFs in the US. The vast majority of ETFs perfectly reinvest both in- and outflows (via their APs) in their existing positions on the same day with a flow-scaling coefficient of 1. The timing and price impact of reinvested flows are more difficult to assess for mutual funds, as holdings are only disclosed monthly or quarterly.

5.2 Qualitative Evidence from Portfolio Sorts

Before diving into the quantitative estimation, we first provide intuitive evidence of the existence of self-inflated fund returns using simple portfolio sorts. Each day, we sort all ETFs into deciles based on their inflows. Within each decile, we split ETFs into two groups: illiquid funds (top decile of $\mathcal{I}_t$) and liquid funds (bottom decile of $\mathcal{I}_t$). We then compute the average return across ETFs in each group and decile.

Figure 3: **Daily ETF Returns and Flows**. This figure shows the average daily excess return of ETFs across flow deciles. Each day, ETFs are sorted into deciles based on their net flows. Within each decile, we compare illiquid ETFs (top decile of $\mathcal{I}_t$, shown in red) and liquid ETFs (bottom decile of $\mathcal{I}_t$, shown in green). Excess returns are computed relative to the market return.



For liquid funds, there is virtually no relationship between daily flows and returns. In contrast, for illiquid funds, returns increase monotonically with inflows. The figure looks mechanical for good reason: it reflects a mechanical relationship. In illiquid funds, inflows drive up the prices of underlying holdings, thereby inflating returns. Appendix C.11 confirms that this pattern holds when using CAPM-adjusted abnormal returns and disappears when sorting solely by portfolio illiquidity $I_{p,t}$ instead of fund illiquidity $\mathcal{I}_t$. This distinction matters: portfolio illiquidity alone is not enough to generate return impact – a 1% inflow into an illiquid portfolio has no effect if the fund is small. Return inflation arises only when the fund is large relative to the liquidity of its holdings – a condition captured by fund illiquidity (portfolio illiquidity times size), rather than by portfolio illiquidity alone. While this provides qualitative evidence that flows can inflate returns in illiquid funds, it does not quantify the effect. The next section addresses this by estimating the price impact parameter (θ) using ordinary least squares in a difference-in-differences framework.

5.3 A Difference-in-Difference Estimator

A potential concern with using flow-driven trading as exogenous variation in investor demand is that the flows themselves may contain information about the underlying securities held by the fund.[17] This may be particularly worrisome for ETFs, which are precisely used by investors to make theme- and sector-specific bets. However, the decomposition of self-inflated returns into fund flows and fund illiquidity allows for a simple difference-in-difference estimator: by directly controlling for flows $f_{i,t}$, one can estimate θ via the interaction of flows and illiquidity, net of any information contained in the flows themselves. In particular, we propose the following pooled regression across fund-day observations:

$$R_{i,t} = \alpha_i + \alpha_t + \gamma f_{i,t} + \beta \mathcal{I}_{i,t-1} + \overbrace{\theta_1 f_{i,t} \mathcal{I}_{i,t-1}}^{\text{Self-Inflated } R^{\mathcal{I}}} + \overbrace{\theta_2 \sum_{j \neq i} f_{j,t} \mathcal{I}_{ji,t-1}}^{\text{Co-Inflated } R^{\mathcal{C}}} + + \epsilon_{i,t} \tag{8}$$

Note that flows may contain information about the underlying, resulting in a positive correlation of $f_{i,t}$ and unobserved return determinants in the cross-section. Self-inflated fund returns, however, come from the interaction of flows and fund illiquidity. Thus separately controlling for flows $f_{i,t}$ and fund illiquidity $\mathcal{I}_{i,t-1}$ results in an implicit difference-in-difference estimator. Intuitively, a positive correlation between flows and returns could be (i) because fund flows contain information, which is captured by γ, (ii) because illiquid funds have higher returns, which is captured by β, or (iii) because of price impact θ, which is the interaction of illiquidity and flows. We estimate 8 over the panel of ETF-day observations including ETF and time-fixed effects from 2017 to 2024 using ordinary least squares. Table 3 reports the estimated coefficients.

To set the stage, we initially estimate a simple ordinary regression of fund returns $R_{i,t}$ onto raw ETF flows $f_{i,t}$. The coefficient is close to 0 but statistically significant, suggesting that there is a cross-sectional correlation between daily ETF flows and returns. However, this coefficient can arise from price impact, price discovery, or any combination of the two. Next, we estimate the difference-in-difference specification using the interaction term with fund illiquidity $f_{i,t}\mathcal{I}_{i,n,t-1}$, controlling for fund and day fixed effects. The coefficient on the interaction term is around 0.085 and is highly statistically significant (t-stat >4). It has the following structural interpretation: if a fund's dollar holdings are, on average, 50% of the daily underlying volume ($\mathcal{I}_{i,n,t} = 0.5$), a 2% inflow causes an additional ETF return of $0.085 \times 2\% \times 0.5 = 0.085\%$. It therefore has the structural interpretation of the impact of

[17] Formally, this implies that $\text{cov}(f_{i,t}, R_{i,t}^{\perp}) \neq 0$, where $R_{i,t}^{\perp}$ are returns driven by determinants other than direct flows.

Table 3: **Price Impact at the Fund-level**. The table reports the estimated price impact coefficients from pooled OLS regressions using daily data on ETF returns and flows. Specification (1) regresses daily fund returns onto flows. (2) estimates the price impact using the interaction of illiquidity and flows $f_{i,t}\mathcal{I}_{i,t-1}$ including date fixed effects. (3) adds ETF fixed effects. (4) estimates co-impact as the coefficient on $\sum_{j\neq i} f_{j,t}\mathcal{I}_{ji,t-1}$. Specification (5) includes style-by-date fixed effects. (6) and (7) split the sample into active and passive ETFs respectively. Standard errors are double clustered at the day and fund level.

	Excess ETF Return						
						Passive Funds	*Active Funds*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$f \times \mathcal{I}$		0.085***	0.084***	0.086***	0.078***	0.072***	0.157**
		(0.019)	(0.019)	(0.019)	(0.017)	(0.017)	(0.057)
Co-Impact				0.052***	0.050***	0.052***	0.047***
				(0.009)	(0.009)	(0.010)	(0.011)
Flow f	0.005*	0.000	0.000	0.000	0.000	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Fund Illiquidity $\mathcal{I}$		-0.000*	-0.000**	-0.000***	-0.000**	-0.000*	-0.001**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Date FE	-	x	x	x	x	x	x
Type-Date FE	-	-	-	-	x	-	-
ETF FE	-	-	x	x	x	x	x
Observations	1196151	1196151	1196151	1196151	1196151	885725	310426
R^2	0.000	0.097	0.098	0.101	0.166	0.110	0.103
R^2 Within	-	0.001	0.001	0.004	0.003	0.004	0.005

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

buying 1% of daily volume and is of the same order of magnitude as micro-structure estimates of price impact.[18] For example, Frazzini et al. (2018) find that buying 1% of daily volume has a permanent price impact of 0.1%. Next, we estimate the co-inflated price impact by controlling for the trades of all other ETFs in co-held stocks $\sum_{j\neq i} f_{j,t}\mathcal{I}_{ji,t-1}$. The co-impact is close in magnitude to the own-impact with a highly statistically significant coefficient of 0.051 (t-stat>5). Last, we split the sample into active and passive ETFs and find a somewhat larger coefficient of 0.157 for active and 0.072 for passive ETFs. The higher price impact of active ETFs may be due to trading in illiquid securities that have a higher price impact not perfectly accounted for by volume, or because their trades are somewhat smaller, which under concave impact leads to larger coefficient estimates. Indeed, Frazzini et al. (2018) document larger trading costs for small caps where buying 1% of daily volume increases prices by 0.19%.

[18] See Tóth et al. (2011), Frazzini et al. (2018), and Bouchaud et al. (2018).

5.4 Further Robustness Tests

This section provides further robustness tests. The results are summarized in Appendix Table C.9.

Triple Difference Estimator. Holding $I_{p,t}$ constant, a larger fund size $\mathcal{S}_t$ implies higher fund illiquidity $\mathcal{I}_t$, and vice versa. This raises two concerns: (i) flows may become more informed as funds grow, or (ii) flows may be more informed for funds holding illiquid portfolios. To address this concern, note that fund illiquidity is the product of portfolio illiquidity and fund size $I_{p,t} \cdot \mathcal{S}_t$. We can thus separately control for $f_t I_{p,t-1}$ and $f_t \mathcal{S}_{t-1}$, turning θ into a triple difference estimator that accounts for a potential correlation of flow informativeness with size and portfolio illiquidity. The estimated price impact remains largely unchanged, declining only modestly from 0.084 to 0.066 – suggesting that flow informativeness is not systematically related to size or illiquidity.

Nonlinear Impact. A nonlinear specification with $\eta = 0.5$ yields a slightly lower estimate of 0.036 (t-stat of 4.5) for self-inflated trades and 0.016 (t-stat of 8) for co-inflated trades. The nonlinear model strongly outperforms the linear specification in a horserace. Under the square root specification, the impact of active and non-passive ETFs becomes statistically indistinguishable, suggesting that the higher impact for active ETFs in the linear specification is due to smaller trade sizes, which are associated with higher impacts in a concave price impact specification.

Reversal. Lastly, we test the short-term reversal of self-inflated fund returns. We estimate permanent versus transitory impact in a distributed lag model of daily fund-level returns onto $S = 20$ lags of flow-driven trades. Formally,

$$R_{i,t} = \sum_{s=0}^{S} \theta_{1,s} (f\mathcal{I})_{i,t-s} + \sum_{s=0}^{S} \theta_{2,s} (f\mathcal{I})^{\mathcal{C}}_{i,t-s} + \text{Controls} + \epsilon_{i,t} \tag{9}$$

where $(f\mathcal{I})_{i,t-s}$ and $(f\mathcal{I})^{\mathcal{C}}_{i,t-s}$ denote shorthand notations for self-inflated and co-inflated flow-driven trades, respectively. The long-run price impact until t^* is given by the cumulative sum of the coefficients $\sum_{s=0}^{t^*} \theta_s$. Appendix Figure C.12 plots the cumulative sum of the coefficients. We do not find significant reversal in self-inflated and co-inflated price impact, at least in the first 20 days after the investment. Note that our sample is too short to statistically test for long-term reversal over several years. However, in our application to mutual funds (Section 7.2) we find significantly negative long-run returns for inflated funds as well as the stocks held by inflated funds in line with the long-run reversal (Ben-David et al., 2022a). Therefore, while inflation may not revert immediately, the negative long-term returns suggest that inflated funds are indeed inflated. Last, we find that ETF flows chase returns at a high frequency. Therefore, even if the price impact were to revert within a month, there could still be significant fund inflation as flows chase returns before they revert (see 6).

6 Do fund flows chase self-inflated returns?

6.1 Return Chasing at a High Frequency

The flow-performance relationship for mutual funds is typically studied at quarterly or monthly frequencies.[19] However, self-inflated returns may only affect performance over shorter windows – either because price impact reverses, or because noise from fundamental returns masks it over time. If investors respond mostly to long-run performance, this limits the positive feedback from chasing self-inflated returns. To test this, we examine whether the flow-performance relationship is driven by recent returns. Specifically, we regress daily ETF flows on up to $L = 60$ lags of daily returns and flows:

$$f_{i,t+1} = \alpha_t + \sum_{s=0}^{L} \beta_s R_{i,t-s} + \text{Controls} + \epsilon_{i,t+1} \tag{10}$$

The return chasing kernel $\{\beta_s\}_{s=0}^{L}$ captures the weights investors place on past returns. Figure 4 shows the cumulative kernel estimated from daily ETF data (2017–2024).

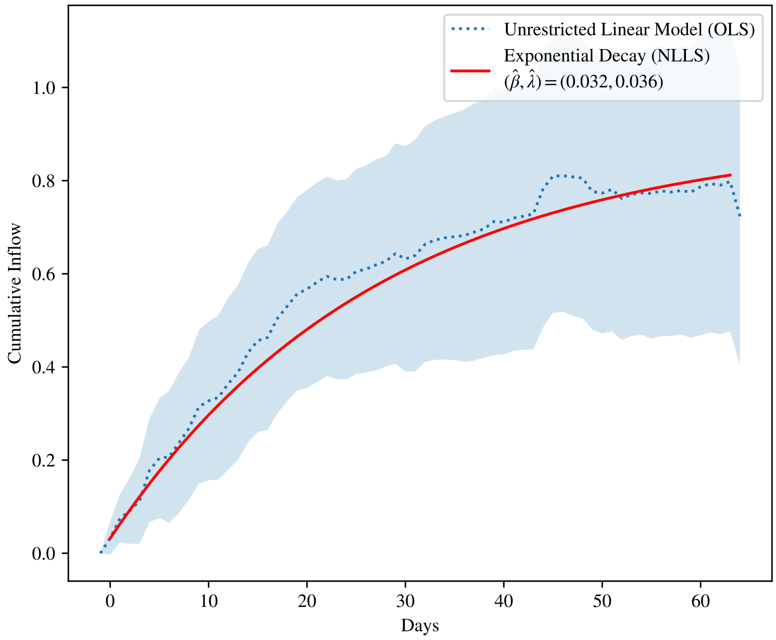
In line with Barber et al. (2016) and Dannhauser and Pontiff (2019), who find that the first monthly return lag contributes most strongly to the flow-performance relationship at lower frequencies, we find that ETF flows respond most strongly to the most recent daily return. The estimated return-chasing pattern places substantially more weight on recent returns, resembling the exponential decay in expectations observed in models of extrapolative investor behavior (Greenwood and Shleifer, 2014; Barberis et al., 2015; Da et al., 2021). Following Barber et al. (2016) we also estimate an exponential decay model with the constraint $\beta_s = \beta e^{-\lambda s}$ (red line) which provides a good fit for the unconstrained OLS coefficients.[20] The cumulative coefficient implies that a 1% return realization leads to an additional $\frac{\hat{\beta}}{1-e^{-\hat{\lambda}}} \approx 0.9\%$ inflows, with the first 0.6% occurring within 30 days of the initial return.

In Figure C.14 we show that the exponential weighting scheme holds generally across sample splits,

[19] See e.g., Ippolito (1992), Chevalier and Ellison (1997), Huang et al. (2007), Goldstein et al. (2017), Barber et al. (2016), Dannhauser and Pontiff (2019).

[20] The exponential decay parameterizes the coefficients on all the lags as a function of time, $\beta_s = \beta e^{-\lambda s}$. We estimate $(\hat{\beta}, \hat{\lambda}) = (0.03, 0.04)$ via nonlinear least squares (NLLS). The exponential decay formulation allows for a parsimonious representation of the return-chasing behavior that is unrelated to the horizon. This is useful when comparing return-chasing behavior across different return decompositions, such as price impact versus fundamental return (as in this paper) or abnormal versus factor return (as in Barber et al. (2016)).

Figure 4: **Return Chasing Kernel**. This figure shows the cumulative return-chasing response estimated from the model $f_{i,t+1} = \alpha_t + \sum_{s=0}^{L} \beta_s R_{i,t-s} + \text{Controls} + \epsilon_{i,t+1}$. The blue line plots the cumulative sum of OLS coefficients using $L = 60$ daily return lags. Shaded areas denote 95% confidence bands, with standard errors double clustered at the day and fund level. Cumulative standard errors account for covariance across lags and are computed as $\sqrt{\mathbf{1}_t^T \Omega_t \mathbf{1}_t}$, where Ω_t is the covariance matrix of $\{\hat{\beta}_s\}_{s=0}^{t}$. The red line shows the cumulative return chasing from an exponential decay model $f_{i,t+1} = \beta \sum_{s=0}^{65} e^{-\lambda s} R_{i,t-s} + \text{Controls} + \epsilon_{i,t+1}$ estimated by nonlinear least squares (NLLS). Controls include log assets under management and 60 lags of past flows.



such as for funds with high vs. low fund illiquidity, benchmarked vs. non-benchmarked ETFs, when adding fund fixed effects, and when estimating the coefficients via AUM-weighted least squares. The exponential overweighting of recent returns allows inflated returns to influence the cross-section of fund flows, even if those returns subsequently mean-revert. Because investors place disproportionate weight on the most recent performance, even short-lived self-inflated returns can have a strong effect on future flows—amplifying feedback dynamics.

6.2 Decomposing Returns

On a given day t, the fund return $R_{i,t}$ can be decomposed into a self-inflated component ($R_{i,t}^{\mathcal{I}}$), the co-inflated component ($R_{i,t}^{\mathcal{C}}$) and a residual component $R_{i,t}^{\perp}$ capturing other determinants. Formally

$$R_{i,t} = R_{i,t}^{\mathcal{I}} + R_{i,t}^{\mathcal{C}} + R_{i,t}^{\perp} \tag{11}$$

For convenience, we henceforth label $R^{\perp}_{i,t}$ as the fundamental fund return. While this has the connotation of "managerial skill", it can encompass a variety of factors such as, noise, risk, or industry exposures, that are not necessarily "skill". We choose the estimated price impact $(\hat{\theta}_1, \hat{\theta}_2) = (0.036, 0.016)$ from the square root model with $\eta = 1/2$ (Table C.9, model (3)), which exhibit the highest statistical precision and consistency across fund types. However, all results also hold for the linear model with $\eta = 1$.[21] For each fund, we compute the self-inflated component $\hat{R}^{\mathcal{I}}_{i,t} = \hat{\theta}_{\eta 1} f^{\eta}_{i,t} \tilde{\mathcal{I}}_{i,t-1}$ and the co-inflated component $\hat{R}^{\mathcal{C}}_{i,t} = \hat{\theta}_{\eta 2} f^{\eta}_{i,t} \tilde{\mathcal{I}}_{i,t-1}$, taking the impact estimates as given. We construct $\hat{R}^{\perp}_{i,t} = R_{i,t} - (\hat{R}^{\mathcal{I}}_{i,t} + \hat{R}^{\mathcal{C}}_{i,t})$ as the residual between the observed fund return and the inflated component. To gauge the economic magnitudes of self and co-inflated fund returns, we compute the monthly volatility of self-inflated and co-inflated components. Appendix Figure C.13 shows that in the cross-section of ETFs, the average monthly volatility of total inflated returns (i.e., self and co-inflated) is 1.15% which is economically large relative to the cross-sectional volatility of raw ETF returns of 4.56%. In the time-series of individual ETFs, the monthly co-inflated return volatility is on average at around 1% for the majority of ETFs (with an AUM-weighted average of 1.1%). The self-inflated component varies considerably across ETFs with thematic and small-cap ETFs exhibiting the highest self-inflated volatility and broad equity ETFs exhibiting negligible self-inflated volatility.

6.3 Chasing Self-Inflated Returns

Following the methodology proposed by Barber et al. (2016), we construct a weighted average of past returns using the exponential decay model estimated above. In particular, we define weighted versions of past fundamental and impact returns as

$$\bar{R}^{\perp}_{i,t} = \sum_{s=0}^{L} w_s R^{\perp}_{i,t-s}, \tag{12}$$

$$\bar{R}^{\mathcal{I}}_{i,t} = \sum_{s=0}^{L} w_s (R^{\mathcal{I}}_{i,t-l} + R^{\mathcal{C}}_{i,t-l}) \tag{13}$$

where the weights $w_s = \frac{e^{-\lambda s}}{\sum_{s=0}^{L} e^{-\lambda s}}$ are determined by the exponential decay λ of the flow-return sensitivity. With a slight abuse of notation, we let $\bar{R}^{\mathcal{I}}_{i,t}$ denote the total inflated return, combining both the self-inflated and co-inflated components. Using exponentially weighted past returns, rather than estimating separate coefficients for each lag, facilitates direct comparison between the sensitivities

[21] See Table 4.

to fundamental and inflated returns, without having to interpret 60 individual lag coefficients. The decomposition $\bar{R}_{i,t} = \bar{R}^{\mathcal{I}}_{i,t} + \bar{R}^{\perp}_{i,t}$ allows assessing whether investors chase both inflated returns and fundamental returns when deciding how to allocate their capital. We run the decomposed regression

$$f_{i,t+1} = \alpha_t + \beta_1 \bar{R}^{\mathcal{I}}_{i,t} + \beta_2 \bar{R}^{\perp}_{i,t} + \text{Controls} + \epsilon_{i,t+1} \tag{14}$$

and report the results in Table 4. To set the stage, we first regress daily fund flows onto raw average

Table 4: **Price Impact Chasing**. The table reports the estimated coefficients of regressing daily flows onto (exponentially weighted) average past returns, as well as decomposed average returns into impact and fundamental components. Specification (1) reports the coefficient to the regression of flows on raw average return. (2) adds the inflated return $\bar{R}^{\mathcal{I}}_{i,t}$. (3) regresses flows on the decomposed returns under the square root impact model ($\eta = 1/2$). (4) uses the linear impact model ($\eta = 1$) with heterogeneous coefficients for active and passive funds from Table 3 Models (5) and (6). (5) uses the calibrated impact model ($\eta = 1$) with a constant $\theta = 0.1$. (6) uses a placebo decomposition based on randomly generated self-inflated returns. Controls include log assets under management and 60 lags of past flows. Standard errors are double clustered at the day and fund level.

	Fund Flow					
				Linear Impact $\eta = 1$	*Calibrated Impact*	*Placebo*
	(1)	(2)	(3)	(4)	(5)	(6)
Past Return $\tilde{R}$	0.890***	0.754***				
	(0.172)	(0.172)				
Skill Return $\tilde{R}^{\perp}$			0.754***	0.857***	0.847***	0.887***
			(0.172)	(0.171)	(0.170)	(0.170)
Inflated Return $\tilde{R}^{\mathcal{I}}$		1.014***	1.768***	2.083**	1.760***	-6.231
		(0.267)	(0.270)	(0.664)	(0.450)	(12.036)
Date FE	x	x	x	x	x	x
Observations	63221	63221	63221	63221	63221	63221
R^2	0.052	0.052	0.052	0.052	0.052	0.052
R^2 Within	0.036	0.036	0.036	0.036	0.036	0.036

Significance levels: $*$ p < 0.05, $**$ p < 0.01, $***$ p < 0.001. Format of coefficient cell: Coefficient (Std. Error)

past returns $\bar{R}_{i,t}$ and obtain a coefficient of 0.89 (t-stat 5.2).[22] We then regress daily fund flows onto average returns controlling for the inflated component. If investors are able to differentiate between price impact and fundamental returns and only chase fundamental returns, we should observe that the coefficient on $\bar{R}^{\mathcal{I}}_{i,t}$ is 0 and statistically insignificant. Instead, we find a highly significant coefficient on the inflated return of 1.02 (t-stat 3.8). We then run the decomposed regression (14). Running the fully

[22]Note that this is roughly equal to the sum of all coefficients of regression (10).

decomposed regression (14), the coefficient increases to 1.7 (t-stat 6.6). The fact that the coefficient on inflated returns is somewhat larger than that on fundamental returns may reflect that investors tend to be more sensitive to past returns for illiquid funds, either because of strategic complementarities (Chen et al., 2010) or because these ETFs target high-attention, speculative themes and receive heightened attention (Ben-David et al., 2023). Regardless of the precise magnitude, fund investors significantly chase both components of realized returns.

As an additional robustness check, we run the decomposed regression using inflated returns derived from two alternative price impact models: (i) linear impact ($\eta = 1$) with heterogeneous coefficients for active and passive funds (see Table 3, Models 5 and 6), and (ii) linear impact with a constant $\theta = 0.1$ as in (Frazzini et al., 2018). Across all specifications, investors significantly chase both fundamental and inflated returns.

Lastly, we conduct a placebo test by simulating daily cross-sections of placebo inflated returns $R_{i,t}^{\mathcal{I},\text{Placebo}}$ drawn from a normal distribution with mean zero and variance equal to the daily cross-sectional variance of actual inflated returns $R_{i,t}^{\mathcal{I}}$. We subtract these from raw returns to construct placebo fundamental returns $R_{i,t}^{\perp,\text{Placebo}}$ and then apply exponential decay weights to obtain $\bar{R}_{i,t}^{\perp,\text{Placebo}}$ and $\bar{R}_{i,t}^{\mathcal{I},\text{Placebo}}$. We regress flows on the placebo decomposed returns and find that investors do not chase placebo inflated returns: the coefficient is statistically insignificant and it enters with the wrong sign. Moreover, the coefficient on the placebo fundamental return is identical to that on the raw return.

7 Inflated Funds and Long-Term Performance

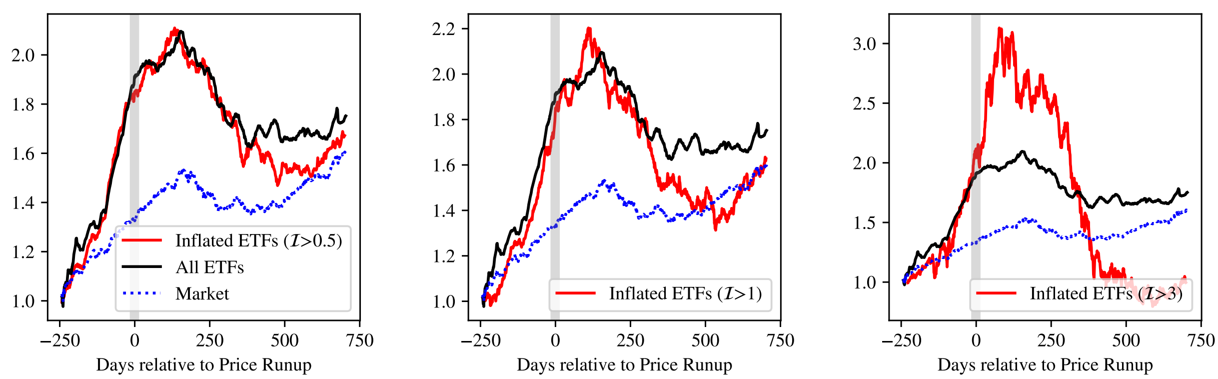
The previous section showed that because investors place a higher weight on the most recent return, even short-lived price pressure can impact the distribution of fund flows. This can cause an endogenous feedback loop: Flows cause a price impact, which generates a realized return that leads to further inflows and amplifies the initial price impact. The challenge is that while the estimated price impact is in line with previous studies, it is unclear whether one can – or should – treat the price impact of *all* flows as inflated returns – an assumption that would imply all capital inflows were non-fundamental in nature. The dumb-money effect (Frazzini and Lamont, 2008) – the tendency of funds with disproportionately high inflows to underperform – suggests that *some* flows are uninformed. However, investors also use funds to express views on specific sectors, styles, or themes – suggesting that flows also contain *some* fundamental information. Ultimately, long-run returns of illiquid funds offer a way to assess the extent to which their trades mechanically inflated prices beyond fundamental values. In this section, we test whether, conditional on our measure of fund illiquidity, we observe negative long-run returns for both the funds and their underlying holdings.

7.1 Motivating Evidence from ETF Data

Given the short sample of the daily ETF data, it is difficult to draw statistically meaningful conclusions about the long-term performance of inflated funds and their underlying holdings. We nevertheless provide simple motivating evidence for the long-run collapse of inflated ETFs, despite the short sample period. Following Greenwood et al. (2019), we select "run-up ETFs" that outperformed the market by over 50% over the previous year at any point in our sample. We compute the cumulative future returns for all run-up ETFs as well as for the subsample of "inflated ETFs" with high fund illiquidity $\mathcal{I}_t$. Figure 5 plots the cumulative returns over the event window for the run-up ETFs and the inflated ETFs. As in Greenwood et al. (2019), excessive outperformance is not followed by a subsequent crash for the average (not-inflated) ETF. Instead, cumulative returns converge back to the market return. In contrast, inflated ETFs experience steep crashes, with cumulative returns falling below -200% in the two years following the run-up. Still, consistent with Greenwood et al. (2019), timing the crash is difficult. On average, inflated ETFs do not crash within the first year of the initial outperformance.

Figure 5: **Long-Term Collapse of Inflated ETFs**. The figure plots the cumulative return of all ETFs that outperformed the market by over 50% in the past two years. The black line reports the average cumulative return across bubble ETFs over the event window. The red line plots the cumulative return of the subset of inflated ETFs whose fund illiquidity $\mathcal{I}_t$ exceeds 0.5, 1, and 3 respectively.

(a) Fund Illiquidity $\mathcal{I}_{i,t} > 0.5$ (b) Fund Illiquidity $\mathcal{I}_{i,t} > 1$ (c) Fund Illiquidity $\mathcal{I}_{i,t} > 3$

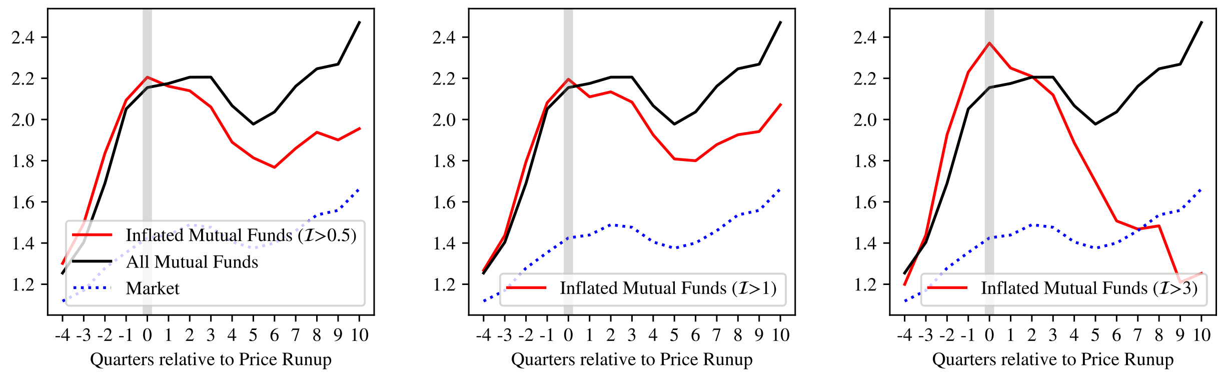


7.2 Application to Mutual Funds

We now turn our attention to the much larger sector: mutual funds. While holdings data are only available quarterly, the key measure driving self-inflation – fund illiquidity – can be readily constructed. Because mutual funds, particularly active ones, are considerably larger than ETFs, we suspect fund illiquidity and self-inflated returns to be a potentially greater issue. Appendix Figure C.15 plots the market share of funds with fund illiquidity $\mathcal{I}_{i,t} > 1$ and confirms this. Among all mutual funds, 25% have a fund illiquidity greater than 1 – compared to only 10% among ETFs. In 2024, the total assets managed by mutual funds with $\mathcal{I}_{i,t} > 1$ amounted to \$3.9 trillion. Figure 6 replicates the simple sort from the previous section using the mutual fund database.[23] The pattern mirrors that of ETFs: inflated

Figure 6: **Long-Term Collapse of Inflated Mutual Funds**. The figure plots the cumulative return of all mutual funds that outperformed the market by over 50% in the past two years. The black line reports the average cumulative return across bubble mutual funds over the event window. The red line plots the cumulative return of the subset of inflated mutual funds whose fund illiquidity $\mathcal{I}_t$ exceeds 0.5, 1, and 3 respectively.

(a) Fund Illiquidity $\mathcal{I}_{i,t} > 0.5$ (b) Fund Illiquidity $\mathcal{I}_{i,t} > 1$ (c) Fund Illiquidity $\mathcal{I}_{i,t} > 3$



mutual funds tend to collapse sharply in the long run following periods of strong outperformance.

The larger mutual fund sample from 2000-2024 with considerably more inflated mutual funds allows for identifiying sufficiently many events of run-ups and inflated funds to conduct statistical tests. We regress future 1-quarter, 1-year and 3-year fund returns in the cross-section onto fund illiquidity. Formally

$$R_{i,t+h} = \alpha_t + \mathcal{I}_{i,t} + \text{Controls} + \epsilon_{i,t+h} \tag{15}$$

where $R_{i,t+h}$ is the average annualized long-run return of fund i over horizon h. Table 5 reports the

[23] From 2000 to 2024, we identify all mutual funds that, at any point, outperformed the market by more than 50% over the prior year. For each of these "run-up" mutual funds, we compute cumulative future returns, both for the full sample and for the subsample of inflated funds with $\mathcal{I}_{i,t} > 1$.

results.

Table 5: **Fund Illiquidity and Long-Run Returns**. This table reports regressions of long-run fund returns $R_{i,t+h}$ on fund illiquidity (see equation 15). The sample includes all funds that outperformed the market by at least 50% as of time t. Column (1) uses future quarterly returns; column (2) uses future 1-year returns. Columns (3) and (4) use average future 3-year returns with varying sets of controls. *Cumulative past flow* measures total inflows over the prior year. *Past excess return* is the cumulative outperformance relative to the market portfolio. We report annualized average returns and winsorize all explanatory variables at the 99th percentile. All variables are standardized. Standard errors are double clustered at the quarter and fund level.

	Future 1Q Fund Return	Future 1Y Fund Return	Future 3Y Fund Return	
	(1)	(2)	(3)	(4)
Fund Illiquidity $\mathcal{I}$	-0.031 (0.018)	-0.012*** (0.004)	-0.052*** (0.006)	-0.049*** (0.008)
Portfolio Illiquidity I_p				-0.035 (0.034)
Cumulative Past Flow				-0.022 (0.031)
Past Excess Return				0.024 (0.033)
Quarter FE	x	x	x	x
Observations	891	767	193	193
R^2	0.625	0.468	0.564	0.577
R^2 Within	0.004	0.023	0.072	0.100

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

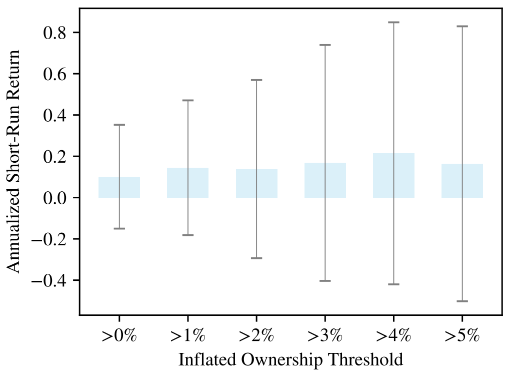
We first focus on the sample of mutual funds that outperformed the market by at least 50% over the previous year up to time t. Within this group of outperforming funds, fund illiquidity significantly predicts lower long-run returns. Funds with a one standard deviation higher fund illiquidity have 5.2% lower long-run returns. Notably, future short-run returns are not significantly lower. Appendix Table C.11 examines alternative sample splits based on thresholds of 10%, 20%, 30%, and 50% outperformance. The estimated coefficient becomes increasingly negative, declining monotonically from –0.012 to –0.049 as the outperformance threshold rises. We conduct a battery of robustness tests. First, we control for raw portfolio illiquidity $I_{p,t}$ and find that the effect is not driven by portfolio illiquidity alone. Rather, it is the interaction of portfolio illiquidity and fund size – captured by fund illiquidity – that predicts lower long-run returns. Second, the effect is not driven by cumulative past inflows. Funds that received large inflows do not systematically underperform. The underperformance is concentrated among the inflated funds – those that received large inflows *and* held an illiquid portfolio. Finally, past outperformance itself does not account for the result: raw outperformance does not predict lower future returns. Among the outperforming funds, only those with high fund illiquidity experience significant long-run underperformance.

7.3 Inflated Stock-level Ownership

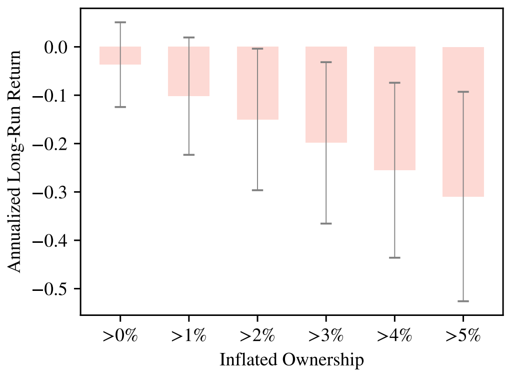
Inflated funds underperform because they expanded their positions in illiquid securities due to inflows without elastically targeting more liquid stocks as they grew. This has pushed up the prices of these positions resulting in high contemporaneous performance and more inflows, but lower long run fund returns. If this is true, we should observe the underperformance at the security level, not only at the fund level. In line with the previous section, we label a fund inflated if it outperformed the market by 50% in the past two years and has a fund illiquidity above 1. While these cutoffs are somewhat arbitrary, Table C.12 shows the results are robust to alternative definitions. For every stock, we compute the ownership by inflated funds. We then sort stocks by their inflated ownership and compute the average future short- and long-horizon returns. Figure C.12 plots the average future short and long-run returns of stocks based on different thresholds of inflated ownership.

Figure 7: **Inflated Ownership and Stock Returns**. The figure plots the future 1-quarter and 3-year average return for stocks with different levels of inflated ownership. Inflated ownership is the total number of shares held by inflated mutual funds relative to shares outstanding. We define inflated funds as funds with $\mathcal{I}_{i,t} > 1$ that outperformed the market by at least 50% over the past year. Average returns are annualized. The error bands indicate 95% confidence intervals with standard errors double clustered at the day and stock level.

(a) Future 1-quarter Returns



(b) Future 3-year Returns



In the short-run, there is no significant relationship between inflated ownership and future returns. However, in the long-run inflated ownership significantly predicts negative returns. Stocks with over 5% inflated ownership tend to crash dramatically with long-run returns of -30%. The extreme negative returns are in line with the collapse of highly inflated funds. For example, ARKK – whose fund illiqudity was $\mathcal{I}_{i,t} > 4$ at the end of 2021 – held 12% of the shares outstanding in Proto Labs (Ticker: PRLB) whose price fell from \$216 to \$50 over the course of 2021 alongside significant outflows from ARKK. Appendix Table C.12 reports regression estimates controlling for stock-specific characteristics. Specifically, we regress stock returns onto inflated ownership controlling for time fixed effects, log book equity, log market equity, momentum, investment, profitability and market beta:

$$r_{n,t+h} = \alpha_t + \mathcal{I}O_{n,t} + \text{Controls} + \epsilon_{i,t} \tag{16}$$

where $\mathcal{I}O_{n,t}$ is inflated ownership. Inflated ownership significantly predicts long-run returns in both equal- and value-weighted regressions. Next, we vary the cutoff used to define inflated funds and find that the negative return predictability of inflated ownership is robust across specifications. Finally, we test whether the effect of inflated ownership on future returns is driven by ordinary mutual fund ownership, ownership by top performing funds, or ownership by funds experiencing large inflows. Controlling for these variables leaves the coefficient on inflated ownership unchanged. This suggests that it is not flow-induced trading or mutual fund ownership in general that leads to overvaluation, but specifically the trades of inflated funds.

8 Conclusion

Price impact generates a realized return for the incumbent holders of an asset, even when driven by non-fundamental demand. The inability of investors to distinguish between price impact and fundamental returns has important implications for capital allocation. We show that when funds grow without adjusting portfolio liquidity, they generate self-inflated returns that trigger a feedback loop of inflows and further price impact — a dynamic akin to fire sales, but in the positive direction.

The key metric that summarizes the potential for self-inflated fund returns via this positive feedback loop is fund illiquidity. Fund illiquidity is the product of portfolio illiquidity and fund size. It measures how much of the daily underlying volume the fund buys in response to a 1% inflow, in excess of what it would have bought had it adjusted to the most liquid portfolio available within its universe. We argue that fund illiquidity is a number that should be disclosed in fund prospectuses, as it serves as a critical indicator for both investors and firms whose shares are held by inflated funds: First, it warns investors that the fund likely had a substantial impact on its holdings by establishing large ownership stakes.

Second, at the company level, it helps identify whether the largest shareholder is an inflated fund, so that share price volatility caused by inflows and outflows of this fund is not mistakenly attributed to fundamentals. Finally – and most importantly – it predicts the long-run collapse of funds, suggesting that investors may not want to treat inflated funds as long-term investments – much like leveraged ETFs, which are unsuitable for holding periods beyond a day due to volatility drag.

The focus of this paper is on managed funds and the self-inflated feedback loop that arises from the combination of illiquid portfolios and the flow-performance relationship. ETFs are a suitable setting to establish first evidence for the interplay of price impact and belief formation because i) we can directly observe demand (via flows) and ii) the proportional reinvestment of flows at a daily frequency allows us to cleanly identify the price impact of non-fundamental demand shocks. However, the underlying drivers of this feedback loop – return chasing and price impact – apply more generally. For example, trend following in futures markets and the $300 billion CTA industry, are likely prone to self-inflated price spirals (see Lempérière et al. (2014) and references therein). Similarly, the "quant crunch" in 2007 (Khandani and Lo, 2011) and other deleveraging spirals can be seen as outcomes of the interaction between return chasing and price impact (Brunnermeier and Pedersen, 2009; Bouchaud et al., 2012; Cont and Wagalath, 2013; Kyle and Obizhaeva, 2023). The increased availability of investor-level holdings and flow data allows quantifying these effects. Revisiting these studies through the lens of portfolio holdings – for example, via structural models of investor demand as in Darmouni et al. (2022), is an exciting avenue for future research. Quite remarkably, our price impact estimate from flow-induced trades matches well the estimates from the recent microstructure literature (e.g., Tóth et al. (2011); Brokmann et al. (2015); Frazzini et al. (2018); Bouchaud et al. (2018)). Bridging the gap between low-frequency portfolio holdings data and trade data at a higher frequency provides an explicit link between market microstructure, intermediary asset pricing, and (eventually) corporate finance.

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Appendix A Additional Derivations

A.1 Co-Inflated Fund Returns

Let N_i denote the subset of stocks in fund i's universe, $V_{i,t} = \sum_{n \in N_i} V_{n,t}$ the total liquidity of that universe, and $v_{i,n,t} = \frac{V_{n,t}}{V_{i,t}}$ the volume-weights specific to fund i's universe. To derive co-inflated fund returns, let $\text{FIT}^x_{n,t}$ denote the total price impact of *excess* flow-induced trading in stock n:

$$\text{FIT}^x_{n,t} = \theta_1 \frac{w^x_{i,n,t-1} F_{i,t}}{V_{n,t}} + \theta_2 \frac{\sum_{j \neq i} w^x_{j,n,t-1} F_{j,t}}{V_{n,t}}$$

where $w^x_{i,n,t} = w_{i,n,t} - v_{i,n,t}$ are excess weights relative to the volume-weighted benchmark portfolio. We allow for different price impacts of the fund's own trade (θ_1) and the trades of other funds (θ_2). Next, we compute the return of fund i's portfolio due to this price impact, i.e., we sum $\text{FIT}_{n,t}$ across i's portfolio weights $w_{i,n,t}$. Then:

$$R^{\text{FIT}}_{i,t} = \sum_{n \in N_i} w_{i,n,t-1} \text{FIT}^x_{n,t} = \theta_1 f_{i,t} \mathcal{I}_{i,t-1} + \theta_2 \sum_{j \neq i} f_{j,t} \underbrace{\frac{A_{j,t-1}}{V_{j,t-1}}}_{\mathcal{S}_{j,t}} \underbrace{\sum_{n \in N_i} w_{i,n,t-1} \frac{w^x_{j,n,t-1}}{v_{j,n,t-1}}}_{\mathcal{I}_{ji,p,t-1}} \tag{17}$$

Let $\mathcal{I}_{ji,t} = \mathcal{S}_{j,t} \cdot \mathcal{I}_{ji,p,t}$ denote co-illiquidity, and define the co-inflated return as $R^{\mathcal{C}}_{i,t} = \theta_2 \sum_{j \neq i} f_{j,t} \mathcal{I}_{ji,t-1}$. The total flow-induced (excess) return is simply the sum of the self-inflated and co-inflated components:

$$R^{\text{FIT}}_{i,t} = \overbrace{\theta_1 f_{i,t} \mathcal{I}_{i,t-1}}^{R^{\mathcal{I}}_{i,t}} + \overbrace{\theta_2 \sum_{j \neq i} f_{j,t} \mathcal{I}_{ji,t}}^{R^{\mathcal{C}}_{i,t}}. \tag{18}$$

When $\eta \neq 1$ the total flow-induced (excess) return is given by

$$R^{\text{FIT}}_{i,t} = \theta_{\eta,1} (f_{i,t} \tilde{\mathcal{I}}_{i,t-1})^\eta + \theta_{\eta,2} \sum_{j \neq i} (f_{j,t} \tilde{\mathcal{I}}_{ji,t-1})^\eta \tag{19}$$

where $\tilde{\mathcal{I}}_{i,t} = \mathcal{S}_{i,t} \cdot \tilde{I}_{p,i,t}$ and $\tilde{\mathcal{I}}_{ji,t} = \mathcal{S}_{j,t} \cdot \tilde{I}_{p,ji,t}$ is the adjusted *fund* illiquidity and co-illiquidity. Adjusted *portfolio* illiquidity and co-illiquidity are given by $\tilde{I}_{p,i,t} = \left(\sum_{n \in N_i} w_{i,n,t-1} (\frac{w^x_{i,n,t}}{v_{i,n,t}})^\eta \right)^{1/\eta}$ and $\tilde{I}_{p,ji,t} = \left(\sum_{n \in N_i} w_{i,n,t-1} (\frac{w^x_{j,n,t}}{v_{j,n,t}})^\eta \right)^{1/\eta}$ respectively.

Appendix B ETF Flow-Induced Trading

We assume that at time t the ETF and the underlying basket have the same price; therefore the ETF return is given by the weighted sum of the underlying returns. During day t, however, the ETF price may deviate from the price of the underlying basket, creating an arbitrage opportunity. For example, high demand for the ETF may drive the ETF price above the underlying. The arbitrage trade involves selling ETF shares (at elevated prices) and buying the underlying. To reduce arbitrage risk, the arbitrageur does not have to bet on the convergence of the spread, but can directly deliver the underlying shares to the provider in exchange for ETF shares, which they can sell in the secondary market. The ETF has $S_{i,t}$ shares outstanding with price $P_{i,t}$, where time (in business days) is denoted by t. Total ETF assets under management are $A_{i,t} = P_{i,t}S_{i,t}$.

B.1 Arbitrage Trades

The ETF provider specifies to the arbitrageur (authorized participant, AP) the creation basket $\{d^{CU}_{i,n,t}\}^N_{n=1}$ for each creation unit of the ETF (also known as the portfolio composition file PCF). The creation basket constituents $d^{CU}_{i,n,t}$ (denominated in dollars based on current market prices) specify the dollar value of the underlying shares the AP must deliver to the ETF provider in order to receive one ETF share. The basket is typically denoted in number of shares. For expositional simplicity (in line with the structural model in the main text), we convert to dollar units using current market prices. The arbitrage-induced trade of an authorized participant i in stock n is given by $\Delta S_{i,t+1}d^{CU}_{i,n,t}$, where $\Delta S_{i,t+1}$ is the number of ETF shares issued between the close of date t and the close of date $t+1$ and $d^{CU}_{i,n,t}$ the creation basket (denominated in dollars based on current market prices) as specified by the ETF provider at the close of date t. The creation basket specifies the dollar value of the underlying shares the AP must deliver to the ETF provider in order to receive one ETF share. For example, by delivering $K \times \{d^{CU}_{i,n,t}\}^N_{n=1}$, the authorized participant receives $\Delta S_t = K$ ETF shares in the primary market and can sell them in the secondary market. Note that the ETF provider has the discretion to supply a trading basket $d^{CU}_{i,n,t}$ that may differ from the actual constituents $D_{i,n,t}$ per unit of ETF share. This flexibility allows the provider to optimize for costs or other operational considerations. However, we have verified that our results remain unaffected by this potential discrepancy.

B.2 Equivalence to Flow-Induced Trades

To see the equivalence to flow-induced trading by ordinary mutual funds, note that the dollar flow $F_{i,t+1}$ into the ETF between t and $t+1$ is the change in ETF shares outstanding multiplied by the price of the ETF $P_{i,t}$, i.e., $F_{i,t+1} = \Delta S_{i,t+1} P_{i,t}$. Similarly, the implied ETF portfolio is given by $w_{i,n,t} = \frac{d^{CU}_{i,n,t}}{\sum_n d^{CU}_{i,n,t}} = \frac{d^{CU}_{i,n,t}}{P_{i,t}}$. Therefore, the arbitrage-induced trade can also be expressed as

$$d^{CU}_{i,n,t} \Delta S_{i,t+1} = w_{i,n,t} F_{i,t+1} \tag{20}$$

which is precisely the flow-induced trade by mutual funds, assuming that 100% of flows are reinvested in line with previous portfolio weights.

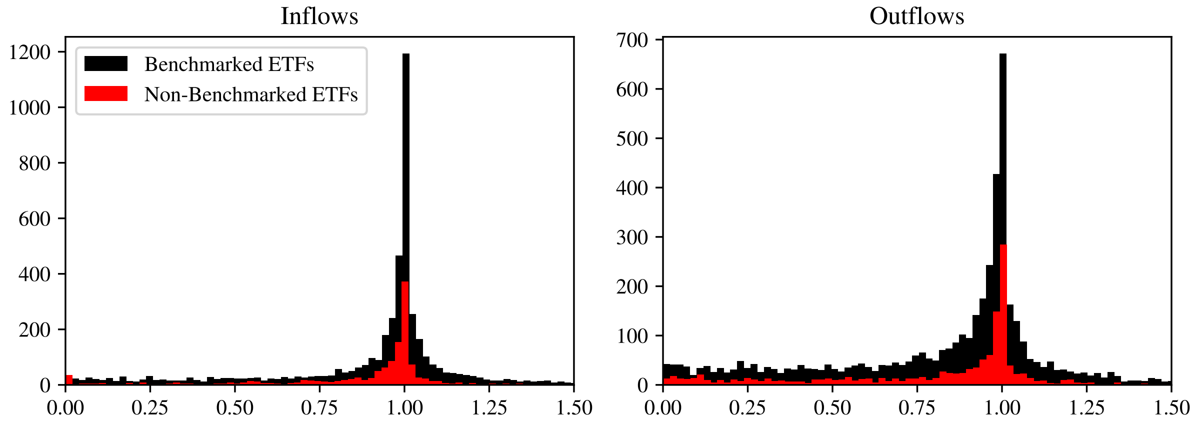
B.3 Reinvested ETF Flows

For each ETF in our sample, we test whether and how quickly ETF flows $f_{i,t+1} = \frac{F_{i,t+1}}{A_{i,t}} = \frac{\Delta S_{i,t+1}}{S_{i,t}}$ are reinvested in the previous holdings (i.e., according to the pre-specified basket weights). Let $q_{i,n,t} = \frac{\Delta Q_{i,n,t}}{Q_{i,n,t-1}}$ denote the percentage change in the ETF's holdings in stock n. We regress trades on flows in a pooled regression at the ETF level

$$\Delta q_{i,n,t} = \alpha_i + \psi_i f_{i,t} + \epsilon_{i,n,t} \tag{21}$$

which yields ETF-specific flow-scaling coefficients ψ_i. Figure B.8 reports the results. The majority of both active and passive ETFs invest their inflows in their existing portfolios on the same day.

Figure B.8: **Reinvested ETF Flows**. The figure plots the daily scaling coefficient of ETF flows. For each ETF in our sample, we estimate the regression $\Delta q_{i,n,t} = \alpha_i + \beta_i f_{i,t} + \epsilon_{i,n,t}$ where $\Delta q_{i,n,t}$ are percent changes in shares held in stock n relative to the previous day and $f_{i,t}$ are daily flows. We estimate ψ_i separately for in and outflows and plot the distribution of ψ for active and passive ETFs.



Appendix C Additional Figures and Tables

Figure C.9: **Market Capitalization and Dollar Volume**. Panel a) plots daily log market capitalization against daily log dollar volume for the cross-section of of US stocks. Panel b) plots the total aggregated US dollar volume and market capitalization from 2017 to 2024.

(a) Cross-Section (b) Time-Series

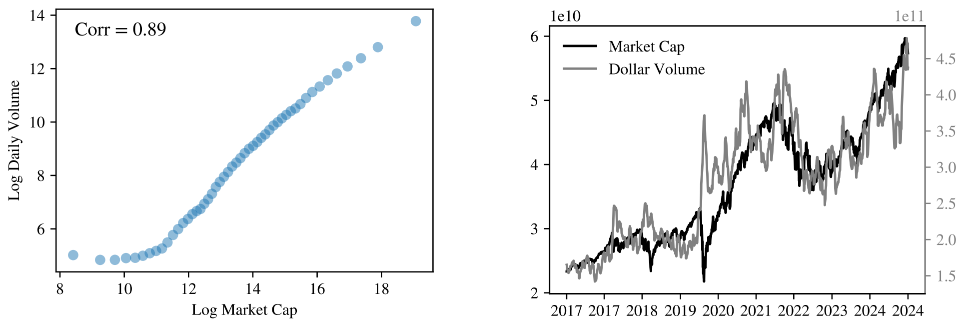


Figure C.10: **Portfolio Illiquidity versus Effective Size in Mutual Funds**. The figure plots the average portfolio illiquidity $I_{p,t}$ and effective size $\mathcal{S}_t$ for each mutual fund in our sample. Each dot represents a single ETF. Portfolio illiquidity (on the y-axis), $I_{p,t} = \sum_n w_{n,t}^2/v_{n,t} - 1$, measures the average deviation from liquid positions. Size (on the x-axis), $\mathcal{S}_t = A_t/V_t$, is total assets relative to the total liquidity of the underlying securities. The labeled dots represent illustrative examples.

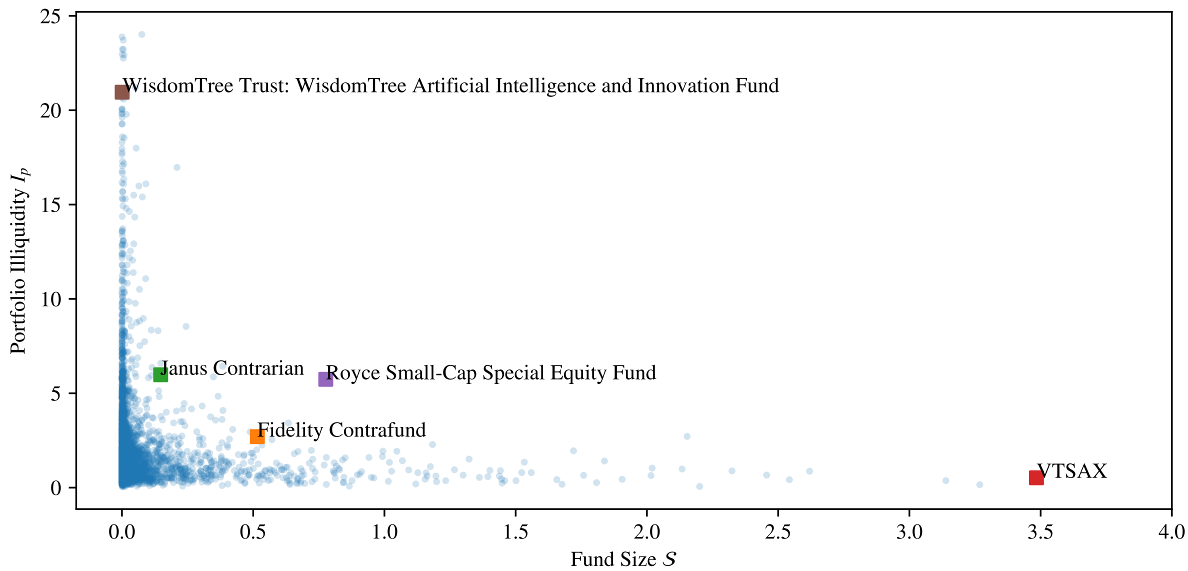
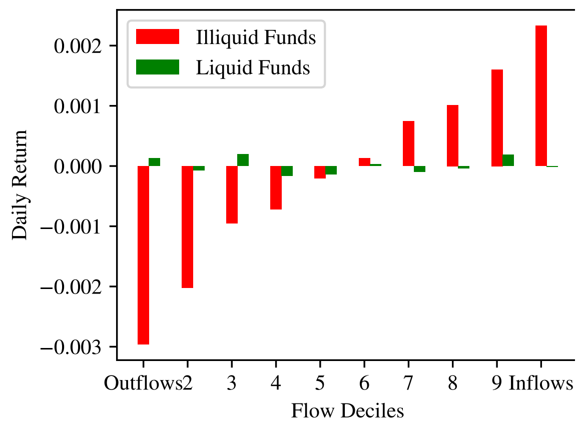


Figure C.11: **Daily ETF Alphas and Flows**. This figure shows the average daily excess return of ETFs across flow deciles. Each day, ETFs are sorted into deciles based on their net flows. Panel a) reports abnormal ETF returns for illiquid ETFs (top decile of $\mathcal{I}_t$, shown in red) and liquid ETFs (bottom decile of $\mathcal{I}_t$, shown in green). Panel b) reports abnormal returns for ETFs sorted on portfolio illiquidity as opposed to fund illiquidity, i.e., (top and bottom decile of $I_{p,t}$). Abnormal returns are computed with respect to the CAPM.

(a) Sorting By Fund Illiquidity $\mathcal{I}_t$



(b) Sorting By Portfolio Illiquidity $I_{p,t}$

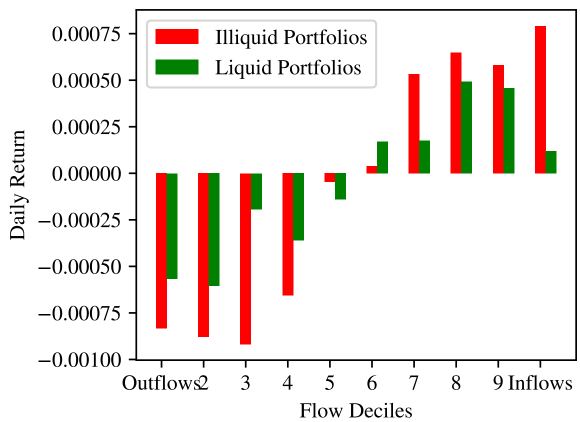
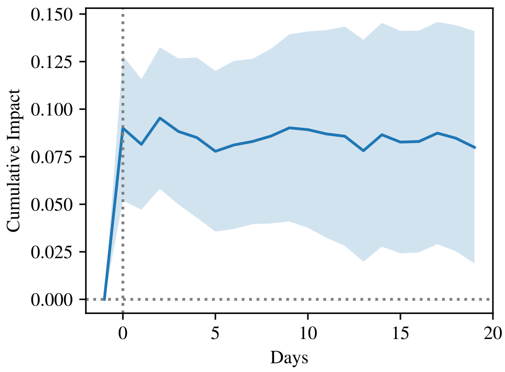


Figure C.12: **Reversal of Self- and Co-Inflated Returns**. The figure plots the cumulative sum of the coefficients from the distributed lag model of daily fund returns onto $S = 20$ lags of self-inflated trades $f_{i,t-s}\mathcal{I}_{i,t-1-s}$ (Panel a) and co-inflated trades $\sum_{j \neq i} f_{j,t-s}\mathcal{I}_{ji,t-1-s}$ (Panel b). The control variables include lagged flows, $\mathcal{I}_{i,t-1}$, for up to 20 days, as well as ETF and date fixed effects. The shaded areas indicate 95% confidence bands where the standard errors are double clustered at the day and fund level. Cumulative standard errors are computed accounting for the covariance across coefficient estimates, i.e., $\sqrt{\mathbf{1}_t^T \Omega_t \mathbf{1}_t}$ where Ω_t is the covariance matrix of the coefficients up until lag t and $\mathbf{1}_t$ is a $t \times 1$ vector of ones.

(a) Self-Inflated Return Decay



(b) Co-Inflated Return Decay

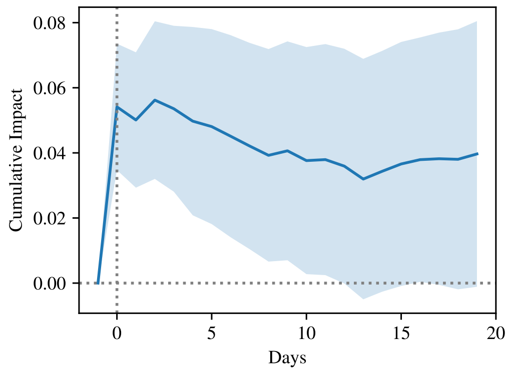
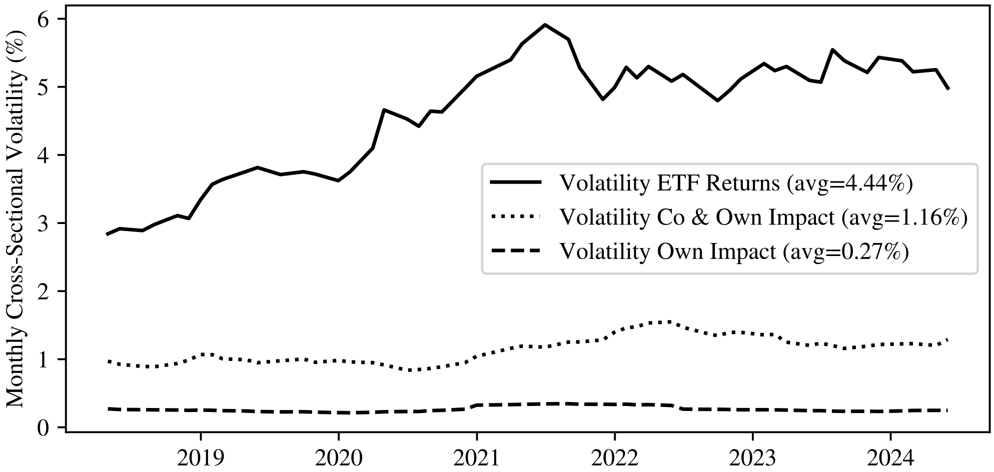


Figure C.13: **Economic Significance**. The figure plots the volatility of self-inflated returns and co-inflated returns, both in the cross-section (Panel a) and in the time-series of ETFs (Panel b). We choose the estimated price impact $(\hat{\theta}_1, \hat{\theta}_2) = (0.036, 0.016)$ from the square root model (Table C.9, model (3)), and compute self-inflated and co-inflated returns as $\hat{R}^{\mathcal{I}}_{i,t} = \hat{\theta}_1 f^{\eta}_{i,t} \tilde{\mathcal{I}}_{i,t-1}$ and $\hat{R}^{\mathcal{C}}_{i,t} = \hat{\theta}_2 f^{\eta}_{i,t} \tilde{\mathcal{I}}_{i,t-1}$ respectively. We then aggregate the inflated returns at the monthly level (given that we do not detect statistically meaningful reversal within the first 20 days) and compute the monthly time-series volatility for each ETF and the cross-sectional volatility across all ETFs. For the time-series, we report the quarterly AUM-weighted average volatilities for all funds and split by fund types.

(a) Cross-sectional Volatility from Self-inflated and Co-inflated Returns



(b) Time-Series Volatility from Self-inflated and Co-inflated Returns

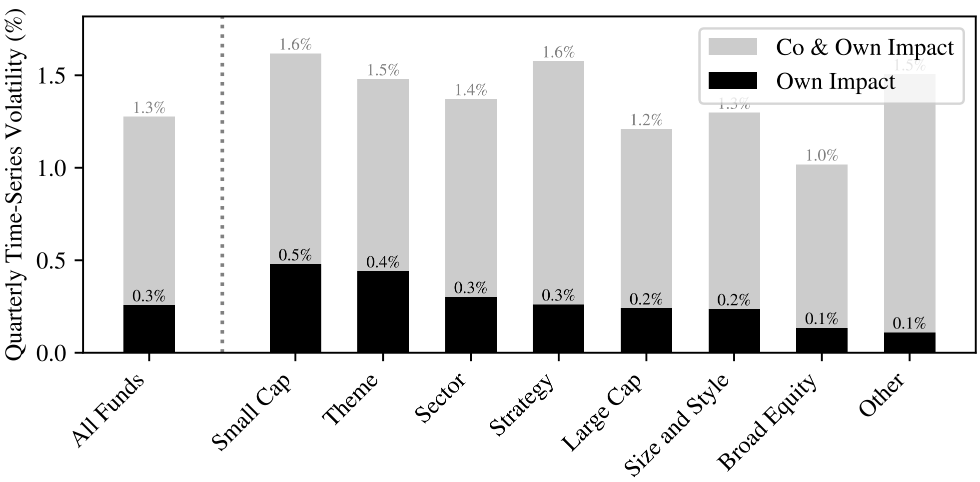
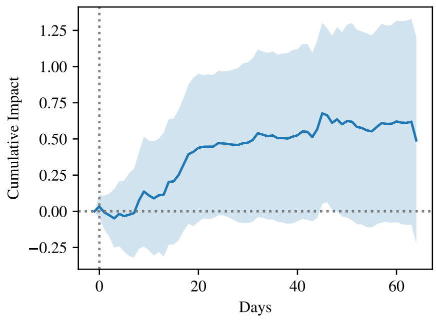
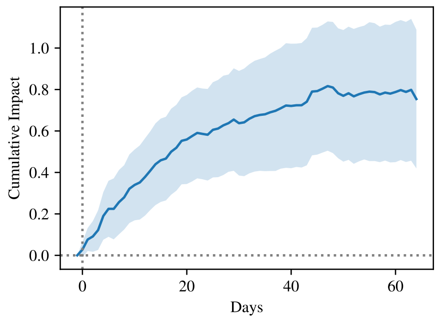


Figure C.14: **Return Chasing Kernel by ETF types**. This figure shows the cumulative return-chasing response estimated from the model $f_{i,t+1} = \alpha_t + \sum_{s=0}^{L} \beta_s R_{i,t-s} + \text{Controls} + \epsilon_{i,t+1}$ across different sample splits. The blue line plots the cumulative sum of OLS coefficients using $L = 60$ daily return lags. Shaded areas denote 95% confidence bands, with standard errors double clustered at the day and fund level. Cumulative standard errors account for covariance across lags and are computed as $\sqrt{\mathbf{1}_t^T \Omega_t \mathbf{1}_t}$, where Ω_t is the covariance matrix of $\{\hat{\beta}_s\}_{s=0}^{t}$. Panels a) and b) split the sample by fund types of high fund illiquidity vs. low illiquidity. Panels c) and d) split funds into benchmark trackers vs. non-benchmarked (active) funds. Panel e) estimates the flow-performance regression via AUM-weighted least squares. Panel f) provides time-series evidence by replacing the time fixed effect with a fund fixed effect. The shaded areas again indicate 95% confidence bands where the cumulative standard errors are double clustered at the day and fund level. Cumulative standard errors are computed accounting for the covariance across coefficient estimates, i.e., $\sqrt{\mathbf{1}_t^T \Omega_t \mathbf{1}_t}$, where Ω_t is the covariance matrix of the coefficients up until lag t and $\mathbf{1}_t$ is a $t \times 1$ vector of ones.

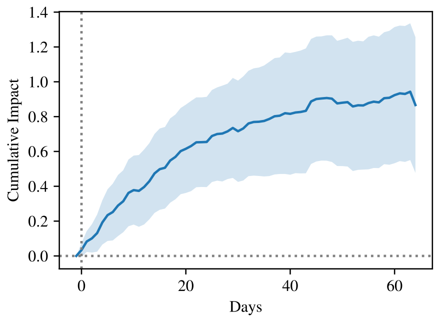
(a) Broad Equity, Large Caps, Other



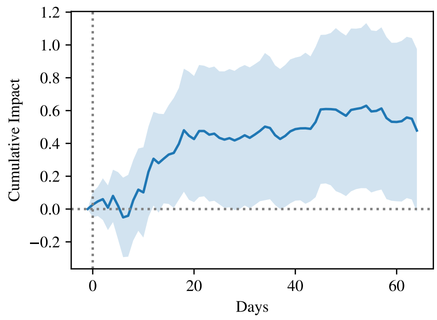
(b) Small Cap, Strategy, Theme etc.



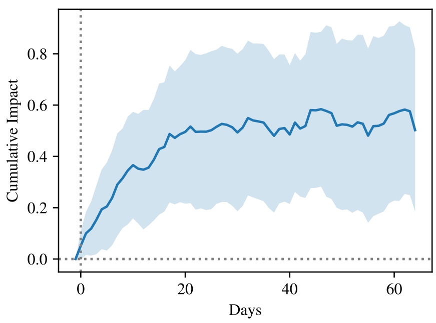
(c) Benchmarked



(d) Not-Benchmarked



(e) AUM-Weighted Least Squares



(f) Fund fixed Effects

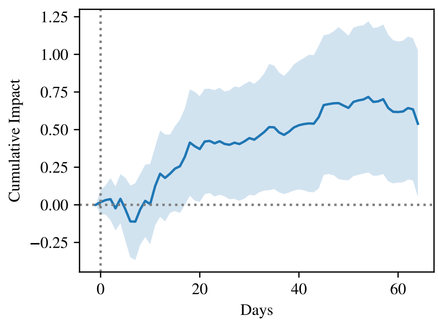


Figure C.15: **Illiquid Funds: Market Share**. The figure plots the fraction of total mutual fund and ETF assets managed by inflated funds with $\mathcal{I}_{i,t} > 1$. The black line shows this fraction for all funds in the CRSP mutual fund survivorship-free database; the grey line reports the corresponding value for all ETFs in the ETF Global database. We plot rolling annual averages, with the time-series average reported in brackets.

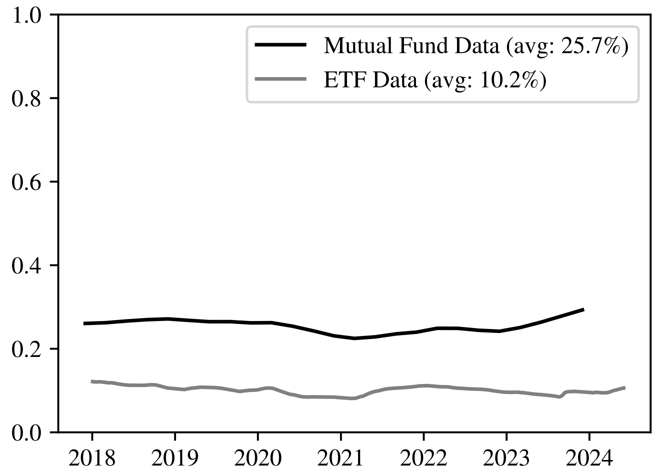


Table C.6: **Summary Statistics: Quarterly Mutual Fund Data**. The table reports summary statistics for the sample of quarterly mutual fund data from 2000 to 2024. We split the sample into passive (direct index trackers) and active (all other) mutual funds. Fund illiquidity $\mathcal{I}$, portfolio illiquidity $\mathcal{I}_p$, and relative fund size $\mathcal{S}$ are defined in Section 3.

(a) Passive Mutual Funds: (N=9935)

	Mean	Std	Min	Q1	Median	Q3	Max
AUM ($ Billion)	4.69	35.38	0.00	0.06	0.31	1.40	1373.41
Quarterly Flow (% AUM)	0.06	0.29	-1.00	-0.04	-0.00	0.07	2.00
Quarterly Flow ($ Billion)	0.05	1.09	-31.34	-0.01	-0.00	0.02	123.94
Number of Stocks	380.00	489.00	6.00	72.00	230.00	443.00	3171.00
Fund Illiquidity $\mathcal{L}$	0.07	0.25	0.00	0.00	0.01	0.04	16.41
Portfolio Illiquidity $\mathcal{L}_p$	1.35	3.03	0.00	0.31	0.49	1.17	397.96
$\mathcal{S}$	0.10	0.32	0.00	0.00	0.01	0.06	7.98

(b) Active Mutual Funds: (N=1743)

	Mean	Std	Min	Q1	Median	Q3	Max
AUM ($ Billion)	1.60	7.01	0.00	0.06	0.24	0.91	292.07
Quarterly Flow (% AUM)	0.01	0.22	-1.00	-0.04	-0.02	0.02	2.00
Quarterly Flow ($ Billion)	-0.01	0.23	-19.84	-0.02	-0.00	0.00	14.48
Number of Stocks	127.00	232.00	6.00	41.00	63.00	108.00	3259.00
Fund Illiquidity $\mathcal{L}$	0.23	0.89	0.00	0.01	0.03	0.14	58.12
Portfolio Illiquidity $\mathcal{L}_p$	4.63	51.69	0.00	0.96	1.53	2.70	7355.65
$\mathcal{S}$	0.11	0.33	0.00	0.00	0.02	0.08	15.02

Table C.7: **Top 10 Most Illiquid ETFs and Mutual Funds.** The table reports the 10 ETFs and mutual funds in the U.S. with the highest fund illiquidity, $\mathcal{I}_t$, given by the product of portfolio illiquidity $I_{p,t}$ and effective fund size $\mathcal{S}_t$.

(a) Exchange-Traded Funds

Ticker	$\mathcal{I}$	I_p	$\mathcal{S}$
CALF	2.18	0.43	5.12
DVY	2.22	1.91	1.16
SLYV	2.30	9.47	0.24
PBW	2.77	25.45	0.11
ROBO	2.78	11.43	0.24
ARKQ	2.98	76.67	0.04
SDY	3.42	4.49	0.76
ARKG	3.94	3.57	1.11
ARKK	4.18	11.13	0.38
IJR	6.56	1.50	4.37

(b) Mutual Funds

Name	$\mathcal{I}$	I_p	$\mathcal{S}$
TETON Westwood Mighty Mites Fund	4.71	12.92	0.37
Putnam Equity Spectrum Fund	5.01	25.33	0.20
W.R. Science and Technology Fund	5.13	36.40	0.14
T Rowe Small-Cap Value	6.03	3.62	1.67
Brown Capital Small Company Fund	6.61	2.76	2.40
RBB Senbanc Fund	7.40	571.58	0.01
Heartland Value Fund	8.40	5.81	1.45
Putnam Capital Spectrum Fund	9.46	24.71	0.38
Aegis Value Fund, Inc	16.35	68.76	0.24
Franklin MicroCap Value Fund	19.38	12.32	1.57

Table C.8: **Fund Illiquidity Drivers: Robustness.** The table reports the robustness tests of the illiquidity choice regressions in Table 2 of the main text. Columns (1) and (2) include ETF type by date fixed effects. Columns (3) and (4) report the illiquidity choice regressions for active funds that track a benchmark. Columns (5) and (6) use illiquid funds (in the top decile of $\mathcal{I}_{i,t}$).

	All Funds		*Active Funds*		*Illiquid Funds*	
	$\Delta \log I_p$	$\log I_p$	$\Delta \log I_p$	$\log I_p$	$\Delta \log I_p$	$\log I_p$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log A$	-0.071***		-0.061***		-0.151***	
	(0.016)		(0.017)		(0.040)	
$\Delta \log V$	0.851***		0.845***		0.843***	
	(0.034)		(0.029)		(0.057)	
$\log A$		-0.050***		-0.095***		-0.114**
		(0.011)		(0.022)		(0.034)
$\log V$		0.641***		0.605***		0.497***
		(0.051)		(0.052)		(0.090)
Log Expense Ratio	-0.005	-0.002	-0.007	0.001	-0.006	0.266
	(0.005)	(0.024)	(0.006)	(0.039)	(0.010)	(0.293)
Flow Volatility	0.107	0.190	0.256	-0.077	-0.389	-0.845
	(0.230)	(0.236)	(0.536)	(0.489)	(0.501)	(0.869)
Date FE	-	-	x	-	x	-
Type-Date FE	x	x	-	-	-	-
ETF FE	-	x	-	x	-	x
Observations	21748	22834	5376	5791	5149	5356
R^2	0.374	0.928	0.395	0.884	0.300	0.912
R^2 Within	0.272	0.175	0.288	0.196	0.253	0.143

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.9: **Price Impact at the Fund-level: Robustness**. The table reports the estimated price impact coefficients from pooled OLS regressions using daily data on ETF returns and flows. Columns (1) and (2) report the estimated price impact from the triple difference estimator that additionally controls for $f_t I_{p,t-1}$ and $f_t \mathcal{S}_{t-1}$, as well as $I_{p,t-1}$ and $\mathcal{S}_{t-1}$. Columns (3)-(6) use self-inflated trades constructed using $\eta = 1/2$ in the specification $(f\tilde{\mathcal{I}}_{t-1})^\eta$, where $\tilde{\mathcal{I}}_t = \mathcal{S}_t \cdot \tilde{\mathcal{I}}_{p,t}$ with $\tilde{I}_{p,t} = \left(\sum_n (\frac{w^x_{n,t}}{v_{n,t}})^\eta w_{n,t-1}\right)^{1/\eta}$. Columns (4) and (5) further split the sample into broad equity index ETFs and sector/style ETFs respectively. Column (6) runs a horserace of the linear specification against the non-linear one. Standard errors are double clustered at the day and fund level.

	Excess ETF Return					
	Triple Difference Estimator		*Square-Root Impact $\eta = 1/2$*			
	(1)	(2)	(3)	(4)	(5)	(6)
$f \times \mathcal{I}$	0.068**	0.066**				-0.014
	(0.023)	(0.024)				(0.012)
$(f \times \mathcal{I})^\eta$			0.027***	0.025***	0.039**	0.030***
			(0.004)	(0.004)	(0.014)	(0.004)
Co-Impact$^\eta$			0.016***	0.017***	0.014***	0.019***
			(0.002)	(0.002)	(0.002)	(0.002)
Co-Impact						-0.019*
						(0.008)
Flow f	-0.000	-0.000				
	(0.002)	(0.002)				
f^η			-0.002*	-0.002	-0.002*	-0.002**
			(0.001)	(0.001)	(0.001)	(0.001)
Fund Illiquidity $\mathcal{I}$	-0.000**	-0.000***				
	(0.000)	(0.000)				
$f \times \mathcal{S}$	0.033	0.034				
	(0.018)	(0.018)				
$f \times I_p$		0.000				
		(0.000)				
Relative Size $\mathcal{S}$	-0.000	-0.000				
	(0.000)	(0.000)				
Portfolio Illiquidity I_p		0.000				
		(0.000)				
$\mathcal{I}^\eta$			-0.002***	-0.002***	-0.001*	-0.002***
			(0.000)	(0.000)	(0.001)	(0.000)
Date FE	x	x	x	x	x	x
ETF FE	x	x	x	x	x	x
Observations	1196151	1196151	1196151	885725	310426	1196151
R^2	0.098	0.098	0.107	0.115	0.108	0.107
R^2 Within	0.001	0.001	0.010	0.010	0.010	0.010

Significance levels: $*$ p < 0.05, $**$ p < 0.01, $***$ p < 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.10: **Price Impact Chasing**. The table reports additional robustness tests supplementing Table 4. It reports the estimated coefficients of regressing daily flows on (exponentially weighted) average past returns, as well as decomposed average returns into an impact and a fundamental component. Specification (1) includes style-date fixed effects. Specifications (2)-(5) are the same regressions over different subsets of funds: (2) includes only illiquid funds ($\mathcal{I}_{i,t}$ in top decile), (3) only active and thematic funds, (4) only liquid funds ($\mathcal{I}_{i,t}$ not in top decile), and (5) only passive funds (broad index funds and large-cap funds). Controls include log assets under management and 60 lags of past flows. Standard errors are double clustered at the day and fund level.

	Fund Flow				
	Style-Fixed Effects	*Illiquid Funds*	*Active & Thematic ETFs*	*Liquid Funds*	*Broad Index ETFs*
	(1)	(2)	(3)	(4)	(5)
Skill Return $\tilde{R}^{\perp}$	0.907***	0.886***	0.879***	0.442	1.230
	(0.182)	(0.179)	(0.233)	(0.294)	(0.699)
Inflated Return $\tilde{R}^{\mathcal{I}}$	2.691***	1.704*	1.584*	11.294	-4.760
	(0.671)	(0.679)	(0.718)	(6.761)	(7.899)
Style-Date FE	x	-	-	-	-
Date FE	x	x	x	x	x
Observations	63221	41201	6322	22020	6322
R^2	0.082	0.054	0.225	0.077	0.091
R^2 Within	0.036	0.034	0.089	0.054	0.036

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.11: **Fund Illiquidity and Long-Run Returns: Alternative Sample Splits**. The table reports regressions of average 3-year future fund returns $R_{i,t+h}$ on fund illiquidity (See equation 15). The columns (1)-(4) each use a different subsample of funds that outperformed the market respectively, by at least 10%, 20%, 30%, and 50% as of time t. We report annualized average returns and winsorize all explanatory variables at the 99th percentile. We standardize all explanatory variables. Standard errors are double clustered at the quarter and fund level.

	Future 3Y Fund Return			
	(1)	(2)	(3)	(4)
Fund Illiquidity $\mathcal{I}$	-0.012***	-0.036***	-0.044***	-0.049***
	(0.003)	(0.006)	(0.010)	(0.008)
Portfolio Illiquidity I_p	0.002	0.004	-0.015	-0.035
	(0.004)	(0.011)	(0.011)	(0.034)
Cumulative Past Flow	-0.009	-0.015	-0.015	-0.022
	(0.005)	(0.011)	(0.018)	(0.031)
Past Excess Return	0.008	0.008	0.017	0.024
	(0.011)	(0.018)	(0.023)	(0.033)
Quarter FE	x	x	x	x
Observations	6697	1776	708	193
R^2	0.496	0.430	0.494	0.577
R^2 Within	0.017	0.060	0.074	0.100

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.12: **Inflated Ownership and Stock Returns**. The table reports regressions of stock-level returns $r_{n,t+h}$ on inflated ownership (See equation 16). Specification (1) uses quarterly future stock returns. Specifications (2)-(6) all use average future 3-year stock returns with varying controls. Specification (3) is a weighted regression with weights given by lagged market cap. Specifications (4) and (5) use alternative cutoffs in the definition of inflated ownership: Cutoff a) includes ownership by funds with fund illiquidity $\mathcal{I}_{i,t} > 2$ and past excess market returns of 50%. Cutoff b) includes ownership by funds with fund illiquidity $\mathcal{I}_{i,t} > 1$ and excess market returns of 30%. The variables MF Ownership, High Flow Ownership, and High Ret. Ownership respectively refer to the fraction of shares outstanding held by all mutual funds, mutual fund ownership weighted by past annual flows, and the fraction of shares outstanding held by mutual funds that outperformed the market by 50% in the past year. We report annualized average returns and standardize all explanatory variables. Standard errors are double clustered at the quarter and stock level.

	Future 1Q Return	Future 3Y Return				
	(1)	(2)	(3)	(4)	(5)	(6)
Inflated Ownership	-2.981 (2.351)	-2.858*** (0.607)	-5.753*** (0.759)			-2.165* (1.080)
Inflated Ownership (Cutoff a)				-2.930*** (0.619)		
Inflated Ownership (Cutoff b)					-1.467* (0.558)	
MF Ownership						0.197*** (0.020)
High Flow Ownership						-0.065 (0.048)
High Ret. Ownership						-0.641 (1.034)
Quarter FE	x	x	x	x	x	x
Observations	309543	217620	217620	217620	217620	217620
R^2	0.157	0.160	0.203	0.160	0.160	0.167
R^2 Within	0.002	0.041	0.024	0.041	0.041	0.049

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)